JMIR Public Health and Surveillance

Impact Factor (2022): 8.5
Volume 7 (2021), Issue 9 ISSN 2369-2960 Editor in Chief: Travis Sanchez, PhD, MPH

Contents

Corrigenda and Addenda

Viewpoint

Editorial

#HealthyClimate: Call for Emergency Action to Limit Global Temperature Increases, Restore Biodiversity, and Protect Health

Lukoye Atwoli[1]; Abdullah H Baqui[2]; Thomas Benfield[3]; Raffaella Bosurgi[4]; Fiona Godlee[5]; Stephen Hancocks[6]; Richard Horton[7]; Laurie Laybourn-Langton[8]; Carlos Augusto Monteiro[9]; Ian Norman[10]; Kirsten Patrick[11]; Nigel Praities[12]; Marcel GM Olde Rikkert[13]; Eric J Rubin[14]; Peush Sahni[15]; Richard Smith[16]; Nick Talley[17]; Sue Turale[18]; Damian Vazquez[19]

[1]Editor in Chief, East African Medical Journal, Kenya
[2]Editor in Chief, Journal of Health, Population, and Nutrition, United States
[3]Editor in Chief, Danish Medical Journal, Denmark
[4]Editor in Chief, PLOS Medicine, United Kingdom
[5]Editor in Chief, The BMJ, United Kingdom
[6]Editor in Chief, British Dental Journal, United Kingdom
[7]Editor in Chief, The Lancet, United Kingdom
[8]Senior Advisor, UK Health Alliance on Climate Change, United Kingdom
[9]Editor in Chief, Revista de Saude Publica, Brazil
[10]Editor in Chief, International Journal of Nursing Studies, Netherlands
[11]Interim Editor in Chief, Canadian Medical Association Journal, Canada
[12]Executive Editor, The Pharmaceutical Journal, United Kingdom
[13]Editor in Chief, Dutch Journal of Medicine, Netherlands
[14]Editor in Chief, New England Journal of Medicine, United States
[15]Editor in Chief, National Medical Journal of India, India
[16]Chair, UK Health Alliance on Climate Change, United Kingdom
[17]Editor in Chief, Medical Journal of Australia, Australia
[18]Editor in Chief, International Nursing Review, Switzerland
[19]Editor in Chief, Pan American Journal of Public Health, United States

Corresponding Author:
Laurie Laybourn-Langton
Senior Advisor, UK Health Alliance on Climate Change
c/o BMJ Publishing Group
Tavistock Square
London, WC1H 9JR
United Kingdom
Phone: +44 (0) 20 7387 4410
Email: laurie.laybourn@ukhealthalliance.org

Abstract

The UN General Assembly in September 2021 will bring countries together at a critical time for marshalling collective action to tackle the global environmental crisis. They will meet again at the biodiversity summit in Kunming, China, and the climate conference (COP26) in Glasgow, UK. Ahead of these pivotal meetings, we—the editors of health journals worldwide—call for urgent action to keep average global temperature increases below 1.5°C, halt the destruction of nature, and protect health.

(JMIR Public Health Surveill 2021;7(9):e32958) doi:10.2196/32958

KEYWORDS

climate change; global warming; emergency action

Wealthy Nations Must Do Much More, Much Faster

The UN General Assembly in September 2021 will bring countries together at a critical time for marshalling collective action to tackle the global environmental crisis. They will meet again at the biodiversity summit in Kunming, China, and the climate conference (COP26) in Glasgow, UK. Ahead of these pivotal meetings, we—the editors of health journals worldwide—call for urgent action to keep average global temperature increases below 1.5°C, halt the destruction of nature, and protect health.

Health is already being harmed by global temperature increases and the destruction of the natural world, a state of affairs health professionals have been bringing attention to for decades [1]. The science is unequivocal; a global increase of 1.5°C above the pre-industrial average and the continued loss of biodiversity risk catastrophic harm to health that will be impossible to reverse [2,3]. Despite the world's necessary preoccupation with covid-19, we cannot wait for the pandemic to pass to rapidly reduce emissions.

Reflecting the severity of the moment, this editorial appears in health journals across the world. We are united in recognizing that only fundamental and equitable changes to societies will reverse our current trajectory.

The risks to health of increases above 1.5°C are now well established [2]. Indeed, no temperature rise is "safe." In the past 20 years, heat related mortality among people aged over 65 has increased by more than 50% [4]. Higher temperatures have brought increased dehydration and renal function loss, dermatological malignancies, tropical infections, adverse mental health outcomes, pregnancy complications, allergies, and cardiovascular and pulmonary morbidity and mortality [5,6]. Harms disproportionately affect the most vulnerable, including among children, older populations, ethnic minorities, poorer communities, and those with underlying health problems [2,4].

Global heating is also contributing to the decline in global yield potential for major crops, falling by 1.8-5.6% since 1981; this, together with the effects of extreme weather and soil depletion, is hampering efforts to reduce undernutrition [4]. Thriving ecosystems are essential to human health, and the widespread destruction of nature, including habitats and species, is eroding water and food security and increasing the chance of pandemics [3,7,8].

The consequences of the environmental crisis fall disproportionately on those countries and communities that have contributed least to the problem and are least able to mitigate the harms. Yet no country, no matter how wealthy, can shield itself from these impacts. Allowing the consequences to fall disproportionately on the most vulnerable will breed more conflict, food insecurity, forced displacement, and zoonotic disease—with severe implications for all countries and communities. As with the covid-19 pandemic, we are globally as strong as our weakest member.

Rises above 1.5°C increase the chance of reaching tipping points in natural systems that could lock the world into an acutely unstable state. This would critically impair our ability to mitigate harms and to prevent catastrophic, runaway environmental change [9,10].

Global Targets Are Not Enough

Encouragingly, many governments, financial institutions, and businesses are setting targets to reach net-zero emissions, including targets for 2030. The cost of renewable energy is dropping rapidly. Many countries are aiming to protect at least 30% of the world's land and oceans by 2030 [11].

These promises are not enough. Targets are easy to set and hard to achieve. They are yet to be matched with credible short and longer term plans to accelerate cleaner technologies and transform societies. Emissions reduction plans do not adequately incorporate health considerations [12]. Concern is growing that temperature rises above 1.5°C are beginning to be seen as inevitable, or even acceptable, to powerful members of the global community [13]. Relatedly, current strategies for reducing emissions to net zero by the middle of the century implausibly assume that the world will acquire great capabilities to remove greenhouse gases from the atmosphere [14,15].

This insufficient action means that temperature increases are likely to be well in excess of 2°C [16], a catastrophic outcome for health and environmental stability. Critically, the destruction of nature does not have parity of esteem with the climate element of the crisis, and every single global target to restore biodiversity loss by 2020 was missed [17]. This is an overall environmental crisis [18].

Health professionals are united with environmental scientists, businesses, and many others in rejecting that this outcome is inevitable. More can and must be done now—in Glasgow and Kunming—and in the immediate years that follow. We join health professionals worldwide who have already supported calls for rapid action [1,19].

Equity must be at the center of the global response. Contributing a fair share to the global effort means that reduction commitments must account for the cumulative, historical contribution each country has made to emissions, as well as its current emissions and capacity to respond. Wealthier countries will have to cut emissions more quickly, making reductions by 2030 beyond those currently proposed [20,21] and reaching net-zero emissions before 2050. Similar targets and emergency action are needed for biodiversity loss and the wider destruction of the natural world.

To achieve these targets, governments must make fundamental changes to how our societies and economies are organized and how we live. The current strategy of encouraging markets to swap dirty for cleaner technologies is not enough. Governments must intervene to support the redesign of transport systems, cities, production and distribution of food, markets for financial investments, health systems, and much more. Global coordination is needed to ensure that the rush for cleaner technologies does not come at the cost of more environmental destruction and human exploitation.

Many governments met the threat of the covid-19 pandemic with unprecedented funding. The environmental crisis demands a similar emergency response. Huge investment will be needed, beyond what is being considered or delivered anywhere in the world. But such investments will produce huge positive health and economic outcomes. These include high quality jobs, reduced air pollution, increased physical activity, and improved housing and diet. Better air quality alone would realize health benefits that easily offset the global costs of emissions reductions [22].

These measures will also improve the social and economic determinants of health, the poor state of which may have made populations more vulnerable to the covid-19 pandemic [23]. But the changes cannot be achieved through a return to damaging austerity policies or the continuation of the large inequalities of wealth and power within and between countries.

Cooperation Hinges on Wealthy Nations Doing More

In particular, countries that have disproportionately created the environmental crisis must do more to support low and middle income countries to build cleaner, healthier, and more resilient societies. High income countries must meet and go beyond their outstanding commitment to provide $100bn a year, making up for any shortfall in 2020 and increasing contributions to and beyond 2025. Funding must be equally split between mitigation and adaptation, including improving the resilience of health systems.

Financing should be through grants rather than loans, building local capabilities and truly empowering communities, and should come alongside forgiving large debts, which constrain the agency of so many low income countries. Additional funding must be marshalled to compensate for inevitable loss and damage caused by the consequences of the environmental crisis.

As health professionals, we must do all we can to aid the transition to a sustainable, fairer, resilient, and healthier world. Alongside acting to reduce the harm from the environmental crisis, we should proactively contribute to global prevention of further damage and action on the root causes of the crisis. We must hold global leaders to account and continue to educate others about the health risks of the crisis. We must join in the work to achieve environmentally sustainable health systems before 2040, recognizing that this will mean changing clinical practice. Health institutions have already divested more than $42bn of assets from fossil fuels; others should join them [4].

The greatest threat to global public health is the continued failure of world leaders to keep the global temperature rise below 1.5°C and to restore nature. Urgent, society-wide changes must be made and will lead to a fairer and healthier world. We, as editors of health journals, call for governments and other leaders to act, marking 2021 as the year that the world finally changes course.

Conflicts of Interest

We have read and understood BMJ policy on declaration of interests and FG serves on the executive committee for the UK Health Alliance on Climate Change and is a Trustee of the Eden Project. RS is the chair of Patients Know Best, has stock in UnitedHealth Group, has done consultancy work for Oxford Pharmagenesis, and is chair of the Lancet Commission of the Value of Death. None further declared.

Provenance and Peer Review
Commissioned; not externally peer reviewed.

Editorial Notice
This editorial is being published simultaneously in many international journals.
Please see the full list here: https://tinyurl.com/3yj453jx.
The editor of *JMIR Public Health and Surveillance*, Travis Sanchez, as well as the publisher JMIR Publications, are signatories of the editorial.

References

1. In support of a healthy recovery. Healthy Recovery. URL: https://healthyrecovery.net [accessed 2021-08-25]
2. Global Warming of 1.5 ºC: an IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Intergovernmental Panel on Climate Change. 2018. URL: https://www.ipcc.ch/sr15/ [accessed 2021-08-25]
3. Summary for policymakers: the global assessment report on biodiversity and ecosystem services. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. 2019. URL: https://ipbes.net/sites/default/files/2020-02/ipbes_global_assessment_report_summary_for_policymakers_en.pdf [accessed 2021-08-25]
4. Watts N, Amann M, Arnell N, Ayeb-Karlsson S, Beagley J, Belesova K, et al. The 2020 report of The Lancet Countdown on health and climate change: responding to converging crises. Lancet 2021 Jan 09;397(10269):129-170. [doi: 10.1016/S0140-6736(20)32290-X] [Medline: 33278353]

5. Rocque RJ, Beaudoin C, Ndjaboue R, Cameron L, Poirier-Bergeron L, Poulin-Rheault RA, et al. Health effects of climate change: an overview of systematic reviews. BMJ Open 2021 Jun 09;11(6):e046333 [FREE Full text] [doi: 10.1136/bmjopen-2020-046333] [Medline: 34108165]
6. Haines A, Ebi K. The imperative for climate action to protect health. N Engl J Med 2019 Jan 17;380(3):263-273. [doi: 10.1056/NEJMra1807873] [Medline: 30650330]
7. Preventing the next pandemic: zoonotic diseases and how to break the chain of transmission. United Nations Environment Programme and International Livestock Research Institute. 2020. URL: https://72d37324-5089-459c-8f70-271d19427cf2.filesusr.com/ugd/056cf4_b5b2fc067f094dd3b2250cda15c47acd.pdf [accessed 2021-08-25]
8. Intergovernmental Panel on Climate Change. Summary for policymakers. In: Climate change and land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. Forthcoming. Geneva, Switzerland: IPCC; 2019.
9. Lenton TM, Rockström J, Gaffney O, Rahmstorf S, Richardson K, Steffen W, et al. Climate tipping points - too risky to bet against. Nature 2019 Nov;575(7784):592-595. [doi: 10.1038/d41586-019-03595-0] [Medline: 31776487]
10. Wunderling N, Donges JF, Kurths J, Winkelmann R. Interacting tipping elements increase risk of climate domino effects under global warming. Earth Syst Dynamics 2021 Jun 03;12(2):601-619. [doi: 10.5194/esd-12-601-2021]
11. High Ambition Coalition. URL: https://www.hacfornatureandpeople.org [accessed 2021-08-25]
12. Are national climate commitments enough to protect our health? Global Climate and Health Alliance. URL: https://climateandhealthalliance.org/initiatives/healthy-ndcs/ndc-scorecards/ [accessed 2021-08-25]
13. Climate strikers: open letter to EU leaders on why their new climate law is 'surrender'. Carbon Brief. 2020. URL: https://www.carbonbrief.org/climate-strikers-open-letter-to-eu-leaders-on-why-their-new-climate-law-is-surrender [accessed 2021-08-25]
14. Fajardy M, Köberle A, MacDowell N, Fantuzzi A. BECCS deployment: a reality check. Grantham Institute Briefing paper No 28. 2019. URL: https://www.imperial.ac.uk/media/imperial-college/grantham-institute/public/publications/briefing-papers/BECCS-deployment---a-reality-check.pdf [accessed 2021-08-25]
15. Anderson K, Peters G. The trouble with negative emissions. Science 2016 Oct 14;354(6309):182-183. [doi: 10.1126/science.aah4567] [Medline: 27738161]
16. Climate Action Tracker. URL: https://climateactiontracker.org [accessed 2021-08-25]
17. Global biodiversity outlook 5. Secretariat of the Convention on Biological Diversity. 2020. URL: https://www.cbd.int/gbo5 [accessed 2021-08-25]
18. Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, et al. Sustainability. Planetary boundaries: guiding human development on a changing planet. Science 2015 Feb 13;347(6223):1259855 [FREE Full text] [doi: 10.1126/science.1259855] [Medline: 25592418]
19. Our calls for action. UK Health Alliance. URL: http://www.ukhealthalliance.org/cop26/ [accessed 2021-08-25]
20. Warming projections global update: May 2021. Climate Action Tracker. URL: https://climateactiontracker.org/documents/853/CAT_2021-05-04_Briefing_Global-Update_Climate-Summit-Momentum.pdf [accessed 2021-08-25]
21. United Nations Environment Programme. Emissions Gap Report 2020. Nairobi, Kenya: UNEP; 2020.
22. Markandya A, Sampedro J, Smith SJ, Van Dingenen R, Pizarro-Irizar C, Arto I, et al. Health co-benefits from air pollution and mitigation costs of the Paris Agreement: a modelling study. Lancet Planet Health 2018 Mar;2(3):e126-e133 [FREE Full text] [doi: 10.1016/S2542-5196(18)30029-9] [Medline: 29615227]
23. Paremoer L, Nandi S, Serag H, Baum F. Covid-19 pandemic and the social determinants of health. BMJ 2021 Jan 28;372:n129 [FREE Full text] [doi: 10.1136/bmj.n129] [Medline: 33509801]

Edited by G Eysenbach; submitted 17.08.21; this is a non–peer-reviewed article;accepted 17.08.21; published 05.09.21.

Please cite as:
Atwoli L, Baqui AH, Benfield T, Bosurgi R, Godlee F, Hancocks S, Horton R, Laybourn-Langton L, Monteiro CA, Norman I, Patrick K, Praities N, Olde Rikkert MGM, Rubin EJ, Sahni P, Smith R, Talley N, Turale S, Vazquez D
#HealthyClimate: Call for Emergency Action to Limit Global Temperature Increases, Restore Biodiversity, and Protect Health
JMIR Public Health Surveill 2021;7(9):e32958
URL: https://publichealth.jmir.org/2021/9/e32958
doi:10.2196/32958
PMID:34483097

Original Paper

Assessing the Electronic Evidence System Needs of Canadian Public Health Professionals: Cross-sectional Study

Bandna Dhaliwal[1], MPH; Sarah E Neil-Sztramko[1,2], PhD; Nikita Boston-Fisher[3], MPH; David L Buckeridge[3], MD, PhD; Maureen Dobbins[1,4], RN, PhD

[1]National Collaborating Centre for Methods and Tools, McMaster University, Hamilton, ON, Canada

[2]Department of Health Research Methods, Evidence and Impact, McMaster University, Hamilton, ON, Canada

[3]School of Population and Global Health, McGill University, Montreal, QC, Canada

[4]School of Nursing, McMaster University, Hamilton, ON, Canada

Corresponding Author:
Maureen Dobbins, RN, PhD
National Collaborating Centre for Methods and Tools
McMaster University
175 Longwood Road South, Suite 210a
Hamilton, ON, L8P 0A1
Canada
Phone: 1 905 525 9140 ext 20450
Email: dobbinsm@mcmaster.ca

Abstract

Background: True evidence-informed decision-making in public health relies on incorporating evidence from a number of sources in addition to traditional scientific evidence. Lack of access to these types of data as well as ease of use and interpretability of scientific evidence contribute to limited uptake of evidence-informed decision-making in practice. An electronic evidence system that includes multiple sources of evidence and potentially novel computational processing approaches or artificial intelligence holds promise as a solution to overcoming barriers to evidence-informed decision-making in public health.

Objective: This study aims to understand the needs and preferences for an electronic evidence system among public health professionals in Canada.

Methods: An invitation to participate in an anonymous web-based survey was distributed via listservs of 2 Canadian public health organizations in February 2019. Eligible participants were English- or French-speaking individuals currently working in public health. The survey contained both multiple-choice and open-ended questions about the needs and preferences relevant to an electronic evidence system. Quantitative responses were analyzed to explore differences by public health role. Inductive and deductive analysis methods were used to code and interpret the qualitative data. Ethics review was not required by the host institution.

Results: Respondents (N=371) were heterogeneous, spanning organizations, positions, and areas of practice within public health. Nearly all (364/371, 98.1%) respondents indicated that an electronic evidence system would support their work. Respondents had high preferences for local contextual data, research and intervention evidence, and information about human and financial resources. Qualitative analyses identified several concerns, needs, and suggestions for the development of such a system. Concerns ranged from the personal use of such a system to the ability of their organization to use such a system. Recognized needs spanned the different sources of evidence, including local context, research and intervention evidence, and resources and tools. Additional suggestions were identified to improve system usability.

Conclusions: Canadian public health professionals have positive perceptions toward an electronic evidence system that would bring together evidence from the local context, scientific research, and resources. Elements were also identified to increase the usability of an electronic evidence system.

(JMIR Public Health Surveill 2021;7(9):e26503) doi:10.2196/26503

KEYWORDS

population surveillance; evidence-informed decision-making; needs assessment; public health; precision public health

Introduction

Background

In the time of growing funding restraints for public health in Canada and across the world, public health professionals and organizations must function efficiently to meet the expanding public health needs. Changes to the funding structure of public health have been underway across Canada for several years [1]. In the province of Quebec, the public health budget was cut by 33% in 2015; cuts of up to 30% were proposed in Ontario in 2019; and more recently, cuts of up to 10% were proposed in Alberta [2-4]. Constraints of public health funding are not limited to Canada; countries such as the United States and England have seen similar trends [5,6]. Exceptions to this trend can occur during times of crisis, including the current COVID-19 (SARS-CoV-2) pandemic, whereby further funding cuts are halted or funding is even increased; however, these exceptions may be limited in duration [7].

In addition to the impacts of restructuring and decreasing funding, the public health sector is challenged to function effectively with the exponential increase in the amount of scientific evidence generated and the local contextual data available, as seen in response to the COVID-19 pandemic. The amount of information available now exceeds the capacity of public health professionals to comprehensively assess, consider, and use in program planning decisions. Given these challenges, there is a need to understand how public health professionals and organizations can meet increasing demands for evidence-informed decision-making with fewer resources [8].

A 2016 scoping review identified 4 factors that were associated with improved efficiency in public health systems: (1) increased financial resources, (2) increased staffing per capita, (3) jurisdictions serving a population of 50,000 to 500,000 people, and (4) evidence-based organizational and administrative features [3]. Although the first 3 factors are controlled at a subnational or federal government level, institutional changes to support evidence-based practices occur at a local level and, therefore, present opportunities for change. Within the category of administrative evidence-based features, one umbrella review identified five high-priority, locally modifiable best practices that contribute to public health system productivity: workforce development, leadership, organizational climate and culture, interorganizational relationships and partnerships, and financial processes [9]. Specifically, access to and free flow of relevant information were identified as factors that can contribute to public health system performance in the short term; this includes ready access to high-quality information and tailored messages for evidence-based decision-making [9].

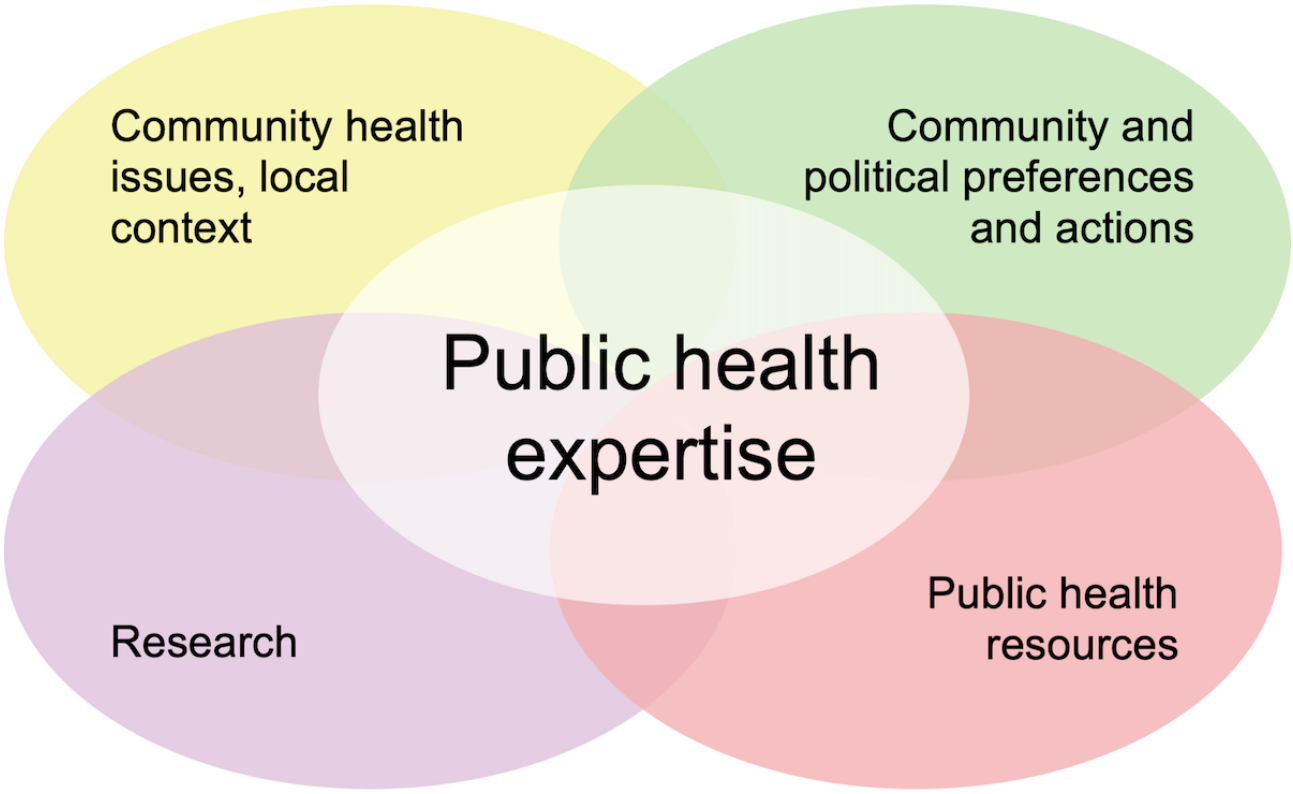
Evidence-based public health and practice is defined as “the process of integrating science-based interventions with community preferences to improve the health of populations” [10], whereas evidence-informed public health is defined as “using research evidence with public health expertise, resources, and knowledge about community health issues, local context, and political climate to make policy and programming decisions” [11,12]. Using the term *informed* rather than *based* allows for nuances of the decision-making process that are not solely based in research evidence, such as considerations of the political climate and expertise of public health professionals [9,13]. Using evidence to inform program planning decisions increases the likelihood that services with known effectiveness will be delivered and supports the efficient use of human and financial resources. Across Canada, evidence-informed decision-making is becoming a central tenant of public health and is now incorporated into public health standards in a growing number of provinces, including Ontario, Nova Scotia, and British Columbia [14-16]. Globally, similar concepts are gaining traction, for example, evidence-informed practice has been acknowledged by the Centers for Disease Control and Prevention as a central component of essential public health services to improve and innovate public health functions [17].

The National Collaborating Centre for Methods and Tools (NCCMT) has developed a model to guide the consideration of different sources of evidence, providing a structure for the use of different types of evidence in the decision-making process (Figure 1) [11]. The 4 spheres of this model are research evidence (published scientific literature, including qualitative or quantitative studies), local context (consideration of the specific needs of the community through quantitative surveillance data, ie, population health indicators), community preferences (using qualitative methods to assess the needs and interests of its members), and resources (human and financial) [11]. Gathering evidence within each of these spheres and making sense of the evidence in relation to a specific jurisdiction is an increasingly daunting task, as the amount of evidence in all spheres grows exponentially [9,18,19]. Previous research has shown that public health professionals value evidence-informed decision-making but encounter barriers such as lack of time; management support; and knowledge and skills to locate, critically analyze, and interpret evidence [9]. Additional challenges exist in appraising, synthesizing, and interpreting different types of evidence, such as limited capacity to apply evidence from the local context and community preferences to program planning [20]. Acquiring and analyzing data to support evidence-informed decision-making can be an intensive process; thus, to truly increase efficiency and effectiveness, system-level support and multiorganization data sharing and computational methods such as artificial intelligence (AI) may offer solutions [9,18,21].

The goal of precision public health is similar to that of evidence-informed decision-making—to put forth effective public health interventions that improve population health [22]. Precision public health is defined as an “emerging practice to more granularly predict and understand public health risks and customize treatments for more specific and homogenous subpopulations, often using new data, technologies and methods” [23]; it aims to improve population health outcomes by enabling the right interventions to be delivered to the right populations at the right time to prevent disease and to protect and promote health [23,24]. Although surveillance systems have traditionally monitored infectious diseases, it is now possible for systems to simultaneously consider data from many sources and apply statistical and AI methods to estimate and monitor the impact of risk factors and diseases on health and other outcomes [21]. AI is a generic term used to define "nonhuman

intelligence that is measured by its ability to replicate human mental skills or acting rationally" [25,26]. A hypothetical evidence system that encompasses multiple sources of data and evidence would require the large statistical capabilities of AI to make use of the evidence feasible. It holds promise as a methodological toolbox for supporting public health decision-making and improving population health outcomes, although the evidence is based on a small number of preliminary studies [27,28]. There are many potential uses of AI methods, such as machine learning, in public health, including processing patterns in complex data, modeling policy decisions, and understanding the causal pathways through which interventions influence health outcomes [29]. However, there has been limited implementation of AI in public health initiatives internationally [30]. Although the potential for AI to significantly impact population health exists, substantial human input is required to develop algorithms that can sort and assess evidence inputs and make recommendations for policy and practice [27].

Figure 1. The National Collaborating Centre for Methods and Tools' evidence-informed decision-making model.



Objectives

The available evidence systems are limited by the type of evidence they provide, requiring large time and expertise input by professionals to gather and analyze data from multiple platforms [18,31-39]. Currently, there are no public health evidence systems described in the literature that bring together multiple evidence sources in 1 central location with large statistical analysis abilities similar to that of AI; to our knowledge, there is little or no information available on the perceived need for such a system among public health professionals across Canada or internationally. An understanding of the preferences of public health professionals for an electronic evidence system and the desired functionality is critical to inform the development of such systems. The purpose of this study is to identify the needs and preferences of Canadian public health professionals for an electronic evidence system that combines data about local population parameters and context with relevant research evidence about health intervention effectiveness and resources required for successful implementation.

Methods

Design

A web-based cross-sectional survey was used to assess the preferences of public health professionals across Canada with respect to an electronic evidence system.

Study Sample

Eligible participants were individuals currently working in any field in public health organizations in Canada. The web-based survey was available for completion in either English or French. Individuals who identified as students studying public health without any indication of work experience were excluded. Participants were recruited over a 2-week period in February 2019 through the NCCMT's mailing list (survey was disseminated via email to 11,525 recipients, and 3288 emails were opened) and the Canadian Public Health Association's bulletin listserv (survey was disseminated via email to 1370 recipients, and 488 emails were opened). Ethics review was not required by the host institution, as this evaluation aimed to inform about the needs for and future development of an electronic evidence system.

Questionnaire Development

The survey was developed by members of the research team with expertise in public health, AI, and informatics. The survey underwent multiple rounds of consultation between study investigators. Once agreement was reached, the questionnaire was translated by a certified French translator. The final questions were mainly multiple-choice questions, with 1 Likert scale question and 3 open-ended questions.

Data Collection

Upon initiation of the questionnaire, via LimeSurvey (LimeSurvey GmbH), respondents were asked to consider the following hypothetical scenario:

> *Imagine an electronic system that combines data about your local population with relevant research evidence about the effectiveness of health interventions. The data in this system would include measures of determinants of health, morbidity, and demographics, and could also be compared to similar measures for other geographic regions / populations. The research evidence could include information on the effectiveness of the interventions in different settings/populations and the resources required for implementing those interventions.*

Participants were asked to complete an 18-item questionnaire comprising questions on respondents' characteristics, preference and need for an electronic evidence system, and barriers and facilitators to use (Multimedia Appendix 1). All responses on LimeSurvey were anonymous, and no identifying data were collected.

Data Analysis

Quantitative analysis was completed using SPSS (version 25.0, IBM Corp). Descriptive statistics were calculated as means and SDs or percentages, where appropriate. Quantitative responses were categorized post hoc into three types of evidence from the evidence-informed decision-making model: community health issues and local context, research evidence, and public health resources [11]. Given the previous findings that preferences for specific sources of evidence vary by position levels within public health [40,41] and understanding the different perspectives that these groups bring, we planned a subgroup analysis to compare responses by position. We compared the responses of 3 independent categories of positions respondents indicated they held whereas other positions had overlap, as respondents were able to select all position levels that applied. These 3 categories are frontline public health or community providers, project or program management, and senior management or administration. For continuous data, the Levene test was used to assess the homogeneity of variance across the three position groups. Where the assumption of homogeneity was met (P=.05), we used a 1-way analysis of variance across the 3 independent groups. When the assumption of homogeneity of variance was not met, the Games-Howell post hoc test was used and the differences among the 3 groups were presented. For categorical data, the Pearson chi-square test was used with comparison across columns. When the cell sizes were less than 5, the Fisher exact test was used to compare the groups.

To analyze the data from the open-ended questions and all other qualitative responses included in the *other* multiple-choice questions open text, data were imported into NVivo (version 12, QSR International). The analysis began with an initial scan of the responses and a discussion of possible themes. Two authors (BD and SENS) independently reviewed the responses using an inductive line-by-line approach and then discussed themes emerging from data and refined the coding scheme [42]. Within the larger theme of needs and preferences, a deductive approach was used where appropriate to code responses according to the following spheres in NCCMT's evidence-informed decision-making model for public health: community health issues and local context, research evidence, and public health resources [11]. Codes and themes were discussed continuously until the final coding was agreed upon by both the authors.

Results

Quantitative Results

A total of 487 respondents clicked on the survey link, initiating the survey. After removing surveys that were not started (n=107) or completed by students (n=9), data from a total of 371 respondents (347 full surveys and 24 partial respondents) were included in this analysis. Respondents were primarily English speakers, with at least a master's degree, and working in either local, provincial, or territorial government (Table 1). Although many respondents selected multiple positions, frontline public health or community provider (73/371, 19.7%), program or project management (55/371, 14.8%), and senior management or administration (25/371, 6.7%) were largely unique. Respondents reported working in an average of 2.3 (SD 1.8) specific areas of public health, the most commonly being the social determinants of health, chronic diseases, and *all areas* of public health.

Table 1. Characteristics of included responses from professionals working in the public health field in February 2019 (N=371).

Characteristics	Respondents, n (%)
Language	
English	361 (97.3)
French	10 (2.7)
Organization type	
Local or regional government	175 (47.2)
Provincial government	72 (19.4)
University or research center	40 (10.8)
Federal government	31 (8.4)
Not-for-profit organizations	26 (7)
Territorial government	8 (2.2)
Indigenous organization	3 (0.8)
Consultant organizations	3 (0.8)
Primary care or hospitals	2 (0.5)
Other or no response	11 (3)
Degree	
Master's	206 (55.5)
Bachelor's	96 (25.9)
Doctorate	42 (11.3)
Diploma	12 (3.2)
Doctor of Medicine	11 (3)
Other or no response	4 (1.1)
Position level	
Program or project staff	110 (29.6)
Consultant specialist	87 (23.5)
Frontline public health or community provider	73 (19.7)
Program or project management (eg, manager)	55 (14.8)
Faculty	29 (7.8)
Senior management or administration (eg, director or executive)	25 (6.7)
Government official including policy	21 (5.7)
Chief medical or medical or associate medical officer of health	4 (1.1)
Other or no response	12 (3.2)
Practice discipline	
Program evaluator or planner	76 (20.5)
Health promoter	74 (19.9)
Public health nurse	68 (18.3)
Epidemiologist	55 (14.8)
Knowledge broker or knowledge translation specialist	52 (14)
Health analyst	38 (10.2)
Policy analyst	36 (9.7)
Administrator or administration	29 (7.8)
Policy advisor	24 (6.5)
Public health educator	21 (5.7)

Characteristics	Respondents, n (%)
University or college educator	20 (5.4)
Dietitian	18 (4.9)
Student	17 (4.6)
Librarian or information specialist	13 (3.5)
Physician	12 (3.2)
Public health inspector	11 (3)
Nutritionist	10 (2.7)
Other health clinician	10 (2.7)
Research staff	6 (1.6)
Dentist	3 (0.8)
Other or no response	7 (1.9)
Area of public health	
Social determinants of health	131 (35.3)
Chronic disease (eg, nutrition and physical activity)	130 (35)
All areas of public health	105 (28.3)
Health policy	88 (23.7)
Mental health including substance use	85 (22.9)
Injury prevention	62 (16.7)
Infectious disease	58 (15.6)
Family health or reproductive health	54 (14.6)
Environmental health	44 (11.9)
Reproductive health	29 (7.8)
Emergency preparedness or response	25 (6.7)
Dental health	17 (4.6)
School or child health	11 (3)
Hospital care	6 (1.6)
Other or no response	9 (2.4)

The majority of respondents reported that the proposed electronic evidence system would extremely (186/371, 50.1%), very much (141/371, 38%), or moderately (37/371, 9.9%) assist them in their roles. Less than 2% of respondents indicated that an electronic evidence system would only slightly (3/371, 0.8%) or not at all (3/371, 0.8%) help with the work they do. Moreover, 0.3% (1/371) of participants did not answer. Participants' preferences for community health issues and local contextual data are shown in Table 2. Interest in risk data, namely, prevalence and incidence of disease, was high, along with demographic characteristics. To a lesser degree, respondents reported wanting system functionality to compare their local population with other regions.

Table 2. Preferences for community health issues and local context among public health professionals who completed the web-based needs assessment in February 2019 (n=370).

	Respondents, n (%)
Data	
Risk	357 (96.5)
Demographics	352 (95.1)
Other	107 (28.9)
Comparisons	
Local to regional	283 (76.5)
To smaller subdivisions	283 (76.5)
To larger regions	255 (68.9)
Other	26 (7)
Risk factors	
Prevalence	351 (94.9)
Incidence	347 (95.1)
Other	41 (11.1)
Demographics	
Age	363 (98.4)
Sex	352 (95.1)
Income	351 (94.6)
Education	336 (90.8)
Ethnicity	326 (88.1)
Other	98 (26.5)

A summary of preferences for the types of research evidence is shown in Table 3. Best practice guidelines, systematic reviews or meta-analyses, and practice-based evidence elicited more favorable responses than quantitative or qualitative single studies. Related specifically to interventions, most respondents wanted information about the magnitude of effect and study quality. The required human and financial resources to deliver the intervention and heterogeneity of effects were selected less frequently.

Table 3. Preferences for research evidence among public health professionals who completed the web-based needs assessment in February 2019 (n=347).

	Respondents, n (%)
Types of research evidence	
Best practice guidelines	323 (93.1)
Systematic reviews or meta-analyses	312 (89.9)
Practice-based evidence	305 (87.9)
Single studies	
Qualitative	131 (37.8)
Quantitative	121 (34.9)
Other	13 (3.7)
Information about interventions	
Magnitude of effect	316 (91.1)
Quality of study	315 (90.8)
Required human resources	271 (78.1)
Required financial resources	261 (75.2)
Heterogeneity in effect	230 (66.3)
Other	47 (13.5)

Information about the preference for information about public health resources required is presented in Table 4. The need for information about human resources, including the type and intensity of staff training, training to sustain a program, and the number of staff required, was frequently selected, more so than staff discipline. With respect to financial resources, a preference for cost-effectiveness was most commonly identified, followed by cost. Information on cost-utility and economic modeling were selected less frequently.

Table 4. Preferences for information on public health resources among public health professionals who completed the web-based needs assessment in February 2019 (n=347).

	Respondents, n (%)
Human resources information	
Type and intensity of training	295 (85)
Type of training to sustain program	277 (79.8)
Number of staff required	273 (78.7)
Discipline of staff	235 (67.7)
Financial resources information	
Cost-effectiveness	310 (89.3)
Cost	263 (75.8)
Cost-utility	160 (46.1)
Economic modelling data	124 (35.7)
Other	23 (6.6)

When comparing preferences across the 3 decision-making levels (ie, frontline staff, program management, and senior management), a few notable differences were found (Table 5). Respondents who indicated they were program or project management providers were more likely to indicate a need for demographic data and heterogeneity in effect compared with frontline public health or community providers. No other differences were statistically significant.

Table 5. Preferences for an electronic evidence system among frontline public health or community providers, project or program management, and senior management or administration who completed the web-based needs assessment in February 2019.

	Frontline public health or community providers, n/n (%)	Program or project management, n/n (%)	Senior management or administration, n/n (%)
What data would you want to be included in such a system?			
Risk factors	71/73 (97)	52/55 (94)	24/25 (96)
Demographics	64/73 (88)[a]	54/55 (98)[a]	25/25 (100)
What would you like to compare your local population with?			
Compare your local region with a similar region in size	53/73 (73)	43/55 (78)	21/25 (84)
Compare subregions within your local regions	59/73 (81)	41/55 (75)	18/25 (72)
Compare your local region with a larger region in size	50/73 (68)	33/55 (60)	19/25 (76)
For data related to risk factors and diseases, which data would you want to be included in the system?			
Prevalence	69/73 (95)	52/55 (95)	25/25 (100)
Incidence	68/73 (93)	50/55 (91)	25/25 (100)
For data related to demographics, which data would you want to be included in the system?			
Age	71/73 (97)	54/55 (98)	25/25 (100)
Sex	68/73 (93)	53/55 (96)	25/25 (100)
Income	66/73 (90)	53/55 (96)	25/25 (100)
Education	68/73 (93)	47/55 (85)	22/25 (88)
Ethnicity	62/73 (85)	51/55 (93)	23/25 (92)
For research evidence about an intervention, what information would you want to be included?[b]			
Magnitude of effect	57/67 (85)	50/53 (94)	22/24 (92)
Quality of study	55/67 (82)	48/53 (91)	22/24 (92)
Required human resources	55/67 (82)	42/53 (79)	18/24 (75)
Required financial resources	52/67 (78)	39/53 (74)	18/24 (75)
Heterogeneity in effect	36/67 (54)[c]	40/53 (75)[c]	15/24 (62)
Which of the following research evidence options would you want to be made available?[b]			
Best practice guidelines	64/67 (95)	50/53 (94)	23/24 (96)
Systematic reviews or meta-analyses	53/67 (79)	45/53 (85)	19/24 (79)
Practice-based evidence (program evaluations)	56/67 (84)	51/53 (96)	20/24 (83)
Single studies			
Qualitative	27/67 (40)	21/53 (40)	6/24 (25)
Quantitative	24/67 (36)	18/53 (34)	7/24 (29)
For human resources, which information would you want available from the evidence?[b]			
Type and intensity of training required to be competent to deliver interventions or programs	23/67 (96)	49/53 (92)	19/24 (79)
Type of training required to sustain program	19/67 (79)	41/53 (77)	21/24 (87)
Number of staff required to implement the program	20/67 (83)	47/53 (89)	20/24 (83)
Discipline of required staff	6/67 (25)[a]	40/53 (75)	19/24 (79)[a]
For financial resources, which information would you want available?[b]			
Cost-effectiveness	61/67 (91)	47/53 (89)	21/24 (87)
Cost	47/67 (70)	41/53 (77)	19/24 (79)
Cost-utility	28/67 (42)	29/53 (55)	12/24 (50)

	Frontline public health or community providers, n/n (%)	Program or project management, n/n (%)	Senior management or administration, n/n (%)
Economic modeling data	23/67 (34)	20/53 (38)	10/24 (42)

[a]Indicates statistically significant difference (P=.04).

[b]Some participants only provided partial answers to the survey; thus, the sample sizes differ across questions.

[c]Indicates statistically significant difference (P=.045).

Qualitative Results

Qualitative data from open-ended questions identified several specific needs, concerns, and suggestions for an electronic evidence system. Echoing the preferences for cross-jurisdictional comparisons found in the quantitative results, respondents identified the ability to compare indicators across geographic areas, the inclusion of equity indicators and epidemiologic data, and the use of geographic information systems as *other* specific requests. Health equity indicators, such as the determinants of health, were seen as important in identifying and describing vulnerable populations. One respondent stated:

> *...generally, any data that might link to poverty measures, immigration status, housing situation (e.g., housed, homeless), recipient of childcare subsidy, recipient of social assistance etc.*

A major theme that emerged with respect to the type of research evidence to be included was the usefulness of research beyond what is typically considered public health interventions, such as organizational interventions and interventions from the fields of education, social services, and law. Regardless of the type of research, there was a strong desire for all evidence to be critically appraised and be presented alongside summaries or statements to help interpret the evidence, as illustrated in the following quote:

> *...while I would be open to including all kinds of research, I would want them to be graded, to ensure that one could assess the quality of the evidence.*

Similarly, participants also emphasized the need for practice-based evidence that provides contextual information on the outcomes of interventions and implementation. This included evidence on the context in which an intervention was implemented, adoption of the intervention, and considerations on how to deliver and sustain it in the community. This is reflected in a respondent's comment:

> *[I] need a way to analyze context where an intervention is used. For example, if previously similar interventions had been tried in an area or subpopulation there may already be a delivery system or key partnerships in place, and there may also be a learning effect from previous work that is beneficial to achieving results with a "new" intervention.*

To support the need for contextual and implementation data, respondents also specifically mentioned the need for qualitative and mixed-methods research and needs assessments conducted within other communities or organizations.

Related to resources and tools for practice, a need for theories, methods, or frameworks to support adaption or to implement a program in their community was identified. Some respondents mentioned specific frameworks, such as the Reach, Effectiveness, Adoption, Implementation, and Maintenance framework, whereas others had general suggestions for *evaluation* or *implementation* frameworks. There were also requests for tools to support practice, such as the Applicability and Transferability Tool [43], which supports public health planners' use of evidence to support appropriate programming for the community, or survey question templates.

In addition to the specific needs for an electronic system, a number of potential concerns or barriers emerged. Concerns were related to either the electronic system itself or the ability to adopt a system within public health organizations. Concerns about keeping a system up to date stemmed from the understanding that evidence is created at rapid rates and new data are constantly being collected. For such a system to be useful, data would need to be current. Sustainability of the system beyond its initial creation was seen as a critical element for successful implementation, with some participants citing concerns if the system were to be funded by a research grant. An understanding of plans for long-term upkeep and sustainability may be a requirement for individual users or organizations to invest time in learning how to use the system.

The potential for duplication of existing resources was another concern related to such a system, with respondents citing specific databases or systems that already exist, and how existing databases and systems would complement or conflict with any new system. One respondent captured this sentiment, stating that:

> *...these systems are difficult to set up AND keep up to date. In addition, other similar systems (except for intervention data) already exist and this may add to the confusion for users (which data is THE official data?) Why do we observe differences between two systems for same indicator? Etc.*

Related to the ability of individuals and organizations to adopt and implement the system, major themes about usability and costs emerged. The cost of the proposed system was seen as a key potential barrier, with questions about who would pay for it arising frequently. Second, the ability of a system to work with existing information technology infrastructure, such as outdated or restrictive computer systems and limited or slow internet connectivity, was raised as a concern. Beyond the initial barriers of cost and access, an organization's ability to adopt the use of a system in their regular workflow was reported to be dependent on the ability of individual staff to use the system adequately, which requires not only buy-in by the individual employee but also senior-level management. Finally, concerns

about data privacy and maintenance of confidentiality were also expressed.

A number of suggestions for success emerged from the qualitative data. The most frequently mentioned requirement to facilitate use of the system were transparency of methodology used, including the criteria to select evidence for inclusion, the methods used to evaluate and synthesize evidence, and the overall quality of the evidence included. One respondent stated that they "...would need a very detailed 'methods' section of this system to be able to be confident in it." Sufficient staff training was also suggested to support the use of the proposed system.

Finally, respondents requested specific functions or system formatting elements, such as the ability to make graphs, print or export data, and retrieve contact information of data sharers on the system.

Discussion

Principal Findings

The purpose of this study is to understand the preferences of Canadian public health professionals for an electronic evidence system. The results indicate that there is a perceived need for an electronic evidence system; however, certain considerations related to the type of information included and how it would be presented must be addressed for such a system to be adopted and used effectively for public health decision-making.

Preferences for all 3 types of evidence (community health issues and local context, research evidence, and public health resources) were generally high. This aligns with previous research that public health professions value different sources of evidence [20]. An important consideration to emerge from both the quantitative and qualitative data was the need to understand the quality of the evidence included within the system. Participants suggested that the evidence included in an electronic evidence system should be preappraised and include a statement of interpretation along with a description of the methodology used to appraise the evidence. Using the best available evidence is a critical component of evidence-informed decision-making [11]. Critical appraisal requires knowledge and skill development through training and time to appraise evidence on a continual basis. Respondents were aware that there was a need for evidence to be appraised but wanted a system to do this for them. This was also the case for the ability to interpret evidence appropriately, and there was recognition that there may be various levels of skills to understand evidence. These findings are in line with previous literature that shows that time, knowledge, and skills in appraising different types of evidence are a barrier to evidence-informed decision-making in public health [9,20]. A qualitative study involving public health decision makers found that clear implication statements from the evidence facilitated uptake of this knowledge in practice and decision-making processes [44]. Including evidence that has been preappraised and accompanied by interpretation statements, possibly through AI approaches within an electronic evidence system, may make it easier for users to understand and use the evidence, effectively overcoming some challenges to the evidence-informed decision-making process.

The need for information to examine and address the determinants of health and health equity came through strongly in this study. This is not surprising given the previous literature that suggests that equity information is commonly lacking in scientific publications. A 2016 scoping review of population health interventions found that most studies included minimal contextual information on the target population and intervention setting [19]. This contextual information is important for effective decision-making, as it is necessary to appropriately apply evidence in different settings. Furthermore, concerns have been raised about the potential of AI to "amplify inequities in society" because of inherent biases in data sets and programming on a large scale [45]. Although AI is useful in identifying which trends are occurring, some AI methods, such as machine learning, may lack the ability to describe why the pattern occurs [46]. An understanding of contextual indicators such as the social determinants of health can improve the adoption and sustainability of public health investment and potentially limit biases embedded within an electronic evidence system [19,45,46].

A key concern that emerged from the qualitative data was avoiding duplication of existing resources, some of which were already in use within their organization. For example, in Canada, the Canadian Best Practice Portal captures intervention evidence on effective health promotion and chronic disease prevention, but it is no longer updated [31]; OpenData shares surveillance evidence nationally and its uses in practice [33]; Statistics Canada provides access to census-based population data [34]; and Health Evidence provides quality assessments of systematic reviews of public health interventions [32]. However, these are independent platforms that search for and synthesize data and do not integrate different types of evidence, such as local context and public health resources, requiring users to search multiple platforms [18]. There have been calls to action from experts in public health and health informatics for pan-Canadian collaborative efforts to facilitate access to databases across the country [29]. Until then, any new electronic evidence system should explore partnerships with relevant existing platforms and mechanisms to avoid duplication of resources and efforts.

Barriers to the use of an electronic evidence system identified in this survey are similar to those found in a previous systematic review on barriers to public health data sharing [47]. In the review, the authors identified six main categories of barriers: technical, motivational, economic, political, legal, and ethical [47]. Regarding technical barriers, concerns about the integration of a new electronic evidence system within the existing information technology infrastructure of an organization emerged from the qualitative data [47]. Economic barriers related to initial and ongoing financial costs were also raised [47]. Some participants in this study expressed concerns with respect to legal barriers, such as data privacy and confidentiality. Both technical and economic barriers illustrate the need for greater organizational capacity development [47]. A previous review suggested allocating 5%-10% of program funds to data collection, monitoring, evaluation, and operational research, while recognizing that larger systems change needs to occur

simultaneously to build sustainable funding mechanisms [47]. Future research is needed to further understand how best to implement such a system in a way that overcomes the known technological barriers such as interoperability and cost, among others.

In our survey, motivational, political, and ethical barriers were not raised; however, the survey did not specifically seek feedback on these factors. Although motivational barriers, which limit data sharing at an individual or organizational level, were not explicitly mentioned, some respondents suggested possible ways to overcome a component of this barrier, disagreements in data use [47]. Respondents suggested providing contact information of researchers who shared the data or the inclusion of a networking component in the electronic evidence system to facilitate discussion about the data, implementation of the possible intervention, successes or failures of interventions in different contexts, etc. The ability to have discussions between the data donor and the researcher using the data may increase trust between both parties, transparency, and reliability of the platform. As mentioned in the 2014 review, the 6 categories of barriers have complex interactions, which need to be addressed with a comprehensive approach to ensure usability of a potential electronic evidence system [47].

An additional barrier identified in the qualitative responses was the need for ongoing training of staff to use the system. Although AI has the potential to compile, process, synthesize, and analyze patterns at rapid rates and to improve efficacy in the use of evidence, blind reliance on its outputs runs the risk of misrepresenting variables or groups of people as it is dependent on data collection methods and evidence inputs [29,46,48]. Experts recommend that AI-specific training is also needed if users are to appropriately address concerns of equity and systemic biases in electronic evidence systems [29,46,48]. This highlights an important consideration for future implementation of such a system. A potential avenue for training can be through web-based learning modules, as they have been found to be effective for public health professionals in one study [49]. Web-based modules that provide training on how to optimize the system and offer other features suggested by respondents, including videos, webinars with creators of the system, and social networking features to connect with other users and researchers, may support public health professionals in using the system efficiently and overcome the aforementioned barriers.

Limitations

There are some limitations to this study, which should be considered when interpreting the findings. First, we did not collect any individual demographic data or years of experience working in public health, limiting the extent to which we can characterize the types of individuals who took part in this survey. In allowing participants to select all that apply for organization type, role, area of public health, and practice discipline, our analysis was limited in its ability to compare differences in preferences across each of these categories. Although the survey was disseminated through two large Canadian-based listservs to recruit public health professionals, there was no qualifying question to confirm that the preferences that emerged were solely of public health professionals in Canada. Second, respondents in the survey ranged across roles, areas, and disciplines, and their results may not be generalizable across all Canadian public health professionals, as respondents who participated may have prior awareness of, or an interest in, electronic evidence systems or evidence-informed decision-making. Finally, the survey questions for a hypothetical electronic evidence system without considerations of feasibility may have skewed responses positively, where respondents more favorably indicated the need for all items listed [50].

Conclusions

Public health professionals and organizations face many hurdles, including changes in structure, lack of funding and time, and exponential increases in new evidence. However, there is broad agreement that the hypothetical electronic evidence system proposed would make informed decisions more accessible. On the basis of our findings, public health professionals see the value in an electronic evidence system that combines local contextual evidence, research and intervention studies, and public health resources and tools. Our findings also highlight a number of elements that should be considered to ensure usability and facilitate trust in such an electronic evidence system. These elements include quality appraisals, interpretations of evidence, and transparent methods and funding models. Such an electronic evidence system may support professionals in evidence-informed decision-making, thereby enabling the Canadian public health system to be more effective in an environment with limited investment.

Acknowledgments

This work was supported by a Canadian Institutes of Health Research project grant (application 397883) awarded to DLB and MD. At the time of the study, DLB held a position as the Canadian Institutes of Health Research Chair in Applied Public Health Research and SENS was supported by a postdoctoral fellowship from the Canadian Institutes of Health Research. Data collection, analysis, and content of this study were not influenced by the funding received from the Canadian Institutes of Health Research.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Categorized needs assessment questionnaire items and answer options.

[PDF File (Adobe PDF File), 43 KB - publichealth_v7i9e26503_app1.pdf]

References

1. Structural profile of public health in Canada. National Collaborating Centre for Healthy Public Policy. 2018. URL: http://www.ncchpp.ca/710/Structural_Profile_of_Public_Health_in_Canada.ccnpps [accessed 2021-05-05]
2. Fedeli V. 2019 Ontario Budget: Protecting What Matters Most. Government of Ontario: Ministry of Finance; 2019. URL: https://budget.ontario.ca/pdf/2019/2019-ontario-budget-en.pdf [accessed 2021-05-05]
3. Guyon A, Perreault R. Public health systems under attack in Canada: evidence on public health system performance challenges arbitrary reform. Can J Public Health 2016 Oct 20;107(3):326-329 [FREE Full text] [doi: 10.17269/cjph.107.5273] [Medline: 27763850]
4. Alberta Health Services performance review. Government of Alberta. 2019. URL: https://open.alberta.ca/publications/alberta-health-services-performance-review-summary-report [accessed 2021-07-30]
5. Himmelstein DU, Woolhandler S. Public health's falling share of US health spending. Am J Public Health 2016 Jan;106(1):56-57. [doi: 10.2105/ajph.2015.302908]
6. PHE annual report and accounts: 2018 to 2019. Public Health England. 2019. URL: https://www.gov.uk/government/publications/phe-annual-report-and-accounts-2018-to-2019 [accessed 2021-07-30]
7. Maani N, Galea S. COVID-19 and underinvestment in the public health infrastructure of the United States. Milbank Q 2020 Jun;98(2):250-259 [FREE Full text] [doi: 10.1111/1468-0009.12463] [Medline: 32333418]
8. Murray CJ, Alamro NM, Hwang H, Lee U. Digital public health and COVID-19. Lancet Pub Health 2020 Sep;5(9):469-470. [doi: 10.1016/s2468-2667(20)30187-0]
9. Brownson RC, Fielding JE, Green LW. Building capacity for evidence-based public health: reconciling the pulls of practice and the push of research. Annu Rev Public Health 2017 Nov 20;39:27-53. [doi: 10.1146/annurev-publhealth-040617-014746] [Medline: 29166243]
10. Kohatsu N, Robinson J, Torner J. Evidence-based public health: an evolving concept. Am J Prev Med 2004 Dec;27(5):417-421 [FREE Full text] [doi: 10.1016/s0749-3797(04)00196-5]
11. A model for evidence-informed decision making in public health. National Collaborating Centre for Methods and Tools. 2009. URL: https://www.nccmt.ca/uploads/media/media/0001/01/d9f5cec8637db62f8edda6a6a2551b293a053ede.pdf [accessed 2021-05-05]
12. Yost J, Dobbins M, Traynor R, DeCorby K, Workentine S, Greco L. Tools to support evidence-informed public health decision making. BMC Public Health 2014 Jul 18;14(1):728 [FREE Full text] [doi: 10.1186/1471-2458-14-728] [Medline: 25034534]
13. Culyer AJ, Lomas J. Deliberative processes and evidence-informed decision making in healthcare: do they work and how might we know? Evid Policy 2006 Aug 01;2(3):357-371. [doi: 10.1332/174426406778023658]
14. Ontario public health standards: requirements for programs, services, and accountability. Ministry of Health and Long-Term Care, Government of Ontario. 2018. URL: https://www.regionofwaterloo.ca/en/regional-government/resources/Documents/Ontario-Public-Health-Standards-OPHS.pdf [accessed 2021-05-05]
15. Nova Scotia public health standards 2011-2016. Government of Nova Scotia. 2016. URL: https://novascotia.ca/dhw/publichealth/documents/Public_Health_Standards_EN.pdf [accessed 2021-07-30]
16. Public health economics. Ministry of Health, British Columbia. 2016 Aug 18. URL: https://www.health.gov.bc.ca/library/publications/year/2017/BC-guiding-framework-for-public-health-2017-update.pdf [accessed 2021-05-05]
17. The 10 essential public health services. Centers for Disease Control and Prevention. 2020. URL: https://www.cdc.gov/publichealthgateway/publichealthservices/essentialhealthservices.html [accessed 2021-07-30]
18. Shaban-Nejad A, Lavigne M, Okhmatovskaia A, Buckeridge D. PopHR: a knowledge-based platform to support integration, analysis, and visualization of population health data. Ann N Y Acad Sci 2017 Jan;1387(1):44-53. [doi: 10.1111/nyas.13271] [Medline: 27750378]
19. Shoveller J, Viehbeck S, Di Ruggiero E, Greyson D, Thomson K, Knight R. A critical examination of representations of context within research on population health interventions. Critical Public Health 2015 Dec 22;26(5):487-500. [doi: 10.1080/09581596.2015.1117577]
20. Martin W, Higgins JW, Pauly B, MacDonald M. "Layers of translation" - evidence literacy in public health practice: a qualitative secondary analysis. BMC Public Health 2017 Oct 11;17(1):803 [FREE Full text] [doi: 10.1186/s12889-017-4837-z] [Medline: 29020953]
21. Groseclose SL, Buckeridge DL. Public health surveillance systems: recent advances in their use and evaluation. Annu Rev Public Health 2017 Mar 20;38(1):57-79. [doi: 10.1146/annurev-publhealth-031816-044348] [Medline: 27992726]
22. Dobbins M, Buckeridge D. Precision public health: dream or reality? Can Commun Dis Rep 2020 Jun 04;46(6):160 [FREE Full text] [doi: 10.14745/ccdr.v46i06a01] [Medline: 32673379]
23. Dolley S. Big data's role in precision public health. Front Public Health 2018 Mar 7;6:68 [FREE Full text] [doi: 10.3389/fpubh.2018.00068] [Medline: 29594091]
24. Buckeridge DL. Precision, equity, and public health and epidemiology informatics - a scoping review. Yearb Med Inform 2020 Aug 21;29(1):226-230. [doi: 10.1055/s-0040-1701989] [Medline: 32823320]

25. De Spiegeleire S, Maas M, Sweijs T. Artificial intelligence and the future of defense: strategic implications for small- and medium-sized force provider. The Netherlands: The Hague Centre for Strategic Studies; 2017.
26. Russell S, Norvig P, Davis E. Artificial Intelligence: A Modern Approach. London, United Kingdom: Pearson; 2010:1-1152.
27. Cresswell K, Callaghan M, Khan S, Sheikh Z, Mozaffar H, Sheikh A. Investigating the use of data-driven artificial intelligence in computerised decision support systems for health and social care: a systematic review. Health Informatics J 2020 Sep 22;26(3):2138-2147 [FREE Full text] [doi: 10.1177/1460458219900452] [Medline: 31964204]
28. Triantafyllidis AK, Tsanas A. Applications of machine learning in real-life digital health interventions: review of the literature. J Med Internet Res 2019 Apr 05;21(4):e12286 [FREE Full text] [doi: 10.2196/12286] [Medline: 30950797]
29. Application of artificial intelligence approaches to tackle public health challenges - workshop report. Canadian Institutes of Health Research. 2018. URL: https://cihr-irsc.gc.ca/e/51018.html [accessed 2021-07-30]
30. Morgenstern JD, Rosella LC, Daley MJ, Goel V, Schünemann HJ, Piggott T. "AI's gonna have an impact on everything in society, so it has to have an impact on public health": a fundamental qualitative descriptive study of the implications of artificial intelligence for public health. BMC Public Health 2021 Jan 06;21(1):40 [FREE Full text] [doi: 10.1186/s12889-020-10030-x] [Medline: 33407254]
31. Canadian best practices portal. Government of Canada. 2014. URL: https://cbpp-pcpe.phac-aspc.gc.ca/# [accessed 2021-05-05]
32. Helping public health use best evidence in practice since 2005. Health Evidence. URL: https://www.healthevidence.org/ [accessed 2021-05-05]
33. Open data. Government of Canada. URL: https://open.canada.ca/en/open-data [accessed 2021-05-05]
34. Data. Statistics Canada. URL: https://www150.statcan.gc.ca/n1/en/type/data?MM=1 [accessed 2021-05-05]
35. HealthLandscape. URL: https://healthlandscape.org/ [accessed 2021-05-05]
36. CDC Wonder. Centers for Disease Control and Prevention. URL: https://wonder.cdc.gov/ [accessed 2021-05-05]
37. Behavioral risk factor surveillance system. Centers for Disease Control and Prevention. URL: https://www.cdc.gov/brfss/index.html [accessed 2021-05-05]
38. Database of promoting health effectiveness reviews (DoPHER). EPPI-Centre. URL: http://eppi.ioe.ac.uk/webdatabases4/Intro.aspx?ID=9 [accessed 2021-05-05]
39. National Center for Health Statistics. Centers for Disease Control and Prevention. 2021. URL: https://www.cdc.gov/nchs/ [accessed 2021-05-05]
40. Peirson L, Ciliska D, Dobbins M, Mowat D. Building capacity for evidence informed decision making in public health: a case study of organizational change. BMC Public Health 2012 Mar 20;12(1):137 [FREE Full text] [doi: 10.1186/1471-2458-12-137] [Medline: 22348688]
41. Dobbins M, Traynor RL, Workentine S, Yousefi-Nooraie R, Yost J. Impact of an organization-wide knowledge translation strategy to support evidence-informed public health decision making. BMC Public Health 2018 Dec 29;18(1):1412 [FREE Full text] [doi: 10.1186/s12889-018-6317-5] [Medline: 30594155]
42. Azungah T. Qualitative research: deductive and inductive approaches to data analysis. Qual Res J 2018 Oct 31;18(4):383-400. [doi: 10.1108/qrj-d-18-00035]
43. Buffet C, Ciliska D, Thomas H. Can I use this evidence in my program decision? Assessing applicability and transferability of evidence. National Collaborating Centre for Methods and Tools. 2007. URL: https://www.nccmt.ca/tools/assessing-applicability-and-transferability-of-evidence [accessed 2021-05-05]
44. Dobbins M, Jack S, Thomas H, Kothari A. Public health decision-makers' informational needs and preferences for receiving research evidence. Worldviews Evid Based Nurs 2007 Sep;4(3):156-163. [doi: 10.1111/j.1741-6787.2007.00089.x] [Medline: 17850496]
45. Panch T, Mattie H, Atun R. Artificial intelligence and algorithmic bias: implications for health systems. J Glob Health 2019 Dec;9(2):010318 [FREE Full text] [doi: 10.7189/jogh.09.020318] [Medline: 31788229]
46. AI for public health equity - workshop report. Canadian Institutes of Health Research. 2019. URL: https://cihr-irsc.gc.ca/e/51425.html [accessed 2021-05-05]
47. van Panhuis WG, Paul P, Emerson C, Grefenstette J, Wilder R, Herbst AJ, et al. A systematic review of barriers to data sharing in public health. BMC Public Health 2014;14:1144 [FREE Full text] [doi: 10.1186/1471-2458-14-1144] [Medline: 25377061]
48. Panch T, Pearson-Stuttard J, Greaves F, Atun R. Artificial intelligence: opportunities and risks for public health. Lancet Dig Health 2019 May;1(1):13-14. [doi: 10.1016/s2589-7500(19)30002-0]
49. Kenefick HW, Ravid S, MacVarish K, Tsoi J, Weill K, Faye E, et al. On your time: online training for the public health workforce. Health Promot Pract 2014 Mar 27;15(1 Suppl):48-55. [doi: 10.1177/1524839913509270] [Medline: 24578365]
50. Lavrakas P. Encyclopedia of Survey Research Methods. Thousand Oaks, California, United States: SAGE Publications; 2008.

Abbreviations

AI: artificial intelligence
NCCMT: National Collaborating Centre for Methods and Tools

Edited by T Sanchez; submitted 14.12.20; peer-reviewed by M Bruno, A Fernandes, R Boumans; comments to author 31.03.21; revised version received 26.05.21; accepted 02.06.21; published 07.09.21.

Please cite as:
Dhaliwal B, Neil-Sztramko SE, Boston-Fisher N, Buckeridge DL, Dobbins M
Assessing the Electronic Evidence System Needs of Canadian Public Health Professionals: Cross-sectional Study
JMIR Public Health Surveill 2021;7(9):e26503
URL: https://publichealth.jmir.org/2021/9/e26503
doi:10.2196/26503
PMID:34491205

Original Paper

Tracking Self-reported Symptoms and Medical Conditions on Social Media During the COVID-19 Pandemic: Infodemiological Study

Qinglan Ding[1,2], MBBS, PhD; Daisy Massey[1], BA; Chenxi Huang[1], PhD; Connor B Grady[3], MPH; Yuan Lu[1,4], ScD; Alina Cohen[5], MSc, MBA; Pini Matzner[5], PhD; Shiwani Mahajan[1,4], MBBS, MHS; César Caraballo[1,4], MD; Navin Kumar[6,7], MPhil; Yuchen Xue[8], MA; Rachel Dreyer[9], PhD; Brita Roy[3,10], MD, MPH, MHS; Harlan M Krumholz[1,4,11], MD, SM

[1]Center for Outcomes Research and Evaluation, Yale New Haven Hospital, New Haven, CT, United States

[2]College of Health and Human Sciences, Purdue University, West Lafayette, IN, United States

[3]Department of Chronic Disease Epidemiology, Yale School of Public Health, New Haven, CT, United States

[4]Section of Cardiovascular Medicine, Department of Internal Medicine, Yale School of Medicine, New Haven, CT, United States

[5]Skai, Tel-Aviv, Israel

[6]Department of Sociology, Yale University, New Haven, CT, United States

[7]Institute for Network Science, Yale University, New Haven, CT, United States

[8]Foundation for a Smoke-Free World, New York, NY, United States

[9]Department of Emergency Medicine, Yale School of Medicine, New Haven, CT, United States

[10]Department of Medicine, Yale School of Medicine, New Haven, CT, United States

[11]Department of Health Policy and Management, Yale School of Public Health, New Haven, CT, United States

Corresponding Author:
Harlan M Krumholz, MD, SM
Center for Outcomes Research and Evaluation
Yale New Haven Hospital
1 Church Street, Suite 200
New Haven, CT, 06510
United States
Phone: 1 203 764 5885
Fax: 1 203 764 5653
Email: harlan.krumholz@yale.edu

Abstract

Background: Harnessing health-related data posted on social media in real time can offer insights into how the pandemic impacts the mental health and general well-being of individuals and populations over time.

Objective: This study aimed to obtain information on symptoms and medical conditions self-reported by non-Twitter social media users during the COVID-19 pandemic, to determine how discussion of these symptoms and medical conditions changed over time, and to identify correlations between frequency of the top 5 commonly mentioned symptoms post and daily COVID-19 statistics (new cases, new deaths, new active cases, and new recovered cases) in the United States.

Methods: We used natural language processing (NLP) algorithms to identify symptom- and medical condition–related topics being discussed on social media between June 14 and December 13, 2020. The sample posts were geotagged by NetBase, a third-party data provider. We calculated the positive predictive value and sensitivity to validate the classification of posts. We also assessed the frequency of health-related discussions on social media over time during the study period, and used Pearson correlation coefficients to identify statistically significant correlations between the frequency of the 5 most commonly mentioned symptoms and fluctuation of daily US COVID-19 statistics.

Results: Within a total of 9,807,813 posts (nearly 70% were sourced from the United States), we identified a discussion of 120 symptom-related topics and 1542 medical condition–related topics. Our classification of the health-related posts had a positive predictive value of over 80% and an average classification rate of 92% sensitivity. The 5 most commonly mentioned symptoms on social media during the study period were anxiety (in 201,303 posts or 12.2% of the total posts mentioning symptoms),

generalized pain (189,673, 11.5%), weight loss (95,793, 5.8%), fatigue (91,252, 5.5%), and coughing (86,235, 5.2%). The 5 most discussed medical conditions were COVID-19 (in 5,420,276 posts or 66.4% of the total posts mentioning medical conditions), unspecified infectious disease (469,356, 5.8%), influenza (270,166, 3.3%), unspecified disorders of the central nervous system (253,407, 3.1%), and depression (151,752, 1.9%). Changes in posts in the frequency of anxiety, generalized pain, and weight loss were significant but negatively correlated with daily new COVID-19 cases in the United States (r=-0.49, r=-0.46, and r=-0.39, respectively; *P*<.05). Posts on the frequency of anxiety, generalized pain, weight loss, fatigue, and the changes in fatigue positively and significantly correlated with daily changes in both new deaths and new active cases in the United States (r ranged=0.39-0.48; *P*<.05).

Conclusions: COVID-19 and symptoms of anxiety were the 2 most commonly discussed health-related topics on social media from June 14 to December 13, 2020. Real-time monitoring of social media posts on symptoms and medical conditions may help assess the population's mental health status and enhance public health surveillance for infectious disease.

(JMIR Public Health Surveill 2021;7(9):e29413) doi:10.2196/29413

KEYWORDS

health conditions; symptoms; mental health; social media; infoveillance; public health surveillance; COVID-19; pandemic; natural language processing

Introduction

The COVID-19 pandemic continues to spread worldwide, with more than 229 million confirmed cases and 4,7028,286 deaths in 188 countries as of September 21, 2021 [1]. As individuals are being encouraged to telecommute and self-quarantine, social media usage has surged by over 40%, emerging as a powerful tool for facilitating communication and disseminating information in a timely manner [2,3]. The general public and health care professionals use social media platforms for health surveillance; to share their feelings, opinions, knowledge, and experiences in relation to the COVID-19 pandemic; and interact with others who share similar characteristics or interests [4-7]. A growing number of people also use social media to seek and share health information that might otherwise be "invisible" to clinicians and medical researchers (eg, self-diagnosis and self-treated symptoms with over-the-counter medications) [8-10]. Harnessing publicly available health-related data posted on social media in real time has the potential to offer insights into how the pandemic impacts the mental health and general well-being of individuals and populations over time [2].

Although prior studies have demonstrated that social media discussions can influence health-related beliefs and behaviors, more studies are needed to understand how social media plays a role during the pandemic [11,12]. Since the emergence of the COVID-19 pandemic, an estimated 41% of US adults have delayed or avoided urgent and routine medical care during the pandemic owing to concerns about COVID-19 [13]. Real-time information regarding self-reported general health status at a population level is lacking. Most literature in this area of research has been focused particularly on mental health or COVID-19 symptoms, with Twitter frequently being utilized as the sole data source [5,14-18]. There was limited information regarding health-related discussions from social media sites other than Twitter. Furthermore, the predictive value of posts on COVID-19 symptoms or related medical conditions on social media sites other than Twitter has not yet been ascertained [19,20]. Extracting and analyzing health-related data from multiple social media sources might provide novel ways of measuring the health status and the full spectrum of symptoms and illness of the population in real time [21,22].

As such, we created a dashboard to extract and monitor posts mentioning symptoms and medical conditions from social media sites other than Twitter over the course of the COVID-19 pandemic. In this study, we sought to answer the following questions: (1) what symptoms and medical conditions were people discussing on social media platforms other than Twitter during the COVID-19 pandemic? (2) How have discussions of symptoms and medical conditions on social media changed over a 6-month period during the pandemic? (3) Were daily fluctuations in health-related social media conversations associated with daily changes in COVID-19 statistics (new cases, new deaths, new active cases, and new recovered cases) in the United States?

Methods

Data Collection

We included English-language social networks and forums worldwide, such as Facebook public pages, Reddit, 4Chan, and the comments sections of news sites such as ABC News [23]. We defined forums as thread-based message boards and topic-specific pages [24]. We chose these sources to provide diversity because they have been studied less than Twitter in this area [25,26]. Additionally, the user base profile of our sources appeared to be more representative of the demographic profile of the broader US population than Twitter. While both Twitter and Reddit were popular among US adults aged ≤30 years, those who lived in urban areas, and were male [27], Facebook appeared to be more popular among female users and US adults older than 30 years [27].

Furthermore, even though there is an overlap between the affordance among our sources and Twitter, Reddit users have more anonymity as they do not need to register an account to access the majority of the content, thus allowing for greater participation [25]. Lastly, forums such as Reddit allow lengthy submissions and are usually topic-specific, which grant opportunities to cover the sensitive topics of our study (eg, mental health disorders and symptoms), which may not typically

be discussed on social media [26,28]. The greater the length of the comments (eg, 40 words per comment for Reddit vs <15 words in tweets, on average) and less frequent use of hashtags associated with forums, which also makes it possible to apply more complex natural language processing (NLP) algorithms more accurately to classify sample posts [26].

We partnered with Signals Analytics, an advanced analytics company, to obtain access to target data sources from a third-party data vendor (NetBase) and to conduct the analysis [29,30]. In order to geotag posts, NetBase used a combination of geotagged social media messages, author profiles, and each country's unique website domain suffix (eg, ".ca" for Canada). All the acquired data were then deidentified by NetBase and transferred to Signals Analytics for analysis.

We also gathered data on COVID-19 cases from the COVID-19 dashboard developed by the Center for System Science and Engineering at Johns Hopkins University, which provides the most comprehensive and up-to-date information on COVID-19 trends [1]. Using the RapidAPI application programming interface (API) [31], we updated the COVID-19 statistics (daily new cases or incidence) on a daily basis.

In this study, all personal identifying information such as usernames, emails, and IP addresses were removed before analysis. The study was exempt from institutional review board review at Yale University as it used publicly available, anonymized data.

Data Analysis

For the analysis of data on symptoms and medical conditions being discussed on social media platforms between June 14 (when many countries began to lift major COVID-19 restrictions) and December 13, 2020 (when the first shipment of the COVID-19 vaccine arrived in the United States), we began by applying NLP algorithms to process social media posts collected from data sources during the study period, and then classified these posts in accordance with symptoms and medical conditions being mentioned.

To accomplish this, NetBase ran a daily scheduled data extraction query that we designed for the study on over 300 million web-based data sources (Multimedia Appendix 1). Additionally, we performed the following filtering steps to include posts relevant to our research questions. First, NLP algorithms were run, and advertisements and posts on sites for pornography were removed (Multimedia Appendix 1). Next, we applied a taxonomy of over 3000 health-related topics to identify key words, phrases, and statements mentioning symptoms and medical conditions (Multimedia Appendix 1). Social media posts that did not contain any of the taxonomy terms or symptoms and medical conditions as keywords were then deleted. Lastly, we removed redundant posts, blog posts, and news articles to ensure that the analysis was based on unique posts from social networks, forums, and comments only.

To evaluate the performance of the NLP algorithms and taxonomy classifications of symptoms and medical conditions, we applied the taxonomy to 4 sets of independent 100-post samples and calculated the positive predictive value and sensitivity of the classification (Multimedia Appendix 1). The algorithms used to identify symptoms and medical conditions topics in our study have been previously validated using real-world data to assess the public's behaviors and perceptions toward COVID-19 [32]. Our study methodology has also been used to provide insights into the characterization and prediction of e-cigarette or vaping product use–associated lung injury outbreaks, known as the EVALI study [33].

Our taxonomy was organized into three levels: categories, subcategories, and topics. Symptoms and medical conditions were the 2 main categories in the taxonomy (Table 1 and Multimedia Appendix 1). The symptoms category included 98 non–COVID-19 topics (symptoms), which were grouped into 7 subcategories based on the affected organ or systems (eg, cardiovascular or respiratory systems). A list of 22 COVID-19–related topics (symptoms) was included as a separate symptom subcategory. The list of COVID-19–related symptoms was defined as outlined by the Centers for Disease Control and Prevention (CDC) on December 22, 2020 [34]. Because our algorithms captured all posts that mentioned any of the listed COVID-19 symptoms in the COVID-19–related symptom subcategory, the included posts may not necessarily represent discussions of symptoms experienced by patients with COVID-19. The medical condition category included 2200 topics (medical diagnoses), which were grouped into 10 subcategories. Categories, subcategories, and topics in the taxonomy were not mutually exclusive; each post could be assigned to multiple categories, subcategories, or topics.

We also created content filters to retain posts mentioning COVID-19 for further analysis. We applied 2 filters, COVID-19 disease status and COVID-19 diagnostic methods, to identify discussions on COVID-19 disease status (tested positive or negative, symptomatic or asymptomatic, recovered, and exposed to a confirmed patient) and diagnostic methods (COVID-19 testing, self-diagnosis, and remote diagnosis). These more restrictive searches were conducted by activating the 2 additional filters using the NLP algorithm, and the resulting posts from that search may not indicate the author's COVID-19 status.

To explore how the discussion of symptoms and medical conditions on social media changed from June 14 to December 13, 2020, we determined the number of posts that included a discussion of each symptom and medical condition over time using NLP classification (Multimedia Appendix 1). To assess whether the frequency of symptom posts was associated with daily COVID-19 statistics, we performed Pearson correlation analysis to determine correlations among the top 5 most discussed symptoms and daily COVID-19 statistics (new cases, new deaths, new active cases [total cases minus recovered and those who have died], and new recovered cases). Additionally, we calculated Pearson correlation coefficients between frequency changes in each of the 5 symptoms and daily fluctuation in any COVID-19 statistic. A 2-tailed *P* value of <.05 was used to indicate statistical significance. Both posts and COVID-19 statistics used in these analyses were restricted to the United States.

Additionally, we compared the trends of the 5 most frequently mentioned symptoms and medical conditions from June 14 to August 31, 2021 (when the United States crossed the 6 million

COVID-19 cases mark), to the trends observed from September 1 to December 13, 2020, by measuring the percent change between the 2 time periods in the number of posts including a discussion of each topic. We compared the 2 time periods to reveal changes in health-related conversations on social media at different stages of the pandemic, as prior literature focused primarily on the early stage of the pandemic (before June 2020). Our approach was also designed to contribute to a better understanding of the impact of COVID-19 on the public's perceptions and attitudes toward different symptoms, medical conditions, and health care–seeking behaviors.

Results

After social media posts were collected from sources, preprocessed, and classified in accordance with the taxonomy by NLP algorithms, our final sample included a total of 9,807,813 posts between June 14 and December 13, 2020, which mentioned at least 1 of the 120 symptoms or 1542 medical condition topics in our taxonomy (Table 1). Our taxonomy classification in the independent sample of 100 posts resulted in a positive predictive value of over 80% and an average classification rate of 92% sensitivity. Furthermore, based on indirect geotagging information provided by NetBase, approximately 70% of all posts collected by the search query were from the United States. The most prevalent symptom subcategory was "neuropsychological symptoms" (568,662/1,649,547, 34.5%), followed by the COVID-19–related symptoms subcategory (501,178/1,649,547, 30.4%). The most prevalent medical condition subcategory was "infectious disease" (6,052,068/8,158,266, 74.2%), followed by the subcategory of "psychiatric or mental health disorders" (484,505/8,158,266, 6.0%) (Table 1).

Irrespective of subcategories classification, the 5 most commonly mentioned symptom topics were anxiety (201,303, 12.20%, of the total posts mentioning symptoms), generalized pain (189,673, 11.5%), weight loss (95,793, 5.8%), fatigue (91,252, 5.5%), and coughing (86,235, 5.2%), accounting for 40.2% of all symptom posts combined (Table 2 and Multimedia Appendix 1). The 5 most discussed medical condition topics were COVID-19 (5,420,276, 66.4%, of the total posts mentioning medical conditions), unspecified infectious disease (469,356, 5.8%), influenza (270,166, 3.3%), unspecified disorders of the central nervous system (CNS) (253,407, 3.1%), and depression (151,752, 1.9%), and together they accounted for 80.5% of all medical conditions discussed on social media during the study period (Table 2 and Multimedia Appendix 1).

Table 1. Number of posts on symptoms and medical conditions mentioned on social media platforms by taxonomy topic (June 14 to December 13, 2020; N=9,807,813).

Relevant taxonomy categories and subcategories (number of topics)	Number of posts with symptoms or medical conditions	Percentage of all posts on symptoms or all medical conditions (%)
Symptoms (n=1,649,547)		
Neuropsychological symptoms (17)	568,662	34.47
COVID-19–related symptoms[a] (22)	501,178	30.38
Respiratory symptoms (7)	128,134	7.77
Gastrointestinal symptoms (13)	120,621	7.31
Dermal symptoms (16)	99,453	6.03
Cardiovascular disease symptoms (4)	34,014	2.06
Musculoskeletal symptoms (7)	33,604	2.04
Other symptoms (34)	163,881	9.93
Medical conditions (n=8,158,266)		
Infectious disease (80)	6,052,068	74.18
Psychiatric or mental health disorders (21)	484,505	5.94
Neurovascular and cardiovascular diseases (63)	465,675	5.71
Respiratory disorders (17)	165,404	2.03
Hematological and oncological disorders (127)	164,159	2.01
Other disorders (1234)	828,786	10.13

[a]COVID-19–related symptoms were based on symptoms of COVID-19 (n=22) updated by the Centers for Disease Control and Prevention on December 22, 2020, which were as follows: runny nose, change in sense of taste, change in sense of smell, chills, bluish lips/face, inability to stay awake, fatigue, headache, sore throat, abdominal pain, vomiting, muscle pain/spasms, drowsiness, nausea, body aches, chest pain, itching/swelling, fever, confusion state, diarrhea, coughing, and difficulty breathing.

Table 2. Frequency of the top 5 most discussed symptoms and medical conditions on social media by taxonomy topic (June 14 to December 13, 2020; N=9,807,813).

Relevant taxonomy categories and topics	Number of posts with topics related to symptoms or medical conditions	Percentage of posts on all topics related to symptoms or all medical conditions (%)
Symptoms (n=1,649,547)		
Anxiety	201,303	12.20
Generalized pain	189,673	11.49
Weight loss	95,793	5.81
Fatigue	91,252	5.53
Coughing	86,235	5.23
Medical conditions (n=8,158,266)		
COVID-19	5,420,276	66.44
Unspecified infectious disease	469,356	5.75
Influenza	270,166	3.31
Unspecified CNS[a] disorders	253,407	3.11
Depression	151,752	1.86

[a]CNS: central nervous system.

Within the COVID-19–related symptoms subcategory, fatigue (91,208, 32.9%) and coughing (86,222, 31.1%) were the most discussed COVID-19–related symptom topics (Table 3). Bluish lips/face (1019, 0.4%) and inability to stay awake (486, 0.2%) were the least commonly discussed COVID-19 symptoms.

After applying the COVID-19 disease status filter to all posts mentioning the top 5 most frequently mentioned symptoms and medical conditions, we noticed that within the posts classified with the medical condition of COVID-19, 62.9% had also discussed testing positive, and 9.1% of the discussions were related to asymptomatic COVID-19 (Table S2, Multimedia Appendix 1). Applying the COVID-19 diagnostic method filter revealed that the most popular COVID-19 diagnostic methods discussed were COVID-19 tests regardless of the symptom or medical condition subcategory (Table S2, Multimedia Appendix 1).

The pattern of changes in top 5 commonly mentioned posts of medical conditions or symptoms and the fluctuation of daily new COVID-19 cases in the United States were displayed in Figures 1 and 2. We noticed a significant increase in daily frequency of posts mentioning the top 5 symptom- and medical condition–related topics in October 2020 and a decrease in late November-December 2020 (Multimedia Appendix 1). Statistical analysis showed that the frequency of symptom posts that was strongly associated with daily new cases included changes in anxiety (r=–0.49; *P*=.009), changes in generalized pain (r=–0.46; *P*=.01), and changes in weight loss (r=–0.39; *P*=.04) (Multimedia Appendix 1). The frequency of symptom-related posts that strongly correlated with daily changes in both new deaths and new active cases included anxiety (r=0.49, *P*=.008; r=0.59, *P*=.002, respectively); generalized pain (r=0.48, *P*=.01; r=0.59, *P*=.001, respectively); weight loss (r=0.39, *P*=.04; r=0.48, *P*=.01, respectively); fatigue (r=0.48, *P*=.01; r=0.53, *P*=.049; and changes in fatigue (r=0.09, *P*=.001; r=0.48, *P*=.009, respectively) (Multimedia Appendix 1).

Correlations between the frequency of the 4 most commonly discussed symptoms and daily recovered cases were significant, and their Pearson correlation coefficients were –0.43 for anxiety, –0.44 for generalized pain, –0.55 for weight loss, and –0.51 for coughing, which indicated a negative and moderate correlation among them (Multimedia Appendix 1).

When examining changes in the frequency of the top 5 most commonly mentioned symptom topic discussions over the 6-month study period, we noted a 24% increase in symptom posts mentioning anxiety, generalized pain, and fatigue during September 1-December 13, 2020 (vs June 14-August 31, 2020) (Multimedia Appendix 1). Compared to June 14-August 31, 2020, posts mentioning the medical condition–related topics influenza, unspecified CNS disorders, and depression increased by more than 27% during September 1-December 13, 2020 (Multimedia Appendix 1). In terms of changes within the COVID-19–related symptoms subcategory, social media posts mentioning runny nose and change in the sense of taste and smell increased over 64%, while posts mentioning difficulty breathing decreased 1.5% during September 1-December 13, 2020 (vs June 14-August 31, 2020) (Multimedia Appendix 1).

Table 3. Comparing changes in the number of posts on COVID-19 symptoms between June 14 and August 31, 2020, with those in September 1 to December 13, 2020 (N=277,401).

COVID-19–related symptoms per the Centers for Disease Control and Prevention's definition[a]	Posts mentioning this COVID-19 symptoms, n (%)	Posts during June 14-August 31, 2020, n	Posts during September 1-December 13, 2020, n	Changes in the number of posts, %
Fatigue	91,208 (32.88)	36,876	54,332	47.33
Coughing	86,222 (31.08)	41,163	45,059	9.46
Fever	59,906 (21.59)	27,729	32,177	16.04
Headache	41,693 (15.02)	18,052	23,641	30.96
Vomiting	39,103 (14.09)	17,364	21,739	25.19
Difficulty breathing	33,589 (12.11)	16,917	16,672	Decreased 1.45
Nausea	29,103 (10.49)	13,039	16,064	23.19
Itching/swelling	28,337 (10.22)	12,953	15,384	18.77
Sore throat	14,694 (5.29)	6424	8270	28.74
Diarrhea	14,140 (5.09)	6716	7424	10.54
Chest pain	9412 (3.39)	4255	5157	21.19
Abdominal pain	9238 (3.33)	4080	5158	26.42
Runny nose	8283 (2.98)	3029	5254	73.46
Body aches	7871 (2.84)	3540	4331	22.34
Change in sense of taste	6510 (2.35)	2447	4063	66.04
Muscle pain/spasms	6321 (2.28)	2816	3505	24.47
Change in sense of smell	6192 (2.23)	2340	3852	64.62
Confusional state	3716 (1.34)	1737	1979	13.93
Chills	2879 (1.04)	1141	1738	52.32
Drowsiness	1256 (0.45)	560	696	24.29
Bluish lips/face	1019 (0.37)	404	615	52.23
Inability to stay awake	486 (0.18)	195	291	49.23

[a]The list of COVID-19 symptoms was updated on December 22, 2020, in accordance with the Centers for Disease Control and Prevention's update. Our algorithms captured all posts mentioning any of these symptoms in the COVID-19 symptom subcategory; consequently, the posts may not necessarily represent patients discussing their own COVID-19 symptoms.

Figure 1. Associations between changes in new daily COVID-19 cases in the United States and the number of medical condition–related posts (June 13-December 13, 2020). (Note: the gray shaded area indicates daily active COVID-19 cases in the United States, while the colored curves showed fluctuations in posts mentioning different medical disorders during the study period). CNS: central nervous system.

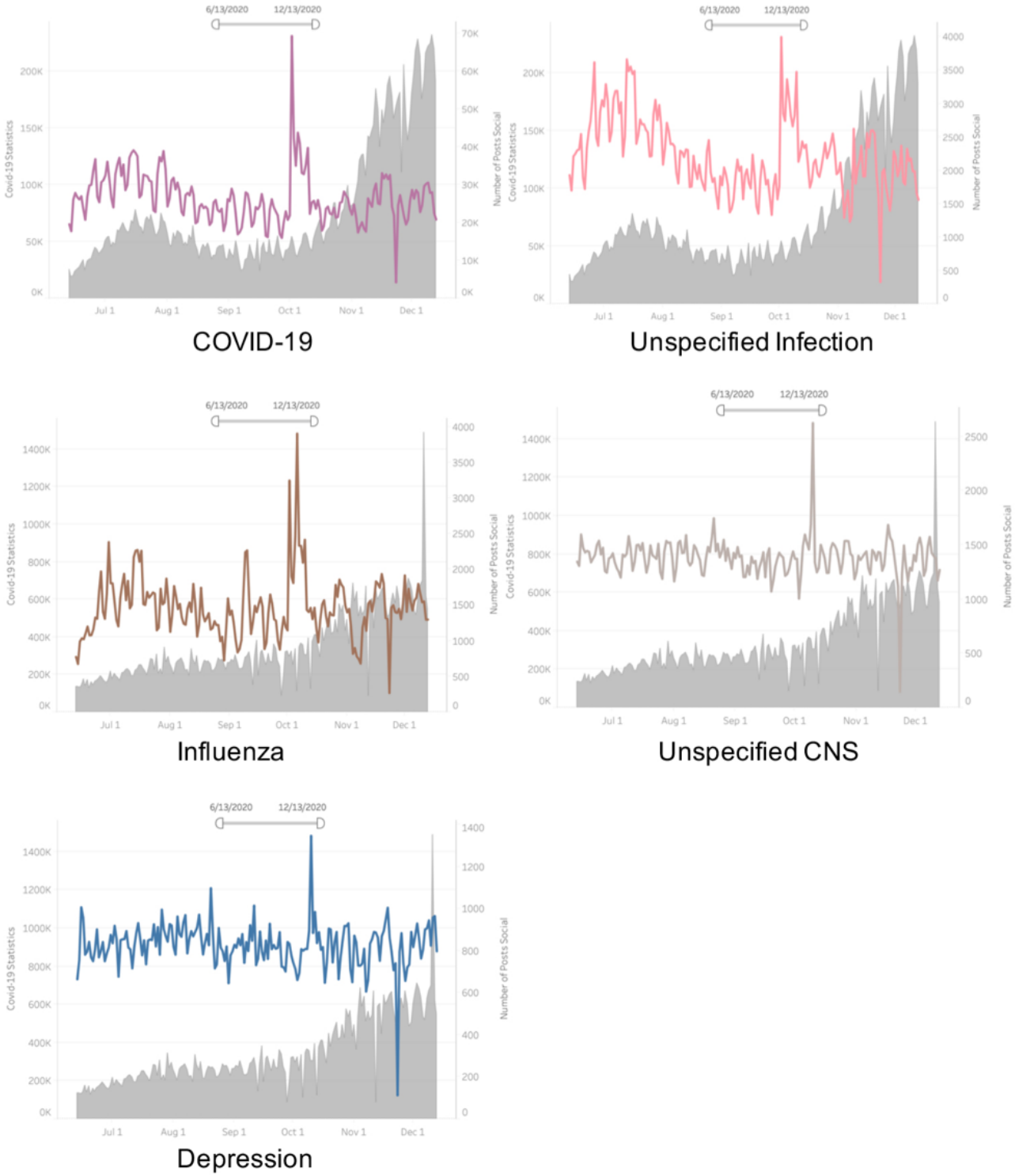
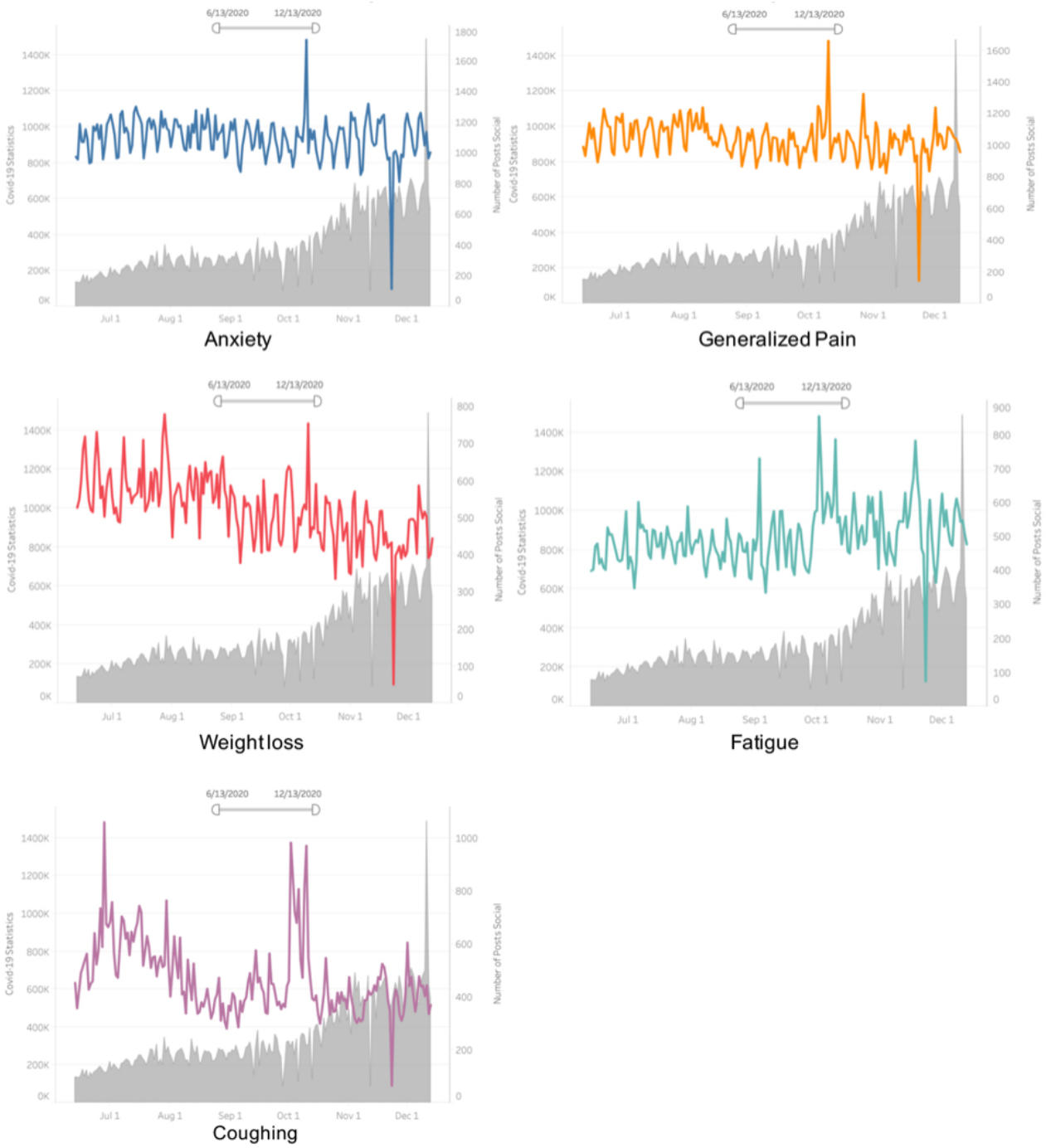


Figure 2. Associations between changes in new daily COVID-19 cases in the United States and the number of symptoms posts (June 13-December 13, 2020). (Note: the gray shaded area indicated daily active COVID-19 cases in the United States, while the colored curves showed fluctuations in posts mentioning different symptoms during the study period).



Discussion

Principal Findings

In this study, we collected and analyzed web-based posts from forums and comments on news sites between June 14 and December 13, 2020. We found that a wide variety of symptoms and medical conditions topics were discussed on non-Twitter social media. While the vast majority of discussions were about COVID-19 infection and COVID-19–related symptoms (as defined by the CDC), neuropsychological symptoms (eg, anxiety) and other medical conditions (eg, infectious diseases and psychiatric disorders) were also frequently mentioned. Additionally, we noticed that changes in posts frequency of anxiety, generalized pain, and weight loss were significant but negatively correlated with daily new COVID-19 cases in the United States, and that the frequency of posts on anxiety, generalized pain, weight loss, fatigue, and the changes in fatigue positively and significantly correlated with daily changes in both new deaths and new active cases in the United States. As COVID-19 cases continued to rise globally, the cumulative volume of posts mentioning anxiety, generalized pain, fatigue, influenza, unspecified CNS disorders, and depression increased

from September 1 to December 13, 2020 (compared to June 13 to August 31, 2020).

Our findings expand on previous observations regarding the mental health effects of the COVID-19 pandemic among social media users by presenting a more complete picture of health-related topics discussed on social media [18]. Our results not only confirm the findings from previous studies that showed high levels of anxiety and depression mentioned by social media users during the pandemic [35,36] but also revealed that the frequency of anxiety and other general health symptom–related posts, including generalized pain, weight loss, and fatigue, was significantly correlated with daily COVID-19 statistics. These data support the idea that social media represents a potential powerful source of information for health care professionals to draw real-time estimations about population health status [18,21]. Understanding health symptom posts commonly associated with COVID-19 statistics may inform public health researchers, clinicians, and policymakers to take timely and appropriate public health and clinical measures accordingly.

Further, as access to the internet becomes more widely available and with the anonymity of social media, people who face barriers to accessing health care and those who have mental health symptoms may use social media to speak openly about their health experiences and seek help [21,37]. Collectively, these results further justify our approach to monitoring symptoms and medical condition posts on social media during the pandemic, and call for further investigation of the possibility of using social media analytics to gain insights into the population's symptoms, including mental health symptoms, which are difficult to monitor outside of the health system, health threats, and to enhance public health preparedness.

As the pandemic progresses, obtaining information on the symptom profile of COVID-19 could help to better diagnose and treat the disease. There has been increasing recognition of the importance of extracting social media information to explore symptom experience and disease progression among patients with COVID-19 [38]. Although we did not restrict our analysis to only social media posts mentioning COVID-19 and could not verify the authors' disease status, the most discussed COVID-19–related symptoms we found (eg, fatigue, cough, fever, headache, and difficulty breathing) were among the most common symptoms reported by patients with COVID-19 in other studies [39-41]. Based on information extracted by applying COVID-19 disease status and diagnostic methods filters, we found that nearly 40% of non-Twitter social media users who discussed the top 5 most commonly mentioned symptom topics, such as fatigue and cough, also talked about the topic of having tested positive for COVID-19.

We also noticed that approximately 15% of these discussions were related to asymptomatic COVID-19. While an in-depth exploration of these posts using qualitative analysis or sentiment analysis is necessary to help verify the users' COVID-19 disease status, our preliminary data indicate the potential for extracting information from social media to understand the full spectrum of symptoms experienced by patients with COVID-19. Interestingly, we noticed an increase of over 60% in the volume of posts mentioning less common COVID-19 symptoms such as changes in the senses of taste and smell during the second stage of our study period (September 1 to December 13, 2020). This surge may be partly due to improvements in knowledge and awareness of COVID-19 symptoms in the general population as the 2 symptoms were recently added to the COVID-19 symptom lists of the CDC and the World Health Organization (late April 2020 and early May 2020, respectively).

While there have been fluctuations in the volume of social media posts on a day-to-day basis, there appeared to be seasonal variation in the volume of discussion of symptoms and medical conditions. We noticed that the volume of most health-related discussions increased more from September 1 to December 13, 2020, than from June 14 to August 31, 2020. These changes may have been due to a combination of colder weather in the northern hemisphere and social distancing and limitations on daily life during the pandemic as well as the second wave of COVID-19, resulting in more social media users and more people being restricted indoors [42]. Additionally, there were several inflection points in the volume of discussion of symptoms and medical conditions in the last 6 months. These changes appeared to have coincided with major news stories and national events, echoing findings from other studies that showed the potential impact of media coverage on web-based discussions [6,18]. For example, the volume of all 5 commonly mentioned symptoms (anxiety, generalized pain, weight loss, fatigue, and cough) and 2 medical conditions (unspecified CNS and depression) peaked on October 10, 2020, the day on which hurricane Delta struck Louisiana and nearby states and left 730,000 homes and businesses without power [43]. However, our study did not find evidence of an association between changes in the volume of symptom discussion over time and the trend of daily new confirmed cases of COVID-19 in the United States.

Limitations

Our study has several limitations. First, information on geolocation, demographics, and COVID-19 disease status was not available for all social media users in the study, owing to various legal limitations (such as General Data Protection Regulation of the European Union). This might have introduced a sampling bias if there were significant differences between social media users' characteristics in our project and the real world. However, by collaborating with social media analytics companies, we have maximized our ability to access thousands of social media data sources worldwide, thus minimizing the possibility of sampling bias. Additionally, the majority of social media users in our study were from the United States. The findings, therefore, may not be generalizable in their application to users located in other countries. Further, we did not conduct formal statistical analyses beyond comparing the trends differences in frequency of health-related posts and new COVID-19 cases; hence, further testing is needed to confirm the associations between patterns of changes in symptom/medical condition posts and the fluctuations of COVID-19 statistics over time. Finally, we did not perform sentiment analysis or qualitative analysis in the study and did not verify whether authors who discussed COVID-19–related topics had COVID-19 themselves. We hope to accomplish and report this analysis in a future study. We also hope that other

studies on social media's role in public health will replicate and validate our exploratory findings in non-Twitter social media platforms.

Conclusions

In this study, we classified web-based posts collected from June 14 to December 13, 2020, in accordance with discussions of symptoms and medical conditions. Neuropsychological symptoms such as anxiety were the most frequently mentioned symptom subcategory. Furthermore, COVID-19 infection was the most commonly mentioned medical condition. Our analysis also showed that frequency of anxiety and other general health symptoms posts, including generalized pain, weight loss, and fatigue, was significantly correlated with daily COVID-19 statistics in the United States. Additionally, health-related discussions were greater from September 1 to December 13, 2020, than from June 14 to August 31, 2020, aligning with the increase in COVID-19 cases in the United States during the winter months. These preliminary findings show promise for real-time monitoring of social media posts to measure the mental health status of a population during a global public health crisis and to assess the public's main health needs that have not been captured or met by the existing health system. Future research may incorporate information from social media into predictive models for the detection of emerging infectious diseases.

Acknowledgments

The authors thank Center for Outcomes Research and Evaluation Yale New Haven Hospital for their coordination of the project. AC and Pini Matzner from Signals Analytics had full access to the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Signals, the analytic company, was acquired and is now part of Skai. QD takes full responsibility for the data interpretation and writing. All authors contributed to the editing and the approving of the final version of the paper for publication. This work was supported by the project Insights about the COVID Pandemic Using Public Data IRES PD: 20-005872 with funding from the Foundation for a Smoke-Free World.

Conflicts of Interest

YL is supported by the National Heart, Lung, and Blood Institute (K12HL138037) and the Yale Center for Implementation Science. RD is supported by an American Heart Association Transformational Project Award (#19TPA34830013) and a Canadian Institutes of Health Research Project Grant (RN356054–401229). In the past 3 years, HMK received expenses and personal fees from UnitedHealth, IBM Watson Health, Element Science, Aetna, Facebook, the Siegfried and Jensen Law Firm, Arnold and Porter Law Firm, Martin/Baughman Law Firm, F-Prime, and the National Center for Cardiovascular Diseases in Beijing. He is an owner of Refactor Health and HugoHealth, and had grants and contracts from the Centers for Medicare & Medicaid Services, Medtronic, the US Food and Drug Administration, Johnson & Johnson, and the Shenzhen Center for Health Information. The remaining authors have no disclosures to report.

Multimedia Appendix 1
Supplementary methods, figures, and tables.
[DOCX File , 2088 KB - publichealth_v7i9e29413_app1.docx]

References

1. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis 2020 May;20(5):533-534 [FREE Full text] [doi: 10.1016/S1473-3099(20)30120-1] [Medline: 32087114]
2. Merchant RM, Lurie N. Social Media and Emergency Preparedness in Response to Novel Coronavirus. JAMA 2020 May 26;323(20):2011-2012. [doi: 10.1001/jama.2020.4469] [Medline: 32202611]
3. Clement J. Share of social media users in the United States who believe they will use select social media more if confined at home due to the coronavirus as of March 2020. Statista. URL: https://www.statista.com/statistics/1106343/social-usage-increase-due-to-coronavirus-home-usa/ [accessed 2020-08-20]
4. Yousuf H, Corbin J, Sweep G, Hofstra M, Scherder E, van Gorp E, et al. Association of a Public Health Campaign About Coronavirus Disease 2019 Promoted by News Media and a Social Influencer With Self-reported Personal Hygiene and Physical Distancing in the Netherlands. JAMA Netw Open 2020 Jul 01;3(7):e2014323 [FREE Full text] [doi: 10.1001/jamanetworkopen.2020.14323] [Medline: 32639569]
5. Abd-Alrazaq A, Alhuwail D, Househ M, Hamdi M, Shah Z. Top Concerns of Tweeters During the COVID-19 Pandemic: Infoveillance Study. J Med Internet Res 2020 Apr 21;22(4):e19016 [FREE Full text] [doi: 10.2196/19016] [Medline: 32287039]
6. Wahbeh A, Nasralah T, Al-Ramahi M, El-Gayar O. Mining Physicians' Opinions on Social Media to Obtain Insights Into COVID-19: Mixed Methods Analysis. JMIR Public Health Surveill 2020 Jun 18;6(2):e19276 [FREE Full text] [doi: 10.2196/19276] [Medline: 32421686]
7. Calvo RA, Deterding S, Ryan RM. Health surveillance during covid-19 pandemic. BMJ 2020 Apr 06;369:m1373. [doi: 10.1136/bmj.m1373] [Medline: 32253180]

8. Li HO, Bailey A, Huynh D, Chan J. YouTube as a source of information on COVID-19: a pandemic of misinformation? BMJ Glob Health 2020 May;5(5):e002604 [FREE Full text] [doi: 10.1136/bmjgh-2020-002604] [Medline: 32409327]
9. Merchant RM, Asch DA, Crutchley P, Ungar LH, Guntuku SC, Eichstaedt JC, et al. Evaluating the predictability of medical conditions from social media posts. PLoS One 2019;14(6):e0215476 [FREE Full text] [doi: 10.1371/journal.pone.0215476] [Medline: 31206534]
10. Guntuku SC, Sherman G, Stokes DC, Agarwal AK, Seltzer E, Merchant RM, et al. Tracking Mental Health and Symptom Mentions on Twitter During COVID-19. J Gen Intern Med 2020 Sep;35(9):2798-2800 [FREE Full text] [doi: 10.1007/s11606-020-05988-8] [Medline: 32638321]
11. Kolliakou A, Bakolis I, Chandran D, Derczynski L, Werbeloff N, Osborn DPJ, et al. Mental health-related conversations on social media and crisis episodes: a time-series regression analysis. Sci Rep 2020 Feb 06;10(1):1342 [FREE Full text] [doi: 10.1038/s41598-020-57835-9] [Medline: 32029754]
12. Fishman JM, Casarett D. Mass media and medicine: when the most trusted media mislead. Mayo Clin Proc 2006 Mar;81(3):291-293. [doi: 10.4065/81.3.291] [Medline: 16529129]
13. Czeisler M, Marynak K, Clarke KE, Salah Z, Shakya I, Thierry JM, et al. Delay or Avoidance of Medical Care Because of COVID-19-Related Concerns - United States, June 2020. MMWR Morb Mortal Wkly Rep 2020 Sep 11;69(36):1250-1257 [FREE Full text] [doi: 10.15585/mmwr.mm6936a4] [Medline: 32915166]
14. Guan W, Ni Z, Hu Y, Liang W, Ou C, He J, China Medical Treatment Expert Group for Covid-19. Clinical Characteristics of Coronavirus Disease 2019 in China. N Engl J Med 2020 Apr 30;382(18):1708-1720 [FREE Full text] [doi: 10.1056/NEJMoa2002032] [Medline: 32109013]
15. Young BE, Ong SWX, Kalimuddin S, Low JG, Tan SY, Loh J, Singapore 2019 Novel Coronavirus Outbreak Research Team. Epidemiologic Features and Clinical Course of Patients Infected With SARS-CoV-2 in Singapore. JAMA 2020 Apr 21;323(15):1488-1494 [FREE Full text] [doi: 10.1001/jama.2020.3204] [Medline: 32125362]
16. Jang H, Rempel E, Roth D, Carenini G, Janjua NZ. Tracking COVID-19 Discourse on Twitter in North America: Infodemiology Study Using Topic Modeling and Aspect-Based Sentiment Analysis. J Med Internet Res 2021 Feb 10;23(2):e25431 [FREE Full text] [doi: 10.2196/25431] [Medline: 33497352]
17. Boon-Itt S, Skunkan Y. Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study. JMIR Public Health Surveill 2020 Nov 11;6(4):e21978 [FREE Full text] [doi: 10.2196/21978] [Medline: 33108310]
18. Valdez D, Ten Thij M, Bathina K, Rutter LA, Bollen J. Social Media Insights Into US Mental Health During the COVID-19 Pandemic: Longitudinal Analysis of Twitter Data. J Med Internet Res 2020 Dec 14;22(12):e21418 [FREE Full text] [doi: 10.2196/21418] [Medline: 33284783]
19. Spurlock K, Elgazzar H. Predicting COVID-19 Infection Groups using Social Networks and Machine Learning Algorithms. 2020 Presented at: 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON); October 28-31, 2020; New York, NY. [doi: 10.1109/uemcon51285.2020.9298093]
20. Tang L, Liu W, Thomas B, Tran HTN, Zou W, Zhang X, et al. Texas Public Agencies' Tweets and Public Engagement During the COVID-19 Pandemic: Natural Language Processing Approach. JMIR Public Health Surveill 2021 Apr 26;7(4):e26720 [FREE Full text] [doi: 10.2196/26720] [Medline: 33847587]
21. Merchant RM. Evaluating the Potential Role of Social Media in Preventive Health Care. JAMA 2020 Feb 04;323(5):411-412. [doi: 10.1001/jama.2019.21084] [Medline: 31922532]
22. Li J, Xu Q, Cuomo R, Purushothaman V, Mackey T. Data Mining and Content Analysis of the Chinese Social Media Platform Weibo During the Early COVID-19 Outbreak: Retrospective Observational Infoveillance Study. JMIR Public Health Surveill 2020 Apr 21;6(2):e18700 [FREE Full text] [doi: 10.2196/18700] [Medline: 32293582]
23. Bernstein M, Monroy-Hernández A, Harry D, André P, Panovich K, Vargas G. 4chan and /b/: An Analysis of Anonymity and Ephemerality in a Large Online Community. 2011 Presented at: Fifth International AAAI Conference on Weblogs and Social Media; July 17-21, 2011; Barcelona URL: https://ojs.aaai.org/index.php/ICWSM/article/view/14134
24. Weichselbraun A, Brasoveanu A, Waldvogel R, Odoni F. Harvest - An Open Source Toolkit for Extracting Posts and Post Metadata from Web Forums. 2020 Presented at: IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT); December 14-17, 2020; Melbourne, VIC. [doi: 10.1109/wiiat50758.2020.00065]
25. Prakasam N, Huxtable-Thomas L. Reddit: Affordances as an Enabler for Shifting Loyalties. Inf Syst Front 2020 Mar 26;23(3):723-751. [doi: 10.1007/s10796-020-10002-x]
26. Babvey P, Capela F, Cappa C, Lipizzi C, Petrowski N, Ramirez-Marquez J. Using social media data for assessing children's exposure to violence during the COVID-19 pandemic. Child Abuse Negl 2021 Jun;116(Pt 2):104747 [FREE Full text] [doi: 10.1016/j.chiabu.2020.104747] [Medline: 33358281]
27. Perrin A, Anderson M. Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018. Pew Research Center. 2019 Apr 10. URL: https://pewrsr.ch/2VxJuJ3 [accessed 2021-06-24]
28. Choi D, Matni Z, Shah C. What social media data should i use in my research?: A comparative analysis of twitter, youtube, reddit, and the new york times comments. Proc Assoc Info Sci Tech 2016 Dec 27;53(1):1-6 [FREE Full text] [doi: 10.1002/pra2.2016.14505301151]
29. meet skai smarter, faster go-to-market. Skai. URL: https://www.signals-analytics.com [accessed 2020-12-13]
30. How can we help drive your business? NetBase Quid. URL: https://netbasequid.com [accessed 2020-12-14]

31. Axisbits. COVID-19 Statistics. Rapid API. URL: https://rapidapi.com/axisbits-axisbits-default/api/covid-19-statistics/details [accessed 2021-01-23]
32. Massey D, Huang C, Lu Y, Cohen A, Oren Y, Moed T, et al. Engagement With COVID-19 Public Health Measures in the United States: A Cross-sectional Social Media Analysis from June to November 2020. J Med Internet Res 2021 Jun 21;23(6):e26655 [FREE Full text] [doi: 10.2196/26655] [Medline: 34086593]
33. Matzner P. Using advance analytics for the early detection of pandemics and outbreaks. Signals Analytics. URL: https://info.signals-analytics.com/research-paper-early-detection-pandemics [accessed 2021-01-23]
34. Symptoms of COVID-19. Centers for Disease Control and Prevention. URL: https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html [accessed 2020-12-22]
35. Ge F, Wan M, Zheng A, Zhang J. How to deal with the negative psychological impact of COVID-19 for people who pay attention to anxiety and depression. Precis Clin Med 2020;3(3):161-168. [doi: 10.1093/pcmedi/pbaa023]
36. Qiu J, Shen B, Zhao M, Wang Z, Xie B, Xu Y. A nationwide survey of psychological distress among Chinese people in the COVID-19 epidemic: implications and policy recommendations. Gen Psychiatr 2020;33(2):e100213 [FREE Full text] [doi: 10.1136/gpsych-2020-100213] [Medline: 32215365]
37. Zhou L, Zhang D, Yang C, Wang Y. Harnessing social media for health information management. Electron Commer Res Appl 2018;27:139-151 [FREE Full text] [doi: 10.1016/j.elerap.2017.12.003] [Medline: 30147636]
38. Picone M, Inoue S, DeFelice C, Naujokas MF, Sinrod J, Cruz VA, et al. Social Listening as a Rapid Approach to Collecting and Analyzing COVID-19 Symptoms and Disease Natural Histories Reported by Large Numbers of Individuals. Popul Health Manag 2020 Oct;23(5):350-360. [doi: 10.1089/pop.2020.0189] [Medline: 32897820]
39. Sarker A, Lakamana S, Hogg-Bremer W, Xie A, Al-Garadi MA, Yang Y. Self-reported COVID-19 symptoms on Twitter: an analysis and a research resource. J Am Med Inform Assoc 2020 Aug 01;27(8):1310-1315 [FREE Full text] [doi: 10.1093/jamia/ocaa116] [Medline: 32620975]
40. Burke RM, Killerby ME, Newton S, Ashworth CE, Berns AL, Brennan S, Case Investigation Form Working Group. Symptom Profiles of a Convenience Sample of Patients with COVID-19 - United States, January-April 2020. MMWR Morb Mortal Wkly Rep 2020 Jul 17;69(28):904-908 [FREE Full text] [doi: 10.15585/mmwr.mm6928a2] [Medline: 32673296]
41. Alimohamadi Y, Sepandi M, Taghdir M, Hosamirudsari H. Determine the most common clinical symptoms in COVID-19 patients: a systematic review and meta-analysis. J Prev Med Hyg 2020 Sep;61(3):E304-E312 [FREE Full text] [doi: 10.15167/2421-4248/jpmh2020.61.3.1530] [Medline: 33150219]
42. Merchant RM, Lurie N. Social Media and Emergency Preparedness in Response to Novel Coronavirus. JAMA 2020 May 26;323(20):2011-2012. [doi: 10.1001/jama.2020.4469] [Medline: 32202611]
43. Aretakis R, Hauck G. Delta lives updates: Hundreds of thousands without power across south; Louisiana governor urges caution as clean-up begins. USA Today. URL: https://www.usatoday.com/story/news/nation/2020/10/10/hurricane-delta-update-damage-weakens-tropical-storm-power-outages/5952093002/ [accessed 2020-12-13]

Abbreviations

API: application programming interface
CDC: Centers for Disease Control and Prevention
CNS: central nervous system
EVALI: e-cigarette or vaping use-associated lung injury
NLP: natural language processing
WHO: World Health Organization

Edited by T Sanchez; submitted 06.04.21; peer-reviewed by S Guntuku, SC Guntuku, J Han; comments to author 12.05.21; revised version received 06.07.21; accepted 26.08.21; published 28.09.21.

Please cite as:
Ding Q, Massey D, Huang C, Grady CB, Lu Y, Cohen A, Matzner P, Mahajan S, Caraballo C, Kumar N, Xue Y, Dreyer R, Roy B, Krumholz HM
Tracking Self-reported Symptoms and Medical Conditions on Social Media During the COVID-19 Pandemic: Infodemiological Study
JMIR Public Health Surveill 2021;7(9):e29413
URL: https://publichealth.jmir.org/2021/9/e29413
doi:10.2196/29413
PMID:34517338

Original Paper

US Physicians' and Nurses' Motivations, Barriers, and Recommendations for Correcting Health Misinformation on Social Media: Qualitative Interview Study

John Robert Bautista[1,2], MPH, RN, PhD; Yan Zhang[1,2], PhD; Jacek Gwizdka[1], PhD

[1]School of Information, The University of Texas at Austin, Austin, TX, United States

[2]Center for Health Communication, Moody College of Communication and Dell Medical School, The University of Texas at Austin, Austin, TX, United States

Corresponding Author:
John Robert Bautista, MPH, RN, PhD
School of Information
The University of Texas at Austin
1616 Guadalupe Street
Austin, TX, 78701
United States
Phone: 1 3462048410
Email: jrbautista@utexas.edu

Abstract

Background: Health misinformation is a public health concern. Various stakeholders have called on health care professionals, such as nurses and physicians, to be more proactive in correcting health misinformation on social media.

Objective: This study aims to identify US physicians' and nurses' motivations for correcting health misinformation on social media, the barriers they face in doing so, and their recommendations for overcoming such barriers.

Methods: In-depth interviews were conducted with 30 participants, which comprised 15 (50%) registered nurses and 15 (50%) physicians. Qualitative data were analyzed by using thematic analysis.

Results: Participants were personally (eg, personal choice) and professionally (eg, to fulfill the responsibility of a health care professional) motivated to correct health misinformation on social media. However, they also faced intrapersonal (eg, a lack of positive outcomes and time), interpersonal (eg, harassment and bullying), and institutional (eg, a lack of institutional support and social media training) barriers to correcting health misinformation on social media. To overcome these barriers, participants recommended that health care professionals should receive misinformation and social media training, including building their social media presence.

Conclusions: US physicians and nurses are willing to correct health misinformation on social media despite several barriers. Nonetheless, this study provides recommendations that can be used to overcome such barriers. Overall, the findings can be used by health authorities and organizations to guide policies and activities aimed at encouraging more health care professionals to be present on social media to counteract health misinformation.

(JMIR Public Health Surveill 2021;7(9):e27715) doi:10.2196/27715

KEYWORDS

correction; COVID-19; physicians; misinformation; infodemic; infodemiology; nurses; social media

Introduction

Background

Health misinformation is defined as any health-related claim of fact that is false based on the current scientific consensus [1]. It is a threat to public health because it impairs individuals' ability to make appropriate health decisions, resulting in poor health behaviors and outcomes [2]. For instance, research has shown that exposure to misinformation, wherein tobacco and alcohol consumption protects people from COVID-19, is associated with greater tobacco and alcohol consumption [3]. Similarly, researchers found that beliefs about COVID-19 misinformation are associated with lower COVID-19 knowledge and lower adherence to preventive behaviors [4].

Various stakeholders have noted that social media is a fertile ground for health misinformation, and interventions are needed to correct it [5-7]. With the global spread of COVID-19, the United Nations [8] and World Health Organization [9] have emphasized that health misinformation, particularly on social media, is a public health threat that needs to be addressed. An intervention that the United Nations [8] has proposed is the formation of digital first responders—volunteers on social media, whose role is to share correct information and, to some extent, correct health misinformation.

Among social media users, health care professionals, particularly physicians and nurses, may serve as role models in correcting health misinformation on social media as they possess clinical knowledge they can share with the public. Research suggests that physicians and nurses have good levels of eHealth literacy [10-12], which enables them to select and share correct web-based health information with the public. Moreover, nurses and physicians are trustworthy sources of health information as they belong to the top US professionals considered honest and ethical [13]. Some health care professionals also have a strong social media following [14] that can be leveraged to amplify the communication of accurate health information on social media. This is evidenced by recent media [15-17] and scholarly [18,19] reports of physicians and nurses who are also social media influencers. Furthermore, research suggests that physicians and nurses tend to have a positive attitude toward using social media professionally as it can improve one's knowledge [20] and facilitate health information sharing among colleagues [21] and the public [22,23].

Despite how well positioned health care professionals are for correcting health misinformation on social media, empirical studies on their motivations and barriers in performing such an act are missing. To date, relevant literature is limited on encouraging health care professionals to be on social media to help correct health misinformation [24-26]. For instance, O'Connor and Murphy [24] encouraged health care professionals to rebut misleading health information on social media by using appropriate sources. Rubin [25] noted that a crucial step in correcting health misinformation is for health care professionals to have a social media presence. Swire-Thompson and Lazer [26] also encouraged health communicators, particularly health care professionals, to correct health misinformation on social media as research suggests that such corrections can prevent people from believing misinformation.

Objectives

If health authorities and organizations would like to encourage health care professionals to be on social media and become digital first responders, it is necessary to understand why health care professionals want to do it and identify barriers that they might face in correcting health misinformation on social media. As part of a larger study on the role of health care professionals in correcting health misinformation [23], this study aims to answer the following three research questions:

- Research question 1: what motivates health care professionals to correct health misinformation on social media?
- Research question 2: what barriers do health care professionals face when correcting health misinformation on social media?
- Research question 3: what are health care professionals' recommendations to overcome barriers in correcting health misinformation on social media?

Methods

Participant Selection

Target participants included US physicians and registered nurses. We focused on physicians and registered nurses as they form the largest group of health care professionals in the United States [27] and are reported by the media as an emerging group of social media influencers [15-17]. In addition, a 2020 Gallup poll showed that these health care professionals are considered the most honest and ethical professionals in the United States [13]. Besides being a licensed physician or registered nurse in the United States, other eligibility criteria included working as a physician or registered nurse for at least a year and being an active social media user.

A combination of purposive (ie, active social media users with active US physician or registered nurse licensure and with ≥1 year of work experience) and snowball sampling strategies (ie, asking for referrals and social media hopping) were used to recruit participants. We communicated with potential participants by sending an email or direct message to their social media accounts on platforms such as Facebook, Twitter, Instagram, and LinkedIn. To achieve maximum variation sampling (ie, recruiting diverse participants to obtain multiple perspectives) [28], we recruited participants from various age groups, sex, and practice areas. This study was approved by the institutional review board of the University of Texas at Austin (2019-10-0149). Participants provided written and verbal consent before the data collection.

Data Collection

Semistructured interviews were conducted between January and March 2020 via video conferencing platforms (ie, Zoom [Zoom Video Communications] or Skype [Microsoft Corporation]) or mobile phone calls. An interview guide was used during the semistructured interviews, which provided the ability to explore insights based on interviewees' responses to questions within the interview guide. Considering that the results presented here are part of a larger qualitative study on health misinformation, the following interview questions were relevant to this study:

- As a health care professional, do you think that you have the responsibility to correct health misinformation on social media? Why?
- What do you think are barriers for health care professionals to correct health misinformation on social media?
- What suggestions or advice can you give to health care professionals when correcting health misinformation on social media?

The interviews were conducted by JRB (first author). The interviewer had the relevant qualifications to conduct the study as he had degrees in nursing (bachelor's), public health

(master's), and communication science (doctorate). In addition, he also published health informatics–related articles based on interview data. Participants did not know the interviewer personally or professionally before recruitment. The interviews lasted an average of 21.69 (SD 6.43) minutes and were audio recorded. Participants were given a US $20 gift voucher as an incentive.

Participants and Characteristics

We invited 212 health care professionals, of whom 30 (14.2% response rate) agreed to participate. The sample was composed of 50% (15/30) physicians and 50% (15/30) registered nurses. The sample size was sufficient for this study based on the advice of Green and Thorogood [29] that rich insights for qualitative work can be obtained after interviewing 20 participants.

Table 1 shows the characteristics of the participants. Most of the 30 participants were women (20/30, 67%). Their ages ranged from 27 to 65 years (mean 43.8 years, SD 9.73), and their work experience as a health care professional ranged from 6 to 40 years (mean 18.05 years, SD 9.69). They came from a variety of practice areas, including pediatrics (5/30, 17%), pediatric nursing (4/30, 13%), public health nursing (3/30, 10%), cardiology (2/30, 7%), emergency medicine (2/30, 7%), and oncology (2/30, 7%). Participants were located in 16 US states, with most practicing in Texas (7/30, 23%) and Pennsylvania (4/30, 13%). Although all participants were using multiple social media platforms (eg, Facebook, Twitter, LinkedIn, and Instagram), all were active Twitter users for the past 6.85 years on average (SD 2.85). All had experienced correcting health misinformation on social media.

Table 1. Participant characteristics (N=30).

Characteristics	Values
Sex, n (%)	
Female	20 (67)
Male	10 (33)
Age (years), mean (SD; range)	43.8 (9.73; 27-65)
Number of years using Twitter, mean (SD; range)	6.85 (2.85; 0.5-11)
Health care profession, n (%)	
Registered nurse	15 (50)
Physician	15 (50)
Number of years as a health care professional, mean (SD; range)	18.05 (9.69; 6-40)
Practice areas[a,b], n (%)	
Pediatrics	5 (17)
Pediatric nursing	4 (13)
Public health nursing	3 (10)
Cardiology/emergency medicine/oncology	2 (7)
Anesthesiology/cardiology nursing/critical care nursing/diabetes nurse consultant/epidemiology/family nurse practitioner/family medicine/float nursing/gastroenterology/hematology/internal medicine/psychiatry/rehabilitation medicine/resuscitation and innovation/school nursing/women's health nursing	1 (3)
Practice location[b], n (%)	
Texas	7 (23)
Pennsylvania	4 (13)
California/Maryland/New Jersey/Utah/Wisconsin	2 (7)
Colorado/Georgia/Illinois/Louisiana/Missouri/New Mexico/New York/North Carolina/Ohio	1 (3)

[a]Some participants had multiple specializations.

[b]Count per item.

Data Analysis

We transcribed the audio recordings and interview notes after each interview. The resulting transcripts and interview notes were uploaded to MAXQDA 2018 (VERBI GmbH) for qualitative data analysis. The data analysis was guided by a phenomenological perspective to thematic analysis [30], considering that the interview data contained participants' perspectives and experiences about their motivations, barriers, and recommendations to correct health misinformation on social media.

Initially, we performed an iterative process of open (ie, to break down data into smaller analytical points) and axial coding (ie, grouping open codes to generate connections between categories and subcategories) to uncover themes and subthemes [28]. Codes were derived from the data (ie, a priori) and classified under

themes (ie, motivations, barriers, and recommendations) and subthemes (eg, personal motivations, intrapersonal barriers, and build a social media presence). Table 2 provides the coding tree.

Table 2. Coding tree (N=30).

Themes and subthemes	Codes (participants per profession), n (%)	
	Physician (n=15)	Registered nurse (n=15)
Motivations to correct health misinformation on social media		
Personal motivations		
Personal choice	1 (7)	1 (7)
Urge to correct people	3 (20)	0 (0)
Professional motivations		
Stand up for what is right as a health care professional	6 (40)	6 (40)
Keep people safe	1 (7)	5 (33)
Opportunity to educate more people	4 (27)	1 (7)
Barriers in correcting health misinformation on social media		
Intrapersonal barriers		
Lack of positive outcome	10 (67)	7 (47)
Lack of time	9 (60)	3 (20)
Lack of self-efficacy	3 (20)	3 (20)
Avoidant behavior	1 (7)	4 (27)
Lack of voice to influence others	2 (13)	2 (13)
Difficulty in producing social media content	3 (20)	0 (0)
Interpersonal barriers		
Harassment and bullying	14 (93)	9 (60)
Difficulty to have a meaningful conversation on the web	13 (87)	6 (40)
Institutional barriers		
Lack of organizational support	6 (40)	4 (27)
Lack of social media training	3 (20)	1 (7)
Recommendations to overcome barriers in correcting health misinformation on social media		
Get misinformation and social media training		
Be familiar with the literature and collate resources	2 (13)	6 (40)
Learn to use social media professionally	2 (13)	2 (13)
Connect with role models or mentors	2 (13)	0 (0)
Learn how to correct misinformation	1 (7)	0 (0)
Build a social media presence		
Be on social media	11 (73)	1 (7)
Disseminate facts	6 (40)	5 (33)
Build an audience	5 (33)	1 (7)
Be part of a community	3 (20)	1 (7)
Maintain professionalism	2 (13)	0 (0)

A total of 3 coders (1 registered nurse, 1 medical student, and 1 information studies graduate student) independently coded a sample of the transcripts. The results showed good interrater reliability (Krippendorff α=.82). After preliminary coding, the research team discussed the codes and resulting themes and subthemes to check whether data saturation was achieved. After several meetings, the research team deemed that data saturation was achieved based on the presence of well-developed and interrelated themes and subthemes. In addition, all codes were accounted for in a particular theme or subtheme, and no new codes could be derived from the data [28].

Trustworthiness

This study adheres to qualitative trustworthiness by observing the principles of credibility, transferability, dependability, and confirmability [31]. We promoted credibility by establishing rapport with the participants to obtain honest remarks and by using iterative questioning to clarify the details. We enhanced transferability by upholding maximum variation sampling (eg, interviewing health care professionals of different ages, sexes, and practice areas). The study was also dependable as the research team followed the approved research protocol. Finally, the results were confirmed by providing anonymous quotes from participants to support our findings.

Reflexivity Statement

The study team was composed of researchers with expertise in health information interaction, information quality, and qualitative research. JRB has 8 years of research experience in these areas, whereas YZ and JG have >10 years of experience. All study team members are social media users and are aware of the negative implications of health misinformation on public health. The research team ventured on health misinformation research in 2019 because of a fellowship awarded to JRB; thus, the research would have been conducted regardless of the COVID-19 pandemic. Nonetheless, this study became much more relevant because of the infodemic that was brought about by the pandemic. JRB was motivated to conduct this study because, as a nurse in the Philippines, he believes that health care professionals can leverage social media to correct health misinformation. Although JRB's belief can present a bias in this study, he maintains neutrality by avoiding agreement or disagreement (verbally and nonverbally) with the participants' statements during interviews and by being self-aware of his biases during data analysis. To further minimize bias, we recruited participants who were not part of our personal or professional network.

Results

Motivations to Correct Health Misinformation on Social Media

Participants identified several personal and professional motivations to correct health misinformation on social media.

Personal Motivations

There were two personal motivations associated with correcting health misinformation on social media. Some (physician: 1/5, 7%; registered nurse: 1/15, 7%) noted that it is a personal choice because they think that it is not their legal obligation to correct health misinformation:

> *Legally speaking, I don't have any obligation to correct or actively correct health misinformation online or even participate on social media. But I chose to do so because I feel that it's probably about it. And know there are no incentives for anyone to necessarily jump to social media to do this but some of us try to do this.* [physician 1]

Similarly, some (physician: 3/15, 20%) noted that they might have the urge to correct people because that seems to be a reflex for them as health care professionals:

> *I will say though, I don't know if it's a duty, I think it's almost a reflex for a clinician to encountering misinformation online to respond and correct it if they have the time and inclination.* [physician 11]

Professional Motivations

There were three professional motivations associated with correcting health misinformation on social media. For instance, some (physician: 6/15, 40%; registered nurse: 6/15, 40%) noted that as health care professionals, they need to correct health misinformation on social media because it is an act of standing up for what is right:

> *Because people look to us as experts in these areas and if we are not standing up and making clear what is accurate information and what's not, I personally feel that we're not doing our job. If we are not debunking misinformation, then it's detrimental to the health of all our community members.* [registered nurse 13]

Others (physician: 1/15, 7%; registered nurse: 5/15, 33%) considered correcting health misinformation on social media as part of their professional responsibility to keep people safe against the ill effects of health misinformation:

> *I think that when we entered this profession and took an oath to do no harm...and if we are allowing health misinformation to run wild out there, especially for our own patients, allowing that information to continue to have an effect is going against what were here to do or were here to achieve.* [physician 1]

A few (physician: 4/15, 27%; registered nurse: 1/15, 7%) noted that such an act is an opportunity to educate more people as social media opens interactions to a global community of health information seekers:

> *50-60 years ago when physicians were trained, they were taught to educate their neighbors, their patients and their community as well as treating people. So now, our community has become a global community. So, I believe that we, as physicians, have the responsibility to educate using whatever medium to reach the largest number of people. Because people are so interconnected and the way that individuals obtain information and get misinformation has changed quite a bit a few years ago.* [physician 13]

Barriers in Correcting Health Misinformation on Social Media

Participants pointed out several barriers that they face to correct health misinformation on social media. Broadly, these barriers can be categorized as intrapersonal, interpersonal, and institutional.

Intrapersonal Barriers

Many (physician: 10/15, 67%; registered nurse: 7/15, 47%) noted that health care professionals might be discouraged from

correcting health misinformation on social media because they do not see the immediate positive change that results from it:

> *I think another barrier online is that it just feels like you are fighting an endless battle because you don't ever see the progress that's being made. I'm lucky enough to have a big enough platform that I actually get to see some of the benefit of it now and so it's really gotten easier for me to do that because I see the difference that it's making. But when you're first starting out, it can just feel overwhelming like you don't make any progress.* [physician 4]

Another intrapersonal barrier was the lack of time. Several (physician: 9/15, 60%; registered nurse: 3/15, 20%) participants noted that given their current clinical workload and other responsibilities, some health care professionals may not have the time to correct health misinformation on social media:

> *Some physicians have the barrier that they just don't have the time. We already have so many demands on our time and physicians just don't have the time to do it and don't want to spend whatever precious time they have going through this.* [physician 13]

Some (physician: 3/15, 20%; registered nurse: 3/15, 20%) also noted a lack of self-efficacy in correcting health misinformation on social media. For instance, health care professionals may not have the specialist knowledge to detect health misinformation and the training to effectively correct it:

> *They just might not know that the information is incorrect themselves or they might not know enough about the truth or the facts to be able to dissuade someone whose sharing falsehoods or falsities. I think that's a major one.* [registered nurse 11]

Others (physician: 1/15, 7%; registered nurse: 4/15, 27%) also noted that some health care professionals may have an avoidant behavior where they would prefer to avoid any confrontation and arguments arising from correcting others or they may not feel comfortable being on social media at all:

> *They might not think of themselves as experts in whatever topic to be able to correct someone. They may not feel comfortable on social media or in person correcting people.* [registered nurse 13]

In addition, some (physician: 2/15, 13%; registered nurse: 2/15, 13%) lamented that their voices on social media might not necessarily be heard because they lack the influence to enact changes (eg, few social media followers):

> *Unfortunately, the loudest voices are heard. It would be great if the nurses, the largest population of health professionals, our voice could have been louder. I feel just because of our sheer number and it could have drowned out the bad health information it could have. But that's not the reality that we're in.* [registered nurse 7]

Finally, a few (physician; 3/15, 20%) noted that producing content (eg, conducting research for the correction, crafting the message, and adding images or videos) to correct health misinformation on social media takes time and considerable expertise that serves as a barrier:

> *Authoring and making content take a lot of time. It takes some skill, it takes writing capacities, it takes communication skills, it takes preparation, if it's video it takes lighting and makeup. No matter how silly that sounds but there's a lot of work involved in that at times.* [physician 10]

Interpersonal Barriers

Many (physician: 14/15, 93%; registered nurse: 9/15, 60%) pointed out that health care professionals are at risk of being bullied and harassed by other social media users as they correct health misinformation. Given that correcting others may result in heated debates and arguments, some participants have experienced bullying and harassment, such as being accused as child predators, conspiring with pharmaceutical companies, and receiving negative reviews and mob attacks on the web:

> *Every single time you post about vaccines you will get harassed if your platform is large enough that people will see it. I've had times where I just post CDC statistics on how many people die from influenza each year and end up having to make all of my accounts private because I get such a vast influx of people just attacking. I've had people come on to my Instagram and comment on pictures of my children saying that they look vaccine-injured and that I am a child abuser and that I'm in bed with big pharma and my kids should be taken away and CPS [Child Protective Services] should be called.* [physician 4]

Bullying and harassment are carried out by social media users with whom the participants are not familiar, such as trolls who operate under the veil of anonymity. For some participants, such negative experiences may deter health care professionals from correcting health misinformation on social media. Although some participants ignored trolls as a means of coping with bullying and harassment, some had to make their social media accounts private, limit interactions, block people, or stop engaging on social media:

> *It was not pleasant [experiencing bullying and harassment] and what I basically did was I just disengaged, and I didn't go back to the post. It did not make me feel good. A matter of fact, it made me feel really disgusted with that elected official, that he would behave that way.* [registered nurse 10]

Another interpersonal barrier was the difficulty of having a meaningful conversation on the web. Most (physician: 13/15, 87%; registered nurse: 6/15, 40%) preferred face-to-face interactions when correcting health misinformation as interactions on the internet remove vital verbal and nonverbal cues that are needed to establish rapport and the relationship required to dispel misinformation. Moreover, as social media users can opt for anonymity, the conversations may not be as fruitful and respectful compared with face-to-face interactions, such as during patient visits, where effective health education sessions can occur:

> *The problem I have with online discourse is this: virtually no tone. It's very difficult unless you're using all caps and exclamation marks to communicate tone on Twitter for instance. Twitter being so short you can come across as curt even if you did not intent to be. Whereas face-to-face, you get all the nonverbal cues, facial expression, sometimes even touch when appropriate.* [physician 11]

Institutional Barriers

Institutional barriers were also identified by the participants. For instance, several participants (physician: 6/15, 40%; registered nurse: 4/15, 27%) noted a lack of organizational support for correcting health misinformation on social media. This stems from the lack of institutional backing for health care professionals to be on social media because of privacy concerns:

> *So primarily, a lot of physicians don't feel comfortable [being on social media]. For years, the health care system has told physicians not to go on social media because of patient privacy and the variety of other issues.* [physician 13]

To distance themselves from their employers, a few participants tended to write a statement in their social media profiles, particularly on Twitter, that their opinion was their own and not representative of their employer or institution:

> *They don't engage [in correcting health misinformation on social media] because, I think, maybe some [health care] professionals are afraid to do it because of the organization they work in. I don't list my organization on Twitter because I don't have enough characters to do it, and also I put a disclaimer that the opinions or mine and a retweet doesn't mean I endorse something. So, I have some disclaimers.* [registered nurse 10]

Although a participant noted that, through the years, "a lot of [health care] organizations are really asking their clinicians to be on social media" [physician 15], there is still a lot of work for health care institutions to support their health care professionals as they create a social media presence. In addition, institutions tend not to provide incentives for health care professionals who correct health misinformation on social media:

> *Like I said, there are no [institutional] incentives for anyone to participate. It's really self-driven.* [physician 1]

Another institutional barrier was the lack of social media training. Some (physician: 3/15, 20%; registered nurse: 1/15, 7%) noted that they just learned to use social media professionally during their practice:

> *We don't get a lot of training on this [social media training] so everybody just makes it up as we go. I think there's more and more an effort to get physicians exposed to best practices and to literature about what's an effective way to communicate. With that, it's still early and it doesn't always penetrate into the entire workforce.* [physician 15]

In addition, formal training in using social media professionally was usually not part of the health care professionals' curriculum and clinical training:

> *None of us get this training in our training programs, on how to use media and social media. So, in correcting people online, I think, first off, there's oftentimes no formal training. People do this just because they often enter into social media, just using it on their own. And then there's just general communication training to which I think we don't really receive a lot of it in both nursing and physician training programs.* [physician 6]

Recommendations to Overcome Barriers in Correcting Health Misinformation on Social Media

To overcome some of the barriers in correcting health misinformation on social media, participants recommended that health care professionals get misinformation and social media training and build their social media presence.

Get Misinformation and Social Media Training

For correcting health misinformation, some participants (physician: 2/15, 13%; registered nurse: 6/15, 40%) noted that it is crucial to be familiar with the literature (eg, up-to-date literature about a specific health issue or condition) and collate resources that can be disseminated when correcting health misinformation. Health care professionals should always project an image of expertise, which can be accomplished by having a command of the literature and resources that are specific to a health topic or issue:

> *I think that we should be careful in our response to show that we're knowledgeable. Don't respond to something if you don't know what you're talking about. That's just going to make the situation worse. But when it's your content area for instance and you know the information is wrong, address it right away. Make sure that you are knowledgeable about what you're saying. But then also provide the person in question with resources to show them that you're not just making something up, you're not like we say talking out of the side of your neck but you actually have evidence to support what it is that you're saying.* [registered nurse 11]

Some (physician: 2/15, 13%; registered nurse: 2/15, 13%) also recommended that health care professionals learn how to use social media professionally. Although institutional training may be limited or unavailable, there are several professional groups (eg, Association for Healthcare Social Media and Doctors on Social Media) that health care professionals can join in to start learning about professional social media use (eg, what to post, creating engaging graphics and videos, and responding to health misinformation):

> *If health care professionals want to do it [correcting health misinformation on social media], they shouldn't go into it without any kind of [professional social media] training or support. They are very likely to run into harm, they can have their reputation*

> *harmed, they can have their job threatened, there's a lot of risks to doing it.* [physician 9]

Few (physician; 2/15, 13%) also noted that it is important to connect with role models or mentors who can advise when correcting health misinformation on social media. Typically, an ideal mentor has a strong social media presence (eg, high social media followers) and is an opinion leader (eg, their posts are shared by many followers):

> *I would tell them to look at the people that have already done it successfully. If they want to speak out on a health issue, see the main experts that are speaking out and kind of see how they are doing it and then be comfortable and then start speaking out for themselves.* [physician 7]

A participant (physician; 1/15, 7%) also noted that it is crucial for health care professionals to understand what misinformation is and the means to correct it:

> *Physicians operate under the assumption that there is an information deficit, this is incorrect. Generally, we're used to people coming to acquire information and being open and receptive to information. The problem is that disinformation is not an information deficit, the problem is that disinformation represents a glut of misinformation. So, you can't simply counter it by providing the correct information. Everybody has the correct information available to them. It's on Google and it's not far away. What physicians need to do and what they will always fail to do to correct misinformation and disinformation until they recognize it is that it's not a matter of just telling people what the reality is, you have to reach them from a point of personal identity, a personal relationship. You have to create cause for spread of disinformation and you basically have to treat it like an information war like a propaganda war and not 'I hope these people just lack information or are ignorant.' They are not ignorant.* [physician 9]

Build a Social Media Presence

After obtaining relevant training, participants also recommended that health care professionals build their social media presence. The first step is to be on social media. For instance, many (physician: 11/15, 73%; registered nurse: 1/15, 7%) participants noted that it is crucial for health care professionals to have a professional social media account like Twitter because it is a good platform for publicly receiving, sharing, and discussing relevant health information:

> *It's really important that people [health care professionals] engage in that they try to get on social media [like Twitter] to help educate the entire world on important topics. We want to make sure that everybody is working together to keep the health of all of our people safe and keep everyone healthy. And we can do that by combatting all this misinformation that's out there.* [physician 13]

After creating a social media account, several (physician: 6/15, 40%; registered nurse: 5/15, 33%) participants noted that health care professionals need to disseminate facts, which serves as a foundation for building an audience:

> *I think it probably starts with sharing good information. I don't know if we can police everybody and correct all the bad information, but I think we really need to stand up as health care professionals and make sure that we are sharing good information so that people can come to us and know what's right basically.* [physician 3]

In addition to using social media as a platform to share facts that might correct health misinformation, some (physician: 5/15, 33%; registered nurse: 1/15, 7%) participants noted that sharing content might also attract followers that can assist in building an audience. This is based on the belief that the more social media followers a person has, the more influential the person's voice becomes when they enact change (eg, dispelling health misinformation):

> *It's really difficult to disrupt things. You need to learn to use it [social media] effectively and build an audience because just being on there alone isn't enough. You kind of have to know how to use it in a way that's going to allow your audience to grow. Otherwise, you're gonna just be talking to [few people] rather than talking to 200, 2000 or 2 million people.* [physician 1]

In addition, part of building an audience is to be part of a community of health care professionals on social media. A few (physician: 3/15, 20%; registered nurse: 1/15, 7%) noted that health care professionals can do this by using relevant hashtags (eg, #NurseTwitter and #MedTwitter) in their Twitter posts. By using hashtags as a means of social learning, health care professionals can become learners and mentors on how to correct health misinformation on social media (eg, having exposed to posts with a #NurseTwitter or #MedTwitter hashtag can provide examples on how to correct):

> *So, there's a hashtag #NurseTwitter or #NursesRetweet or #NurseAcademics or whatever. I believe it sets an example for other nurse colleagues who may be new to Twitter or may not know how to respond to misinformation and then they could see by example that basically we just need to share the correct information but not engage in some big argument and get into some kind of dramatic engagement on Twitter and social media because it doesn't do any good.* [registered nurse 10]

Finally, 2 participants (physician; 2/15, 13%) emphasized that health care professionals should maintain professionalism. This is evidenced by being respectful to others (regardless of how disrespectful others are) and providing credible evidence to any statement posted on social media:

> *Don't get into fight with people. Maintain your professionalism. Make sure that whatever you're saying, you're saying it with evidence. That's the most important thing. You don't wanna get into kind of a back and forth tug of war with somebody who is just trying to goad you along. So, you just need to make*

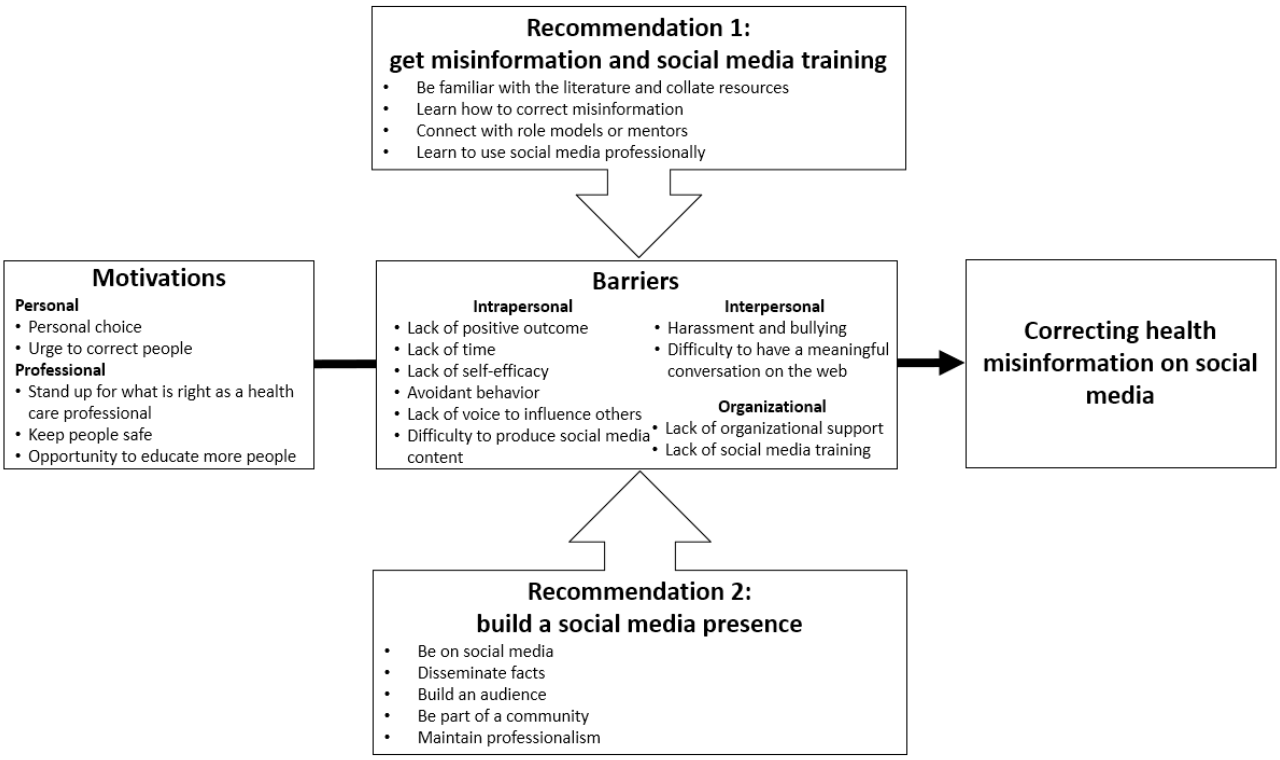
sure that you are behaving in a professional manner and remember that you're still being representative of your profession while you're on social media. So, whatever you post just think 'what would something I would say to that person's face?' If it is – then you are free to post it. If not, then don't post it. [physician 13]

Discussion

Principal Findings

This qualitative study among 30 US physicians and nurses revealed several motivations, barriers, and recommendations related to correcting health misinformation on social media. Figure 1 shows a model that summarizes these findings.

Figure 1. A model depicting US physicians' and nurses' motivations, barriers, and recommendations for correcting health misinformation on social media.



In terms of motivations, we found that participants were motivated to correct health misinformation for both personal (ie, urge to correct people and personal choice) and professional (ie, stand up for what is right as a health care professional, opportunity to educate more people, and keep people safe) reasons. Although there is no legal mandate for them to correct health misinformation on social media, they are likely to be motivated by professional reasons. This is expected considering that correcting health misinformation on social media is an action that is compatible with their professional identity as health care professionals [32]. Specifically, correcting health misinformation is an opportunity for participants to demonstrate their clinical knowledge and skills with the intention of promoting health and doing good [32]. Besides, given their good levels of eHealth literacy [10,11] and positive attitudes toward social media [20-23], they are likely to leverage social media to demonstrate their professional identity.

This study also identified barriers for health care professionals to correct health misinformation on social media. A key contribution of this study is the grouping of barriers as intrapersonal, interpersonal, and institutional barriers. Intrapersonal barriers included lack of positive outcomes, lack of voice to influence others, lack of time, difficulty producing social media content, lack of self-efficacy, and avoidant behavior. Interpersonal barriers included harassment and bullying, as well as the difficulty of having a meaningful conversation on the web. Institutional barriers included lack of organizational support and lack of social media training. In general, the barriers identified are reminiscent of journalists' barriers when correcting misinformation or disinformation [33,34]. Nonetheless, it is interesting to note that a serious consequence for both health care professionals and journalists who correct misinformation or disinformation on social media is harassment. Scholars have suggested that social media are breeding grounds for trolls and troublemakers [35], who can perpetuate several types of web-based harassment, such as cyberbullying, cyber-mob attacks, trolling, hateful speech, and web-based threats [36]. In fact, recent reports show that 1 in 4 US physicians experience personal attacks and sexual harassment on social media [37]. Research suggests that nurses experience cyberbullying and harassment, which can have a negative impact on their practice [38]. Thus, we argue that harassment is one of the greatest barriers to encouraging more physicians and nurses to correct health misinformation on social media, considering that they do not deserve such treatment when providing a voluntary service. As such, this finding serves as a call for health authorities and organizations to provide support (eg, institutional backing and providing social media training)

when health care professionals decide to engage in misinformation correction activities.

In addition to motivations and barriers, participants also shared their recommendations on how health care professionals can overcome some of the barriers associated with correcting health misinformation on social media. First, they encouraged health care professionals to obtain misinformation and social media training by learning how to correct misinformation, being familiar with the literature and collating sources, learning to use social media professionally, and connecting with role models or mentors. In general, such recommendations point to the need to incorporate social media training as part of health profession education. Traditionally, communication training in health professions focuses on interpersonal communication between providers and patients and among providers [39]. With the global adoption of social media, there is a need to equip health care professionals with skills for effectively communicating health information in this channel [23-26,40]. Therefore, to effectively communicate with the public when correcting health misinformation on social media, in addition to interpersonal communication training, it is crucial to incorporate mass communication training, as social media is a hybrid of interpersonal and mass communication [41]. As such, this study calls for the reevaluation of communication training programs for health care professionals to effectively use social media for professional health communication. Such training is needed if we expect them to be on social media as health care professionals who can help correct health misinformation.

In addition to getting misinformation and social media training, participants recommended their peers build a social media presence by being on social media, disseminating facts, building an audience, being part of a community, and maintaining professionalism. Establishing a professional social media presence is needed to increase the probability of shaping the audience's attitudes toward a specific issue [42]. In this study, participants highlighted the need to build a social media presence so that the corrections they post can be shared by many, which can then increase the chances that the correction can dispel misperceptions. To date, several organizations are helping health care professionals establish a social media presence. For instance, health care social media organizations, such as Doctors on Social Media [43] and the Association for Healthcare Social Media [44], provide support and training for nurses and physicians to improve their social media presence and effectively correct health misinformation. Furthermore, YouTube announced that it would provide support to health care professionals to increase their social media presence as a strategy to combat health misinformation [45].

Limitations

This study has two limitations. First, participants in this study were represented by physicians and registered nurses. Although they comprise most of the US health care workforce [27], insights from other health care professionals (eg, dentists, pharmacists, and physical therapists) can be added in future studies. Second, the findings were derived from interviews with US participants. Hence, the findings may not be fully comparable with the experiences of health care professionals based outside the US. Future cross-country studies are needed to determine whether other factors (eg, perceived practice autonomy and perceived authority) could play a role in motivating health care professionals to correct health misinformation on social media.

Conclusions

Given how widespread health misinformation is on social media (as demonstrated by the COVID-19 infodemic), health care professionals can lend their time to mitigate this public health concern. In this study, we found that US physicians and nurses are professionally and personally motivated to correct health misinformation on social media despite some of the barriers they face in performing such an act. It also sheds light on specific recommendations to minimize or overcome such barriers. In general, the findings can be used by health authorities and educational institutions when developing campaigns or educational programs to train health care professionals to correct health misinformation on and off social media.

Acknowledgments

This work was supported by the Bullard Research Fellowship awarded to JRB by the School of Information, The University of Texas at Austin. The authors would like to express their gratitude to the 30 US health care professionals who agreed to be interviewed for this study despite the worsening COVID-19 pandemic at the time of data collection.

Authors' Contributions

JRB secured funding for this study. JRB, YZ, and JG designed the study and data collection procedures. JRB collected the data under the supervision of YZ and JG. JRB, YZ, and JG participated in the data analysis and interpretation of the findings. JRB drafted the manuscript. All authors contributed to the refinement of all sections and critically edited the manuscript.

Conflicts of Interest

None declared.

References

1. Chou WS, Gaysynsky A, Cappella JN. Where We Go From Here: Health misinformation on social media. Am J Public Health 2020 Oct;110(S3):273-275. [doi: 10.2105/ajph.2020.305905]

2. Rodgers K, Massac N. Misinformation: A threat to the public's health and the public health system. J Public Health Manag Pract 2020;26(3):294-296. [doi: 10.1097/PHH.0000000000001163] [Medline: 32235211]
3. Luk T, Zhao S, Weng X, Wong J, Wu Y, Ho S, et al. Exposure to health misinformation about COVID-19 and increased tobacco and alcohol use: a population-based survey in Hong Kong. Tob Control 2020 Aug 27:A. [doi: 10.1136/tobaccocontrol-2020-055960] [Medline: 32855353]
4. Lee JJ, Kang K, Wang MP, Zhao SZ, Wong JY, O'Connor S, et al. Associations between COVID-19 misinformation exposure and belief with COVID-19 knowledge and preventive behaviors: cross-sectional online study. J Med Internet Res 2020 Nov 13;22(11):e22205 [FREE Full text] [doi: 10.2196/22205] [Medline: 33048825]
5. Bode L, Vraga EK. See Something, Say Something: Correction of global health misinformation on social media. Health Commun 2018 Sep;33(9):1131-1140. [doi: 10.1080/10410236.2017.1331312] [Medline: 28622038]
6. Suarez-Lledo V, Alvarez-Galvez J. Prevalence of health misinformation on social media: systematic review. J Med Internet Res 2021 Jan 20;23(1):e17187 [FREE Full text] [doi: 10.2196/17187] [Medline: 33470931]
7. Wang Y, McKee M, Torbica A, Stuckler D. Systematic literature review on the spread of health-related misinformation on social media. Soc Sci Med 2019 Nov;240:112552 [FREE Full text] [doi: 10.1016/j.socscimed.2019.112552] [Medline: 31561111]
8. UN launches new initiative to fight COVID-19 misinformation through ‘digital first responders’. UN News. 2020. URL: https://news.un.org/en/story/2020/05/1064622 [accessed 2021-05-03]
9. Countering misinformation about COVID-19 - a joint campaign with the Government of the United Kingdom. Pan American Health Organization and World Health Organization. 2020. URL: https://www.paho.org/en/news/13-5-2020-countering-misinformation-about-covid-19 [accessed 2021-05-03]
10. Shiferaw KB, Mehari EA. Internet use and eHealth literacy among health-care professionals in a resource limited setting: a cross-sectional survey. Adv Med Educ Pract 2019;10:563-570 [FREE Full text] [doi: 10.2147/AMEP.S205414] [Medline: 31440113]
11. Cho H, Han K, Park B. Associations of eHealth literacy with health-promoting behaviours among hospital nurses: a descriptive cross-sectional study. J Adv Nurs 2018 Jul;74(7):1618-1627 [FREE Full text] [doi: 10.1111/jan.13575] [Medline: 29575085]
12. Gartrell K, Han K, Trinkoff A, Cho H. Three-factor structure of the eHealth Literacy Scale and its relationship with nurses' health-promoting behaviours and performance quality. J Adv Nurs 2020 Oct;76(10):2522-2530 [FREE Full text] [doi: 10.1111/jan.14490] [Medline: 33463741]
13. Saad L. U.S. Ethics ratings rise for medical workers and teachers. Gallup, Inc. 2020. URL: https://news.gallup.com/poll/328136/ethics-ratings-rise-medical-workers-teachers.aspx [accessed 2021-05-03]
14. Renfrow J. Social media influencers in healthcare you should know in 2020. FierceHealthcare. 2019. URL: https://www.fiercehealthcare.com/special-report/top-social-media-influencers-healthcare-for-2019 [accessed 2021-05-03]
15. Jennings R. The rise of the nursefluencer: The doctor will fave you now. Vox Media. 2019. URL: https://www.vox.com/the-goods/2019/5/10/18535853/doctor-instagram-nurse-doctor-mike-influencer [accessed 2021-05-03]
16. Ohlheiser A. Doctors are now social-media influencers. They aren’t all ready for it. MIT Technology Review. 2020. URL: https://www.technologyreview.com/2020/04/26/1000602/covid-coronavirus-doctors-tiktok-youtube-misinformation-pandemic/ [accessed 2021-05-03]
17. Wells G. Doctors are tweeting about coronavirus to make facts go viral. The Wall Street Journal. 2020. URL: https://www.wsj.com/articles/doctors-are-tweeting-about-coronavirus-to-make-facts-go-viral-11589558880 [accessed 2021-05-03]
18. Sierro TJ, Young PM, Kassabian SK, Wu KK, Armstrong AW. Dermatologists in social media: a study on top influencers, posts, and user engagement. J Am Acad Dermatol 2020 Nov;83(5):1452-1455. [doi: 10.1016/j.jaad.2020.03.001] [Medline: 32151630]
19. Varady NH, Chandawarkar AA, Kernkamp WA, Gans I. Who should you be following? The top 100 social media influencers in orthopaedic surgery. World J Orthop 2019 Sep 18;10(9):327-338 [FREE Full text] [doi: 10.5312/wjo.v10.i9.327] [Medline: 31572669]
20. Alanzi T, Al-Yami S. Physicians' attitude towards the use of social media for professional purposes in Saudi Arabia. Int J Telemed Appl 2019 Dec 02;2019:6323962 [FREE Full text] [doi: 10.1155/2019/6323962] [Medline: 31885550]
21. Bautista J, Lin T. Nurses' use of mobile instant messaging applications: a uses and gratifications perspective. Int J Nurs Pract 2017 Oct;23(5):e12577 [FREE Full text] [doi: 10.1111/ijn.12577] [Medline: 28752519]
22. Panahi S, Watson J, Partridge H. Social media and physicians: exploring the benefits and challenges. Health Informatics J 2014 Jul 18;22(2):99-112. [doi: 10.1177/1460458214540907] [Medline: 25038200]
23. Bautista JR, Zhang Y, Gwizdka J. Healthcare professionals' acts of correcting health misinformation on social media. Int J Med Inform 2021 Apr;148:104375. [doi: 10.1016/j.ijmedinf.2021.104375] [Medline: 33461008]
24. O'Connor C, Murphy M. Going viral: doctors must tackle fake news in the covid-19 pandemic. Br Med J 2020 Apr 24;369:m1587. [doi: 10.1136/bmj.m1587] [Medline: 32332066]
25. Rubin R. Getting Social: Physicians can counteract misinformation with an online presence. J Am Med Assoc 2019 Aug 20;322(7):598-600 [FREE Full text] [doi: 10.1001/jama.2019.10779] [Medline: 31365030]

26. Swire-Thompson B, Lazer D. Public health and online misinformation: challenges and recommendations. Annu Rev Public Health 2020 Apr 02;41(1):433-451. [doi: 10.1146/annurev-publhealth-040119-094127] [Medline: 31874069]
27. The U.S. Health Workforce Chartbook – in brief. National Center for Health Workforce Analysis. 2018. URL: https://bhw.hrsa.gov/sites/default/files/bureau-health-workforce/data-research/hrsa-us-health-workforce-chartbook-in-brief.pdf [accessed 2021-05-03]
28. Tracy S. Qualitative Research Methods: Collecting Evidence, Crafting Analysis, Communicating Impact, 2nd Edition. Hoboken, New Jersey, United States: WIley-blackwell; 2019:1-432.
29. Green J, Thorogood N. Qualitative Methods for Health Research (4th ed). Thousand Oaks, California, United States: SAGE Publications Ltd; 2018:1-440.
30. Giorgi A. The theory, practice, and evaluation of the phenomenological method as a qualitative research procedure. J Phenomenol Psychol 1997;28(2):235-260. [doi: 10.1163/156916297x00103]
31. Shenton AK. Strategies for ensuring trustworthiness in qualitative research projects. Educ Inf 2004 Jul 19;22(2):63-75. [doi: 10.3233/EFI-2004-22201]
32. Fitzgerald A. Professional identity: a concept analysis. Nurs Forum 2020 Jul;55(3):447-472 [FREE Full text] [doi: 10.1111/nuf.12450] [Medline: 32249453]
33. Balod HS, Hameleers M. Fighting for truth? The role perceptions of Filipino journalists in an era of mis- and disinformation. Journalism 2019 Jul 24:1464884919865109. [doi: 10.1177/1464884919865109]
34. Haigh M, Haigh T, Kozak NI. Stopping Fake News. Journal Stud 2017 Apr 25;19(14):2062-2087. [doi: 10.1080/1461670x.2017.1316681]
35. Bradshaw S, Howard P. Troops, Trolls and Troublemakers: A global inventory of organized social media manipulation. Computational Propaganda Research Project. 2017. URL: http://governance40.com/wp-content/uploads/2018/11/Troops-Trolls-and-Troublemakers.pdf [accessed 2021-07-21]
36. Defining “Online Abuse”: a glossary of terms. Online Harassment Field Manual. URL: https://onlineharassmentfieldmanual.pen.org/defining-online-harassment-a-glossary-of-terms/ [accessed 2021-05-03]
37. Pendergrast TR, Jain S, Trueger NS, Gottlieb M, Woitowich NC, Arora VM. Prevalence of personal attacks and sexual harassment of physicians on social media. JAMA Intern Med 2021 Apr 01;181(4):550-552. [doi: 10.1001/jamainternmed.2020.7235] [Medline: 33393965]
38. D’Souza N, Forsyth D, Tappin D, Catley B. Workplace cyberbullying in New Zealand nursing. School of Management, Massey University, Auckland, New Zealand. 2017. URL: https://www.massey.ac.nz/shadomx/apps/fms/fmsdownload.cfm?file_uuid=D5ECA077-0C0D-4603-894F-AC2EBADE3FBE [accessed 2021-06-01]
39. Spitzberg BH. (Re)Introducing communication competence to the health professions. J Public Health Res 2013 Dec 01;2(3):e23 [FREE Full text] [doi: 10.4081/jphr.2013.e23] [Medline: 25170494]
40. Trethewey SP. Strategies to combat medical misinformation on social media. Postgrad Med J 2020 Jan;96(1131):4-6 [FREE Full text] [doi: 10.1136/postgradmedj-2019-137201] [Medline: 31732511]
41. Neubaum G, Krämer NC. Opinion climates in social media: blending mass and interpersonal communication. Hum Commun Res 2017 Jun 30;43(4):464-476. [doi: 10.1111/hcre.12118]
42. Magno F, Cassia F. The impact of social media influencers in tourism. Anatolia 2018 May 24;29(2):288-290. [doi: 10.1080/13032917.2018.1476981]
43. Your Health is in YOUR Hands: Empower yourself by learning directly from experts. Doctors on Social Media. URL: https://doctorsonsocialmedia.com/ [accessed 2021-05-03]
44. Association for Healthcare Social Media. 2021. URL: https://ahsm.org/ABOUT-US [accessed 2021-05-03]
45. Bailey T. YouTube backs local creators, healthcare professionals to combat misinformation on platform. KXAN Austin. 2021. URL: https://www.kxan.com/news/local/austin/youtube-backs-local-creators-healthcare-professionals-to-combat-misinformation-on-platform/ [accessed 2021-05-03]

Edited by Y Khader; submitted 12.02.21; peer-reviewed by A Efthymiou, M Renfrew, D Liu; comments to author 05.04.21; revised version received 10.05.21; accepted 02.06.21; published 01.09.21.

Please cite as:
Bautista JR, Zhang Y, Gwizdka J
US Physicians’ and Nurses’ Motivations, Barriers, and Recommendations for Correcting Health Misinformation on Social Media: Qualitative Interview Study
JMIR Public Health Surveill 2021;7(9):e27715
URL: https://publichealth.jmir.org/2021/9/e27715
doi:10.2196/27715
PMID:34468331

Original Paper

Increasing Testing Options for Key Populations in Burundi Through Peer-Assisted HIV Self-Testing: Descriptive Analysis of Routine Programmatic Data

Tiffany Lillie[1], MHS, PhD; Dorica Boyee[2], BSc, MPH; Gloriose Kamariza[3], BSc; Alphonse Nkunzimana[3], MD; Dismas Gashobotse[3], MBBS, MD; Navindra Persaud[1], MBBS, MPH, MD

[1]Family Health International 360, Washington, DC, United States

[2]Family Health International 360, Dar es Salaam, United Republic of Tanzania

[3]Family Health International 360, Bujumbura, Burundi

Corresponding Author:
Tiffany Lillie, MHS, PhD
Family Health International 360
1825 Connecticut Avenue
Suite 800
Washington, DC, 20009
United States
Phone: 1 202 884 8000
Email: tlillie@fhi360.org

Abstract

Background: In Burundi, given the low testing numbers among key populations (KPs), peer-assisted HIV self-testing (HIVST) was initiated for female sex workers (FSWs), men who have sex with men (MSM), and transgender people to provide another testing option. HIVST was provided by existing peer outreach workers who were trained to provide support before, during, and after the administration of the test. People who screened reactive were referred and actively linked to confirmatory testing, and those confirmed positive were linked to treatment. Standard testing included HIV testing by clinical staff either at mobile clinics in the community or in facilities.

Objective: This study aims to improve access to HIV testing for underserved KPs, improve diagnoses of HIV serostatus among key populations, and link those who were confirmed HIV positive to life-saving treatment for epidemic control.

Methods: A descriptive analysis was conducted using routine programmatic data that were collected during a 9-month implementation period (June 2018 to March 2019) for peer-assisted HIVST among FSWs, MSM, and transgender people in 6 provinces where the US Agency for International Development–and US President's Emergency Plan for AIDS Relief–funded LINKAGES (Linkage across the Continuum of HIV Services for KP Affected by HIV) Burundi project was being implemented. Chi-square tests were used to compare case-finding rates among individuals who were tested through HIVST versus standard testing. Multivariable logistic regression was performed to assess factors that were independently associated with HIV seropositivity among FSWs and MSM who used HIVST kits.

Results: A total of 2198 HIVST kits were administered (FSWs: 1791/2198, 81.48%; MSM: 363/2198, 16.52%; transgender people: 44/2198, 2%). HIV seropositivity rates from HIVST were significantly higher than those from standard testing for FSWs and MEM and nonsignificantly higher than those from standard testing for transgender people (FSWs: 257/1791, 14.35% vs 890/9609, 9.26%; P<.001; MSM: 47/363, 12.95% vs 90/2431, 3.7%; P<.001; transgender people: 10/44, 23% vs 6/36, 17%; P=.50). Antiretroviral therapy initiation rates were significantly lower among MSM who were confirmed to be HIV positive through HIVST compared to those among MSM who were confirmed to be HIV positive through standard testing (40/47, 85% vs 89/90, 99%; P<.001). No significant differences in antiretroviral therapy initiation rates were found between the FSW and transgender groups. Multivariable analyses among FSWs who used HIVST kits showed that being aged ≥25 years (adjusted odds ratio 1.9, 95% CI 1.4-2.6) and having >8 clients per week (adjusted odds ratio 1.3, 95% CI 1.0-1.8) were independently associated with HIV seropositivity.

Conclusions: The results demonstrate the potential effectiveness of HIVST in newly diagnosing underserved KPs and linking them to treatment.

(JMIR Public Health Surveill 2021;7(9):e24272) doi:10.2196/24272

KEYWORDS

HIV; HIV self-testing; key populations; case finding; ART initiation; Burundi

Introduction

Background

In October 2016, following the World Health Organization (WHO) recommendations, HIV self-testing (HIVST) was included in the Burundi national testing guidelines for key populations (KPs), including female sex workers (FSWs) and men who have sex with men (MSM), to help achieve the UNAIDS (The Joint United Nations Program on HIV/AIDS) first 90 goal—to have 90% of all people living with HIV know their status [1,2]. In addition, the Burundi HIV 2018-2022 National Strategic Plan puts greater emphasis on KPs than past plans and sets the country's own *90* goals: 90% of KPs should be reached with prevention messages and access to prevention commodities, 90% should know their HIV status, 90% of those diagnosed with HIV should have access to antiretroviral therapy (ART), and 90% of those on ART should be virally suppressed [3]. Achieving ambitious targets like these requires that HIV programs find new ways to identify individuals who are HIV positive and initiate them on treatment.

The HIV epidemic in Burundi is considered a low-prevalence mixed epidemic. HIV prevalence among the general population in 2017 was estimated at 1%; however, recent studies have found significantly higher HIV prevalence among KPs [4]. Data from the 2014 Priorities for Local AIDS Control Efforts study showed an HIV prevalence of 21.3% among FSWs and 4.8% among MSM [5]. In addition, testing rates in both populations were low; 43% of FSWs and 32% of MSM reported that they had tested for HIV in the past year [5]. In Burundi, sex work and homosexuality are criminalized, which increases stigma and discrimination, harassment, and arrests among KPs [6,7]. Laws and prevailing cultural and social norms that stigmatize KPs not only infringe on their rights but also amplify risk and vulnerability and limit their access to HIV services [6-8]. Therefore, public health programs must find unique and innovative ways to offer differentiated service delivery (DSD), both to address the unique challenges experienced by KPs and to provide individuals with a range of options that meet their needs.

The Burundi Ministry of Health and the National AIDS and Sexually Transmitted Infections Program, supported by the US President's Emergency Plan for AIDS Relief and the US Agency for International Development through the LINKAGES (Linkages across the Continuum of HIV Services for KPs Affected by HIV) project [9], drafted an implementation plan in 2018 for HIVST in Burundi. HIVST with OraQuick (OraSure Technology, Inc) [10] was initiated in June 2018 for FSWs, MSM, and transgender people to provide another testing option. HIV testing using rapid tests was offered in the community and facilitated by trained medical staff before HIVST. With the introduction of HIVST, lay workers, for the first time, were able to offer peers HIV testing in their preferred locations in the community and at convenient times. The aim was to improve access to HIV testing to underserved KPs, increase HIV positivity rates, and link those who were confirmed HIV positive with life-saving treatment for epidemic control.

A growing body of evidence shows that HIVST is highly acceptable, feasible, convenient, and viewed as more confidential than standard testing services among harder-to-reach and higher-risk populations, including KPs [11-19]. According to early systematic reviews, HIVST, both supervised and unsupervised, had high acceptability among participants [18] and was preferred over standard testing as it was convenient and private [15,17]. A Nigerian study [12], which explored the uptake of HIVST among MSM, found in a survey conducted 3 months after HIVST kits were distributed that almost all the men had used the kit, and most reported that the test was easy to use, confidential, and convenient. Another study among MSM in Uganda found that HIVST was viewed as more confidential and easier to use, and the men appreciated that the results were provided quickly compared with standard testing services [16]. In a study of FSWs in Kenya [13], women found HIVST to be acceptable and accessible. In numerous studies, people have generally preferred HIVST over conventional testing strategies for its convenience and confidentiality, which has increased access to testing services [12,15-17,19].

However, peer-reviewed HIVST literature has raised implementation concerns such as the lack of pre- and posttest counseling [15,17], lack of immediate emotional support and barriers to successful linkage and referral to other needed services [14,16,17,20,21], concern that the test provides unreliable results for those unfamiliar with its administration, and possible user error for those who choose unassisted HIVST [15,16,22,23]. Choko et al [23] found that about 10% of Malawian participants did make some administrative errors in using the kits and that the same percentage required extra help in performing the test. Another study found that first-time testers were less confident about accessing follow-up support compared with previous testers after a reactive test [14].

Numerous studies have concluded that more information, research, and stronger programming to ensure linkage to confirmatory testing and treatment after HIVST is necessary [11-13,17,18,20,21,23-26]; however, few have actually explored this relationship [11-13,20,21,25,26]. Varying rates of linkage to confirmatory testing and treatment were found in studies that used both assisted and unassisted HIVST [11-13,20,25-27]. One systematic review and meta-analysis on unsupervised HIVST among MSM in high-resource countries reported a range of linkage to care from 31.3%-100% [20]. There were a couple of studies that explored the relationship between unsupervised HIVST and linkage to treatment in KPs in Sub-Saharan African countries [11,12]. Both had high linkage rates; however, one had active follow-up and access to a KP-friendly drop-in-center component [12], and the other was not statistically significant from the standard service [13]. There were several studies that

described a peer-assisted HIVST model [18,23,25,26]; however, only two have explored the relationship between peer-assisted HIVST and linkage to other services [21,22]. Both studies were from Asia, targeting KPs; one demonstrated a high linkage rate, and the other had no linkage evidence [25,26].

Objectives

There is a dearth of data describing which HIVST models targeted to KPs in Africa can be effective in closing gaps in testing and treatment. This study aims to improve access to HIV testing for underserved KPs, improve diagnosis of HIV serostatus among key populations, and link those who were confirmed HIV positive with life-saving treatment for epidemic control. We describe our experience with peer-assisted HIVST distribution and implementation among FSWs, MSM, and transgender people in Burundi and compare HIV seropositivity and ART linkage among people screened through HIVST with those screened during standard HIV testing services (HTS).

Methods

Geographic Locations

A descriptive analysis was conducted on routine programmatic data that were collected during a 9-month implementation period (June 2018 to March 2019) for peer-assisted HIVST where LINKAGES operated: Bujumbura Mairie (urban), Bujumbura Rural (periurban), Kayanza (periurban and rural), Ngozi (periurban and rural), Kirundo (periurban and rural), and Gitega (urban). The 6 provinces were selected through the US President's Emergency Plan for AIDS Relief strategic planning processes based on national and subnational epidemiological data and stakeholder consultation. In each province, the selection of communes (a lower administrative unit) for implementing HIVST was based on project-specific mapping and size estimation, routine program monitoring data on testing, and in-country consultation.

Implementation of Standard HIV Testing by CBOs

The CBOs had previously established outreach programs that delivered services to KPs in a variety of hot spots (geographic areas where KPs were present and where high-risk behaviors were practiced), such as karaoke bars, short-term guest houses, massage parlors, and truck stops. The CBOs hired, trained, and paid peer outreach workers (POWs) to provide KPs with prevention services and referrals to testing for HIV and sexually transmitted infections. The POWs hired by CBOs were recruited from identified hot spots, and selection criteria included identifying as an FSW, a man who has sex with men, or a transgender person; the willingness to work on an HIV project; good communication and leadership skills; and the ability to motivate peers to seek health services. LINKAGES conducted programmatic hot spot mapping and size estimation per venue, and POWs were selected to cover a specific number of venues. POWs had a list of peers that they provided HIV outreach services to, and they usually conducted outreach services on weekends during evening hours when the maximum number of KPs were available. POWs chose their own hours but were supervised and coached by the CBO staff on planning their outreach schedule on a monthly basis.

Clinical staff provided standard testing services (blood-based testing) in the community through mobile testing and in the health facilities. Staff who provided services in the mobile and health facilities followed the national HIV testing algorithm, using a rapid HIV blood-based test. The CBOs also used the programmatic mapping and size-estimation results as well as the peer educators' information on how many FSWs, MSM, and transgender people needed an HIV test to schedule the mobile testing unit's monthly operational calendar. POWs also referred KP peers to the facility for HIV testing and other services based on need (ie, HIV testing every 3 months and sexually transmitted infection symptoms) and demand.

HIVST Implementation Through POWs

The OraQuick HIV self-test kit from OraSure Technologies, with 93% sensitivity and 99% specificity [28,29], was used in the LINKAGES KP program. A total of 87 POWs were trained to conduct peer-assisted HIVST. In the HIVST strategy, trained POWs increased awareness about HIVST among their peers (defined as someone in the same KP group), discussed the benefits of HIVST and reduced the misconceptions about the test, assessed peers' eligibility for HIVST (ie, not tested in the last 3 months), demonstrated how the HIVST kit was administered, provided abbreviated pre- and posttest counseling, supported the administration of the test, managed the screening results and ethical issues, and provided referrals for follow-up services. The KP peer chose the location and time that they preferred to take the HIVST. Then, the peer self-administered the test with the POW sitting by them to support the individual in taking the sample, timing, and reading the results. The POW would offer posttest counseling and assistance to access other preventative services or confirmation testing based on the results of the test. POWs received a stipend of BIF 30,000 (US $15.30) per month for their involvement in the HIVST program.

The POWs were asked to reach out to other KPs in their communities who would benefit from HTS. The POWs used standardized screening forms to determine peer eligibility for HIVST kits. To be eligible for standard or self-testing, the peer needed to be a KP at high behavioral risk and not tested in the last 3 months. High behavioral risk was determined based on affirmative responses to any of the following questions: having sex with a man in the last month (MSM), receiving money or gifts for sex (MSM and FSW), having >8 sexual partners in the last week (FSW), not using condoms consistently (MSM and FSW), and consuming alcohol and drugs regularly (MSM and FSW). The screening tool for standard testing asked about KP status but not about the number of sexual partners in the last week, consistent condom use, or regular alcohol or drug use. Eligible KP members who were already accessing standard testing services were encouraged to continue testing through this modality every 3 months or to use HIVST if that was preferable. High-risk KP members who were never tested or tested rarely (defined as not tested in the last 6 months) or requested HIVST were offered HIVST. None of the patients who had already accessed standard testing or were rarely or never tested were denied an HIVST kit if they wanted to be tested through this modality. Individuals who did not meet the criteria for participating in HIVST, including those who already knew they were HIV positive, were linked to other HIV services

based on need. Once KP peers accepted HIVST, the POWs provided peer-assisted testing.

If the test was nonreactive, peers were offered prevention services, such as risk reduction messages, condoms, and lubricants, and asked to get tested for HIV within 3 months if the risk behaviors continued. All those who had a reactive screening test were either accompanied by the POW or referred to a facility of their choice for confirmatory testing. Individuals with a confirmed positive test result were provided counseling and offered same-day treatment. POWs were supported and mentored by supervisors to ensure that they provided effective counseling and demonstrated good communication skills, could successfully administer the test and interpret the test results, and were able to link their peers to other health services. At the end of the training, HIVST kits were provided to CBOs and POWs to distribute to and assist high-risk and eligible peers.

Target Populations

The target populations for HIVST implementation were FSWs, MSM, and transgender people. FSWs were defined as women who were aged at least 18 years and who received money or goods in exchange for sexual services, either regularly or occasionally. MSM were defined as men who engaged in sexual relations with other men in the last 12 months. Transgender people were those whose gender identity and expression did not conform to the norms and expectations traditionally associated with the sex assigned to them at birth and included transgender women and men.

Data Collection and Management

During service delivery, paper-based data collection tools adopted from the LINKAGES global guidance [30] were used by the outreach staff to screen if individuals were members of a KP group and captured data on HIV risk, sociodemographic information, HIVST results, results of follow-up confirmatory tests, and services received by those who were HIV positive. As HIVST was peer assisted, the result of the HIVST was recorded immediately in the main HIVST register. All other services received, including acceptance of a confirmatory test among those who had a reactive screening results and enrollment in treatment, were recorded in the same register. At the end of the 9 months of implementation, data were stripped of all personal identifiers and entered into an electronic database by dedicated program data clerks. The monitoring and evaluation officer reviewed the accuracy of the data, compared the paper records with the information entered in the database, and guided data entry clerks to make corrections where necessary.

For this analysis, the HIVST program database was reviewed, and data were extracted for selected variables, including location, age, KP type, ever tested, tested in the last 6 months, exchange sex for money, number of clients per week (if FSW), condom use, alcohol use, HIVST screening results, confirmatory testing and results, and treatment initiation for all those who received an HIVST kit during the 9-month period. Data on standard testing clients were obtained from the project's aggregated report for each month during the same period of HIVST implementation. The monthly aggregate reports were made by summarizing client-level data collected using standardized paper-based data collection tools.

Data Analysis

Descriptive analysis was conducted initially to describe case-finding rates; links to treatment; and sociodemographic, sexual, and health-seeking behaviors of those who screened reactive via HIVST. HIV seropositivity rates and links to treatment were compared among KPs who were screened using HIVST with those tested using standard methods. When comparing HIV seropositivity rates among FSWs and MSM who used HIVST kits with those tested using standard methods, stratified analysis was conducted to adjust the outcome for age. Among FSWs and MSM who used HIVST kits, bivariate analyses were first used to identify sociodemographic characteristics and sexual and health-seeking behaviors associated with HIV seropositivity. Multivariable logistic regression was then used to determine factors independently associated with HIV seropositivity. Variables that were significant in the univariate analysis and geographic area of residence were included in the logistic regression model. The chi-square test or Fisher exact test (when the expected cell value was <5) was used to test for differences in proportions for categorical variables. The two-tailed Student *t* test was used to test for differences in the means of continuous variables. For all comparisons, P=.05 was considered significant. All analyses were performed using Stata 14 (StataCorp LLC).

Ethical Issues

Following local and international norms, all individuals who presented at a testing service and requested an HIV test received either abbreviated pre- and posttest counseling from a POW during HIVST or pre- and posttest counseling from a clinical staff member during standard HIV testing. All KPs provided oral informed consent before the test was conducted. The authors had no access to individual identifying information of those who received either HIVST or standard testing as all data were extracted from a database that contained no personal identifiers. The request to conduct secondary analysis of program data that did not contain any personal identifying information was reviewed by the institutional review board of the Family Health International 360 and was classified as nonhuman-subjects research.

Results

HIVST Distribution and User Characteristics

From June 2018 to March 2019, a total of 2198 HIVST kits were distributed and used (FSWs: 1791/2198, 81.48%; MSM: 363/2198, 16.52%; transgender people: 44/2198, 2%). The distribution of the kits was unequal across the 6 geographic areas; of the 2198 kits distributed, 1090 (49.59%) were distributed in Bujumbura Mairie, the capital, and 50 (2.27%) kits in Gitega (Table 1). The mean age of the individuals using the self-test kits was 27 years (SD 7.6). Of the total number of users, 60.05% (1320/2198) were receiving an HIV test for the first time, and 7.05% (155/2198) had been tested for HIV at least once but not in the last 6 months (Table 1).

Table 1. Characteristics of those who used self-test kits (N=2198).

Indicator	FSW[a] (n=1791)	MSM[b] (n=363)	Transgender people (n=44)	All key populations (n=2198)
Test kits used, n (%)	1791 (100)	363 (100)	44 (100)	2198 (100)
Bujumbura Mairie	819 (45.7)	230 (63.4)	41 (93.2)	1090 (49.6)
Bujumbura rural	28 (1.6)	21 (5.8)	3 (6.8)	52 (2.4)
Gitega	44 (2.5)	6 (1.7)	0 (0)	50 (2.3)
Kayanza	446 (24.9)	49 (13.5)	0 (0)	495 (22.5)
Kirundo	43 (2.4)	21 (5.8)	0 (0)	64 (2.9)
Ngozi	411 (22.9)	36 (9.9)	0 (0)	447 (20.3)
Age using self-test kits (years), mean (SD)	27.0 (7.5)	29.60 (8.0)	28.2 (5.5)	27.4 (7.6)
HIV testing status, n (%)				
First-time testers	1013 (56.6)	272 (74.9)	35 (79.5)	1320 (60.1)
Previously tested more than 6 months ago	105 (5.9)	46 (12.7)	4 (9.1)	155 (7.1)
Previously tested less than 6 months ago	673 (37.6)	45 (12.4)	5 (11.4)	723 (32.9)

[a]FSW: female sex worker.

[b]MSM: men who have sex with men.

HIVST Cascade Outcomes

Of the total number of KPs, 16.65% (366/2198) were reactive to HIV screening on HIVST, 95.9% (351/366) sought confirmatory testing, 89.5% (314/351) were confirmed to be HIV positive, and 95.9% (301/314) were initiated on treatment.

HIV seropositivity rates were significantly higher among those tested through HIVST compared with standard testing for FSWs (adjusted odds ratio [aOR] 1.7, 95% CI 1.4-1.9) and MSM (aOR 2.7, 95% CI 1.9-3.9) but not among transgender people. ART initiation rates were lower among MSM who tested through HIVST than those who tested through standard testing (40/47, 85% vs 89/90, 99%; *P*<.001; Table 2).

Table 2. HIV seropositivity rates from HIVST[a] compared with standard testing for FSWs[b], MSM[c], and transgender people in Burundi, June 2018 to March 2019 (N=14,274).

Indicator and testing model	FSWs	MSM	Transgender people	All KPs[d]
Number of KP members confirmed HIV positive				
HIVST, n (%)	257 (14)	47 (13)	10 (23)	314 (14)
Standard testing, n (%)	890 (9)	90 (4)	6 (17)	986 (8)
OR[e] (95% CI)	1.7 (1.4-1.9)[f]	2.7 (1.9-3.9)[f]	1.5 (0.4-5.5)	1.9 (1.6-2.2)
P value	<.001	<.001	.50	<.001
Number of KP members linked and initiated on ART[g]				
Linked from HIVST, n (%)	251 (98)	40 (85)	10 (100)	301 (96)
Linked from standard testing, n (%)	864 (97)	89 (99)	6 (100)	959 (97)
OR (95% CI)	1.2 (0.5-3.8)	0.1 (0.0-0.5)	1	0.6 (0.3-1.4)
P value	.61	<.001	__[h]	.21

[a]HIVST: HIV self-testing.

[b]FSW: female sex worker.

[c]MSM: men who have sex with men.

[d]KP: key population.

[e]OR: odds ratio.

[f]Adjusted for age.

[g]ART: antiretroviral therapy.

[h]Not available (*P* value cannot be calculated because cell has a value of 0).

User Characteristics Affecting Reactive Results

The multivariable logistic regression model among FSWs indicated that being aged ≥25 years (aOR 1.9, 95% CI 1.4-2.6) and having >8 clients per week (aOR 1.3, 95% CI 1.0-1.8) were significantly associated with a reactive HIVST. Among MSM, being aged ≥25 years and having an HIV test in the last 6 months were significantly associated with HIV seropositivity on bivariate analyses; however, these associations disappeared in the multivariable logistic model. Among MSM, living in Ngozi was significantly associated with a reactive HIVST in the multivariable model (aOR 4.3, 95% CI 1.8-10.5; Table 3).

Table 3. Sexual and health-seeking behaviors associated with a reactive HIVST[a] result (N=2198).

Characteristics and categories	FSW[b]					MSM[c]				
	HIVST outcome confirmed positive, n (%)	Unadjusted		Adjusted		HIVST outcome confirmed positive, n (%)	Unadjusted		Adjusted	
		OR[d] (95% CI)	*P* value	OR (95% CI)	*P* value		OR (95% CI)	*P* value	OR (95% CI)	*P* value
Age (years)	N/A[e]	N/A	<.001	N/A	<.001	N/A	N/A	.03	N/A	.08
<24	83 (10.2)	1.0 (reference)	N/A	1.0 (reference)	N/A	7 (7)	1.0 (reference)	N/A	1.0 (reference)	N/A
>25	174 (17.8)	1.9 (1.4-2.5)	N/A	1.9 (1.4-2.6)	N/A	40 (15.9)	2.5 (1.1-5.7)	N/A	2.2 (0.9-5.1)	N/A
Number of clients per week	N/A	N/A	.005	N/A	.03	N/A	N/A	N/A	N/A	N/A
<8	139 (12.5)	1.0 (reference)	N/A	1.0 (reference)	N/A	N/A	N/A	N/A	N/A	N/A
>8	117 (17.4)	1.5 (1.1-1.9)	N/A	1.3 (1.0-1.8)	N/A	N/A	N/A	N/A	N/A	N/A
Ever tested for HIV	N/A	N/A	.46	N/A	N/A	N/A	N/A	.37	N/A	N/A
No	151 (15)	1.0 (reference)	N/A	N/A	N/A	33 (12.5)	1.0 (reference)	N/A	N/A	N/A
Yes	105 (13.7)	0.9 (0.7-1.2)	N/A	N/A	N/A	14 (16.3)	1.4 (0.7-2.7)	N/A	N/A	N/A
Recently tested in the last 6 months	N/A	N/A	.54	N/A	N/A	N/A	N/A	.02	N/A	.10
No	165 (14.6)	1.0 (reference)	N/A	N/A	N/A	36 (11.8)	1.0 (reference)	N/A	1.0 (reference)	N/A
Yes	91 (13.7)	0.9 (0.7-1.2)	N/A	N/A	N/A	11 (24.4)	2.4 (1.1-5.2)	N/A	2.3 (0.9 6.4)	N/A
Do you use condoms for every sexual intercourse?	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Never	49 (14.8)	1.0 (reference)	N/A	N/A	N/A	22 (19.8)	1.0 (reference)	N/A	N/A	N/A
Sometimes	199 (14.3)	0.9 (0.7-1.4)	.83	N/A	N/A	21 (9.4)	0.4 (0.2-0.8)	.009	N/A	N/A
Always	5 (9.4)	0.6 (0.2-1.6)	.30	N/A	N/A	3 (21.4)	1.1 (0.3-4.3)	.89	N/A	N/A
Geographical areas										
Bujumbura Mairie	139 (17)	1.0 (reference)	N/A	1.0 (reference)	N/A	19 (8.7)	1.0 (reference)	N/A	1.0 (reference)	N/A
Bujumbura	9 (32.1)	2.3 (1.0-5.2)	.04	1.9 (0.8-4.4)	.12	7 (33.3)	5.2 (1.9-14.6)	.001	2.6 (0.8-8.9)	.13
Gitega	10 (23.8)	1.5 (0.7-3.2)	.26	1.2 (0.6-2.6)	.64	1 (16.7)	2.1 (0.2-18.9)	.51	1.4 (0.1-13.1)	.79
Kayanza	48 (10.8)	0.6 (0.4-0.8)	.003	0.6 (0.4-0.8)	.002	7 (14.3)	1.7 (0.7-4.4)	.24	1.9 (0.7-4.8)	.19
Kirundo	5 (11.9)	0.7 (0.3-1.7)	.39	0.7 (0.3-1.8)	.45	3 (14.3)	1.7 (0.5-6.5)	.40	1.6 (0.4-6.1)	.48
Ngozi	46 (11.2)	0.6 (0.4-0.9)	.008	0.6 (0.4-0.9)	.01	10 (27.8)	4.0 (1.7-9.6)	.002	4.3 (1.8-10.5)	.001

[a]HIVST: HIV self-testing.

[b]FSW: female sex worker.

[c]MSM: men who have sex with men.

[d]OR: odds ratio.

[e]N/A: not applicable.

Discussion

Principal Findings

The aim of the HIVST strategy was to increase access to HTS among KPs, increase new HIV diagnoses, and ensure effective treatment initiation once a reactive test was confirmed positive. Through this strategy, we were able to provide access to HTS to many MSM, FSWs, and transgender people not previously tested and who would likely not test given the stigma and discrimination from health care workers and lack of convenience and privacy at facilities. It was found that individuals initially screened through HIVST had a higher HIV positivity rate compared with those who chose standard HIV testing. ART initiation was similar between standard testing and HIVST for both FSWs and transgender people. However, lower rates of ART initiation were observed among MSM newly diagnosed through HIVST compared with standard testing. HIVST is an additional testing option that can help reach the most marginalized. It is an approach to support the achievement of the first and second 95 UNAIDS goals.

Offering peer-assisted HIVST to KPs provided the opportunity for those who never tested or rarely tested to access HTS and learn their serostatus. For the first time in Burundi, POWs were able to offer and aid peers in taking an HIV test in a private and confidential location of their choice and at a day and time convenient to them. Several studies supported Burundi's peer-assisted network implementation strategy by showing that KP members prefer to receive HIVST services at the community level through existing KP-friendly drop-in centers, peers, or hot spots [16,19,31]. In our study, of those who accepted HIVST, over half of the FSWs (1013/1791, 56.56%) had never tested previously, and 74.9% (272/363) of the MSM and 80% (35/44) of transgender people had never accessed HTS, and approximately 12.7% (46/363) of MSM and 9% (4/44) of transgender people who had tested previously had not tested in the last 6 months, which is consistent with other study findings [19,20,27]. Although new users did not have a statistically significant higher HIV positivity rate compared with those who tested in the last 6 months, the high number of new users who accessed HTS through HIVST is a public health success, given the low testing rates among KPs in Burundi [5]. The introduction of HIVST in Burundi was successful in its ability to expand HIV testing options to higher-risk populations who were not otherwise served by current HIV services and could learn their serostatus, which could overcome the underdiagnosis of HIV among KPs.

The HIVST strategy enabled the program to reach underserved populations and achieved higher HIV positivity rates compared with standard testing for FSWs and MSM. This could be attributed to several factors. First, KPs had more options for community-based testing, which they preferred over clinic-based models. This is especially important in settings such as Burundi, where high levels of stigma and discrimination exist. It is well documented that Burundi's KP community has high HIV prevalence levels, low testing rates, and high levels of criminalization and discrimination, which directly affect service use [6,8]. Second, HIVST (oral fluid based) is less invasive than standard testing (blood based). Third, HIVST is peer-assisted through POWs, whereas standard facility-based testing requires interaction with non-peer clinical staff. Fourth, with HIVST, KPs can choose when and where to take the HIVST without the need to visit a health facility. Not all KP individuals are comfortable accessing standard medical services even if they are provided by KP-friendly staff. Finally, POWs used a more targeted screening tool to determine eligibility for HIVST compared with standard testing; however, no one was denied an HIVST if it was their preferred testing method. The high proportion of KPs who were never or rarely tested and chose HIVST is a demonstration that this testing modality is meeting an unmet need for a certain segment of KPs. Other studies also found that those who accessed HIVST had a higher HIV positivity rate compared with standard testing services [19,24,32]. A meta-analysis of two randomized controlled trials found that offering HIVST to MSM doubled the likelihood of an HIV-positive diagnosis [24]. Many HIV programs struggle to engage and test KPs despite high HIV prevalence, given the multiple barriers to services such as stigma, discrimination, and criminalization—indicating service delivery gaps [33]. The Burundi HIVST achievement demonstrates the need for programs to constantly assess their current service delivery packages and creatively expand them based on specific population needs.

The sexual and health behaviors of those who had reactive results through HIVST were explored to better understand the risk characteristics underlying higher positivity rates. Among FSWs, having >8 clients per week and being aged >24 years were factors affecting higher HIV positivity rates, which is consistent with the overall HIV epidemic in Burundi [4]. Among MSM, there were no health-seeking or behavioral factors that were statistically significant between those who were nonreactive and those who were reactive; however, a large number of MSM used condoms inconsistently, which is a high-risk behavior associated with greater infection rates. MSM living in Ngozi also had higher HIV positivity rates, which may warrant expanding and strengthening HIV services in the province.

A key concern in the literature is the ability for those who test reactive through HIVST and are subsequently confirmed HIV positive to be effectively linked to care and treatment services [17,20,21]. A systematic review and meta-analysis of HIVST among MSM reported that linkage to care ranged from 31.3%-100%, indicating programmatic gaps and reluctance to seek additional services [20]. When reviewing other

peer-assisted HIVST models [18,23,25,26], it was noted that only a couple of studies explored the relationship with linkage to confirmation testing and treatment services and had varying levels of success [25,26]. Studies investigating unsupervised HIVST with linkage to confirmation testing and treatment services also showed varying achievement levels [12,13,20,21]. In this study of peer-assisted HIVST, the rate of linkage to treatment was lower overall among KPs who tested positive via HIVST compared with standard testing; however, when data were disaggregated by population, there was no difference in FSWs and transgender people, but linkage to ART was lower among MSM. LINKAGES started implementing the HIV program for KPs in August 2016 and, historically, had a high treatment initiation rate, >90%, for FSWs, MSM, and transgender people [34]. Therefore, when ART initiation rates among MSM who were newly diagnosed through HIVST was 85%, it was a concern, given the consistently high linkage rates over the previous 2 years. Since the inception of the program, a key component to LINKAGES was training and hiring strong KP community members to become peer navigators (PNs) [35]. PNs provided ART adherence support in the community, acted as advocates for HIV-positive KPs within facilities, and strengthened the client-patient relationship. PNs were also present during standard community-based testing provided by clinical staff. Then, when someone tested HIV positive through the community-based testing site, peer navigation support was offered, and, if accepted, the PN then provided accompaniment to the clinic for ART initiation. With the advent of HIVST, PNs were trained on HIVST and asked to provide it within their peer networks. Then, if a peer was reactive, PNs offered the same linkage and adherence support as they had historically provided and recorded the linkage and support through the monitoring system. Therefore, although there could have been a measurement issue within the community-based HIVST program in its inability to accurately track an individual from a reactive test to confirmation testing and ART initiation, the program did not give this concern as much weight, given PNs' historical role in monitoring. Then, as confirmatory testing for both HIVST and standard testing were mostly conducted within the same facilities, no measurement gap could be attributed at this stage. This study offers additional information and recommendations on how expanding testing modalities within an HIV program can meet an existing unmet need in populations.

Currently, in Burundi, HIV treatment is only available at registered facilities, including MSM drop-in centers. LINKAGES sensitized the providers at supported clinical sites on the provision of KP-friendly services using the Health4All training curriculum [36]. The training focused on how to provide quality, stigma-free HIV services, including clinical competencies for each of the KP groups. In addition, LINKAGES worked with the local and district health, law enforcement, and administrative authorities on stigma and discrimination reduction to create a more favorable environment for KP health programs. The activities to strengthen KP-friendly services within the LINKAGES program were successful, with 97.1% (864/890) MSM who were newly diagnosed with HIV through standard services initiating treatment. The rate of MSM who were newly diagnosed and initiated on treatment from standard services was substantially higher than the rate of MSM newly diagnosed and initiated on ART from HIVST (40/47, 85% of newly diagnosed linked to ART). For achieving the three 90 UNAIDS goals, service delivery will have to become more diversified and client-centered. Otherwise, HIV transmission and acquisition will persist in certain segments of the population, and epidemic control will remain a challenge. The WHO recommends that treatment programs offer DSD and emphasizes the need to have various options so that individuals can choose which model best meets their needs. Therefore, although the standard testing and facility-based ART model in Burundi is well suited for most MSM, there remains a service delivery gap for a certain segment of MSM clients.

The Burundi example confirms that HIVST is a highly acceptable and feasible testing modality among KPs. Key concerns about HIVST in the literature include the lack of pre- and posttest counseling and an individual's ability to successfully self-administer the test. The Burundi strategy addressed these concerns by providing peer-assisted HIVST kits with trained POWs. The trained POWs provided abbreviated pre- and posttest counseling, aided peers in test administration, and supported those who tested reactive to confirmatory testing or facilitated confirmatory testing in the community. The implementation strategy allowed the program to successfully track individuals through the HIVST monitoring cascade from use, test result, confirmation testing, and ART initiation if the individual was confirmed HIV positive. The program did not offer unsupervised HIVST during this implementation period, given the challenge in offering follow-up services, such as counseling and ART initiation, to those who may have a reactive result. However, after more than a year of implementation, the program is planning to offer unsupervised testing to sexual partners of KP members who are HIV positive and reluctant to access standard testing.

Limitations

The implementation and analysis were not without limitations. First, there were differences in the two populations who chose either HIVST or standard testing, such as HIVST users having a high rate of never tested or not tested in the last 6 months. The authors acknowledge these differences but note that the 2 groups chose the testing modality based on personal preferences. Those who chose HIVST also chose not to access existing standard services, which is a lesson learned for present and future HIV programs targeting KP. In the future, the authors can conduct additional analyses on the similarities and differences between the 2 users to better understand users' key characteristics that may affect the testing modality of choice. Second, the authors were not able to determine whether the high rates of testing among never testers were because of increased access or HIVST alone. Third, as the analysis was based on programmatic data among people reached by POWs in specific geographic areas, the findings may not be generalizable to all FSWs, MSM, and transgender people in Burundi. Fourth, for HIVST, client records were kept in an electronic database; however, for standard testing, all client records were maintained in a paper-based system. As a result, we were unable to comprehensively compare those tested with HIVST versus standard testing across variables such as date of last HIV test, HIV risk, and health care–seeking behaviors. In addition, the

high positivity rates among KP members who used HIVST kits could possibly be affected by repeat testers who already knew their HIV-positive status. Therefore, when asked if they knew their HIV serostatus by the POW, they could have falsely reported their testing history and serostatus as they wanted to confirm their HIV-positive serostatus. We attempted to reduce this possibility by comparing newly diagnosed individuals among HIVST and standard testing with existing programmatic records and could not find duplicate records; however, this possibility cannot be totally eliminated. KP members who tested nonreactive could also have used more than one HIVST kit over the recruitment period, although it should be noted that most KP members reported never or rarely tested (not tested in the last 6 months). Finally, higher positivity rates could be an effect of the POW networks and their ability to access higher-risk and more highly infectious individuals; however, to further explore this relationship, additional analysis will have to be performed. Future analyses could explore the relationship between higher positivity rates and individual POWs to see if there is a correlation. If there is a correlation, then programs should attempt to saturate the social and sexual networks of those POWs to further increase HIV diagnoses.

The authors wished to explore the effectiveness of how adding a new HIV testing modality to the Burundi KP program could reach individuals who were not currently accessing services because of structural, social, site, or personal barriers. Given the WHO call for DSD, the authors wished to demonstrate how adding one new HIV testing modality could significantly improve service uptake among those who chose not to access existing services. The authors acknowledge the limitations of programmatic data, which restrict their ability to explore all differences in the 2 groups; however, given the success of HIVST among KPs in Burundi in both case finding and treatment uptake, they felt it important to share with other public health professionals that HIVST is a means to achieve the first and second 90 in a low-resourced setting among a highly stigmatized and criminalized population.

Conclusions

The results demonstrated the effectiveness of the peer-assisted HIVST implementation model in identifying newly diagnosed HIV positive cases in Burundi. More widespread implementation of HIVST within other high-risk populations and other geographical areas could accelerate progress toward epidemic control.

Acknowledgments

The authors wish to acknowledge all of those who participated in the implementation of HIV self-testing in Burundi, especially the Association Nationale de Soutien aux Séropositifs et Malades du SIDA and the Society for Women Against AIDS in Africa—two subpartners of LINKAGES (Linkages across the Continuum of HIV Services for Key Populations Affected by HIV). The authors deeply appreciate the dedication and commitment of key population members in Burundi, especially the peer outreach workers who led HIV self-testing in the field. The authors also wish to acknowledge the technical comments and recommendations from Meghan DiCarlo and Chris Akolo. This publication was made possible by the generous support of the American people through the US Agency for International Development and the US President's Emergency Plan for AIDS Relief through the LINKAGES project (cooperative agreement number: AID-OAA-A-14-00045). The contents of this publication are the sole responsibility of LINKAGES and do not necessarily reflect the views of the US Agency for International Development, the US President's Emergency Plan for AIDS Relief, or the US government.

Conflicts of Interest

None declared.

References

1. National HIV and STI strategy 2018-2022. NSHS. 2018.
2. World Health Organization. Guidelines on HIV Self-Testing and Partner Notification: Supplement to Consolidated Guidelines on HIV Testing. Geneva: World Health Organization; Dec 2016.
3. Ministry of Health, Burundi. National guidelines on using antiretrovirals for the prevention and treatment of HIV. Bujumbura: MOH and National AIDS Control Program; 2016. URL: https://minisante.bi/wp-content/uploads/pnls/Directives%20Nationales%202016.pdf
4. Troisième Enquête Démographique et de Santé au Burundi (EDSB-III) 2016-2017. République du Burundi. 2017. URL: https://www.dhsprogram.com/pubs/pdf/FR335/FR335.pdf/ [accessed 2019-10-22]
5. Burundi PLACE report. Priorities for local AIDS control efforts. Measure Evaluation. 2014. URL: http://www.measureevaluation.org/resources/publications/tr-14-99/ [accessed 2019-10-22]
6. Burundi, types of criminalization. Human Dignity Trust. 2020. URL: https://www.humandignitytrust.org/country-profile/burundi/ [accessed 2020-06-19]
7. The status of lesbian, gay, bisexual and transgender rights in Burundi, a shadow report. Mouvement pour les Libertes Individuelles (Moli), Heartland Alliance, Vermont Law School, Rainbow Candlelight. 2014. URL: https://www.ecoi.net/en/file/local/1243359/1930_1412779853_int-ccpr-css-bdi-18263-e.pdf [accessed 2020-06-19]

8. Differentiated prevention/testing/ART delivery for MSM and TG people, Burundi. International AIDS Society (IAS). 2018. URL: http://www.differentiatedcare.org/Portals/0/adam/Content/rCIfflHmIUi2q6xTF7ih9w/File/MOLI%20Burundi.pdf [accessed 2020-06-19]
9. Linkages across the Continuum of HIV Services for Key Populations Affected by HIV (LINKAGES). FHI 360/LINKAGES. 2014. URL: https://www.fhi360.org/projects/linkages-across-continuum-hiv-services-key-populations-affected-hiv-linkages/ [accessed 2020-06-19]
10. OraQuick. 2016. URL: http://www.oraquick.com/ [accessed 2020-04-05]
11. Agot K, Cain M, Medley A, Kimani J, Gichangi P, Kiio C, et al. Formative assessment to identify perceived benefits and barriers of HIV oral self-testing among female sex workers, service providers, outreach workers, and peer educators to inform scale-up in Kenya. AIDS Care 2021 Mar 03:1-8. [doi: 10.1080/09540121.2021.1894318] [Medline: 33657929]
12. Tun W, Vu L, Dirisu O, Sekoni A, Shoyemi E, Njab J, et al. Uptake of HIV self-testing and linkage to treatment among men who have sex with men (MSM) in Nigeria: A pilot programme using key opinion leaders to reach MSM. J Int AIDS Soc 2018 Jul 22;21 Suppl 5:e25124 [FREE Full text] [doi: 10.1002/jia2.25124] [Medline: 30033680]
13. Chanda MM, Ortblad KF, Mwale M, Chongo S, Kanchele C, Kamungoma N, et al. HIV self-testing among female sex workers in Zambia: a cluster randomized controlled trial. PLoS Med 2017 Dec;14(11):e1002442 [FREE Full text] [doi: 10.1371/journal.pmed.1002442] [Medline: 29161260]
14. Dean J, Lui C, Mutch A, Scott M, Howard C, Lemoire J, et al. Knowledge and awareness of HIV self-testing among Australian gay and bisexual men: a comparison of never, sub-optimal and optimal testers willingness to use. AIDS Care 2019 Feb;31(2):224-229. [doi: 10.1080/09540121.2018.1524120] [Medline: 30230360]
15. Figueroa C, Johnson C, Verster A, Baggaley R. Attitudes and acceptability on HIV self-testing among key populations: a literature review. AIDS Behav 2015 Nov;19(11):1949-1965 [FREE Full text] [doi: 10.1007/s10461-015-1097-8] [Medline: 26054390]
16. Okoboi S, Twimukye A, Lazarus O, Castelnuovo B, Agaba C, Immaculate M, et al. Acceptability, perceived reliability and challenges associated with distributing HIV self-test kits to young MSM in Uganda: a qualitative study. J Int AIDS Soc 2019 Mar;22(3):e25269 [FREE Full text] [doi: 10.1002/jia2.25269] [Medline: 30932364]
17. Krause J, Subklew-Sehume F, Kenyon C, Colebunders R. Acceptability of HIV self-testing: a systematic literature review. BMC Public Health 2013 Aug 08;13(1):735 [FREE Full text] [doi: 10.1186/1471-2458-13-735] [Medline: 23924387]
18. Pant Pai N, Sharma J, Shivkumar S, Pillay S, Vadnais C, Joseph L, et al. Supervised and unsupervised self-testing for HIV in high- and low-risk populations: a systematic review. PLoS Med 2013;10(4):e1001414 [FREE Full text] [doi: 10.1371/journal.pmed.1001414] [Medline: 23565066]
19. Green KE, Vu BN, Phan HT, Tran MH, Ngo HV, Vo SH, et al. From conventional to disruptive: upturning the HIV testing status quo among men who have sex with men in Vietnam. J Int AIDS Soc 2018 Jul 22;21 Suppl 5(S5):e25127 [FREE Full text] [doi: 10.1002/jia2.25127] [Medline: 30033557]
20. Zhang C, Li X, Brecht M, Koniak-Griffin D. Can self-testing increase HIV testing among men who have sex with men: a systematic review and meta-analysis. PLoS One 2017 Nov 30;12(11):e0188890 [FREE Full text] [doi: 10.1371/journal.pone.0188890] [Medline: 29190791]
21. Ren X, Wu Z, Mi G, McGoogan J, Rou K, Zhao Y, et al. HIV care-seeking behaviour after HIV self-testing among men who have sex with men in Beijing, China: a cross-sectional study. Infect Dis Poverty 2017 Jul 28;6(1):112 [FREE Full text] [doi: 10.1186/s40249-017-0326-y] [Medline: 28655340]
22. Simwinga M, Kumwenda M, Dacombe R, Kayira L, Muzumara A, Johnson C, et al. Ability to understand and correctly follow HIV self-test kit instructions for use: applying the cognitive interview technique in Malawi and Zambia. J Int AIDS Soc 2019 Mar;22 Suppl 1:e25253 [FREE Full text] [doi: 10.1002/jia2.25253] [Medline: 30907496]
23. Choko AT, Desmond N, Webb EL, Chavula K, Napierala-Mavedzenge S, Gaydos CA, et al. The uptake and accuracy of oral kits for HIV self-testing in high HIV prevalence setting: a cross-sectional feasibility study in Blantyre, Malawi. PLoS Med 2011 Oct;8(10):e1001102 [FREE Full text] [doi: 10.1371/journal.pmed.1001102] [Medline: 21990966]
24. Johnson CC, Kennedy C, Fonner V, Siegfried N, Figueroa C, Dalal S, et al. Examining the effects of HIV self‐testing compared to standard HIV testing services: a systematic review and meta‐analysis. J Int AIDS Soc 2017 May 15;20(1):21594. [doi: 10.7448/ias.20.1.21594]
25. Wulandari LP, Kaldor J, Guy R. Uptake and acceptability of assisted and unassisted HIV self-testing among men who purchase sex in brothels in Indonesia: a pilot intervention study. BMC Public Health 2020 May 19;20(1):730 [FREE Full text] [doi: 10.1186/s12889-020-08812-4] [Medline: 32429950]
26. Nguyen VT, Phan HT, Kato M, Nguyen Q, Le Ai KA, Vo SH, et al. Community-led HIV testing services including HIV self-testing and assisted partner notification services in Vietnam: lessons from a pilot study in a concentrated epidemic setting. J Int AIDS Soc 2019 Jul 19;22 Suppl 3(S3):e25301 [FREE Full text] [doi: 10.1002/jia2.25301] [Medline: 31321903]
27. Qin Y, Tang W, Nowacki A, Mollan K, Reifeis SA, Hudgens MG, et al. Benefits and potential harms of human immunodeficiency virus self-testing among men who have sex with men in china: an implementation perspective. Sex Transm Dis 2017 Apr;44(4):233-238 [FREE Full text] [doi: 10.1097/OLQ.0000000000000581] [Medline: 28282650]
28. Nkenfou C, Kembou J, Temgoua E, Djikeng A, Mouafo L, Ndzie E, et al. Evaluation of OraQuick® HIV-1/2 as oral rapid test. Afr J Infect Dis 2013 Aug 09;7(2):27-30 [FREE Full text] [doi: 10.4314/ajid.v7i2.2] [Medline: 28451078]

29. Choko AT, MacPherson P, Webb EL, Willey BA, Feasy H, Sambakunsi R, et al. Uptake, accuracy, safety, and linkage into care over two years of promoting annual self-testing for HIV in Blantyre, Malawi: a community-based prospective study. PLoS Med 2015 Oct;12(9):e1001873 [FREE Full text] [doi: 10.1371/journal.pmed.1001873] [Medline: 26348035]
30. LINKAGES system assessment and routine data quality assessment tool. FHI 360/LINKAGES. 2016. URL: https://www.fhi360.org/ [accessed 2021-08-31]
31. Wongkanya R, Pankam T, Wolf S, Pattanachaiwit S, Jantarapakde J, Pengnongyang S, et al. HIV rapid diagnostic testing by lay providers in a key population-led health service programme in Thailand. J Virus Erad 2018 Jan 01;4(1):12-15 [FREE Full text] [Medline: 29568547]
32. Lightfoot MA, Campbell CK, Moss N, Treves-Kagan S, Agnew E, Kang Dufour M, et al. Using a social network strategy to distribute HIV self-test kits to African American and Latino MSM. J Acquir Immune Defic Syndr 2018 Sep 01;79(1):38-45. [doi: 10.1097/QAI.0000000000001726] [Medline: 29771792]
33. Sharma M, Ying R, Tarr G, Barnabas R. Systematic review and meta-analysis of community and facility-based HIV testing to address linkage to care gaps in sub-Saharan Africa. Nature 2015 Dec 03;528(7580):S77-S85 [FREE Full text] [doi: 10.1038/nature16044] [Medline: 26633769]
34. Weber A, Lillie T, Boyee D, Gashobotse D. Linking HIV-positive key population members to treatment: Burundi's five secrets to success. LINKAGES project blog. 2019. URL: http://www.linkedin.com/pulse/linking-hiv-positive-key-population-members-treatment-weber-mph?articleId=6564156792161525760/ [accessed 2020-05-20]
35. Peer navigation for key populations: implementation guide. FHI 360/LINKAGES. 2017. URL: http://www.fhi360.org/sites/default/files/media/documents/resource-linkages-peer-navigation.pdf [accessed 2021-06-13]
36. Health4All: Training health workers for the provision of quality, stigma-free HIV services for key populations. FHI 360/LINKAGES. 2018. URL: https://www.fhi360.org/resource/health4all [accessed 2021-04-04]

Abbreviations

aOR: adjusted odds ratio
ART: antiretroviral therapy
CBO: community-based organization
DSD: differentiated service delivery
FSW: female sex worker
HIVST: HIV self-testing
HTS: HIV testing service
KP: key population
LINKAGES: Linkages across the Continuum of HIV Services for Key Populations Affected by HIV
MSM: men who have sex with men
PN: peer navigator
POW: peer outreach worker
UNAIDS: The Joint United Nations Program on HIV/AIDS
WHO: World Health Organization

Edited by T Sanchez; submitted 11.09.20; peer-reviewed by E Op de Coul, J Torres; comments to author 03.03.21; revised version received 27.04.21; accepted 29.06.21; published 30.09.21.

Please cite as:
Lillie T, Boyee D, Kamariza G, Nkunzimana A, Gashobotse D, Persaud N
Increasing Testing Options for Key Populations in Burundi Through Peer-Assisted HIV Self-Testing: Descriptive Analysis of Routine Programmatic Data
JMIR Public Health Surveill 2021;7(9):e24272
URL: https://publichealth.jmir.org/2021/9/e24272
doi:10.2196/24272
PMID:34591018

Original Paper

Trends in Health Information Technology Use Among the US Population With and Without Cardiovascular Risk Factors, 2012-2018: Evidence From the National Health Interview Survey

Nikhila Gandrakota[1], MBBS, MPH; Mohammed K Ali[2], MD, MSc, MBA; Megha K Shah[1], MD, MSc

[1]Department of Family & Preventive Medicine, Emory University School of Medicine, Atlanta, GA, United States

[2]Hubert Department of Global Health, Rollins School of Public Health, Emory University, Atlanta, GA, United States

Corresponding Author:
Nikhila Gandrakota, MBBS, MPH
Department of Family & Preventive Medicine
Emory University School of Medicine
4500 N Shallowford Rd
Atlanta, GA, 30338
United States
Phone: 1 4047786920
Email: nikhila.gandrakota@emory.edu

Abstract

Background: The COVID-19 pandemic has required clinicians to pivot to offering services via telehealth; however, it is unclear which patients (users of care) are equipped to use digital health. This is especially pertinent for adults managing chronic diseases, such as obesity, hypertension, and diabetes, which require regular follow-up, medication management, and self-monitoring.

Objective: The aim of this study is to measure the trends and assess factors affecting health information technology (HIT) use among members of the US population with and without cardiovascular risk factors.

Methods: We used serial cross-sectional data from the National Health Interview Survey for the years 2012-2018 to assess trends in HIT use among adults, stratified by age and cardiovascular risk factor status. We developed multivariate logistic regression models adjusted for age, sex, race, insurance status, marital status, geographic region, and perceived health status to assess the likelihood of HIT use among patients with and without cardiovascular disease risk factors.

Results: A total of 14,304 (44.6%) and 14,644 (58.7%) participants reported using HIT in 2012 and 2018, respectively. When comparing the rates of HIT use for the years 2012 and 2018, among participants without cardiovascular risk factors, the HIT use proportion increased from 51.1% to 65.8%; among those with one risk factor, it increased from 43.9% to 59%; and among those with more than one risk factor, it increased from 41.3% to 54.7%. Increasing trends in HIT use were highest among adults aged >65 years (annual percentage change [APC] 8.3%), who had more than one cardiovascular risk factor (APC 5%) and among those who did not graduate from high school (APC 8.8%). Likelihood of HIT use was significantly higher in individuals who were younger, female, and non-Hispanic White; had higher education and income; were married; and reported very good or excellent health status. In 2018, college graduates were 7.18 (95% CI 5.86-8.79), 6.25 (95% CI 5.02-7.78), or 7.80 (95% CI 5.87-10.36) times more likely to use HIT compared to adults without high school education among people with multiple cardiovascular risk factors, one cardiovascular risk factor, or no cardiovascular risk factors, respectively.

Conclusions: Over 2012-2018, HIT use increased nationally, with greater use noted among younger and higher educated US adults. Targeted strategies are needed to engage wider age, racial, education, and socioeconomic groups by lowering barriers to HIT access and use.

(JMIR Public Health Surveill 2021;7(9):e29990) doi:10.2196/29990

KEYWORDS

telemedicine; cardiovascular risk factors; health information technology; telehealth; digital health; public health; surveillance

Introduction

The COVID-19 pandemic has significantly changed ambulatory care delivery, which has likely impacted the ability of adults living with cardiovascular disease (CVD) risk factors to manage their health conditions. Factors including shortages of testing supplies, personal protective equipment, state and health system mandates, and difficulty maintaining adequate staffing led to most providers deferring elective and annual physical examinations [1,2] or adapting to telemedicine to decrease the spread of the virus [2-4]. Patients have also avoided in-person visits due to the risk of exposure [4]. Further local and state recommendations, promoting social distancing, have also influenced adults seeking care for chronic diseases. Studies show that in-person outpatient visits dropped by almost 60% early in the pandemic [5]. Thus, regular follow-up with clinicians for care of chronic conditions has likely been delayed or forgone.

Most recent estimates suggest almost half of the US population report having one CVD risk factor, such as obesity, high blood pressure, or diabetes [6]. To prevent disease progression and reduce the risk of complications, these conditions require regular self-management (ie, numerous daily decisions on diet, exercise, and medication use) and follow up with their clinicians for continued health education and medication titration [7].

The current environment has provided an opportunity for a digital revolution in health care, with unparalleled, rapid expansion of telehealth and telemedicine. Previous literature showed that 74% of American adults access the internet, 57% of American households have broadband connections, and 61% of adults obtain health information on the web [8]. However, the extent to which Americans living with CVD risk factors access and use digital technology and their ability to do so are unknown. It also remains unclear which demographic groups and other subgroups of American adults with CVD risk factors access health technology. Using nationally representative data, we examined trends in health information technology (HIT) use in the years prior to the COVID-19 pandemic. We compared adults with and without CVD risk factors in the last decade, and we examined which Americans were at highest risk of limited digital access.

Methods

Data Source

We used data from the National Health Interview Survey (NHIS) from 2012 to 2018. The NHIS is an annual survey that collects health-related information on a representative sample of the noninstitutionalized population of the United States [9]. The National Center for Health Statistics oversees the annual cross-sectional collection of NHIS data. NHIS samples approximately 45,000 households and 110,000 persons every year. The survey uses a 3-stage stratified cluster-probability sampling design, and all data are self-reported. One adult from each sampled household is randomly selected to provide detailed information on health indicators, social characteristics, and demographics. The annual response rates for the NHIS were 77.6%, 75.7%, 73.8%, 70.1%, 67.9%, 66.5%, and 64.2% of the eligible households in the sample for the years 2012-2018, respectively. More details of the NHIS sampling procedures are reported elsewhere [10]. This study was considered to be exempt by the Emory University Institutional Review Board.

Measures

We used HIT use questions from the years 2012-2018 for the study. Respondents were asked, “During the past 12 months, have you ever used computers for any of the following: (1) to look up health information on the Internet, (2) to fill a prescription, (3) to schedule a web-based appointment with a health care provider, (4) to communicate with a health care provider by email?” If an individual indicated use for any of these four purposes, they were considered to have used HIT in the past 12 months. Participants were classified as “Used HIT for a general purpose” if they looked up health information on the internet and as “Used HIT for a clinical purpose” if they filled a prescription on the web, scheduled a web-based appointment, or communicated with a health care provider by email.

The CVD risk factors included in the study were self-reported diabetes, hypertension, hyperlipidemia, and obesity, as these are the most common conditions at risk for heart disease [11]. We identified the participants as having one or more of the four CVD risk factors when they responded yes to the question “Have ever been told by a doctor or health care provider that you have hypertension/diabetes/high cholesterol?” or obesity, defined as a reported BMI classified as overweight (25.0-29.9 kg/m^2) or obese (>30.0 kg/m^2) [12]. We stratified the population into adults with no CVD risk factors, one CVD risk factor, and multiple CVD risk factors for the CVD risk factors mentioned above.

We examined a range of household-, individual-, and health-related factors expected to impact HIT use. Individual-level characteristics included race/ethnicity (Hispanic, non-Hispanic White, non-Hispanic, Black, non-Hispanic Asian, and non-Hispanic all other race groups), insurance type (uninsured, insured–private or public), age (18-25, 26-44, 45-64, and ≥65 years), education (<high school, high school graduate, some college, and college graduate) and sex (male, female). Household-level characteristics included marital status (married and unmarried), geographic region (Northeast, Midwest, South, and West) and poverty. Poverty was determined using the poverty income ratio variable in NHIS, which measures the ratio of the annual family income divided by the household-adjusted federal poverty level in dollars, as defined by the Census Bureau for that survey year [13]. This variable was recoded as in poverty/near poverty for ratios <2.00 and not in poverty/near poverty for ratios ≥2.00. Health-related factors included an indicator variable on perceived health status (poor, fair, good, very good, and excellent), as prior evidence suggests that a poor perceived health status might decrease the likelihood of HIT use [14]. English proficiency of the adults was classified into two categories: not at all/not well and well/very well. However, this information was only available for the year 2018.

Statistical Analysis

The unit of analysis was the individual. Sampling weights (assigned by the NHIS) were used to account for uneven data collection probabilities stemming from the NHIS sample design and nonresponse. SAS, version 9.4 (SAS Institute) was used for the analyses. Sampling weights were used to obtain nationwide representative estimates and standard errors because NHIS uses a multistage probability complex sampling design that incorporates stratification, clustering, and oversampling of some subpopulations (eg, Black, Hispanic, and Asian). Weighted means along with 95% confidence intervals are reported for all continuous variables.

The proportion of HIT use among respondents by CVD risk status (no risk factors, one risk factor, or multiple CVD risk factors) were compared for the years 2012 and 2018 using chi-square tests. We also compared characteristics of the respondents with and without HIT use for the years 2012 and 2018. Among HIT users, the proportions using the internet for clinical use and general use were also compared for the years 2012 and 2018.

Using linear trend analysis, we then compared adults by CVD risk factor status, highest level of education, and age groups of 18-25, 26-44, 45-64, and ≥65 years to examine HIT use trends over the years 2012-2018. The annual percentage changes (APCs) of HIT use were calculated for each of the age, CVD risk factor, and education groups.

Independent predictors of HIT use were identified using multiple logistic regression models adjusted for age and sex for each of the risk factor groups of one CVD risk factor condition, multiple CVD risk factors, and no CVD risk factors for the years 2012 and 2018.

Results

Demographics

Among a total of 58,992 respondents in the years 2012 (n=33,885) and 2018 (n=25,107), males comprised 45.5% of the total respondents in both 2012 and 2018. In 2012, 69.4% of the total respondents were non-Hispanic White and 12.5% were non-Hispanic Black, while in 2018, 66.9% of the total respondents were non-Hispanic White and 12.7% were non-Hispanic Black (Table 1). In 2012, 26% of people had no CVD risk factors, 37% had one CVD risk factor, and 37% had more than one CVD risk factor. In 2018, just over 20% had no CVD risk factors, 37% had one CVD risk factor, and 40% had more than one CVD risk factor.

Table 1. General characteristics of the National Health Interview Survey populations in 2012 (n=33,885) and 2018 (n=25,107).

	Values, n (%)							
	2012				2018			
	Used HIT[a]	Used HIT for a general purpose[b]	Used HIT for a clinical purpose[c]	Did not use HIT	Used HIT	Used HIT for a general purpose	Used HIT for a clinical purpose	Did not use HIT
Age (years)								
18-25	1856 (47.7)	1788 (45.9)	346 (8.9)	2039 (52.3)	1371 (63.1)	1314 (60.5)	513 (23.6)	801 (36.9)
26-44	5597 (50.3)	5386 (48.4)	1403 (12.6)	5524 (49.7)	5050 (68.5)	4791 (65.0)	2303 (31.2)	2323 (31.5)
45-64	5087 (43.8)	4825 (41.5)	1506 (13.0)	6534 (56.2)	5126 (61.5)	4764 (57.1)	2505 (30.0)	3209 (38.5)
≥65	1764 (24.3)	1622 (22.4)	555 (7.7)	5484 (75.7)	3097 (42.9)	2808 (38.9)	1443 (20.0)	4130 (57.1)
Sex								
Male	5522 (36.8)	5218 (34.8)	1488 (9.9)	9476 (63.2)	6121 (53.6)	5632 (49.3)	2723 (23.8)	5299 (46.4)
Female	8782 (46.5)	8403 (44.5)	2322 (12.3)	10,105 (53.5)	8523 (62.3)	8045 (58.8)	4041 (29.5)	5164 (37.7)
Ethnicity								
Hispanic	1601 (27.7)	1524 (26.4)	353 (6.1)	4172 (72.3)	1407 (44.7)	1330 (42.3)	514 (16.3)	1740 (55.3)
Non-Hispanic White	9956 (48.6)	9498 (46.4)	2734 (13.4)	10,518 (51.4)	10,905 (62.8)	10,181 (58.6)	5237 (30.1)	6472 (37.2)
Non-Hispanic Black	1654 (32.1)	1564 (30.3)	391 (7.6)	3502 (67.9)	1378 (47.2)	1282 (43.9)	577 (19.7)	1543 (52.8)
Non-Hispanic Asian	969 (45.8)	915 (43.2)	308 (14.6)	1147 (54.2)	789 (60.7)	727 (56.0)	392 (30.1)	510 (39.3)
Non-Hispanic all other race groups	124 (33.9)	120 (32.8)	24 (6.5)	242 (66.1)	165 (45.5)	157 (43.3)	44 (12.1)	198 (54.5)
Educational status								
<High school	958 (14.9)	909 (14.1)	149 (2.3)	5483 (85.1)	927 (26.7)	860 (24.8)	266 (7.7)	2541 (73.3)
High school graduate	2232 (29.0)	2109 (27.4)	462 (6.0)	5466 (71.0)	2242 (41.5)	2073 (38.4)	797 (14.7)	3163 (58.5)
Some college	5004 (48.2)	4774 (45.9)	1209 (11.6)	5387 (51.8)	4730 (62.5)	4412 (58.3)	2012 (26.6)	2835 (37.5)
College graduate	5792 (65.8)	5528 (62.8)	1861 (21.2)	3010 (34.2)	6366 (78.2)	5972 (73.4)	3466 (42.6)	1770 (21.8)
Poverty								
In poverty/near poverty	3415 (30.3)	3302 (29.3)	641 (5.7)	7852 (69.7)	2774 (44.5)	2625 (42.1)	920 (14.7)	3466 (55.5)
Not in poverty/near poverty	9047 (53.4)	8555 (50.5)	2756 (16.3)	7883 (46.6)	10,023 (66.5)	9334 (61.9)	5061 (33.6)	5045 (33.5)
Marital status								
Unmarried	6486 (38.1)	6188 (36.3)	1625 (9.5)	10,548 (61.9)	6470 (52.9)	6050 (49.4)	2750 (22.4)	5769 (47.1)
Married	7794 (46.5)	7410 (44.2)	2181 (13.0)	8982 (53.5)	8152 (63.6)	7606 (59.3)	4004 (31.2)	4669 (36.4)
Region								
Northeast	2486 (43.9)	2389 (42.2)	575 (10.1)	3181 (56.1)	2419 (59.3)	2286 (56.0)	1050 (25.7)	1661 (40.7)
Midwest	3119 (44.3)	2982 (42.4)	792 (11.2)	3921 (55.7)	3481 (59.1)	3262 (55.4)	1593 (27.0)	2411 (40.9)
South	4691 (38.1)	4463 (36.3)	1171 (9.5)	7614 (61.9)	5074 (55.2)	4740 (51.6)	2342 (25.5)	4110 (44.8)
West	4008 (45.2)	3787 (42.7)	1272 (14.3)	4865 (54.8)	3670 (61.7)	3389 (56.9)	1779 (29.9)	2281 (38.3)
Insurance								
Uninsured	1947 (32.3)	1917 (31.8)	223 (3.7)	4082 (67.7)	987 (45.4)	960 (44.1)	234 (10.7)	1188 (54.6)
Public	2387 (28.8)	2280 (27.5)	567 (6.8)	5913 (71.2)	3355 (45.8)	3096 (42.2)	1392 (19.0)	3975 (54.2)

	Values, n (%)							
	2012				2018			
	Used HIT[a]	Used HIT for a general purpose[b]	Used HIT for a clinical purpose[c]	Did not use HIT	Used HIT	Used HIT for a general purpose	Used HIT for a clinical purpose	Did not use HIT
Private	9935 (51.1)	9390 (48.3)	3014 (15.5)	9511 (48.9)	10,265 (66.1)	9585 (61.8)	5130 (33.0)	5255 (33.9)
Perceived health status								
Excellent	4104 (47.1)	3916 (44.9)	1050 (12.0)	4612 (52.9)	3988 (63.8)	3732 (59.7)	1772 (28.3)	2265 (36.2)
Very good	5185 (49.1)	4939 (46.7)	1416 (13.4)	5380 (50.9)	5311 (63.8)	4977 (59.8)	2541 (30.5)	3010 (36.2)
Good	3586 (37.9)	3386 (35.8)	960 (10.2)	5867 (62.1)	3748 (54.0)	3474 (50.0)	1719 (24.8)	3192 (46.0)
Fair	1151 (29.4)	1118 (28.6)	299 (7.7)	2759 (70.6)	1263 (45.9)	1184 (43.1)	584 (21.2)	1488 (54.1)
Poor	273 (22.2)	258 (21.0)	83 (6.8)	954 (77.8)	330 (39.6)	306 (36.7)	147 (17.6)	503 (60.4)
English proficiency								
Not good/none	No information	No information	No information	No information	183 (17.0)	170 (15.8)	38 (3.5)	893 (83.0)
Very good/ good	No information	No information	No information	No information	14,460 (60.2)	13,506 (56.2)	6725 (28.0)	9567 (39.8)
Cardiometabolic risk status								
No risk factors	3946 (49.1)	3817 (47.5)	936 (11.6)	4096 (50.9)	3414 (65.5)	3269 (62.7)	1512 (29.0)	1798 (34.5)
One risk factor	4984 (41.6)	4761 (39.7)	1195 (10.0)	7009 (58.4)	5005 (59.2)	4709 (55.7)	2145 (25.3)	3453 (40.8)
Multiple risk factors	4597 (38.9)	4308 (36.5)	1493 (12.6)	7214 (61.1)	5227 (54.1)	4761 (49.3)	2611 (27.0)	4438 (45.9)

[a]HIT: health information technology.

[b]Used HIT for general purposes: looked up health information on the internet.

[c]Used HIT for clinical purposes: filled a prescription on the web, scheduled a web-based appointment with a health care provider, or communicated with a health care provider by email. Note: [b] and [c] are not mutually exclusive.

Prevalence of HIT Use and CVD Risk Factors

In 2012, 41.6% of the total weighted sample of respondents looked up health information on the internet, representing 42.3 million Americans. Of those who used HIT, 6.8% filled a prescription on the internet, less than 5% made web-based appointments with their health care provider, and 5.8% communicated with their health care provider via email. In 2018, 54.2% of the total weighted sample of respondents looked up health information on the internet, representing 60.5 million. Approximately 11% filled a prescription on the internet, approximately 16% made web-based appointments with their health care provider, and 16.5% communicated with their health care provider via email (Table 1).

Overall, in 2012, 44.5% of the total weighted sample of respondents reported using HIT for any one of the four purposes listed above, representing 44.5 million, and in 2018, this proportion increased to 58.6%, representing 64.7 million.

Prevalence of HIT use among respondents without any CVD risk factors (weighted percentage 51.1%, 95% CI 49.8%-52.5%) was significantly higher than respondents with one CVD risk factor (weighted percentage 43.9%, 95% CI 42.8%-45%) or multiple CVD risk factors (weighted percentage 41.3%, 95% CI 40.1%-42.4%) in 2012. Although there was an increase in the prevalence of HIT use in 2018 among all the CVD risk groups compared to 2012, the highest use of HIT was still among respondents without any CVD risk factors (weighted percentage 65.8%, 95% CI 64.1%-67.4%) compared to respondents with one CVD risk factor (weighted percentage 60%, 95% CI 57.5%-60.4%) or multiple CVD risk factors (weighted percentage 54.7%, 95% CI 53.4%-55.9%). A detailed comparison of types of HIT use by respondents with and without CVD risk factors in the years 2012 and 2018 is shown in Table 2.

Table 2. Use of HIT by year for the general National Health Information Survey and CVD risk factor strata for 2012 and 2018.

HIT[a] use	Value (%)[b]							
	2012 (n=33,885; N=99,819,805)				2018 (n=25,107; N=110,273,504)			
	All	No CVD[c] risk factors	One CVD risk factor	Multiple CVD risk factors	All	No CVD risk factors	One CVD risk factor	Multiple CVD risk factors
Any health information technology use	44.5	51.1	43.9	41.2	58.6	65.8	60.0	54.7
Looked up health information on the internet	41.5	48.7	41.6	38.1	54.2	62.7	55.2	49.5
Filled a prescription on the internet	6.7	5.6	5.4	9.1	11.3	9.5	9.3	14.0
Scheduled a medical appointment on the internet	4.6	5.8	4.5	4.2	16.3	19.7	16.7	14.2
Communicated with a health care provider by email	5.8	6.4	5.7	6.0	16.4	17.7	15.0	17.2

[a]HIT: health information technology.

[b]All percentages are weighted.

[c]CVD: cardiovascular disease.

Trend Analyses

In the linear trend analysis stratified by CVD risk status, age, and education from 2012 to 2018 (Figure 1), the APC in HIT use from 2012 to 2018 increased by 4.4% (95% CI 3.4%-5.5%) in adults aged 18-25 years, 4.3% (95% CI 1.5%-7.1%) in the 26-44 years age group, 4.5% (95% CI 2.8%-6.2%) in the 45-64 years age group, and 8.3% (95% CI 6.7-9.8) in the ≥65 years age group.

Respondents with none of the CVD risk factors were the highest HIT users (Figure 2); however, they had a smaller APC of 4.3% (95% CI 1.7%-7.0%) from 2012 to 2018. People with one CVD risk factor had an APC of 4.9% (95% CI 2.8%-7.1%), and those who had multiple CVD risk factors showed an APC of 5% (95% CI 3.5%-6.6%) from 2012 to 2018. The highest APC of 8.8% (95% CI 5.7%-12%) by education status was seen among people who had not graduated from high school (Figure 3).

Figure 1. Trends in health information technology use by age, 2012-2018. APC: annual percentage change.

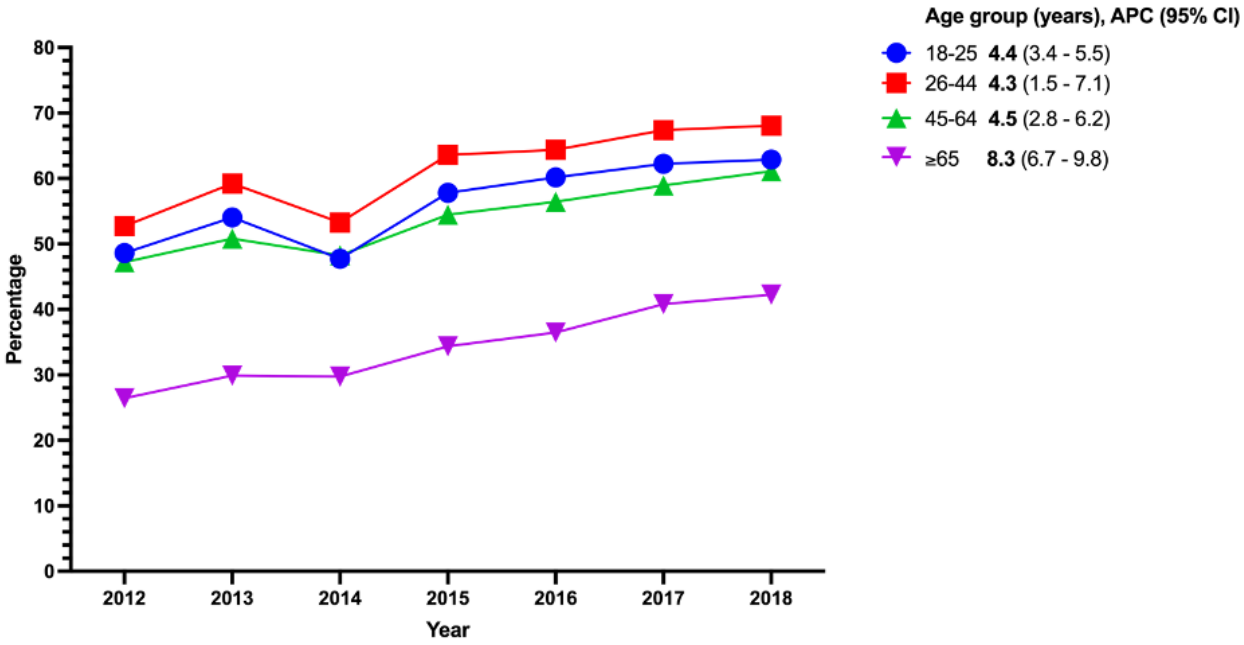


Figure 2. Trends in health information technology use by cardiovascular disease risk status, 2012-2018. APC: annual percentage change.

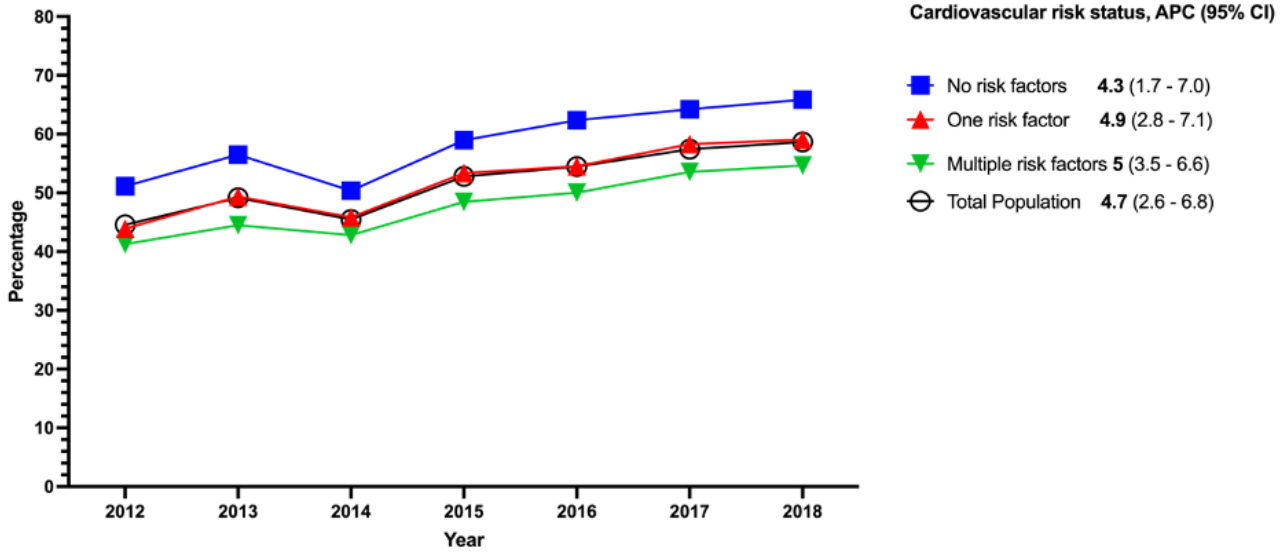
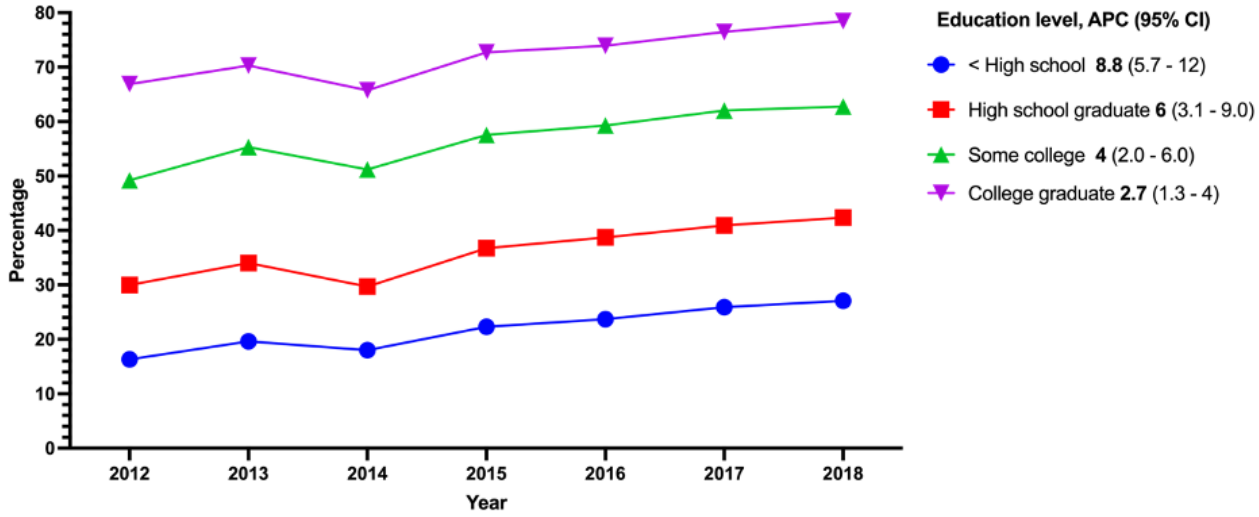


Figure 3. Trends in health information technology use by highest level of education, 2012-2018. APC: annual percentage change.



Characteristics Associated With HIT Use Among Adults With and Without CVD Risk Factors

In 2012, among those with multiple CVD risk factors, college graduation was associated with the highest odds of HIT use (odds ratio [OR] 8.59, 95% CI 7.03-10.50) compared to adults without high school education. This gap remained in 2018, when college graduates were over 7 times more likely to use HIT (OR 7.18, 95% CI 5.86-8.79) than adults without high school education. Similar associations were seen in those with a single CVD risk factor or no CVD risk factors (Table 3).

Table 3. Factors associated with health information technology use by CVD risk status: results from multivariable logistic regression for 2012 and 2018.

	Odds ratio (95% CI)							
	2012				2018			
	Multiple CVD risk factors (n= 35,133,127)	One CVD risk factor (n= 35,057,617)	No CVD risk factors (n= 24,644,831)	All (n= 94,835,575)	Multiple CVD risk factors (n= 40,877,272)	One CVD risk factor (n= 38,466,418)	No CVD risk factors (n= 23,891,951)	All (n= 103,235,641)
Age (years; reference: 18-25)								
26-44	0.88 (0.59-1.32)	0.91 (0.76-1.08)	*0.82 (0.68-0.98)* [a]	*0.86 (0.77-0.96)*	0.84 (0.52-1.36)	0.89 (0.72-1.09)	0.93 (0.75-1.15)	0.92 (0.80-1.05)
45-64	*0.53 (0.35-0.78)*	*0.64 (0.54-0.77)*	*0.59 (0.49-0.71)*	*0.63 (0.57-0.71)*	*0.48 (0.30-0.76)*	*0.67 (0.54-0.83)*	*0.59 (0.48-0.74)*	*0.65 (0.57-0.74)*
≥65	*0.22 (0.15-0.33)*	*0.28 (0.22-0.35)*	*0.21 (0.16-0.29)*	*0.27 (0.24-0.31)*	*0.20 (0.12-0.33)*	*0.29 (0.23-0.37)*	*0.25 (0.19-0.32)*	*0.29 (0.25-0.33)*
Sex (reference: male)								
Female	*1.79 (1.60-2.00)*	*2.12 (1.91-2.36)*	*1.79 (1.56-2.05)*	*1.86 (1.75-1.98)*	*1.53 (1.38-1.70)*	*2.13 (1.89-2.41)*	*1.67 (1.41-1.98)*	*1.75 (1.63-1.88)*
Race/ethnicity (reference: non-Hispanic White)								
Hispanic	*0.56 (0.47-0.67)*	*0.59 (0.50-0.69)*	*0.63 (0.53-0.75)*	*0.58 (0.52-0.63)*	*0.66 (0.54-0.80)*	*0.53 (0.45-0.62)*	*0.65 (0.52-0.82)*	*0.58 (0.52-0.64)*
Non-Hispanic Black	*0.59 (0.51-0.70)*	*0.61 (0.52-0.71)*	*0.61 (0.50-0.75)*	*0.60 (0.55-0.66)*	*0.71 (0.60-0.83)*	*0.63 (0.53-0.76)*	*0.47 (0.36-0.63)*	*0.63 (0.56-0.71)*
Non-Hispanic Asian	*0.54 (0.39-0.75)*	*0.82 (0.65-1.05)*	*0.70 (0.56-0.87)*	*0.68 (0.60-0.78)*	*0.60 (0.45-0.78)*	*0.60 (0.46-0.79)*	*0.52 (0.39-0.70)*	*0.56 (0.47-0.66)*
Non-Hispanic all other race groups	0.70 (0.40-1.22)	0.92 (0.55-1.54)	0.97 (0.53-1.78)	0.81 (0.57-1.14)	0.79 (0.48-1.28)	0.59 (0.32-1.09)	0.45 (0.19-1.03)	*0.65 (0.46-0.93)*
Educational status (reference: <high school)								
High school graduate	*1.73 (1.44-2.08)*	*1.90 (1.57-2.30)*	*1.50 (1.18-1.90)*	*1.74 (1.56-1.93)*	*1.55 (1.27-1.88)*	*1.44 (1.16-1.79)*	*1.83 (1.38-2.44)*	*1.59 (1.39-1.80)*
Some college	*4.02 (3.34-4.84)*	*3.26 (2.74-3.89)*	*3.17 (2.54-3.95)*	*3.54 (3.21-3.91)*	*3.80 (3.18-4.55)*	*3.07 (2.51-3.76)*	*3.01 (2.23-4.06)*	*3.37 (2.98-3.82)*
College graduate	*8.59 (7.03-10.50)*	*6.14 (5.07-7.43)*	*7.17 (5.63-9.10)*	*7.02 (6.30-7.82)*	*7.18 (5.86-8.79)*	*6.25 (5.02-7.78)*	*7.80 (5.87-10.36)*	*6.91 (6.07-7.86)*
Poverty (reference: not in poverty)								
In poverty/near poverty	*0.57 (0.50-0.66)*	*0.65 (0.56-0.74)*	*0.84 (0.72-0.98)*	*0.67 (0.62-0.72)*	*0.61 (0.53-0.70)*	*0.83 (0.72-0.97)*	*0.83 (0.68-1.01)*	*0.73 (0.67-0.79)*
Marital status (reference: unmarried)								
Married	*1.23 (1.10-1.38)*	1.10 (0.99-1.22)	1.08 (0.95-1.23)	*1.17 (1.10-1.25)*	*1.27 (1.13-1.42)*	*1.17 (1.04-1.31)*	*1.20 (1.01-1.43)*	*1.23 (1.15-1.31)*
Region (reference: Northeast)								
Midwest	1.07 (0.88-1.30)	1.06 (0.88-1.28)	1.14 (0.95-1.38)	1.07 (0.96-1.20)	1.14 (0.96-1.35)	0.89 (0.73-1.10)	1.13 (0.85-1.50)	1.02 (0.90-1.16)
South	1.01 (0.84-1.21)	0.97 (0.81-1.15)	0.89 (0.75-1.05)	0.95 (0.86-1.06)	1.12 (0.96-1.32)	0.93 (0.77-1.13)	0.87 (0.67-1.14)	1.00 (0.89-1.12)
West	*1.01 (1.19-1.81)*	*1.31 (1.08-1.58)*	*1.32 (1.08-1.60)*	*1.34 (1.19-1.51)*	*1.39 (1.15-1.67)*	1.18 (0.96-1.46)	*1.32 (1.00-1.73)*	*1.27 (1.11-1.45)*
Insurance (reference: uninsured)								
Public	1.03 (0.85-1.25)	0.89 (0.75-1.06)	1.17 (0.94-1.47)	1.04 (0.94-1.15)	1.27 (0.97-1.65)	1.11 (0.90-1.37)	1.20 (0.91-1.57)	*1.20 (1.05-1.37)*

	Odds ratio (95% CI)							
	2012				2018			
	Multiple CVD risk factors (n= 35,133,127)	One CVD risk factor (n= 35,057,617)	No CVD risk factors (n= 24,644,831)	All (n= 94,835,575)	Multiple CVD risk factors (n= 40,877,272)	One CVD risk factor (n= 38,466,418)	No CVD risk factors (n= 23,891,951)	All (n= 103,235,641)
Private	*1.22 (1.00-1.48)*	*1.16 (1.00-1.35)*	*1.36 (1.13-1.62)*	*1.25 (1.13-1.38)*	*1.42 (1.08-1.87)*	*1.25 (1.02-1.52)*	1.21 (0.94-1.56)	*1.30 (1.14-1.49)*
Perceived health status (reference: excellent)								
Very good	1.06 (0.89-1.27)	*1.34 (1.18-1.53)*	*1.26 (1.08-1.47)*	*1.32 (1.21-1.43)*	1.15 (0.96-1.39)	*1.38 (1.19-1.61)*	1.08 (0.91-1.27)	*1.26 (1.14-1.39)*
Good	1.07 (0.91-1.25)	*1.19 (1.04-1.37)*	1.15 (0.97-1.37)	*1.24 (1.14-1.36)*	1.02 (0.84-1.24)	*1.24 (1.05-1.46)*	1.09 (0.88-1.34)	*1.21 (1.09-1.34)*
Fair	1.05 (0.86-1.27)	*1.49 (1.17-1.89)*	1.00 (0.70-1.43)	*1.30 (1.15-1.47)*	1.17 (0.95-1.44)	*1.42 (1.12-1.79)*	0.93 (0.64-1.36)	*1.31 (1.16-1.49)*
Poor	0.87 (0.64-1.17)	1.15 (0.74-1.77)	1.08 (0.53-2.21)	1.06 (0.86-1.29)	0.98 (0.74-1.29)	1.34 (0.85-2.12)	1.10 (0.57-2.11)	1.18 (0.97-1.43)

[a]Italic text indicates statistically significant results.

Among those respondents who reported no or multiple CVD risk factors, there was no difference in the odds of HIT use by health status. However, for those with one CVD risk factor, health status was associated with HIT use; in 2012, adults who reported their health status as “fair” were 1.49 times more likely to use HIT than adults who reported their health status as “excellent” (95% CI 1.17-1.89), and in 2018, they were 1.42 times more likely to do so (95% CI 1.12, 1.79). Overall, the significant predictors of HIT use were similar across all the three risk factor groups. In particular, after adjusting for health and sociodemographic factors, respondents who were relatively young, non-Hispanic White, female, and more educated; had private insurance and high income; and resided in the West were significantly more likely to be HIT users (Table 3).

Discussion

Principal Findings

HIT use increased by 10 to 15 percentage points in American adults over 2012-2018. Overall, the proportion of respondents using HIT for general purposes was greater than the proportion of people using HIT for clinical purposes in both 2012 and 2018. HIT users were more likely to be younger, female, and non-Hispanic White; have higher education and income; be married; and report their health status as very good or excellent.

The widespread, easy access to the internet for various purposes in recent times may have boosted the overall increasing trends of HIT use from 2012 to 2018 among all the risk factor groups [15]. Our findings show that in 2018, HIT use was the highest (66%) among adults with no CVD risk factors, followed by adults with one risk factor (59%); meanwhile, HIT use was the lowest among adults with multiple risk factors (55%). The lower use of HIT among respondents with multiple risk factors could be attributed to older age and disability. However, we found that the highest annual percentage change was seen among those with multiple CVD risk factors and those aged ≥65 years, which represents a positive change to address the potential digital divide by CVD risk status and older age, a known risk factor for limited digital access. The highest use of HIT among adults with no CVD risk factors may have been expected, because these groups also are likely to be younger [16]. A recent study [17] also demonstrated the rapid shift to telehealth during the COVID-19 pandemic; however, our findings demonstrate that the older sections of the population with multiple comorbidities may have been ill-equipped for this transition.

Our results also revealed wide variation in the odds of HIT use by individual, household-related, and health-related characteristics. Similar to previous studies, women had the highest odds of HIT use compared to men [18,19]. For example, in 2011, the US Centers for Disease Control and Prevention stated that women and adults aged 18-64 years belonging to higher income groups had the highest usage of the internet for health information than men and other age groups, respectively [20]. Socioeconomic factors, especially education, had higher influence on HIT use than health-related characteristics. Thus, despite widespread internet access in the United States, socioeconomic status disparities persist, suggesting the need for target strategies to improve HIT use/access.

Despite a significant recent increase in HIT use in the older population in recent times, a digital divide between younger and older persons persists [18,19,21]. Although there has been an increasing trend of HIT use among older adults, our findings reveal they have both the lowest use of HIT and also the highest rates of CVD risk factors [16]. Data from the Pew Research Center indicate that nationally, approximately 66% of adults aged over 65 years used the internet in the United States in 2018 [22]; however, our findings show that a much lower percentage of adults in this age group used HIT. Recent studies have shown that older adults are expressing a demand for HIT use [23] and would benefit the most from HIT use due to their comorbid conditions. Thus, studies and interventions are needed to increase HIT use for older adults, especially for clinical purposes. This could be achieved through designing easier technologies [24] to help older adults and those with hearing

or visual impairments navigate HIT, as well as through clearing misconceptions and emphasizing the potential benefits of HIT use to improve care access [25].

The variations in HIT use related to race/ethnicity also deserve further attention. People who are White were more likely to use HIT than those in other race groups. A myriad of social and economic factors have likely created this divide, including the higher income, education, lifespan, and hence overall higher affordability and accessibility of HIT for White people compared to those in other race groups [26]. Chronic CVD-related disabilities, which are more common among other race groups than among White people [27,28], may create further barriers to digital access that could explain the lower proportions of HIT use among these groups. Language, cultural barriers, and access to care also influence the likelihood of HIT use among people of these races compared to White people [29,30], leading to the disparities we see in these findings. The perpetual racial and socioeconomic disparities in the digital divide [17] are a major public health concern as we continue to recover from the COVID-19 pandemic.

Among the types of HIT use, we observed that a majority reported seeking web-based health information compared to other types of use. This observation is in line with other studies showing that patients are increasingly relying on the internet as their primary source of answers to health-related questions [15,31,32]. Given the speed at which misinformation can spread on the internet, to ensure the credibility of health information obtained by patients, health systems and clinicians can play a key role in directing patients and HIT users to credible sources of information. This could include regular assessments at clinic visits of the sites where patients seek information on the web and provision of feedback or evidence-based resources for patients. Given the urgent need to use multiple methods to reach and improve access for patients during the ongoing pandemic, further investigation and interventions to address factors associated with low rates of HIT use for clinical purposes (to make appointments, email health care providers, fill prescriptions via internet) are needed.

Strengths

Our study has several strengths. This study is the first to use nationally representative data to examine the prevalence of and factors associated with HIT use among people with and without CVD risk factors. The survey response rate is very good at 65-77%. Further, the study has a large sample size and was able to measure the trends through multiple years, from 2012-2018. To our knowledge, this study provides the first national assessment of HIT use among adults with CVD risk factors prior to the COVID-19 pandemic.

Limitations

The general limitations of the NHIS data apply to this study as well. Firstly, the data are self-reported, and the questions pertaining to HIT use inquire about whether participants used HIT in the past 12 months, which means the responses could be subjected to recall bias. Second, the cross-sectional nature of the data limits the possibility to establish causal pathways between factors noted in our analysis and HIT use; cross-sectional data may also increase the risk of reverse causality. Further, the data lack information on English proficiency for the years 2012-2017. This is a limitation of the analysis, as English proficiency may have affected the rate of HIT use. Last, we are unable to quantify the amount of HIT use among the respondents, as some could be daily users and some could be monthly users; this may bear weight in the health access and knowledge of HIT tools.

Conclusions

Our study provides a pre–COVID-19 assessment of HIT use among Americans with and without CVD risk factors. We found an increasing trend of HIT use among adults with and without CVD risk factors in the United States from 2012-2018. However, wide variation exists in use among Americans with CVD risk factors, who should be regularly accessing care. This variation has likely been exacerbated during the ongoing COVID-19 pandemic. Namely, older adults, racial and ethnic minority populations, and adults with multiple CVD risk factors are at high risk of having less access to HIT. A multipronged approach that includes education initiatives, affordable access to technology, and emphasis of health systems on creating platforms that all Americans can access are needed. Future studies to address these gaps are also needed to understand best practices.

Acknowledgments

NG and MKS are supported by K23 MD015088-01 from the National Institute on Minority Healthy and Health Disparities. MKA is supported by P30DK111024 from the Georgia Center for Diabetes Translation Research, funded by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK).

Conflicts of Interest

None declared.

References

1. Mehlman E, Mendelson D. Healthcare leaders grapple with deferred care crisis. Healthcare Financial Management Association. URL: https://www.hfma.org/topics/financial-sustainability/article/the-crisis-within-the-crisis--preparing-for-the-wave-of-covid-19.html [accessed 2021-02-24]

2. Grimm C. Hospital Experiences Responding to the COVID-19 Pandemic: Results of a National Pulse Survey March 23–27. US Department of Health and Human Services, Office of Inspector General. 2021 Feb 24. URL: https://oig.hhs.gov/oei/reports/oei-06-20-00300.pdf [accessed 2021-09-10]
3. OneCare Vermont. Telemedicine on the rise in Vermont, survey results show. OneCare Vermont. 2020 Jun 23. URL: https://www.onecarevt.org/telemedicine-survey/ [accessed 2021-02-14]
4. Czeisler, Marynak K, Clarke KEN, Salah Z, Shakya I, Thierry JM, et al. Delay or avoidance of medical care because of COVID-19-related concerns - United States, June 2020. MMWR Morb Mortal Wkly Rep 2020 Sep 11;69(36):1250-1257 [FREE Full text] [doi: 10.15585/mmwr.mm6936a4] [Medline: 32915166]
5. The impact of the COVID-19 pandemic on outpatient care: visits return to prepandemic levels, but not for all providers and patients. The Commonwealth Fund. 2020 Oct 15. URL: https://www.commonwealthfund.org/publications/2020/oct/impact-covid-19-pandemic-outpatient-care-visits-return-prepandemic-levels [accessed 2021-03-24]
6. Global Burden of Cardiovascular Diseases Collaboration, Roth GA, Johnson CO, Abate KH, Abd-Allah F, Ahmed M, et al. The burden of cardiovascular diseases among US states, 1990-2016. JAMA Cardiol 2018 May 01;3(5):375-389 [FREE Full text] [doi: 10.1001/jamacardio.2018.0385] [Medline: 29641820]
7. Arnett DK, Blumenthal RS, Albert MA, Buroker AB, Goldberger ZD, Hahn EJ, et al. 2019 ACC/AHA guideline on the primary prevention of cardiovascular disease: a report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. Circulation 2019 Sep 10;140(11):e596-e646 [FREE Full text] [doi: 10.1161/CIR.0000000000000678] [Medline: 30879355]
8. The social life of health information. Pew Research Center. 2009 Jun 11. URL: https://www.pewresearch.org/internet/2009/06/11/the-social-life-of-health-information/ [accessed 2021-02-04]
9. National Health Interview Survey. US Centers for Disease Control and Prevention. 2020 Dec 02. URL: https://www.cdc.gov/nchs/nhis/index.htm [accessed 2021-02-04]
10. About the National Health Interview Survey. US Centers for Disease Control and Prevention. 2020 Sep 16. URL: https://www.cdc.gov/nchs/nhis/about_nhis.htm [accessed 2021-02-04]
11. Know Your Risk for Heart Disease. US Centers for Disease Control and Prevention. 2019 Dec 09. URL: https://www.cdc.gov/heartdisease/risk_factors.htm [accessed 2021-02-01]
12. Defining adult overweight and obesity. US Centers for Disease Control and Prevention. 2020 Jun 07. URL: https://www.cdc.gov/obesity/adult/defining.html [accessed 2021-07-14]
13. How the Census Bureau measures poverty. United States Census Bureau. URL: https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html [accessed 2021-07-14]
14. Gracia E, Herrero J. Internet use and self-rated health among older people: a national survey. J Med Internet Res 2009 Dec 02;11(4):e49 [FREE Full text] [doi: 10.2196/jmir.1311] [Medline: 19955041]
15. Atkinson NL, Saperstein SL, Pleis J. Using the internet for health-related activities: findings from a national probability sample. J Med Internet Res 2009 Feb 20;11(1):e4 [FREE Full text] [doi: 10.2196/jmir.1035] [Medline: 19275980]
16. Dhingra R, Vasan RS. Age as a risk factor. Med Clin North Am 2012 Jan;96(1):87-91 [FREE Full text] [doi: 10.1016/j.mcna.2011.11.003] [Medline: 22391253]
17. Weiner JP, Bandeian S, Hatef E, Lans D, Liu A, Lemke KW. In-person and telehealth ambulatory contacts and costs in a large US insured cohort before and during the COVID-19 pandemic. JAMA Netw Open 2021 Mar 01;4(3):e212618 [FREE Full text] [doi: 10.1001/jamanetworkopen.2021.2618] [Medline: 33755167]
18. Hong YA, Cho J. Has the digital health divide widened? Trends of health-related internet use among older adults from 2003 to 2011. J Gerontol B Psychol Sci Soc Sci 2017 Sep 01;72(5):856-863. [doi: 10.1093/geronb/gbw100] [Medline: 27558403]
19. Kontos E, Blake KD, Chou WS, Prestin A. Predictors of eHealth usage: insights on the digital divide from the Health Information National Trends Survey 2012. J Med Internet Res 2014 Jul 16;16(7):e172 [FREE Full text] [doi: 10.2196/jmir.3117] [Medline: 25048379]
20. Cohen RA, Adams PF. Use of the internet for health information: United States, 2009. NCHS Data Brief 2011 Jul(66):1-8 [FREE Full text] [Medline: 22142942]
21. Mitchell U, Chebli P, Ruggiero L, Muramatsu N. The digital divide in health-related technology use: the significance of race/ethnicity. Gerontologist 2019 Jan 09;59(1):6-14. [doi: 10.1093/geront/gny138] [Medline: 30452660]
22. Internet/broadband fact sheet. Pew Research Center. URL: https://www.pewresearch.org/internet/fact-sheet/internet-broadband/ [accessed 2021-02-15]
23. Tech-Savvy Seniors Want Online Options to Access Care from Home, Accenture Survey Shows. Accenture Newsroom. 2015 Mar 02. URL: https://newsroom.accenture.com/industries/health-public-service/tech-savvy-seniors-want-online-options-to-access-care-from-home-accenture-survey-shows.htm [accessed 2021-02-15]
24. Bailey S. Technology: Health Care Solve for Elders? Today's Geriatric Medicine. URL: https://www.todaysgeriatricmedicine.com/news/ex_091415.shtml [accessed 2021-02-15]
25. Adams B, Gerber-Somers S. How to engage seniors with digital health. Managed Healthcare Executive. 2019 Dec 10. URL: https://www.managedhealthcareexecutive.com/view/how-engage-seniors-digital-health [accessed 2021-02-15]

26. Pew Research Center. 2013 Aug 22. URL: https://www.pewresearch.org/social-trends/2013/08/22/chapter-3-demographic-economic-data-by-race/ [accessed 2021-02-15]
27. Manton K, Stallard E, National Research Council (US) Committee on Population, Martin LG, Soldo BJ. Health and disability differences among racial and ethnic groups. In: Racial and Ethnic Differences in the Health of Older Americans. Washington, DC: National Academies Press; 1997.
28. Mensah GA, Dunbar SB. A framework for addressing disparities in cardiovascular health. J Cardiovasc Nurs 2006;21(6):451-456. [doi: 10.1097/00005082-200611000-00007] [Medline: 17293734]
29. López L, Green AR, Tan-McGrory A, King RS, Betancourt JR. Bridging the digital divide in health care: the role of health information technology in addressing racial and ethnic disparities. Jt Comm J Qual Patient Saf 2011 Oct;37(10):437-445. [doi: 10.1016/S1553-7250(11)37055-9]
30. Amante DJ, Hogan TP, Pagoto SL, English TM, Lapane KL. Access to care and use of the Internet to search for health information: results from the US National Health Interview Survey. J Med Internet Res 2015 Apr 29;17(4):e106 [FREE Full text] [doi: 10.2196/jmir.4126] [Medline: 25925943]
31. Miller EA, West DM, Wasserman M. Health information Websites: characteristics of US users by race and ethnicity. J Telemed Telecare 2007 Jun 24;13(6):298-302. [doi: 10.1258/135763307781644852] [Medline: 17785031]
32. Jacobs W, Amuta AO, Jeon KC. Health information seeking in the digital age: an analysis of health information seeking behavior among US adults. Cogent Social Sciences 2017 Mar 13;3(1):1302785. [doi: 10.1080/23311886.2017.1302785]

Abbreviations

APC: annual percentage change
CVD: cardiovascular disease
HIT: health information technology
NHIS: National Health Interview Survey

Edited by H Bradley; submitted 27.04.21; peer-reviewed by R Krukowski, R Halkes, S Hajesmaeel Gohari, F Yamin; comments to author 14.07.21; revised version received 19.07.21; accepted 30.07.21; published 30.09.21.

Please cite as:
Gandrakota N, Ali MK, Shah MK
Trends in Health Information Technology Use Among the US Population With and Without Cardiovascular Risk Factors, 2012-2018: Evidence From the National Health Interview Survey
JMIR Public Health Surveill 2021;7(9):e29990
URL: https://publichealth.jmir.org/2021/9/e29990
doi:10.2196/29990
PMID:34591026

Original Paper

Using Machine Learning Techniques to Predict Factors Contributing to the Incidence of Metabolic Syndrome in Tehran: Cohort Study

Firoozeh Hosseini-Esfahani[1*], PhD; Behnaz Alafchi[2*], PhD; Zahra Cheraghi[3,4*], PhD; Amin Doosti-Irani[4,5*], PhD; Parvin Mirmiran[1*], PhD; Davood Khalili[6,7], MD, PhD; Fereidoun Azizi[6], MD

[1]Department of Clinical Nutrition and Dietetics, Faculty of Nutrition Sciences and Food Technology, National Nutrition and Food Technology Research Institute, Shahid Beheshti University of Medical Sciences, Tehran, Iran

[2]Department of Biostatistics, School of Public Health, Hamadan University of Medical Sciences, Hamadan, Iran

[3]Modeling of Noncommunicable Diseases Research Center, Hamadan University of Medical Sciences, Hamadan, Iran

[4]Department of Epidemiology, School of Public Health, Hamadan University of Medical Sciences, Hamadan, Iran

[5]Health and Research Center for Health Sciences, Hamadan University of Medical Sciences, Hamadan, Iran

[6]Prevention of Metabolic Disorders Research Center, Research Institute for Endocrine Sciences, Shahid Beheshti University of Medical Sciences, Tehran, Iran

[7]Department of Biostatistics and Epidemiology, Research Institute for Endocrine Sciences, Shahid Beheshti University of Medical Sciences, Tehran, Iran

[*]these authors contributed equally

Corresponding Author:
Zahra Cheraghi, PhD
Modeling of Noncommunicable Diseases Research Center
Hamadan University of Medical Sciences
Shahid Fahmideh Ave
Hamadan, 65157835129
Iran
Phone: 98 9183177990
Fax: 98 81338380509
Email: cheraghiz@ymail.com

Abstract

Background: Metabolic syndrome (MetS), a major contributor to cardiovascular disease and diabetes, is considered to be among the most common public health problems worldwide.

Objective: We aimed to identify and rank the most important nutritional and nonnutritional factors contributing to the development of MetS using a data-mining method.

Methods: This prospective study was performed on 3048 adults (aged ≥20 years) who participated in the fifth follow-up examination of the Tehran Lipid and Glucose Study, who were followed for 3 years. MetS was defined according to the modified definition of the National Cholesterol Education Program/Adult Treatment Panel III. The importance of variables was obtained by the training set using the random forest model for determining factors with the greatest contribution to developing MetS.

Results: Among the 3048 participants, 701 (22.9%) developed MetS during the study period. The mean age of the participants was 44.3 years (SD 11.8). The total incidence rate of MetS was 229.9 (95% CI 278.6-322.9) per 1000 person-years and the mean follow-up time was 40.5 months (SD 7.3). The incidence of MetS was significantly (P<.001) higher in men than in women (27% vs 20%). Those affected by MetS were older, married, had diabetes, with lower levels of education, and had a higher BMI (P<.001). The percentage of hospitalized patients was higher among those with MetS than among healthy people, although this difference was only statistically significant in women (P=.02). Based on the variable importance and multiple logistic regression analyses, the most important determinants of MetS were identified as history of diabetes (odds ratio [OR] 6.3, 95% CI 3.9-10.2, P<.001), BMI (OR 1.2, 95% CI 1.0-1.2, P<.001), age (OR 1.0, 95% CI 1.0-1.03, P<.001), female gender (OR 0.5, 95% CI 0.38-0.63, P<.001), and dietary monounsaturated fatty acid (OR 0.97, 95% CI 0.94-0.99, P=.04).

Conclusions: Based on our findings, the incidence rate of MetS was significantly higher in men than in women in Tehran. The most important determinants of MetS were history of diabetes, high BMI, older age, male gender, and low dietary monounsaturated fatty acid intake.

(JMIR Public Health Surveill 2021;7(9):e27304) doi:10.2196/27304

KEYWORDS

metabolic syndrome; Tehran Lipid and Glucose Study; data mining

Introduction

Metabolic syndrome (MetS), a major contributor to cardiovascular disease and diabetes, is considered to be among the most common public health problems worldwide [1]. According to the World Health Organization and the International Diabetes Federation, MetS is defined as the simultaneous occurrence of three of the following five medical conditions: abdominal obesity, high blood pressure, hyperglycemia, high triglyceride levels, and low high-density lipoprotein cholesterol (HDL-C) levels [2].

The incidence of MetS is estimated to be 34% in the United States [3], 12%-37% in Asian countries [4], and 12%–26% in European populations [5]. In Iran, the overall pooled prevalence and incidence rate of MetS among the general population was reported to be 0.26 (95% CI 0.25-0.29) and 97.96 per 1000 person-years (95% CI 75.98-131.48), respectively, and was higher in women living in urban areas and in men living in rural areas.

The overall pooled prevalence of MetS was higher in urban areas compared to rural areas (0.39 vs 0.26) and the pooled prevalence of MetS was higher in women than in men (0.34 vs 0.22) [6].

According to previous studies, the etiology of MetS is controlled by several risk factors, including abdominal obesity, insulin resistance, glucose tolerance disorder, hypertension, genetic factors, psychosocial stressors, and nutritional and diet factors [7-11]. Previous studies have often investigated the predictive factors using classical approaches and neglected the interpretability of the results. For example, among the explanatory variables, the risk/protective factors have a more important role in the outcomes. One of the simplest and very common ranking techniques is random forest (RF), which is a data-mining approach. The most important features of this model are simplicity and interpretation of the model, flexibility in applying a large number of predictor variables, working with an infinite sample size, and determination of important variables in predicting the outcome. The RF model is also useful when predictor variables are nonlinear concerning disease, because there is no assumption or any constraint on the form of the relationships [12-14]. Considering the high prevalence of MetS and its importance in cardiovascular disease, identifying and ranking the most important nutritional and nonnutritional factors in the occurrence of MetS is an essential analysis with respect to public health. Data-mining methods are strong tools in predicting different outcomes and emphasizing interpretability with benefits for precision prediction. Hence, we aimed to identify and rank the most important nutritional and nonnutritional factors in the occurrence of MetS among the general population of Tehran, Iran, using the RF data-mining method.

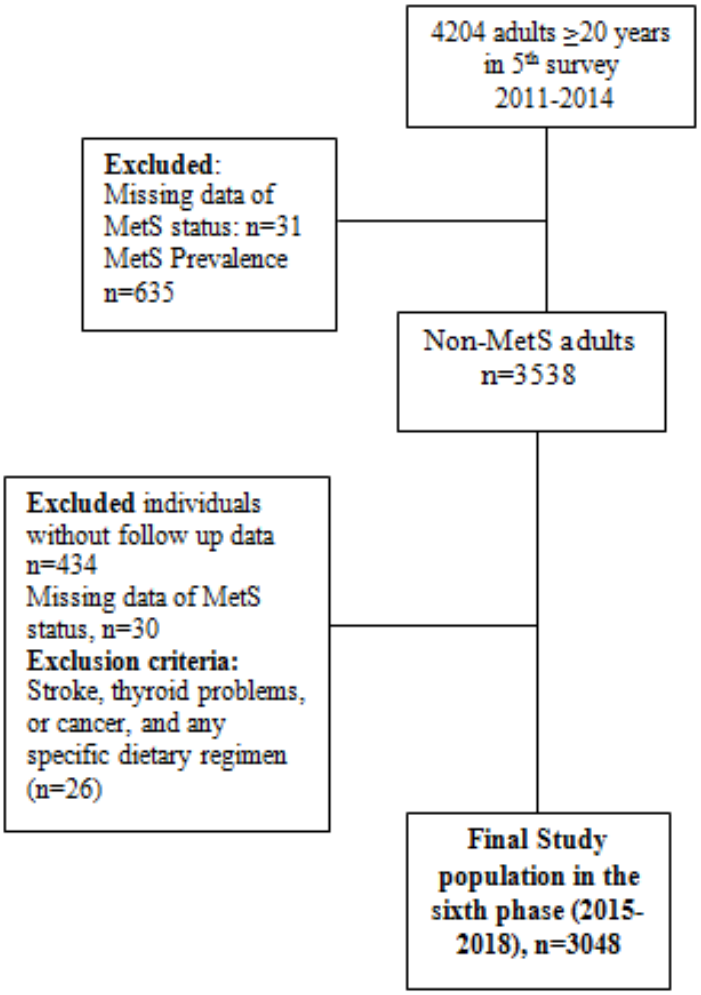
Methods

Design and Participants

This prospective study (Code: IR.UMSHA.REC.1398.864) was performed under the framework of the Tehran Lipid and Glucose Study, a population-based study to determine risk factors for noncommunicable diseases in a sample of residents of District 13 of the Tehran metropolis [15,16]. The first examination survey was performed from 1999 to 2001 on 15,005 individuals aged ≥3 years. Subsequently, follow-up examinations were performed every 3 years (2002-2005, 2005-2008, 2008-2011, 2011-2014, and 2015-2018) to identify recently developed diseases (see Multimedia Appendix 1 for more details on the survey).

In the fifth follow-up examination (2011-2014), 4204 adults (aged ≥20 years) participated. These participants completed the Food Frequency Questionnaire (FFQ), and their dietary data were available. The exclusion criteria in this study were as follows: individuals diagnosed with MetS (n=635); people with missing data regarding MetS status (n=61); no follow-up (n=434); stroke, thyroid, or cancer complications (n=18); and following a specific dietary regimen (n=8). Finally, 3048 adults without MetS at baseline were included in the study (Figure 1). All invited participants signed the informed written consent form. The study was performed in adherence with the Declaration of Helsinki. The ethics committee of the Research Institute for Endocrine Sciences, Shahid Beheshti University of Medical Sciences approved the study protocol.

Figure 1. Flowchart of the study participants (MetS: metabolic syndrome; TLGS: Tehran Lipid and Glucose Study).



Outcomes

MetS was defined according to the modified definition of the National Cholesterol Education Program/Adult Treatment Panel III [17,18] as having at least three of the following symptoms simultaneously: (1) abdominal obesity (waist circumference >90 cm in both genders); (2) serum HDL-C level <40 mg/dl in men and <50 mg/dl in women or taking HDL-C–elevating drugs; (3) hypertension (systolic blood pressure ≥130 mmHg, diastolic blood pressure ≥85 mmHg, or taking antihypertensive drugs); (4) hyperglycemia (fasting blood glucose ≥100 mg/dl or taking hypoglycemic drugs); and (5) hypertriglyceridemia (serum triglyceride level ≥150 mg/dl or taking triglyceride-lowering drugs).

Risk Factor Assessment

In this study, the FFQ was used to measure the exact amount of food intake. The FFQ is a valid and reliable tool for measuring 147 food items (Multimedia Appendix 2) [18]. Trained nutritionists helped the participants to complete the questionnaires through face-to-face interviews. The usual average size of each food item was explained to each participant, considering the frequency of consumption on a daily, weekly, or monthly basis [18,19]. Portion sizes were converted to grams using household measures. Due to the incompleteness of the Iranian food composition table, the United States Department of Agriculture food consumption table was used to analyze foods in terms of their macro- and micronutrients [20,21]. A literature review was performed to select effective nutrients for MetS [22-24].

Weight was measured to the nearest 100 g using digital scales (Seca, Hamburg, Germany) while subjects were minimally clothed and not wearing shoes. Height was measured to the nearest 0.5 centimeter using a stadiometer while the subjects were in a standing position, with their shoulders in normal alignment and without shoes. Information on age, gender, marital status (single, divorced, widowed), history of hospitalization in the previous 3 months, history of cancer, education (primary, intermediate, high school, and academic education), and smoking (never smoked, past smoker, current smoker) was collected using a general information questionnaire.

Statistical Analysis

The χ^2 test and *t* test were applied to explore the differences in qualitative and quantitative variables between groups. Since the data-mining approach cannot reveal the direction of the association of variables on the outcome, multiple logistic regression was used to estimate the adjusted effect of variables. The backward-selection method was applied to choose the variables in this model. To remove variables from the model, the *P* value threshold was set to .20. R software (version 3.6.1)

with the *randomForest* and *caret* packages was used for data analysis.

RF Analysis

RF, proposed by Leo Breiman [25], is an ensemble learning method that grows many classification trees. A random sample with replacement of the original training dataset was used to construct the trees in RF. The algorithm only searches across a random subset of the input variables at each node to determine the best split. Finally, RF chooses the class with the most votes over all the trees in the forest [25]. RF has exhibited superior performance over other machine-learning methods such as support vector machine, artificial neural network, and k-nearest neighbor [26-28].

Moreover, although most machine-learning classifiers are useful for classifying, they do not provide any insight into the most important variables based on the derived classifier. However, RF provides variable importance measurements that can be used in model interpretation [26]. The most common method to find the most important variable is to use the mean decrease in accuracy and the mean decrease in the Gini index [26,29].

Evaluation Criteria

Our dataset consisted of 2259 adults (after removing variables with missing data) divided into training and testing sets. We randomly chose 70% of the data as the training set and the remaining 30% as the test set. The RF classifier was trained using the training dataset. The test dataset was used to evaluate the performance of the method. To evaluate the performance of the RF classifier, we used several evaluation criteria of sensitivity, specificity, negative predictive value (NPV), positive predictive value (PPV), negative likelihood ratio (LR–), and positive likelihood ratio (LR+) (see Multimedia Appendix 3).

Results

Baseline Characteristics

The dataset included 3048 adults, 701 (22.9%) of whom developed MetS and 2347 (77.1%) of whom did not develop MetS. The mean age of the participants at baseline was 44.3 years (SD 11.8). The total MetS incidence rate was 229.98 (95% CI 278.6-322.9) per 1000 person-years. The incidence of MetS was significantly higher in men than in women (27% vs 20%). In both genders, those affected by MetS were older, married, had diabetes, and a lower level of education (P<.001) than their counterparts. In men, a greater frequency of smokers were affected by MetS (P=.05), and the percentage of hospitalized subjects in patients with MetS syndrome was higher than that among healthy people, although this difference was only statistically significant in women (P=.02) (Table 1).

The distribution of the characteristics of subjects in the training and test datasets is presented in Table 2. The results showed no statistically significant differences between the training and test sets.

Table 1. Baseline characteristics of participants who developed and did not develop metabolic syndrome (MetS) by gender.

Variables	Men			Women			All		
	No MetS (n=838)	MetS (n=311)	*P* value[a]	No MetS (n=1509)	MetS (n=390)	*P* value	No MetS (n=2347)	MetS (n=701)	*P* value
Age (years), mean (SD)	45.8 (13.6)	47.1 (12.9)	.08	41.9 (10.1)	51.4 (10.6)	<.001	43.6 (12.1)	49.5 (12.3)	<.001
BMI (kg/m^2), mean (SD)	25.7 (3.9)	28.3 (3.8)	<.001	26.5 (3.1)	30.4 (4.3)	<.001	26.2 (4.2)	29.5) (4.3)	<.001
Marital status, n (%)			.008			.84			.002
Married	673 (80.4)	271 (87.1)		1201 (79.7)	326 (83.6)		1874 (80.0)	597 (85.2)	
Single/divorced/widowed	164 (19.6)	40 (12.9)		306 (20.3)	64 (16.4)		470 (20.0)	104 (14.5)	
Smoking, n (%)			.05			.18			.66
Never	662 (79.0)	243 (78.4)		1441 (95.7)	381 (97.7)		2103 (89.7)	624 (89.4)	
Current/past	176 (21.0)	67 (21.6)		65 (4.3)	9 (2.3)		241 (10.3)	76(10.7)	
Education level, n (%)			.003			<.001			<.001
Higher than diploma	406 (48.6)	121 (39.0)		710 (47.2)	74 (19.4)		1111 (47.7)	195 (28.3)	
Diploma/below diploma	372 (44.6)	173 (55.8)		717 (47.5)	792 (65.8)		1082 (46.4)	423 (61.3)	
Illiterate/primary School	57 (6.8)	16 (5.2)		80 (5.3)	56 (14.8)		137 (5.9)	72 (10.4)	
Cancer history, n (%)	3 (0.4)	1 (0.3)	.93	7 (0.5)	4 (1.0)	.19	10 (0.4)	5 (0.7)	.34
Hospitalization, n (%)	15 (1.8)	5 (1.6)	.84	20 (1.3)	12 (3.1)	.02	35 (1.5)	17 (2.4)	.09
Diabetes, n (%)	21 (2.7)	26 (9.1)	<.001	20 (1.5)	66 (18.7)	<.001	41 (1.9)	92 (14.4)	<.001
Systolic blood pressure (mmHg), mean (SD)	112.9 (12.6)	120.69 (14.1)	<.001	104.34 (12.3)	117.84 (15.7)	<.001	107.5 (13.2)	119.1 (15.5)	<.001
Waist circumference (cm), mean (SD)	91.3 (10.5)	98.1 (96.6)	<.001	87.6 (10.4)	98.2 (9.8)	<.001	88.9 (10.6)	98.2 (9.8)	<.001
High triglyceride, n (%)	141 (16.8)	246 (80.0)	<.001	168 (11.1)	299 (76.7)	<.001	309 (13.2)	545 (75.8)	<.001
Physical activity (km/week), mean (SD)	2.8 (0.4)	2.5 (0.4)	.10	1.5 (0.2)	0.38 (0.1)	.02	2.1 (0.2)	0.6 (0.3)	.08

[a]*P* values are based on the unpaired *t* test and by the χ^2 test for qualitative variables.

Table 2. Comparison of baseline characteristics in the training and test datasets (N=2259).

Variable	Training set (n=1581)	Test set (n=678)	*P* value[a]
Marital status, n (%)			.70
Single	239 (15.1)	95 (14.0)	
Married	1279 (80.9)	550 (81.1)	
Divorced	30 (1.9)	17 (2.5)	
Widowed	33 (2.1)	16 (2.4)	
Gender, n (%)			.96
Men	622 (39.3)	266 (39.2)	
Women	959 (60.7)	412 (60.8)	
Cancer history, n (%)			.38
No	5 (0.3)	4 (0.6)	
Yes	1576 (99.7)	674 (99.4)	
Smoking, n (%)			.81
Never	178 (11.3)	72 (10.6)	
Current/past	1403 (88.7)	606 (89.4)	
Hospitalization, n (%)			.59
No	31 (2.0)	11 (1.6)	
Yes	1550 (98.0)	667 (98.4)	
Diabetes, n (%)			.26
No	1514 (95.8)	642 (94.7)	
Yes	67 (4.2)	36 (5.3)	
Education, n (%)			.49
Higher than diploma	95 (6.0)	34 (5.0)	
Diploma/below diploma	788 (49.8)	330 (48.7)	
Illiterate/primary school	698 (44.1)	314 (46.3)	
Age (years), mean (SD)	44.4 (11.7)	44.1 (12.2)	.34
BMI (kg/m^2), mean (SD)	26.8 (4.4)	26.8 (4.4)	.70
Energy (kilocalories), mean (SD)	2278.6 (811.6)	2326.3 (1239.3)	.90
Protein (g), mean (SD)	86.3 (35.7)	87.2 (51.1)	.35
Carbohydrates (g), mean (SD)	338.1 (124.2)	346.3 (215.6)	.81
Monosaturated fatty acids (g), mean (SD)	25.2 (12.5)	25.6 (13.6)	.93
Total fat (g), mean (SD)	74.6 (32.3)	75.9 (37.7)	.92
Carotenoids (mg), mean (SD)	1231.2 (1246.76)	1226.45 (1029.22)	.54
Calcium (mg),mean (SD)	1379.6 (628.8)	1385.5 (681.9)	.65
Magnesium (mg), mean (SD)	471.1 (186.1)	478.0 (367.9)	.30
Zinc (mg), mean (SD)	13.5 (9.6)	13.2 (9.5)	.24
Total fiber (g), mean (SD)	43.5 (20.0)	44.5 (32.9)	.71
Glucose (g), mean (SD)	17.8 (9.5)	18.3 (11.0)	.40
Fructose (g), mean (SD)	21.1 (11.6)	21.6 (13.4)	.52
Sodium (mg), mean (SD)	3464.8 (1578.6)	4699.3 (29481.7)	.34
Folate (mg), mean (SD)	559.9 (202.5)	570.1 (275.3)	.86

[a]*P* values are based on the *t* test for quantitative variables and on the χ^2 test for qualitative variables.

RF Model

The variable importance obtained by the training set using RF is presented in Table 3, showing the results for each variable when all variables were used as input in the RF algorithm. Here, the variable importance was determined by the average decrease in the Gini index. Based on variable importance, the most important determinants of MetS were diabetes, BMI, age, marital status, monounsaturated fatty acids, female gender, and total fat. According to multiple logistic regression analysis, the direction of the association for these variables was as follows: history of diabetes (odd ratio [OR] 6.32, 95% CI 3.92-10.20; *P*<.001), increased BMI (OR 1.19, 95% CI 1.15-1.22; *P*<.001), increased age (OR 1.02, 95% CI 1.01-1.03; *P*<.001), female gender (OR 0.50, 95% CI 0.38-0.63; *P*<.001), and increased dietary monounsaturated fatty acid (OR 0.97, 95% CI 0.94-0.99, *P*=.04) (Multimedia Appendix 4 and Table 3).

History of diabetes (OR=6.32, 95% CI: 3.92, 10.20; *P*<.001), increased BMI (OR=1.19, 95% CI: 1.15, 1.22; *P*<.001), increased age (OR=1.02, 95% CI: 1.01, 1.03; *P*<.001), female gender (OR=0.50, 95% CI: 0.38, 0.63; *P*<.001), and increased monounsaturated fatty acid (OR=0.97, 95% CI: 0.94, 0.99, *P*=.04) (Multimedia Appendix 4 and Table 3).

We obtained an overall out-of-bag correct classification of 98.67% (Table 4). The proportion of error for subjects with and without MetS was 99.24% and 96.55%, respectively.

Table 3. Variable importance obtained by random forest for predicting metabolic syndrome.

Variable	Variable importance
Diabetes	100
BMI	67.8
Age	25.2
Gender	15.8
Monosaturated fatty acids	13.9
Carotenoids	13.6
Education	12.5
Calcium	12.0
Protein	10.7
Total Fiber	10.7
Sodium	9.8
Total fat	9.4
Folates	8.9
Zinc	8.8
Magnesium	8.8
Smoking	8.6
Energy	7.9
Carbohydrates	7.8
Fructose	7.6
Hospitalization	7.0
Cancer history	6.9
Marriage	6.9
Glucose	6.6

Table 4. Out-of-bag correct classification rates.

Predicted status	Actual status		Correct classification rate
	MetS[b]	No MetS	
MetS	140	5	96.6
No MetS	4	529	99.3

[a]MetS: metabolic syndrome.

Evaluation Criteria

The RF algorithm had high sensitivity (0.97) and specificity (0.99) for the test set. The NPV and PPV performance of RF for the test set were 0.99 and 0.96, respectively. Both the LR+ (103.83) and LR– (0.03) for the test set showed the high ability of the RF algorithm to predict a correct diagnosis of MetS.

Finally, partial plots provided the marginal effect of predictors on MetS (Multimedia Appendix 5).

Discussion

Principal Findings

In this prospective study, the total incidence rate of MetS was 229.98 per 1000 person-years. The most important determinants of MetS were a history of diabetes, increased BMI, older age, male gender, and low dietary monounsaturated fatty acid intake.

In this study, diabetes was identified as the most important risk factor (ranking first) for MetS. This finding is expected to be associated with common risk factors of diabetes and MetS (eg, increased BMI, hypertension, high-fat diet, and insulin resistance–linked obesity). In addition, some analytical studies have shown that MetS predicts diabetes independently of other factors [30]. Another study showed that MetS was associated with a 3 to 5-fold increase in the risk of developing type 2 diabetes mellitus [31].

BMI was identified as the second most important risk factor for the incidence of MetS. The development of insulin resistance and the role of inflammatory mediators in MetS are the most important mechanisms in the pathogenesis of obesity. Various studies have shown relationships among hyperinsulinemia, insulin resistance, and increased inflammatory mediators such as C-reactive protein with the development and progression of MetS [14,17,32].

Increased age was the third-ranking factor that was associated with MetS in this study. Aging usually leads to decreased physical activity, followed by an increase in BMI, which can contribute to MetS. Previous studies showed that less than 10% of people in their 20s and 30s were affected by MetS, whereas MetS affected 40% of those over 60 years of age [33,34].

Male gender was the fourth-ranking factor associated with MetS. We observed a significantly higher incidence of MetS among men than among women (27% vs 20%). Although previous studies in Iran showed that the prevalence of MetS was higher among women than among men [35,36], more recent studies confirm our findings, demonstrating the opposite pattern [7]. One reason behind this phenomenon may be the higher prevalence of basic MetS-related characteristics in the men of our study, such as hypertension, higher waist-hip ratio, and higher triglyceride levels.

A low monounsaturated fatty acid intake was identified as the fifth most important factor for a lower occurrence of MetS. Our result is consistent with a recent systematic review that reported that a diet with decreased monounsaturated fats was associated with improving lipoprotein profiles and triglyceride levels [37]. As mentioned earlier, hyperlipidemia is one of the components of MetS. Thus, this finding is consistent with other studies in this area.

Strengths and Limitations

This study used a population-based cohort (as the gold standard in observational studies) designed based on standard tools for measuring clinical and other variables. This study had some limitations. First, the role of socioeconomic status as an important factor influencing the dietary pattern of subjects was not determined; however, this study was performed on people living in District 13 of Tehran, which is classified as an area with an average income level.

Another limitation of this study was use of the FFQ. Completing a long list of foods consumed over the past year has the potential for recall bias and consequently measurement error, which may distort the results [38,39]. Another important factor for the incidence of MetS is physical activity status; this variable was not included in the analysis due to the large number of missing data.

Finally, the main strength of this study was that the most important risk factors and nutritional factors were ranked. In contrast, previous studies often investigated the predictive factors using classical approaches and neglected the importance of paying attention to risk/protective factors by considering the ranking of the impact of each factor on the outcome. Therefore, lifestyle modification (eg, having a balanced weight and healthy diet) is one of the most important ways to reduce the incidence of MetS.

Conclusion

In summary, our findings show that the incidence rate of MetS in Tehran was 229.98 per 1000 person-years. The most important determinants of MetS were history of diabetes, increased BMI, increased age, male gender, and decreased dietary monounsaturated fatty acid.

Acknowledgments

We would like to express our gratitude to the Research Institute for Endocrine Sciences authorities at Shahid Beheshti University for sharing their valuable data. Moreover, we are grateful to the Vice Chancellor of Hamadan University of Medical Sciences. This study (ID: IR.UMSHA.REC.1398.864) was funded by the Vice Chancellor of Research and Technology of Hamadan University of Medical Sciences (grant number 9811018348). The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Short summary profile of the Tehran Lipid and Glucose Study (TLGS).
[DOCX File , 19 KB - publichealth_v7i9e27304_app1.docx]

Multimedia Appendix 2
Food Frequency Questionnaire (FFQ) "Tehran Lipid and Glucose Study."
[DOCX File , 40 KB - publichealth_v7i9e27304_app2.docx]

Multimedia Appendix 3
Formulas used in this study for model evaluation.
[DOCX File , 19 KB - publichealth_v7i9e27304_app3.docx]

Multimedia Appendix 4
Influence of nutritional and other predictors for developing MetS in the whole population based on the multivariable logistic regression model.
[DOCX File , 21 KB - publichealth_v7i9e27304_app4.docx]

Multimedia Appendix 5
The partial plots of variables that presented variable importance.
[DOCX File , 161 KB - publichealth_v7i9e27304_app5.docx]

References

1. Cardiology Research and Practice. Retracted: A comprehensive review on metabolic syndrome. Cardiol Res Pract 2019;2019:4301528. [doi: 10.1155/2019/4301528] [Medline: 30993018]
2. Alberti KGMM, Zimmet P, Shaw J. Metabolic syndrome--a new world-wide definition. A Consensus Statement from the International Diabetes Federation. Diabet Med 2006 May;23(5):469-480. [doi: 10.1111/j.1464-5491.2006.01858.x] [Medline: 16681555]
3. Ford ES, Giles WH, Dietz WH. Prevalence of the metabolic syndrome among US adults: findings from the third National Health and Nutrition Examination Survey. JAMA 2002 Jan 16;287(3):356-359. [doi: 10.1001/jama.287.3.356] [Medline: 11790215]
4. Ranasinghe P, Mathangasinghe Y, Jayawardena R, Hills AP, Misra A. Prevalence and trends of metabolic syndrome among adults in the Asia-Pacific region: a systematic review. BMC Public Health 2017 Jan 21;17(1):101 [FREE Full text] [doi: 10.1186/s12889-017-4041-1] [Medline: 28109251]
5. Kolovou GD, Anagnostopoulou KK, Salpea KD, Mikhailidis DP. The prevalence of metabolic syndrome in various populations. Am J Med Sci 2007 Jun;333(6):362-371. [doi: 10.1097/MAJ.0b013e318065c3a1] [Medline: 17570989]
6. Fatahi A, Doosti-Irani A, Cheraghi Z. Prevalence and incidence of metabolic syndrome in Iran: a systematic review and meta-analysis. Int J Prev Med 2020;11:64 [FREE Full text] [doi: 10.4103/ijpvm.IJPVM_489_18] [Medline: 32577194]
7. Hadaegh F, Hasheminia M, Lotfaliany M, Mohebi R, Azizi F, Tohidi M. Incidence of metabolic syndrome over 9 years follow-up; the importance of sex differences in the role of insulin resistance and other risk factors. PLoS One 2013;8(9):e76304 [FREE Full text] [doi: 10.1371/journal.pone.0076304] [Medline: 24086723]
8. Ghotboddin Mohammadi S, Mirmiran P, Bahadoran Z, Mehrabi Y, Azizi F. The association of dairy intake with metabolic syndrome and its components in adolescents: Tehran Lipid and Glucose Study. Int J Endocrinol Metab 2015 Jul;13(3):e25201 [FREE Full text] [doi: 10.5812/ijem.25201v2] [Medline: 26425126]
9. Cheraghi Z, Nedjat S, Mirmiran P, Moslehi N, Mansournia N, Etminan M, et al. Effects of food items and related nutrients on metabolic syndrome using Bayesian multilevel modelling using the Tehran Lipid and Glucose Study (TLGS): a cohort study. BMJ Open 2018 Dec 18;8(12):e020642 [FREE Full text] [doi: 10.1136/bmjopen-2017-020642] [Medline: 30567817]
10. Cheraghi Z, Mirmiran P, Mansournia MA, Moslehi N, Khalili D, Nedjat S. The association between nutritional exposures and metabolic syndrome in the Tehran Lipid and Glucose Study (TLGS): a cohort study. Public Health 2016 Nov;140:163-171. [doi: 10.1016/j.puhe.2016.07.003] [Medline: 27498945]
11. Bagry HS, Raghavendran S, Carli F. Metabolic syndrome and insulin resistance: perioperative considerations. Anesthesiology 2008 Mar;108(3):506-523 [FREE Full text] [doi: 10.1097/ALN.0b013e3181649314] [Medline: 18292688]
12. Kohavi R, Quinlan J. Data mining tasks and methods: Classification: decision-tree discovery. In: Klösgen W, Zytkow JM, editors. Handbook of data mining and knowledge discovery. New York, NY: Oxford University Press; 2002:267-276.

13. Krishnaiah V, Narsimha G, Chandra D. Diagnosis of lung cancer prediction system using data mining classification techniques. Int J Comput Sci Inf Technol 2013;4(1):39-45.
14. Yu C, Lin Y, Lin C, Wang S, Lin S, Lin SH, et al. Predicting metabolic syndrome with machine learning models using a decision tree algorithm: retrospective cohort study. JMIR Med Inform 2020 Mar 23;8(3):e17110 [FREE Full text] [doi: 10.2196/17110] [Medline: 32202504]
15. Azizi F, Rahmani M, Emami H, Mirmiran P, Hajipour R, Madjid M, et al. Cardiovascular risk factors in an Iranian urban population: Tehran lipid and glucose study (phase 1). Soz Praventivmed 2002;47(6):408-426. [doi: 10.1007/s000380200008] [Medline: 12643001]
16. Hosseini-Esfahani F, Bahadoran Z, Moslehi N, Asghari G, Yuzbashian E, Hosseinpour-Niazi S, et al. Metabolic syndrome: findings from 20 years of the Tehran Lipid and Glucose Study. Int J Endocrinol Metab 2018 Oct;16(4 Suppl):e84771 [FREE Full text] [doi: 10.5812/ijem.84771] [Medline: 30584438]
17. Alberti KGMM, Eckel RH, Grundy SM, Zimmet PZ, Cleeman JI, Donato KA, International Diabetes Federation Task Force on EpidemiologyPrevention, Hational Heart, Lung,Blood Institute, American Heart Association, World Heart Federation, International Atherosclerosis Society, International Association for the Study of Obesity. Harmonizing the metabolic syndrome: a joint interim statement of the International Diabetes Federation Task Force on Epidemiology and Prevention; National Heart, Lung, and Blood Institute; American Heart Association; World Heart Federation; International Atherosclerosis Society; and International Association for the Study of Obesity. Circulation 2009 Oct 20;120(16):1640-1645. [doi: 10.1161/CIRCULATIONAHA.109.192644] [Medline: 19805654]
18. Azizi F, Hadaegh F, Khalili D, Esteghamati A, Hosseinpanah F, Delavari A, et al. Appropriate definition of metabolic syndrome among Iranian adults: report of the Iranian National Committee of Obesity. Arch Iran Med 2010 Sep;13(5):426-428 [FREE Full text] [doi: 10.010135/AIM.0011] [Medline: 20804311]
19. Malekshah AF, Kimiagar M, Saadatian-Elahi M, Pourshams A, Nouraie M, Goglani G, et al. Validity and reliability of a new food frequency questionnaire compared to 24 h recalls and biochemical measurements: pilot phase of Golestan cohort study of esophageal cancer. Eur J Clin Nutr 2006 Aug;60(8):971-977. [doi: 10.1038/sj.ejcn.1602407] [Medline: 16465196]
20. Mirmiran P, Hosseini Esfahani F, Mehrabi Y, Hedayati M, Azizi F. Reliability and relative validity of an FFQ for nutrients in the Tehran Lipid and Glucose Study. Public Health Nutr 2009 Oct 7;13(05):654. [doi: 10.1017/s1368980009991698]
21. Esfahani FH, Asghari G, Mirmiran P, Azizi F. Reproducibility and relative validity of food group intake in a food frequency questionnaire developed for the Tehran Lipid and Glucose Study. J Epidemiol 2010;20(2):150-158 [FREE Full text] [doi: 10.2188/jea.je20090083] [Medline: 20154450]
22. Ford ES, Ajani UA, McGuire LC, Liu S. Concentrations of serum vitamin D and the metabolic syndrome among U.S. adults. Diabetes Care 2005 May;28(5):1228-1230. [doi: 10.2337/diacare.28.5.1228] [Medline: 15855599]
23. Ford ES, Mokdad AH, Giles WH, Brown DW. The metabolic syndrome and antioxidant concentrations: findings from the Third National Health and Nutrition Examination Survey. Diabetes 2003 Sep;52(9):2346-2352 [FREE Full text] [doi: 10.2337/diabetes.52.9.2346] [Medline: 12941775]
24. Esmaillzadeh A, Kimiagar M, Mehrabi Y, Azadbakht L, Hu FB, Willett WC. Fruit and vegetable intakes, C-reactive protein, and the metabolic syndrome. Am J Clin Nutr 2006 Dec;84(6):1489-1497. [doi: 10.1093/ajcn/84.6.1489] [Medline: 17158434]
25. Breiman L. Random forests. Machine Lang 2001 Oct 01;45(1):5-32. [doi: 10.1023/A:1010933404324]
26. Breiman L. Statistical modeling: the two cultures (with comments and a rejoinder by the author). Statist Sci 2001 Aug 1;16(3):199-231. [doi: 10.1214/ss/1009213726]
27. Meyer D, Leisch F, Hornik K. The support vector machine under test. Neurocomputing 2003 Sep;55(1-2):169-186. [doi: 10.1016/s0925-2312(03)00431-4]
28. Verikas A, Gelzinis A, Bacauskiene M. Mining data with random forests: A survey and results of new tests. Pattern Recognition 2011 Feb;44(2):330-349. [doi: 10.1016/j.patcog.2010.08.011]
29. Aličković E, Subasi A. Breast cancer diagnosis using GA feature selection and rotation forest. Neural Comput Applic 2015 Nov 18;28(4):753-763. [doi: 10.1007/s00521-015-2103-9]
30. Lorenzo C, Okoloise M, Williams K, Stern MP, Haffner SM, San Antonio Heart Study. The metabolic syndrome as predictor of type 2 diabetes: the San Antonio heart study. Diabetes Care 2003 Nov;26(11):3153-3159. [doi: 10.2337/diacare.26.11.3153] [Medline: 14578254]
31. Wilson PWF, D'Agostino RB, Parise H, Sullivan L, Meigs JB. Metabolic syndrome as a precursor of cardiovascular disease and type 2 diabetes mellitus. Circulation 2005 Nov 15;112(20):3066-3072. [doi: 10.1161/CIRCULATIONAHA.105.539528] [Medline: 16275870]
32. Wang H, Steffen LM, Vessby B, Basu S, Steinberger J, Moran A, et al. Obesity modifies the relations between serum markers of dairy fats and inflammation and oxidative stress among adolescents. Obesity (Silver Spring) 2011 Dec;19(12):2404-2410. [doi: 10.1038/oby.2011.234] [Medline: 21779090]
33. Morley J. The metabolic syndrome and aging. J Gerontol A Biol Sci Med Sci 2004 Mar;59(2):139-142. [doi: 10.1093/gerona/59.2.m139] [Medline: 14999026]
34. Bonomini F, Rodella LF, Rezzani R. Metabolic syndrome, aging and involvement of oxidative stress. Aging Dis 2015 Mar;6(2):109-120 [FREE Full text] [doi: 10.14336/AD.2014.0305] [Medline: 25821639]

35. Zabetian A, Hadaegh F, Azizi F. Prevalence of metabolic syndrome in Iranian adult population, concordance between the IDF with the ATPIII and the WHO definitions. Diabetes Res Clin Pract 2007 Aug;77(2):251-257. [doi: 10.1016/j.diabres.2006.12.001] [Medline: 17234299]
36. Janghorbani M, Amini M. Incidence of metabolic syndrome and its risk factors among type 2 diabetes clinic attenders in Isfahan, Iran. ISRN Endocrinol 2012;2012:167318. [doi: 10.5402/2012/167318] [Medline: 22474593]
37. Garg A. High-monounsaturated-fat diets for patients with diabetes mellitus: a meta-analysis. Am J Clin Nutr 1998 Mar;67(3 Suppl):577S-582S. [doi: 10.1093/ajcn/67.3.577S] [Medline: 9497173]
38. Kristal AR, Peters U, Potter JD. Is it time to abandon the food frequency questionnaire? Cancer Epidemiol Biomarkers Prev 2005 Dec;14(12):2826-2828 [FREE Full text] [doi: 10.1158/1055-9965.EPI-12-ED1] [Medline: 16364996]
39. Lutsey PL, Steffen LM, Stevens J. Dietary intake and the development of the metabolic syndrome: the Atherosclerosis Risk in Communities study. Circulation 2008 Mar 12;117(6):754-761. [doi: 10.1161/CIRCULATIONAHA.107.716159] [Medline: 18212291]

Abbreviations

FFQ: Food Frequency Questionnaire
HLDL-C: high-density lipoprotein cholesterol
LR: likelihood ratio
MetS: metabolic syndrome
NPV: negative predictive value
OR: odds ratio
PPV: positive predictive value
RF: random forest

Edited by Y Khader; submitted 20.01.21; peer-reviewed by T Kahlon, B Oh, B Narayan, Z Feng, J Menon, B Eapen; comments to author 04.03.21; revised version received 23.04.21; accepted 17.05.21; published 02.09.21.

Please cite as:
Hosseini-Esfahani F, Alafchi B, Cheraghi Z, Doosti-Irani A, Mirmiran P, Khalili D, Azizi F
Using Machine Learning Techniques to Predict Factors Contributing to the Incidence of Metabolic Syndrome in Tehran: Cohort Study
JMIR Public Health Surveill 2021;7(9):e27304
URL: https://publichealth.jmir.org/2021/9/e27304
doi:10.2196/27304
PMID:34473070

Corrigenda and Addenda

Correction: The Characteristics and Risk Factors of Web-Based Sexual Behaviors Among Men Who Have Sex With Men in Eastern China: Cross-sectional Study

Lin Chen[1], MD; Wanjun Chen[1], MD; Tingting Jiang[1], MD; Zhikan Ni[1], MD; Qiaoqin Ma[1], College Degree of Medicine; Xiaohong Pan[1], MD

Zhejiang Provincial Center for Disease Control and Prevention, Hangzhou, China

Corresponding Author:
Xiaohong Pan, MD
Zhejiang Provincial Center for Disease Control and Prevention
3399 Binsheng Road, Binjiang District
Hangzhou, 310051
China
Phone: 86 057187115191
Email: xhpan@cdc.zj.cn

Related Article:

Correction of: https://publichealth.jmir.org/2021/9/e25360

(JMIR Public Health Surveill 2021;7(9):e33430) doi:10.2196/33430

In "The Characteristics and Risk Factors of Web-Based Sexual Behaviors Among Men Who Have Sex With Men in Eastern China: Cross-sectional Study" (JMIR Public Health Surveill 2021;7(9):e25360), one error was noted.

Due to a system error, the name of one author, Lin Chen, was replaced with the name of another author on the paper, Xiaohong Pan. In the originally published paper, the order of authors was listed as follows:

> *Xiaohong Pan, Wanjun Chen, Tingting Jiang, Zhikan Ni, Qiaoqin Ma, Xiaohong Pan*

This has been corrected to:

> *Lin Chen, Wanjun Chen, Tingting Jiang, Zhikan Ni, Qiaoqin Ma, Xiaohong Pan*

In the originally published paper, the ORCID of author Lin Chen was incorrectly published as follows:

> *0000-0003-3373-3393*

This has been corrected to:

> *0000-0003-2197-2733*

The correction will appear in the online version of the paper on the JMIR Publications website on September 8, 2021, together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.

Submitted 07.09.21; this is a non–peer-reviewed article;accepted 07.09.21; published 08.09.21.

Please cite as:
Chen L, Chen W, Jiang T, Ni Z, Ma Q, Pan X
Correction: The Characteristics and Risk Factors of Web-Based Sexual Behaviors Among Men Who Have Sex With Men in Eastern China: Cross-sectional Study
JMIR Public Health Surveill 2021;7(9):e33430
URL: https://publichealth.jmir.org/2021/9/e33430
doi:10.2196/33430
PMID:34495868

Original Paper

COVID-19 Data Utilization in North Carolina: Qualitative Analysis of Stakeholder Experiences

Jenny Rees Patterson[1], MPH; Donna Shaw[2], MEd; Sharita R Thomas[3], MPP; Julie A Hayes[4], BS; Christopher R Daley[4], BS; Stefania Knight[4], MFA; Jay Aikat[4], MS, PhD; Joanna O Mieczkowska[4], MA; Stanley C Ahalt[4], MS, PhD; Ashok K Krishnamurthy[4], MS, PhD

[1]University of Iowa, Iowa City, IA, United States

[2]North Carolina State University, Raleigh, NC, United States

[3]Cecil G. Sheps Center for Health Services Research, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States

[4]Renaissance Computing Institute, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States

Corresponding Author:
Jenny Rees Patterson, MPH
University of Iowa
145 N. Riverside Drive
Iowa City, IA, 52242
United States
Phone: 1 3147490050
Email: jennifer-patterson@uiowa.edu

Abstract

Background: As the world faced the pandemic caused by the novel coronavirus disease 2019 (COVID-19), medical professionals, technologists, community leaders, and policy makers sought to understand how best to leverage data for public health surveillance and community education. With this complex public health problem, North Carolinians relied on data from state, federal, and global health organizations to increase their understanding of the pandemic and guide decision-making.

Objective: We aimed to describe the role that stakeholders involved in COVID-19–related data played in managing the pandemic in North Carolina. The study investigated the processes used by organizations throughout the state in using, collecting, and reporting COVID-19 data.

Methods: We used an exploratory qualitative study design to investigate North Carolina's COVID-19 data collection efforts. To better understand these processes, key informant interviews were conducted with employees from organizations that collected COVID-19 data across the state. We developed an interview guide, and open-ended semistructured interviews were conducted during the period from June through November 2020. Interviews lasted between 30 and 45 minutes and were conducted by data scientists by videoconference. Data were subsequently analyzed using qualitative data analysis software.

Results: Results indicated that electronic health records were primary sources of COVID-19 data. Often, data were also used to create dashboards to inform the public or other health professionals, to aid in decision-making, or for reporting purposes. Cross-sector collaboration was cited as a major success. Consistency among metrics and data definitions, data collection processes, and contact tracing were cited as challenges.

Conclusions: Findings suggest that, during future outbreaks, organizations across regions could benefit from data centralization and data governance. Data should be publicly accessible and in a user-friendly format. Additionally, established cross-sector collaboration networks are demonstrably beneficial for public health professionals across the state as these established relationships facilitate a rapid response to evolving public health challenges.

(JMIR Public Health Surveill 2021;7(9):e29310) doi:10.2196/29310

KEYWORDS

qualitative research; interview; COVID-19; SARS-CoV-2; pandemic; data collection; data reporting; data; public health; coronavirus disease 2019

Introduction

In 2020, the World Health Organization declared the outbreak of COVID-19—a public health emergency of international concern [1]. First identified in Wuhan, China, the virus quickly became a global pandemic, with over 181 million recorded cases and 3.94 million deaths reported worldwide as of June 2021 [2]. As of June 2021, the United States had more than 33 million COVID-19 cases and more than 600,000 COVID-19 deaths [2]. At the time of this study (in June 2020), North Carolina public health workers witnessed the growing national crisis and felt a sense of urgency to respond due to a state average of 1859 new infections each week [3].

Almost two decades ago, the Centers for Disease Control and Prevention established preparedness and response guidance in response to the 2003 SARS outbreak [4]. This guidance was intended to inform future infectious disease emergencies and included 4 overarching themes: (1) the need for up-to-date local, national, and global data; (2) rapid and effective institution of control measures; (3) appropriate resources and decision-making structure; and (4) trained staff vital to swift and decisive implementation [5]. While these recommendations were intended to prepare the country to handle a pandemic, few were truly prepared for the exceptionally rapid and widespread impact of the COVID-19 virus. As COVID-19 continued to spread, policy makers and public health officials at every level were forced to recognize the severity of the virus and take action to mitigate the spread.

As news of this complex public health problem spread in early 2020, North Carolinians relied on data from local, state, federal, and global health organizations to increase their understanding of the pandemic and guide decision-making. We aimed to understand how organizations across the state were collecting, analyzing, and reporting COVID-19 data. We were interested in the sources of data, as well as its uses. Additionally, we asked how data were aggregated, centralized, and disseminated.

Methods

Study Design

We used an exploratory qualitative study design to investigate North Carolina's COVID-19 data collection efforts [6-8]. In-depth interviews were used to gather information and document the evolution of North Carolina's COVID-19 response, with a focus on gaining a better understanding of COVID-19 data sources; data collection and reporting protocols and objectives; data uses and dissemination; data aggregation and centralization; and COVID-19 testing.

Recruitment

Key informants were identified as experts in their fields who were known to be involved with COVID-19–related data. Potential interviewees were identified through a series of steps that included project team discussions, external peer consultations, and internet-based searches. Prior to conducting interviews, the project team met to prioritize the list of potential interviewees based on their involvement in and proximity to COVID-19 data. A snowball sampling approach was utilized to recruit key informants beyond the initially identified expert group [9,10].

After identifying potential interview participants, we prioritized and randomly assigned interviews among the project team. The interviewers contacted their assigned interview participants via email to request an interview and explain the overall project aim—to understand how COVID-19 data are being collected and reported across the state. Interviewers identified themselves in the recruitment email as members of the research team led by the Renaissance Computing Institute at University of North Carolina Chapel Hill and funded by the North Carolina Policy Collaboratory. The recruitment email also included the interview questions.

The interviews were not intended to be statistically representative of the state, and the number of interviewees does not affect the integrity of data collected. However, we attempted to obtain coverage from all regions of North Carolina to account for geographic and demographic differences. Recruitment of interview participants ended once thematic saturation was reached in response data and no new topics emerged [11].

Interviews

We developed a semistructured interview guide (Textbox 1), which included open-ended questions covering the topics of data sources, uses, and how data were aggregated and reported [12].

Textbox 1. Questions about data collection processes in North Carolina.

When did you begin collecting COVID-related data?
What were your objectives when you started collecting data?
Has the objective evolved? In what ways?
What guidance, if any, have you received from other organizations?
What were the biggest barriers in your work?
What type of patient-level/individual data is your organization collecting?
What challenges have you experienced in collecting individual-level data?
How does your organization collect data on patient contact/contact tracing?
How are hospital capacities being reported?
How are hospital utilizations being reported?
How is comorbidity being addressed?
How are the results of data collection being reported up to NCDHHS?
How are COVID-19 diagnoses and outcomes being centralized?
What is the purpose of data models you use?
Is there data that you need, but don't have, for your models to be more accurate?
How are decisions made by your organization regarding data accessibility and dissemination?
What are some ways in which data dissemination has informed on or positively impacted the state of the pandemic?

The interviews were conducted by 4 team members (JA, JOM, SCA, and AKK). Interviews were conducted in an informal conversational manner in which interviewees were assured of their expertise so that they felt comfortable in freely stating their views. The goal here was to gain the trust of the interviewee and foster an environment of power equality [12,13]. Interviewers practiced the techniques of active listening and used follow-up questions when needed for clarification to capture accurate and thorough data [14].

Confidentiality

Interview participants were told of the voluntary nature of this project and verbal consent to record and transcribe responses for analyses was obtained prior to the start of the interview. Interview participants were informed that the recordings would be deleted after the conclusion of the study and would not be shared outside of the project team or used for any other projects in the future. Interviewers explained the aim of the research, and how interview responses would be used to inform a report describing the use of COVID-19 data in the state. Furthermore, interview participants were told that the content of the interview would be deidentified, and any information used in the report would not cite an interviewee by name unless permission was given voluntarily.

Analysis

Interviews were recorded and transcribed via Zoom (Zoom Inc). Scribes attended each interview to transcribe in real time and subsequently reviewed and edited transcripts for accuracy using the recordings.

Transcribed data were imported and analyzed using NVivo qualitative data analysis software (versions 11 and 12; QSR International). Data were analyzed using a hybrid approach to content analysis, which is a suitable methodology for interview transcripts [15-17]. First, 2 qualitative analysts used the interview guide questions to deductively choose categories, which served as the basis of the codebook (eg, data uses, challenges) [18]. As such, some codes were defined beforehand from the interview guide, while the remaining codes were defined as they emerged during analysis. To increase validity, 3 team members who were knowledgeable and experienced in qualitative research methods independently reviewed the transcripts and developed inductive codes (eg, modeling, dashboards, data lags, data consistency) [15]. This approach allowed for themes to arise directly from the data. Themes were identified through the techniques of cutting and sorting, repetition, and similarities or differences [19]. Analysis team members set regular meetings to compare, review, and refine codes. Discrepancies in codes were resolved through discussion [20]. Emerging themes and coding memo notes were also shared and discussed as a group. As analysis progressed, the transcripts coded early in the process were reread to refine and recode in consideration of codes developed later as more interviews were completed and more data became available.

Rigor was ensured by (1) triangulating different sources of data (eg, key informant interviews, literature and grey literature review, and notes) [21]; (2) employing independent coding of transcripts and intercoder agreement; and (3) utilizing an iterative process in which data collection and analysis happened concurrently, allowing for data collection to end only once thematic saturation was observed (ie, no more interviews were required) [12].

Results

Interview Participants

The response rate for interview requests was 59% (41/69). Key informants (n=41) participated in a total of 29 in-depth videoconference interviews during the period from June through November 2020. Interview participants included hospital workers, academics, individuals from health research organizations, state health department employees, health educators, laboratory employees, and others (Table 1). In some instances, there were multiple interviewees from the same organization. When this occurred, we sought to identify interviewees with varying roles within the organization so that their relationships with and perspectives on the data were different and provided a comprehensive and robust data set. During these interviews, each interviewee was provided time to respond to each question, and their responses provided insight into their roles within the organization. Most interview participants had roles in collecting, analyzing, and reporting or modeling data. No compensation was offered for participation in interviews.

Table 1. Participants' demographic information.

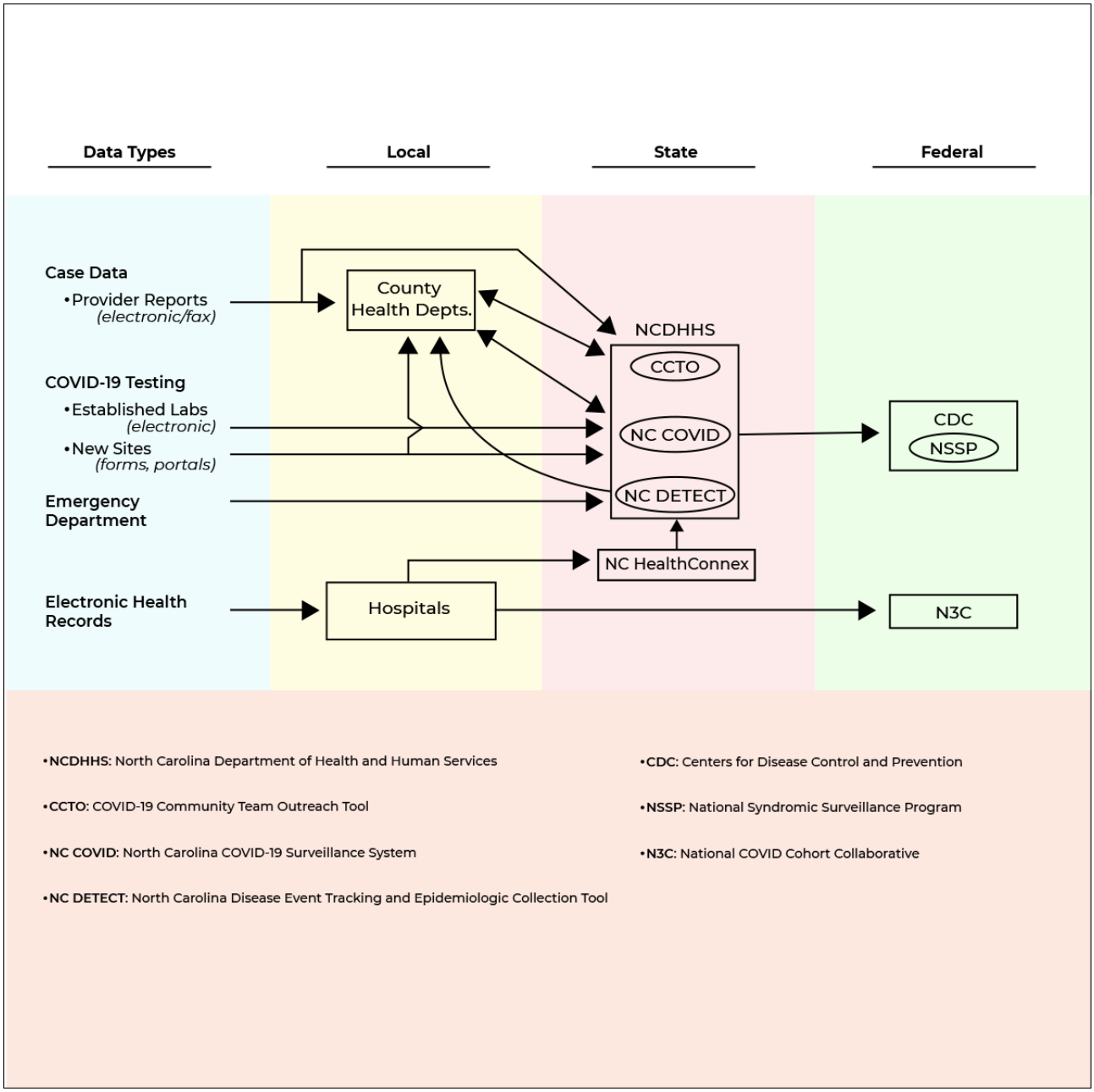
Characteristic	Value (n=41), n (%)
Gender	
Male	22 (54)
Female	19 (46)
Relationship to COVID-19 data[a]	
Collects	34 (83)
Analyzes	40 (98)
Reports or models	34 (83)
Work environment	
Hospital	11 (27)
Academia	7 (17)
Health research organization	6 (15)
State health department	5 (12)
Health education center	4 (10)
Laboratory	3 (7)
Nonprofit research organization	3 (7)
Health care management	2 (5)

[a]More than 1 category is possible; therefore, percentages do not add to 100%.

COVID-19 Data Flow

Interviewees provided our research team with information regarding the flow of COVID-19 data across North Carolina (Figure 1). In North Carolina, COVID-19 data is generated from cases, COVID-19 testing, emergency departments, and electronic health records (EHRs).

Figure 1. COVID-19 data flow in North Carolina in 2020.



Case data, or data from COVID-19 case investigations, are in the form of medical provider reports, sent both electronically and via fax to local health departments and the North Carolina Department of Health and Human Services (NCDHSS). The local health departments then have a 2-way flow of case data with NCDHHS' COVID-19 Community Team Outreach Tool for tracing efforts, and NCDHHS' COVID-19 Surveillance System.

COVID-19 testing data are gathered from established laboratories electronically and from new testing sites via forms and newly developed portals; the data are sent to local health departments and NCDHHS' COVID-19 Surveillance System. COVID-19 tests are completed by private companies (eg, pharmacies, private laboratories) and public organizations (eg, county testing sites). As of December 2020, physicians, laboratories, and other health care providers in North Carolina were mandated to report COVID-19 test results, and key data fields (eg, patient, laboratory, and test data) have been identified [22].

Data from emergency departments are sent directly to NCDHHS' North Carolina Disease Event Tracking and Epidemiologic Collection Tool [23], which, as the state syndromic surveillance system that has long been used by hospitals to report emergency department data electronically, then communicates these data to local health departments.

COVID-19 data from EHRs are sent from local hospitals to (1) the state's health information exchange system (NC HealthConnex platform) and (2) the National COVID Cohort Collaborative. NC HealthConnex also sends this information on to NCDHHS.

Finally, all the COVID-19 data received by NCDHHS are then communicated at the federal level to the Centers for Disease

Control and Prevention and the National Syndromic Surveillance Program.

Data Collection Objectives

Most interview participants started collecting COVID-19–related data in mid to late March 2020. None of the interview participants indicated having a predetermined objective or established protocol to guide the data collection process, but all mentioned feeling compelled to take some action. A common initial objective for collecting COVID-19 data was the need to monitor hospital resource supply and utilization, including tracking intensive care unit volumes, negative pressure rooms, patients testing positive for COVID-19, and consumption rates for personal protective equipment. This evolved so that later more complex systems were in place to focus on hospitalizations and capacity.

Many interviewees noted their overall main objective in collecting COVID-19–related data remained unchanged since the start of the pandemic. Nonetheless, approaches were adapted as more was learned about the virus to reflect the broader community's needs and overall response to the pandemic. Small adjustments in data collection were a direct result of state and federal mandates for COVID-19 data. A few ways in which data requests evolved included a departure from solely reporting the percentage of positive tests to now also requiring negatives as well as comparing asymptomatic and symptomatic positivity rates. According to interviewees this was an important development as, up until that time, data from hospitals and laboratories were only based on individuals testing positive, meaning when a patient tested negative, they would no longer be a part of hospital-based reporting. Furthermore, state mandates in the summer added order-based questions to reporting, which included indicating race and ethnicity and whether patients were symptomatic or pregnant. Others noted a shift in requirements for patient types and counts (ie, a shift from overall inpatient counts to COVID-19–related deaths). As a result of these changes, some interview participants mentioned the need to retrospectively look at data not initially reported in order to understand trends over time.

Data Sources

The primary source of COVID-19 data used most by interview participants was their health care facilities' EHR systems. One type of EHR system—EPIC—was mainly utilized. One interview participant collected qualitative primary data through surveys and interviews to gain the perspective of local government leaders on how COVID-19 was affecting their community. Another group used surveys to determine how to modify people's behavior to mitigate spread of the virus.

Almost all interview participants reported using COVID-19 data available from secondary data sources. Publicly accessible secondary sources used by many of the interview participants included The New York Times COVID-19 data on GitHub [24], The News & Observer [25], and the WRAL website [26]. The New York Times was mentioned by multiple interview participants who expressed its importance in understanding regional differences and time trends in the county-level data.

One interview participant noted that insurance claims data from BlueCross, BlueShield, or Medicaid was not a good source because of data lag, which is the difference in time from when an event happens or is reported to when the relevant data becomes available for use. Insurance claim data, which can provide insight on individual-level interactions with health systems, often lag by 3 to 6 months [27]. Others mentioned using secondary data sources made available by NCDHHS, such as the North Carolina Disease Event Tracking and Epidemiologic Collection Tool and the COVID-19 Surveillance System.

Additional secondary sources utilized for COVID-19 data activities included SafeGraph [28], scientific literature, annual demographic poll data, PolicyMap [29], and mobility and weather data found on the internet. One interviewee mentioned scanning websites for manufacturer press releases to remain informed on ventilators and other personal protective equipment.

Uses of COVID-19–Related Data

Dashboards

The most common use of COVID-19–related data, mentioned by approximately one-third of interview participants, was the creation of dashboards. Web-based dashboards can serve as a user-friendly tool to help policy makers, public health professionals, and the public visualize COVID-19 data in real time. Some interview participants developed dashboards in response to requests from NCDHHS to help predict cases and provide the public and other health professionals with up-to-date information. Others took it upon themselves to make data that was already available more useful to the public so that they could have a better understanding of their current risk. Interview participants reported using dashboards internally within organizations as well as externally and across organizations. Dashboards incorporated data from EHRs, the internet, and other public data sources.

While no previous protocol for data collection of this type existed, interview participants mentioned existing processes that could be adapted and applied to the COVID-19 pandemic's data needs. One interviewee said that the creation of an operational dashboard was facilitated through the preestablished practice of capacity tracking for isolation rooms, negative pressure rooms, and ventilators through their hospital's EHR system. Other dashboards utilized standardized weekly reporting to keep regional organizations informed on current state resources and utilization.

Modeling

Throughout the evolution of COVID-19–related data requests, the need for modeling to project the future number of cases and impact on the state's health care system remained constant; however, model developers reported that the components and parameters used to model future outcomes evolved substantially, since assumptions were updated as more was learned about COVID-19. Early models were basic and used case counts, though these quickly pivoted to incorporate transmission and disease progression parameters. While NCDHHS primarily uses time-trend modeling for predicting peak surge capacity and

informing resource allocation, it has begun partnering with subject-matter experts for predictive modeling [30].

Hospital Management

Some interview participants (n=5) described establishing command centers at hospitals to help guide strategic planning. COVID-19 data were used in an operational manner to provide decision support for clinical and administrative executives developing hospital response plans. This included reviewing surveillance reports and inpatient data to monitor positive and negative cases, test volumes, hospitalizations and deaths by age group, and the racial and ethnic breakdown of admissions.

Many hospitals utilized data to predict volumes and develop plans to convert or add hospital space to accommodate COVID-19 patients if needed. Furthermore, interview participants noted how the effective collection and reporting of COVID-19 data meant a hospital would be well-positioned to receive needed allocations of personal protective equipment and treatments.

Community Outreach

The importance of transparency and community education was an important theme that arose among interview participants. Webinars and virtual engagements, publications, and televised public service announcements were some of the methods interview participants used to disseminate COVID-19-related information. County school systems, journalists, underserved populations, and local governments and community leaders were among groups targeted by interview participants. One interviewee noted that her group was very cognizant of information overload, contributing to what has been termed *COVID fatigue*, in the general public. In response, they were very intentional when considering what information to release and attempted to tie information to state or local regions to make it more relatable.

COVID-19 Data Collection Challenges

Data Definitions and Consistency

The lack of standardized definitions at the federal level resulted in significant variation in interpreting COVID-19 data within North Carolina. For example, there are several ways organizations can define capacity, and there are different methods for calculating positivity rates. Interview participants made clear their irritation with a lack of clear and consistent definitions across organizations. During interviews, some shared their skepticism surrounding the state's data quality stemming from the potential for misinterpretation of data or from some groups not being committed to quality control.

Collection Process

Participants expressed their frustration with the amount of time needed for COVID-19 data collection. Each new request from the state and federal levels for additional data types required resources to determine what aspects of existing systems needed to be changed or updated. In addition, requests often consisted of continually evolving data requirements and did not take into account the amount of time necessary to adjust established processes to comply with new or modified requests. The ability to meet regulatory requirements was further impacted by a lack of clear authority and defined roles (who to contact for approval of data sharing or to have questions resolved in a timely manner). Many interview participants found themselves unable to access data that they needed and experienced delays caused by waiting for data use agreements. The high number of data requests, changes in data requests, and the urgent nature of these requests led to staff fatigue and burnout. All of these issues proved especially problematic for those working at smaller labs, hospitals, and facilities operating with limited staff and resources.

Modeling

Data lags have impacted COVID-19 models, which often require more data to be more accurate. The need for data use agreements has led to frustration among interviewees who were modelers, with one group reporting that if more data had been available to them in the first 90 days or less of building the model, it could have been built faster and more precisely. Others reported now having a better understanding of which information can be requested and shared than they did in March 2020; they therefore request data that does not require a data use agreement. One interview participant remarked that the type of modeling his group has been doing typically takes years and doing so amid a pandemic where information needs are urgent and parameters are constantly changing was a significant added stressor.

Contact Tracing

Interview participants cited major obstacles in conducting contact tracing. Since the start of the pandemic, there was an overall increase in the number of cases considered lost to follow up because people were either difficult to reach by phone or unwilling to cooperate with public health officials. For example, interviewees reported that when people were located as part of contact tracing efforts, they seemed reluctant to name who they were in contact with during 2 weeks before symptom onset because those contacts would be required to quarantine. This resulted in a decreasing number of named close contacts among traced individuals. Universities and organizations, mostly health care facilities, were also engaged in contact tracing outside of local health departments. These organizations have trained staff carrying out comprehensive COVID-19 contact tracing plans. Interviewees from some organizations reported carrying out contact tracing for employees only and expressed difficulties in contact tracing outside of their respective institutions.

Cross-sector Collaboration

A positive byproduct of the COVID-19 pandemic has been the capacity and demand for cross-sector collaboration. Cross-sector collaboration was identified by interviewees as something that North Carolina did very well. Collaborative efforts were mentioned by every interview participant. Some of the groups involved in these collaborations included school systems, government organizations, health systems, pharmaceutical and medical supply companies, think tanks, consulting firms, nonprofit institutions, researchers, educators, health professionals, and foundations. The collaborations were effective in proactively establishing mechanisms to receive state and federal data, facilitating data centralization, and synergizing modeling efforts. On the other hand, the fast-paced and always

evolving environment created by COVID-19 was at times difficult to navigate among collaborators. In addition, some interviewees reported there were lost opportunities for collaboration, such as when a lack of awareness of work being done by others resulted in duplicated efforts.

Technology Integration

Technology plays a critical role in effective data collection and reporting. Several organizations noted success in terms of software or system integrations between the state health department and electronic labs reporting interfaces. Interviewees reported that information technology systems and services were forced to improve or stabilize their products as a byproduct of their data collection and reporting efforts. Furthermore, NCDHHS responded quickly to develop and deploy electronic methods for providers and laboratories to upload data.

Discussion

Principal Findings

Through this study, we were able to gather valuable information about COVID-19 data collection and reporting processes from some of the utmost experts and stakeholders in North Carolina. These findings help to inform what happened in North Carolina early in the pandemic, what worked well, and what could be improved.

Interviewees shared a collective goal in serving the people of North Carolina and keeping them informed with up-to-date information that clearly communicated their risk level. The most cited source of COVID-19 data was electronic health records, which was one of several sources utilized to create dashboards. In the United States, all 50 state governments use COVID-19 dashboards that are publicly available. These dashboards contain interactive maps and graphs and report indicators such as deaths, cases, and hospitalizations [31,32]. Widely used during the current pandemic, models have served a number of purposes, including predicting the spread of the virus [33-37] and for evaluating mitigation strategies [38-40]. In North Carolina, COVID-19 data informed the development or adaptation of existing models, which helped forecast the pandemic's impact on the state's health care system.

Typically, health care systems and health departments have not used the same software, systems, or data formats, making it difficult to identify trends during outbreaks and develop mitigation strategies [41]. Key informants reported success in integrating and revising multiple data collection systems, and NCDHHS provided timely guidance to stakeholders who upload COVID-19 data. System integration can play a pivotal role in the success of reporting data during future pandemics, and public health infrastructure would benefit from additional funding for data-related health information technology projects at state and federal levels. Innovative integrated technologies would help public health researchers, health care workers, and government officials remain connected, by providing data that is needed to understand outbreaks and coordinate responses.

Interviewees faced a number of challenges when collecting and using COVID-19 data. At the root of these issues was the fast pace at which knowledge about the virus evolved. This directly affected the type of data requested from state and federal governments and turnaround time for submission. Further exacerbating these issues was a lack of standardized data definitions and defined roles (who to contact when clarification was needed). This experience was not unique to North Carolina, but rather common among research institutes where a lack of time led to an inability to coordinate data standardization and define and share vocabularies, which slowed or prevented the ability to collaborate and share data [42].

Interviewees reported that the pervasive sense of urgency and need to collect and report the most accurate data possible led to significant stress and burnout among staff participating in these efforts. This finding is in alignment with those from a study [43] of public health workers who worked in state, local, tribal, or territorial health departments during 2020. When asked about the preceding 2 weeks, 53% reported experiencing symptoms of at least 1 mental health condition (depression, anxiety, posttraumatic stress disorder, or suicidal ideation) and 72% had felt overwhelmed by workload or family–work balance. Fortunately, interviewees in our study described a strong support system that emerged in North Carolina from the cross-sector collaboration of those involved in data collection. These partnerships allowed them to synergize efforts to identify issues and work together to proffer solutions. Guiding these efforts was the strong leadership from NCDHHS which provided much needed support throughout the entire process.

Our findings provide insight that can be used to inform the state responses to future public health emergencies. Based on the findings of this study, we compiled the following lessons learned for North Carolina to improve pandemic response and better prepare for future public health crises.

Future pandemic response requires centralization through the North Carolina Department of Health and Human Services. Standardized and coordinated information sharing is the foundation of effective pandemic response. Interview participants voiced their appreciation for the leadership exemplified by NCDHHS following the COVID-19 outbreak and a desire for streamlined processes when preparing for and responding to future pandemics. They expressed frustration over requirements imposed by the federal government that were made without appropriate guidance and with very short timelines for compliance. Interview participants emphatically asserted that, even in such cases, the leadership and coordination provided by NCDHHS helped alleviate the difficult circumstances.

Cross-sector collaborative networks established during the COVID-19 outbreak should be supported and sustained. Cross-sector collaboration was a consistent theme mentioned by key informants, who considered it a major facilitator in the collection and use of COVID-19–related data. Many of these collaborations developed from existing relationships and a desire to maximize the combined impact of the work being performed by colleagues at different institutions. North Carolina is fortunate to have a number of strong research institutes and would benefit from formalizing many of the collaborative networks that have organically developed since March 2020. In supporting these partnerships, and defining the roles of each team member, the

state could encourage even more data synergy and consistency in data collection processes moving forward.

Pandemic-related data should be publicly accessible and available in a format that is easy to use and understand, such as real-time dashboards. As was the case with COVID-19, pandemic response can result in frequent changes to data and surveillance systems, which may not always be well explained, leading to public and provider mistrust. Data transparency via open access can build trust during outbreaks and encourage public adherence to disease prevention and control mandates [44]. Proactive data collection and analysis facilitate identification of patterns and timely dissemination of information. To increase access, North Carolina should release data in an easy-to-download format to not only inform the public but also to facilitate analysis by data scientists. Open and accessible data sharing can promote collaboration among scientists, public health professionals, and lawmakers and inform policies and interventions to mitigate future outbreaks. Furthermore, data should be translated in a manner useful to the greater public, by using summaries and highlighting key messages [45]. Alternatively, health departments could create a public version of future dashboards that contain information and metrics specifically considered to be of value to the public [46].

Limitations

We note several limitations in this study. The main limitation is that qualitative research does not provide generalizability. Nor does it provide statistical representation of larger populations. While we have obtained and summarized common themes expressed among interview participants, these themes cannot be generalized to the larger population of North Carolina. The information presented here is descriptive and meant to provide insight into the experiences and opinions of stakeholders represented by the sample population. Additionally, in recruiting interviewees, we were unable to obtain participation from city or county public health workers. At the time of recruitment, the state health department reported that not all counties had the capacity to collect data, and there was no comprehensive list of county-level data collection. Because surveillance data were being aggregated at the state level, we decided to collect data from state health department workers. Furthermore, due to the rapid evolution of the pandemic, there was an urgency to disseminate the results of this study as quickly as possible to inform data collection efforts in North Carolina. We, therefore, were unable to address some of these limitations. Future research may be helpful to understand the successes or challenges experienced by city and county health department workers in North Carolina during the early phases of the COVID-19 pandemic.

Conclusion

The fast-paced nature of the COVID-19 pandemic has required an agile response from those collecting and using COVID-19 data to inform preparation and response at national, state, and local levels. Study results show the importance of data flow in a pandemic, the value of dashboards and modeling in decision-making, and the vital role of cross-sector collaboration. It is important to note that the experiences and challenges of key informants were likely not exclusive to North Carolina; however, stakeholders benefited from the strong leadership of the state health department in coordinating data collection and reporting. As the state moves closer to having the majority of the population vaccinated, and ideally, herd immunity, we look optimistically toward a new normal in a post–COVID-19 era. Nonetheless, more pandemics are inevitable, and successful preparedness can increase readiness and the ability to react swiftly. This study's results can be used to build on ongoing pandemic-related work and help develop a strong nationally coordinated approach to data collection, reporting, dissemination, and intercommunication among stakeholders.

Acknowledgments

This study was supported by the University of North Carolina at Chapel Hill's North Carolina Policy Collaboratory through funds from a State appropriation by the North Carolina General Assembly per subdivision (23) of Section 3.3. of Session Law 2020-4 (H1043) and per the Coronavirus Aid, Relief, and Economic Security Act.

Conflicts of Interest

None declared.

References

1. COVID-19 public health emergency of international concern (PHEIC). World Health Organization. 2020 Feb 12. URL: https://www.who.int/publications/m/item/covid-19-public-health-emergency-of-international-concern-(pheic)-global-research-and-innovation-forum [accessed 2021-01-20]
2. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis 2020 May;20(5):533-534 [FREE Full text] [doi: 10.1016/S1473-3099(20)30120-1] [Medline: 32087114]
3. Unwin HJT, Mishra S, Bradley VC, Gandy A, Mellan TA, Coupland H, et al. State-level tracking of COVID-19 in the United States. Nat Commun 2020 Dec 03;11(1):6189 [FREE Full text] [doi: 10.1038/s41467-020-19652-6] [Medline: 33273462]
4. Srinivasan A, McDonald LC, Jernigan D, Helfand R, Ginsheimer K, Jernigan J, SARS Healthcare Preparedness Response Plan Team. Foundations of the severe acute respiratory syndrome preparedness and response plan for healthcare facilities. Infect Control Hosp Epidemiol 2004 Dec;25(12):1020-1025. [doi: 10.1086/502338] [Medline: 15636287]

5. Public health guidance for community-level preparedness and response to severe acute respiratory syndrome (SARS). Centers for Disease Control and Prevention. 2004 Jan 08. URL: https://www.cdc.gov/sars/guidance/index.html [accessed 2021-01-19]
6. Savin-Baden M, Howell-Major C. Qualitative Research: The Essential Guide to Theory and Practice. Oxfordshire: Routledge; 2013.
7. Matua GA, Van Der Wal DM. Differentiating between descriptive and interpretive phenomenological research approaches. Nurse Res 2015 Jul;22(6):22-27. [doi: 10.7748/nr.22.6.22.e1344] [Medline: 26168810]
8. Hunter DJ, McCallum J, Howes D. Defining Exploratory-Descriptive Qualitative (EDQ) research and considering its application to healthcare. J Nurs Healthc 2019;4(1):180272 [FREE Full text]
9. Tyrer S, Heyman B. Sampling in epidemiological research: issues, hazards and pitfalls. BJPsych Bull 2016 Apr;40(2):57-60 [FREE Full text] [doi: 10.1192/pb.bp.114.050203] [Medline: 27087985]
10. Etikan I, Alkassim R, Abubakar S. Comparision of snowball sampling and sequential sampling sechnique. Biom Biostat Int J 2016 Jan 2;3(1):55. [doi: 10.15406/bbij.2016.03.00055]
11. Moser A, Korstjens I. Series: Practical guidance to qualitative research. part 3: Sampling, data collection and analysis. Eur J Gen Pract 2018 Dec;24(1):9-18 [FREE Full text] [doi: 10.1080/13814788.2017.1375091] [Medline: 29199486]
12. Isaacs A. An overview of qualitative research methodology for public health researchers. Int J Med Public Health 2014;4(4):318-323. [doi: 10.4103/2230-8598.144055]
13. Karnieli-Miller O, Strier R, Pessach L. Power relations in qualitative research. Qual Health Res 2009 Feb;19(2):279-289. [doi: 10.1177/1049732308329306] [Medline: 19150890]
14. Newcomer K, Hatry H, Wholey J. Handbook of Practical Program Evaluation, 4th ed. Hoboken: Jossey-Bass; 2015.
15. Bengtsson M. How to plan and perform a qualitative study using content analysis. NursingPlus Open 2016;2:8-14. [doi: 10.1016/j.npls.2016.01.001]
16. Cho J, Lee E. Reducing confusion about grounded theory and qualitative content analysis: similarities and differences. Qual Rep 2014 Aug;19(32):1-20. [doi: 10.46743/2160-3715/2014.1028]
17. Lindgren B, Lundman B, Graneheim UH. Abstraction and interpretation during the qualitative content analysis process. Int J Nurs Stud 2020 Aug;108:103632. [doi: 10.1016/j.ijnurstu.2020.103632] [Medline: 32505813]
18. Elliott V. Thinking about the coding process in qualitative data analysis. Qual Rep 2018 Nov 24;23(11):2850-2861. [doi: 10.46743/2160-3715/2018.3560]
19. Ryan GW, Bernard HR. Techniques to identify themes. Field Methods 2003 Feb 01;15(1):85-109. [doi: 10.1177/1525822x02239569]
20. Korstjens I, Moser A. Series: Practical guidance to qualitative research. part 4: trustworthiness and publishing. Eur J Gen Pract 2018 Dec;24(1):120-124. [doi: 10.1080/13814788.2017.1375092] [Medline: 29202616]
21. Fusch P, Fusch GE, Ness LR. Denzin's paradigm shift: revisiting triangulation in qualitative research. J Soc Change 2018 Jan 01;10(1):19-32. [doi: 10.5590/josc.2018.10.1.02]
22. NCDHHS guidance for reporting of COVID-19 diagnostic test results. North Carolina Department of Health and Human Services. 2020 Dec 14. URL: https://covid19.ncdhhs.gov/media/454/download [accessed 2020-12-15]
23. North Carolina Department of Health and Human Services, University of North Carolina School of Medicine. NC DETECT. North Carolina Department of Health and Human Services. URL: https://ncdetect.org/ [accessed 2020-01-20]
24. The New York Times COVID-19-data. GitHub. 2021. URL: https://github.com/nytimes/covid-19-data [accessed 2021-01-20]
25. Coronavirus. The News & Observer. 2021. URL: https://www.newsobserver.com/news/coronavirus [accessed 2021-01-24]
26. NC coronavirus updates and latest news. WRAL. 2021. URL: https://www.wral.com/coronavirus/ [accessed 2021-01-23]
27. Majumder M, Rose S. Health Affairs. Health care claims data may be useful for COVID-19 research despite significant limitations. 2020. URL: https://www.healthaffairs.org/do/10.1377/hblog20201001.977332/full/ [accessed 2021-01-18]
28. Safegraph. Safegraph. 2021. URL: https://www.safegraph.com/ [accessed 2021-01-22]
29. PolicyMap. PolicyMap. 2021. URL: https://www.policymap.com/ [accessed 2021-01-22]
30. North Carolina COVID-19 modeling shows social distancing necessary to slow the spread and preserve hospital capacity to save lives. North Carolina Department of Health and Human Services. URL: https://www.ncdhhs.gov/news/press-releases/2020/04/06/north-carolina-covid-19-modeling-shows-social-distancing-necessary-slow-spread-and-preserve-hospital [accessed 2021-08-23]
31. Fareed N, Swoboda CM, Chen S, Potter E, Wu DTY, Sieck CJ. U.S. COVID-19 state government public dashboards: an expert review. Appl Clin Inform 2021 Mar;12(2):208-221. [doi: 10.1055/s-0041-1723989] [Medline: 33853140]
32. Zylla E, Hartman L. State COVID-19 data dashboards. State Health and Value Strategies. 2020 Apr 09. URL: https://www.shvs.org/state-covid-19-data-dashboards/ [accessed 2021-06-29]
33. Wu JT, Leung K, Leung GM. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. Lancet 2020 Feb 29;395(10225):689-697. [doi: 10.1016/S0140-6736(20)30260-9] [Medline: 32014114]
34. Park SW, Cornforth DM, Dushoff J, Weitz JS. The time scale of asymptomatic transmission affects estimates of epidemic potential in the COVID-19 outbreak. Epidemics 2020 Jun;31:100392 [FREE Full text] [doi: 10.1016/j.epidem.2020.100392] [Medline: 32446187]

35. Li R, Pei S, Chen B, Song Y, Zhang T, Yang W, et al. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). Science 2020 Mar 16;368(6490):489-493. [doi: 10.1126/science.abb3221] [Medline: 32179701]
36. Kucharski AJ, Russell TW, Diamond C, Liu Y, Edmunds J, Funk S, Centre for Mathematical Modelling of Infectious Diseases COVID-19 working group. Early dynamics of transmission and control of COVID-19: a mathematical modelling study. Lancet Infect Dis 2020 May;20(5):553-558 [FREE Full text] [doi: 10.1016/S1473-3099(20)30144-4] [Medline: 32171059]
37. Li L, Yang Z, Dang Z, Meng C, Huang J, Meng H, et al. Propagation analysis and prediction of the COVID-19. Infect Dis Model 2020;5:282-292 [FREE Full text] [doi: 10.1016/j.idm.2020.03.002] [Medline: 32292868]
38. Koo JR, Cook AR, Park M, Sun Y, Sun H, Lim JT, et al. Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a modelling study. Lancet Infect Dis 2020 Jun;20(6):678-688 [FREE Full text] [doi: 10.1016/S1473-3099(20)30162-6] [Medline: 32213332]
39. Pan A, Liu L, Wang C, Guo H, Hao X, Wang Q, et al. Association of public health interventions with the epidemiology of the COVID-19 outbreak in Wuhan, China. JAMA 2020 Apr 10;323(19):1915-1923 [FREE Full text] [doi: 10.1001/jama.2020.6130] [Medline: 32275295]
40. Prem K, Liu Y, Russell TW, Kucharski AJ, Eggo RM, Davies N, Centre for the Mathematical Modelling of Infectious Diseases COVID-19 Working Group, et al. The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. Lancet Public Health 2020 May;5(5):e261-e270 [FREE Full text] [doi: 10.1016/S2468-2667(20)30073-6] [Medline: 32220655]
41. He W, Zhang ZJ, Li W. Information technology solutions, challenges, and suggestions for tackling the COVID-19 pandemic. Int J Inf Manage 2021 Apr;57:102287 [FREE Full text] [doi: 10.1016/j.ijinfomgt.2020.102287] [Medline: 33318721]
42. Dagliati A, Malovini A, Tibollo V, Bellazzi R. Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. Brief Bioinform 2021 Mar 22;22(2):812-822 [FREE Full text] [doi: 10.1093/bib/bbaa418] [Medline: 33454728]
43. Bryant-Genevier J, Rao CY, Lopes-Cardozo B, Kone A, Rose C, Thomas I, et al. Symptoms of Depression, Anxiety, Post-Traumatic Stress Disorder, and Suicidal Ideation Among State, Tribal, Local, and Territorial Public Health Workers During the COVID-19 Pandemic - United States, March-April 2021. MMWR Morb Mortal Wkly Rep 2021 Jul 02;70(26):947-952 [FREE Full text] [doi: 10.15585/mmwr.mm7026e1] [Medline: 34197362]
44. Finset A, Bosworth H, Butow P, Gulbrandsen P, Hulsman RL, Pieterse AH, et al. Effective health communication - a key factor in fighting the COVID-19 pandemic. Patient Educ Couns 2020 May;103(5):873-876 [FREE Full text] [doi: 10.1016/j.pec.2020.03.027] [Medline: 32336348]
45. Huston P, Edge VL, Bernier E. Reaping the benefits of open data in public health. Can Commun Dis Rep 2019 Oct 03;45(11):252-256 [FREE Full text] [doi: 10.14745/ccdr.v45i10a01] [Medline: 31647060]
46. Dixon BE, Grannis SJ, McAndrews C, Broyles AA, Mikels-Carrasco W, Wiensch A, et al. Leveraging data visualization and a statewide health information exchange to support COVID-19 surveillance and response: application of public health informatics. J Am Med Inform Assoc 2021 Jan 22;28(7):1363-1373 [FREE Full text] [doi: 10.1093/jamia/ocab004] [Medline: 33480419]

Abbreviations

EHR: electronic health record
NCDHHS: North Carolina Department of Health and Human Services

Edited by T Sanchez; submitted 01.04.21; peer-reviewed by R Boyapati, S Six, J Delgado-Ron; comments to author 16.05.21; revised version received 05.06.21; accepted 15.07.21; published 02.09.21.

Please cite as:
Patterson JR, Shaw D, Thomas SR, Hayes JA, Daley CR, Knight S, Aikat J, Mieczkowska JO, Ahalt SC, Krishnamurthy AK
COVID-19 Data Utilization in North Carolina: Qualitative Analysis of Stakeholder Experiences
JMIR Public Health Surveill 2021;7(9):e29310
URL: https://publichealth.jmir.org/2021/9/e29310
doi:10.2196/29310
PMID:34298500

Original Paper

The Characteristics and Risk Factors of Web-Based Sexual Behaviors Among Men Who Have Sex With Men in Eastern China: Cross-sectional Study

Lin Chen[1], MD; Wanjun Chen[1], MD; Tingting Jiang[1], MD; Zhikan Ni[1], MD; Qiaoqin Ma[1], College Degree of Medicine; Xiaohong Pan[1], MD

Zhejiang Provincial Center for Disease Control and Prevention, Hangzhou, China

Corresponding Author:
Xiaohong Pan, MD
Zhejiang Provincial Center for Disease Control and Prevention
3399 Binsheng Road, Binjiang District
Hangzhou, 310051
China
Phone: 86 057187115191
Email: xhpan@cdc.zj.cn

Related Article:

This is a corrected version. See correction statement: https://publichealth.jmir.org/2021/9/e33430

Abstract

Background: Finding casual sex partners on the internet has been considered a huge challenge for HIV transmission among men who have sex with men (MSM) in China.

Objective: This study aimed to identify the characteristics and risk factors of finding causal sex partners on the internet among MSM in Zhejiang Province, China.

Methods: This was a cross-sectional study. Participants were enrolled by 4 community-based organizations (CBOs) and 10 Voluntary Counselling and Testing (VCT) clinics through advertisements in bathrooms, bars, and gay hook-up apps from June to December 2018. A CBO- or physician-assisted survey was conducted to collected information on finding casual sex partners, perceived HIV infection, and HIV risk behaviors.

Results: Among 767 participants, 310 (40.4%) reported finding causal sex partners on the internet. Factors associated with finding casual sex partners on the internet included watching pornographic videos on the internet more than once a week (adjusted odds ratio [aOR]=1.881, 95% CI 1.201-2.948), discussing “hooking-up online” with friends (aOR=4.018, 95% CI 2.910-5.548), and perceiving that the likelihood of HIV infection among casual sex partners sought on the internet was “medium” (aOR=2.034, 95% CI 1.441-2.873) or “low” (aOR=2.548, 95% CI 1.524-4.259). Among the participants who reported finding casual sex partners on the internet, 30.2% (91/310) reported having unprotected sex with casual sex partners encountered on the internet in the past 6 months. On multivariate logistic regression analyses, knowing the HIV infection status of casual sex partners sought on the internet was significantly associated with performing inserted intercourse (aOR=1.907, 95% CI 1.100-3.306) and a decreased risk of inconsistent condom use (aOR=0.327, 95% CI 0.167-0.642).

Conclusions: Web-based casual sexual behavior is becoming more prevalent, and the rate of unprotected sex among MSM in Zhejiang Province is high. Future HIV prevention approaches should emphasize the importance for MSM to proactively determine the HIV infection status of potential casual sex partners sought on the internet.

(JMIR Public Health Surveill 2021;7(9):e25360) doi:10.2196/25360

KEYWORDS

HIV; men who have sex with men; casual sexual partners; internet; cross-sectional study

Introduction

Globally, men who have sex with men (MSM) continue to be disproportionately affected by HIV [1,2]. Homosexual behavior has been the main route of HIV transmission in China. In 2019, HIV infection through male-male sexual contact accounted for 40% of all cases of HIV infection in Zhejiang Province (data not published). There are many risky factors of HIV infection among MSM, such as substance abuse, multiple sex partners, and sex position [3,4]. One challenge to the prevention of HIV transmission among MSM is the increasing trend of finding casual sex partners on websites and smartphone apps [5].

The internet's role as a platform enabling MSM to engage with other men for both social and sexual purposes began with the establishment of web-based chat rooms in the late 1990s in the United States [6,7]. Popular hook-up apps accessible on smartphones include Grindr, Jack'd, Manhunt, Scruff, and Black Gay Chat in the United States [7,8]. In China, Blued is the most popular hook-up app among MSM; it was launched in 2009 and has more than 30 million registered MSM users, accounting for roughly 4.1% of all adult men in China. The number of MSM registered as users on Blued were 409,000 in Zhejiang Province, China [9].

With the rapid increase in popularity of hook-up apps, more MSM are finding casual sex partners on the internet. The benefits of finding casual sex partners on the internet include greater convenience, accessibility, and anonymity. The rate of MSM finding sex partners on the internet ranged from 30% to 86% in different countries [10,11]. Finding casual sex partners on the internet was associated with HIV infection [5]. Studies on the characteristics and the difference of risky behavior between web-based groups and offline groups are rare.

There has been no definite conclusion about the reasons for finding casual sex partners on the internet and for condom use among sex partners sought on the internet. Serosorting was an effective strategy, first acknowledged in the 1990s [12,13]. A Joint United Nations Programme on HIV/AIDS report indicated that condom use with other men without regard to HIV serostatus was the only major risky behavior among MSM [14,15]. The Chinese Center for Disease Control and Prevention released a guide for preventing HIV among MSM (2016 version), which emphasizes educating MSM on the importance of proactively determining the HIV infection status of sexual partners. However, users are not required to disclose their HIV infection status on Blued or other apps, which affects decision-making regarding condom use. Little is known about the effect of this strategy on condom use with casual sex partners sought on the internet.

To explore the status of individuals finding casual sex partners on the internet and to examine the factors related, we investigated the characteristics of MSM seeking casual sex partners on the internet and compared the risky behavior between a web-based group and an offline group. We also investigated whether peer communication, perceived risk of HIV infection, alcohol consumption, and exchange of information regarding HIV infection status were associated with the risky sexual behavior.

Methods

Study Population

This cross-sectional study examined MSM between June and December 2018 in Zhejiang Province. Criteria for enrollment were males who (1) have had anal or oral intercourse with a male within the past 6 months, (2) were aged 18 years and older, (3) resided locally for more than 6 months, and (4) consented to participate in the study.

Study Design and Data Collection

Subjects were enrolled by 4 local CBOs and 10 Voluntary Counselling and Testing (VCT) clinics in Zhejiang Province through venues for gay men and networks formed by gay men. They serve more than 50% of all MSM in Zhejiang Province and are located in the cities of Hangzhou, Ningbo, Wenzhou, Shaoxing, and Taizhou. They placed advertisements regarding the study in bathrooms, bars, and in chat groups on Blued, WeChat, and Tencent to target MSM. A CBO- or physician-assisted survey was conducted through an electronic questionnaire. All participants were asked to scan a 2D code and were directed to the electronic questionnaire. All participants received face-to-face or telephone training on the questionnaire. Electronic informed consent was obtained before beginning the survey. Participants received a gift worth 30 RMB (approximately US $5.00) for completing the investigation. Cellphone numbers were used to filter duplication, and no duplicated participants were found.

We calculated the sample size on the basis of the rate of finding sexual partners on the internet, which ranges from 40% to 60%. The minimum sample size required for this study was estimated at 266 people, with a Cronbach α of .10 and β value of .10, calculated using PASS (version 11.0, NCSS, LLC).

In total, 812 individuals participated in this study. Of these, 793 (97.7%) were eligible to participate during the data collection period, 26 of whom did not complete the survey. Ultimately, 767 participants were enrolled in this study.

Two questions were asked to evaluate "finding casual sex partners online" or "offline": "Have you ever dated and had sexual intercourse with men you met on the Internet, such as with Blued, WeChat, a chat room, or other?" and "Have you ever have sexual intercourse with men you met in a bar, park, bathing pool, or other place?"

One question was asked to evaluate "Knows HIV epidemic": "Are MSM the most seriously affected by AIDS in China at present?" For the logistic regression analyses, replying with "No" or "unknown" was defined as "No." Inconsistent condom use was deemed as "ever have sex intercourse with no condom."

Ethics Approval and Consent for Publication

All procedures performed in the study were approved by the Ethics Committee of Zhejiang Provincial Center for Disease Control and Prevention (2018-033). This study did not involve any animals. All participants signed electronic inform consent.

Statistical Analysis

We used SPSS (version 19.0, IBM Corp) to analyze the data. Descriptive analyses were used to describe the demographic characteristics of all subjects finding casual sex partners on the internet. The chi-square test was used to examine the differences between proportions in accordance with the studied characteristics. We performed univariate and multivariate logistic regression analyses (Backward: LR) to identify the independent risk factors associated with finding casual sex partners on the internet and inconsistent condom use with casual sex partners sought on the internet. All variables were included in the model. Missing data were not included in the analysis. *P* values of <.05 were considered to indicate statistical significance.

Results

The demographic and behavioral assessments included 767 MSM. Of them, 76.1% (585/767) were aged 16-34 years, and 62.0% (476/767) had a college education or above. A total of 422/767 (55.0%) were registered residents in Zhejiang Province, and 54.2% (416/767) had lived locally for more than 5 years. A total of 227/767 reported annual incomes exceeding 100,000 RMB (US $14,700). Among all subjects, 62.2% (477/767) self-identified as gay and 31.7% (243/767) as bisexual. Among the 767 MSM, 310 (40.4%) had met at least 1 partner on the internet in their lifetime. (Table 1).

Table 1. Sociodemographic characteristics of all men who have sex with men and those who found partners on the internet (N=767).

Characteristics	All men who have sex with men (n=767), n (%)	Men who have sex with men who found partners on the internet (n=310), n (%)
Age (years)		
16-24	248 (32.3)	105 (33.9)
25-34	337 (43.9)	141 (45.5)
≥35	182 (23.7)	64 (20.6)
Education level		
High school or below	291 (38.0)	115 (37.1)
College or bachelor's degree	449 (58.5)	176 (56.8)
Master's degree or doctorate	27 (3.5)	19 (6.1)
Registered permanent residence		
Zhejiang Province	422 (55.0)	183 (59.0)
Other provinces	345 (45.0)	127 (41.0)
Length of local residence (years)		
0-1	47 (6.1)	30 (9.7)
1-3	190 (24.8)	75 (24.2)
3-5	114 (14.9)	37 (11.9)
≥5	416 (54.2)	168 (54.2)
Annual income (10,000 RMB)[a]		
0-5	247 (32.2)	96 (31.0)
5-10	293 (38.2)	120 (38.7)
≥10	227 (29.6)	94 (30.3)
Sexual orientation		
Gay	477 (62.2)	205 (66.1)
Bisexual	243 (31.7)	95 (30.6)
Heterosexual/unsure	47 (6.1)	10 (3.2)

[a]1 RMB=US $0.15.

Of the 310 MSM who found casual sex partners on the internet, 62.9% (195) found partners only on the internet and 37.1% (115) found partners both on the internet and offline. Overall, 93.5% (290/310) of these MSM found partners using Blued, as opposed to 19.4% (60/310) of those who used other hook-up apps, and 8.4% (26/310) using social apps or websites. More than one-third (60.4%, 177/293) had sexual intercourse with casual sex partners sought on the internet at a hotel, karaoke lounge, or club, and 90.0% (269/299) of them dated in their local city. Among MSM who found partners on the internet, 24.6% (91/301) reported inconsistent condom use in the past 6

months with casual sex partners sought on the internet (Table 2).

Compared to MSM who found partners only on the internet, those who found partners both on the internet and offline were more likely to report ≥2 web-based dates per month (76.3%, 87/114 vs 54.6%, 106/194; *P*<.001), ≥2 casual sex partners sought on the internet (79.2% 84/106 vs 68.5%, 126/184; *P*=.048), inconsistent condom use with casual sex partners sought on the internet (39.5% 45/114, vs 24.6%, 46/187; *P*=.006), and no condom use during intercourse after drinking alcohol (19.1% 22/115, vs 5.2%, 10/184; *P*=.001) (Table 2).

Table 2. Association between seeking casual sex partners on the internet in the past 6 months and the frequency of dating, condom use, and location where sexual intercourse occurred among men who have sex with men who found partners on the internet only or both on the internet and offline (N=310).

Variables	Men who have sex with men who found partners only on the internet, n (%)	Men who have sex with men who found partners on the internet and offline, n (%)	Total	Chi-square (*df*)	*P* value
Frequency of finding partners on the internet (times/month) in the past 6 months				14.421 (*1*)	<.001
1	88 (45.4)	27 (23.7)	115		
≥2	106 (54.6)	87 (76.3)	193		
Missing	1	1	2		
Number of casual sex partners sought on the internet in the past 6 months				3.903 (*1*)	.048
1	58 (31.5)	22 (20.8)	80		
≥2	126 (68.5)	84 (79.2)	210		
Missing	11	9	20		
Condom use with casual sex partners sought on the internet in the past 6 months				7.429 (*1*)	.006
Every time	141 (75.4)	69 (60.5)	210		
Sometimes/never	46 (24.6)	45 (39.5)	91		
Missing	8	1	9		
Place where sexual intercourse occurred with casual sex partners sought on the internet in the past 6 months				4.448 (*1*)	.04
Hotel, karaoke lounge, or club	102 (55.7)	75 (68.2)	177		
Home	81 (44.3)	35 (31.8)	116		
Missing	12	5	17		
City where sexual intercourse occurred with casual sex partners sought on the internet in the past 6 months				3.426 (*1*)	.06
Local city	172 (92.6)	97 (85.8)	269		
Other cities	14 (7.4)	16 (14.2)	30		
Missing	9	2	11		
Sexual intercourse with men who have sex with men without a condom after drinking alcohol in the past 6 months				15.191 (*1*)	.001
No	184 (94.8)	93 (80.9)	277		
Yes	10 (5.2)	22 (19.1)	32		
Missing	1	0	1		
Sexual intercourse with men who have sex with men without a condom after watching erotic videos in the past 6 months				0.746 (*1*)	.39
No	171 (88.6)	98 (85.2)	262		
Yes	22 (11.4)	17 (14.8)	39		
Missing	9	0	9		
Number of HIV tests until now				0.397 (*1*)	.53
0	71 (36.4)	46 (40.0)	117		
≥1	124 (63.6)	69 (60.0)	193		

Multivariate modeling revealed that the likelihood of finding casual sexual partners in the past 6 months was higher among MSM who watched pornographic videos on the internet more than once per week than among those who never did so (adjusted

odds ratio [aOR]=1.881, 95% CI 1.201-2.948). In addition, those who discussed "hooking-up online" with friends were more likely to find partners on the internet than among those who never did so (aOR=4.018, 95% CI 2.910-5.548). Compared to MSM who perceived that the HIV infection risk from casual sex partners sought on the internet was "high," those who perceived that the risk of HIV infection was "medium and low" were more likely to finding sex partners on the internet, with an aOR of 2.034 (95% CI 1.441-2.873) and 2.528 (95% CI 1.530-4.176), respectively (Table 3). All of the above results pertained to the past 6 months (Table 3).

Table 3. Uni- and multivariate logistic regression analyses of the risk factors associated with finding partners on the internet among men who have sex with men in China (N=767).

Characteristics	Met partners on the internet, % (n/n)	Odds ratio (95% CI)	*P* value	Adjusted odds ratio (95% CI)	*P* value
Age (years)					
16-24	43.3 (105/248)	1	—[a]	—	—
25-34	41.8 (141/337)	0.980 (0.703-1.366)	.90	—	—
≥35	35.2 (64/182)	0.739 (0.498-1.096)	.13	—	—
Education level					
High school or below	39.5 (115/291)	1	—	—	—
College or above	41.0 (195/476)	1.062 (0.789-1.430)	.69	—	—
Registry area					
Native	43.4 (183/422)	1	—	—	—
Other	36.8 (127/345)	0.761 (0.568-1.018)	.07	—	—
Sex role					
Receives	38.5 (77/200)	1	—	—	—
Inserts/both	41.1 (233/567)	1.780 (0.645-1.249)	.06	—	—
Knowledge of HIV infection					
Correct	41.8 (264/631)	1	—	—	—
Incorrect/no knowledge	33.8 (46/136)	0.711 (0.482-1.048)	.09	—	—
Watched a pornographic video on the internet in the past 6 months					
Never	25.0 (40/160)	1	—	1	—
<1/week	42.0 (111/264)	2.176 (1.411-3.357)	<.001	1.565 (0.979-2.503)	.06
≥1/week	46.4 (159/343)	2.592 (1.710-3.930)	<.001	1.881 (1.201-2.948)	.006
Discussed the topic of finding partners on the internet with friends in the past 6 months					
No	24.2 (103/425)	1	—	1	—
Yes	60.5 (207/342)	4.794 (3.515-6.537)	<.001	4.018 (2.910-5.548)	<.001
Perceived risk of HIV infection from casual sex partners sought on the internet[b]					
High	28.8 (102/354)	1	—	1	—
Medium	49.3 (149/302)	2.406 (1.743-3.321)	<.001	2.034 (1.441-2.873)	<.001
Low	53.3 (49/92)	2.815 (1.760-4.503)	<.001	2.528 (1.530-4.176)	<.001

[a]—: not determined.

[b]Missing data: perceived risk of HIV infection among casual sex partners sought on the internet=19.

Our study also evaluated factors correlated with condom use with casual sex partners sought on the internet. On univariate and multivariate logistic regression analyses, factors independently associated with inconsistent condom use with casual sex partners sought on the internet in the past 6 months included performing inserted intercourse (aOR=1.907, 95% CI 1.100-3.306) compared with performing receptive intercourse only and knowing the HIV status of most or all of casual sex partners sought on the internet (aOR=0.327, 95% CI 0.167-0.642) compared to those who do not know or know the status of only some of their casual sex partners sought on the internet (Table 4).

Table 4. Uni- and multivariate logistic regression analyses of the risk factors associated with inconsistent condom use with casual sex partners sought on the internet among men who have sex with men in China (N=301).

Characteristics	Inconsistent condom uses with casual sex partners sought on the internet, % (n/n)	Odds ratio (95% CI)	*P* value	Adjusted odds ratio (95% CI)	*P* value
Age (years)					
16-24	23.8 (24/101)	1	—[a]	—	—
25-34	31.2 (43/138)	1.452 (0.811-2.601)	.21	—	—
≥35	38.7 (24/62)	2.026 (1.020-4.025)	.04	—	—
Education level					
High school and under	37.8 (42/111)	1	—	—	—
College and above	25.8 (49/190)	0.571 (0.345-0.944)	.03	—	—
Registry area					
Native	26.1 (46/176)	1	—	—	—
Other	36.0 (45/125)	1.590 (0.968-2.612)	.06	—	—
Knowledge of HIV infection					
Correct	31.8 (82/258)	1	—	—	—
Incorrect/no knowledge	20.9 (9/43)	0.568 (0.260-1.239)	.16	—	—
Number of casual sex partners sought on the internet in the past 6 months[b]					
≤2	26.6 (46/173)	1	.09	—	—
2	36.0 (40/111)	1.555 (0.931-2.600)	—	—	—
Sex role					
Only receives	25.5 (51/200)	1	.01	1	.02
Inserts	39.6 (40/101)	1.916 (1.150-3.190)	—	1.907 (1.100-3.306)	—
Watched pornographic videos on the internet in the past 6 months					
No	37.5 (15/40)	1	—	—	—
Yes	29.1 (76/261)	0.876 (0.342-1.370)	.84	—	—
Discussed the topic of finding partners on the internet with friends in the past 6 months					
No	37.8 (37/98)	1	—	—	—
Yes	26.6 (54/203)	1.015 (0.358-0.999)	.98	—	—
Perceived risk of HIV infection from casual sex partners sought on the internet[c]					
High	28.3 (28/99)	1	—	—	—
Medium/low	32.1 (62/193)	0.329 (0.705-2.042)	.18	—	—
Knows HIV status of casual sex partners sought on the internet in the past 6 months[d]					
None/some	35.4 (75/212)	1	.001	1	.001
Most/all	16.3 (14/86)	0.355 (0.188-0.672)	—	0.327 (0.167-0.642)	—

[a]—: not determined.

[b]Missing number of casual sex partners sought on the internet=17.

[c]Missing data: perceived risk of HIV infection from casual sex partners sought on the internet=9.

[d]Missing number of individuals who know the status of casual sex partners sought on the internet in the past 6 months=3.

Discussion

Principal Findings

This study found that 39% of MSM reported finding partners on the internet, and 30.2% reported having unprotected sex with sex partners sought on the internet. The factors related to sexual behavior over the internet and unprotected sexual behavior were also explored in this study.

Finding casual sex partners on the internet became popular among MSM in recent years in China. The proportion of finding partners on the internet was lower this study than in many other studies in China and other countries [16-18]. Hook-up apps for MSM have only recently become popular in China, so the proportion of individuals engaging in web-based dating is not as high as in Europe and the United States. We identified some notable characteristics of web-based hook-ups: for example, two-thirds of MSM found partners on the internet only and one-third found partners both on the internet and offline; most MSM met partners they found on the internet at a hotel, karaoke lounge, or club. This information suggests that the intervention can be complemented through apps and hotel visits.

Previous studies have revealed that MSM who find partners on the internet were more likely to engage in risky sexual behaviors [19]. This study revealed an important outcome that the frequency of casual sexual behavior, number of casual sex partners, and sex without a condom were much higher among MSM who found partners both on the internet and offline than among those who found partners only on the internet. This result indicates the key group of individuals among those who engage in web-based dating, who need more intervention.

Discussing finding partners on the internet with friends was an important risk factor for finding casual sex partners on the internet. Based on the theory of diffusion of innovations, the behavior of an individual is influenced by other members of the same group, which is called the peer effect [20]. In this study, MSM who discussed web-based hook-ups with friends might have been influenced by their friends to behave similarly. To reduce HIV-related risky behavior, peers and CBOs should focus on sharing health-related information [21,22].

Men's perception of the danger of their sex partners is another important variable. With the popularity of hook-up platforms and apps, people find casual sex partners on the internet because of novelty, without considering the risk to their health. Commercial sex workers are always difficult to identify if they find customers on the internet [15,23]. Furthermore, pornographic videos and electronic books have become more accessible, arousing people sexually and leading them to seek a sexual release [24]. The characteristics of pornographic videos that trigger hook-up behaviors need to be explored for further intervention.

This study also found that knowing the HIV status of casual sex partners encountered on the internet was significantly associated with safer sexual behaviors. Compared with the serosorting strategy, cognizance of the HIV infection status of partners may help people make decisions leading to safer sex [25,26]. People who share their HIV status with partners are always aware of their health. The likelihood of condom use is increased if they do not know the HIV infection status of partners found on the internet. In fact, the proportion of MSM knowing the HIV status of partners found on the internet was very low in this study and in other studies [27]. There are many reasons for this: for example, MSM usually do not carry documents showing their HIV status, where this may be perceived as a violation of their privacy. Future efforts need to focus on providing documentation regarding HIV status in MSM and encouraging them to share their HIV test results on apps before hooking up.

In this study, MSM performing insertive sex were more likely to report unprotected sexual behavior. Sexual pleasure, self-efficacy in the area of sexual control, and psychosocial health mediate differences among sexual roles in terms of condom use [28-30]. Furthermore, the proportions of MSM who use drugs for sexual pleasure increased from 5% in 2003 to 40% in 2014 [5]. Further research needs to examine the mechanism of how sexual roles impact condom use.

Although this study initially revealed the relationship between the use of hook-up apps and risky sexual behavior, it is not directly related. Sociological and psychological factors may be potential directly related as well. These associations should be explored by future studies.

Limitations

Our study has several limitations. First, our study population might not be representative of the general MSM population in Zhejiang Province. Self-selected men who volunteered to participate in the study were recruited, so the sample was subject to selection bias. The participants completed the questionnaire in confidence, so it might have been subject to social desirability and information biases. To minimize bias, the introductory section of the questionnaire emphasized the need for commitment form the participant to ensure high-quality data. Furthermore, all questionnaires were checked once a week and revised if an input error or missing data were identified. This has been shown to reduce information bias by self-reporting. Finally, this study was cross-sectional; hence, our findings do not extend to all MSM in Zhejiang Province, and a cohort study is needed to validate these findings.

Conclusion

Internet-based casual sexual behavior is becoming popular among MSM in Zhejiang Province. Those who found casual sex partners both on the internet and offline reported a higher rate of unprotected sexual behavior and more casual sex partners. Watching pornographic videos on the internet more than once per week, discussing "hooking-up online" with friends, and perceiving the risk of HIV infection among casual sex partners sought on the internet as "low" or "medium" were associated with finding casual sex partners on the internet. Performing insertive sex, knowing the HIV status of casual sex partners found on the internet decreased the risk of inconsistent condom use with these casual sex partners. Intervention programs are required to encourage MSM to exchange information regarding their HIV infection status with prospective sex partners. Peer education could play an important role in

helping MSM consider their health and making correct decisions.

Acknowledgments

The authors would like to thank the staff of the community-based organizations (CBOs) for their assistance with the design of the implementation plan, the questionnaire, and the fieldwork conducted in this study; these CBOs include the Coastal, Glowworm-light, Love, and Blue-sky public welfare groups. This work was supported by the Key Projects in the National Science & Technology Pillar Program during the 13th Five-year Plan period (grant no. 2017ZX10201101). This funding supported the study design and implementation, data collection, and revision of the manuscript. From June to December 2018, we enrolled 767 participants and collected data.

Authors' Contributions

XP designed the study. LC, WC, TJ, and ZN coordinated the field research. LC performed the statistical analysis and drafted the manuscript. QM and XP reviewed and revised the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

References

1. Beyrer C, Baral SD, Collins C, Richardson ET, Sullivan PS, Sanchez J, et al. The global response to HIV in men who have sex with men. Lancet 2016 Jul 09;388(10040):198-206. [doi: 10.1016/S0140-6736(16)30781-4] [Medline: 27411880]
2. Raymond HF, Al-Tayyib A, Neaigus A, Reilly KH, Braunstein S, Brady KA, et al. HIV Among MSM and Heterosexual Women in the United States: An Ecologic Analysis. J Acquir Immune Defic Syndr 2017 Jul 01;75 Suppl 3:S276-S280. [doi: 10.1097/QAI.0000000000001422] [Medline: 28604428]
3. Melendez-Torres GJ, Bourne A. Illicit drug use and its association with sexual risk behaviour among MSM: more questions than answers? Curr Opin Infect Dis 2016 Feb;29(1):58-63. [doi: 10.1097/QCO.0000000000000234] [Medline: 26694620]
4. Vu N, Holt M, Phan H, La L, Tran G, Doan T, et al. The Relationship Between Methamphetamine Use, Sexual Sensation Seeking and Condomless Anal Intercourse Among Men Who Have Sex With Men in Vietnam: Results of a Community-Based, Cross-Sectional Study. AIDS Behav 2017 Apr;21(4):1105-1116. [doi: 10.1007/s10461-016-1467-x] [Medline: 27351193]
5. Piyaraj P, van Griensven F, Holtz T, Mock P, Varangrat A, Wimonsate W, et al. The finding of casual sex partners on the internet, methamphetamine use for sexual pleasure, and incidence of HIV infection among men who have sex with men in Bangkok, Thailand: an observational cohort study. Lancet HIV 2018 Jul;5(7):e379-e389 [FREE Full text] [doi: 10.1016/S2352-3018(18)30065-1] [Medline: 29861202]
6. Landovitz RJ, Tseng C, Weissman M, Haymer M, Mendenhall B, Rogers K, et al. Epidemiology, sexual risk behavior, and HIV prevention practices of men who have sex with men using GRINDR in Los Angeles, California. J Urban Health 2013 Aug;90(4):729-739 [FREE Full text] [doi: 10.1007/s11524-012-9766-7] [Medline: 22983721]
7. Chan PA, Towey C, Poceta J, Rose J, Bertrand T, Kantor R, et al. Online Hookup Sites for Meeting Sexual Partners Among Men Who Have Sex with Men in Rhode Island, 2013: A Call for Public Health Action. Public Health Rep 2016;131(2):264-271 [FREE Full text] [doi: 10.1177/003335491613100210] [Medline: 26957661]
8. Beymer MR, Weiss RE, Bolan RK, Rudy ET, Bourque LB, Rodriguez JP, et al. Sex on demand: geosocial networking phone apps and risk of sexually transmitted infections among a cross-sectional sample of men who have sex with men in Los Angeles County. Sex Transm Infect 2014 Nov;90(7):567-572 [FREE Full text] [doi: 10.1136/sextrans-2013-051494] [Medline: 24926041]
9. Hu M, Xu C, Wang J. Spatiotemporal Analysis of Men Who Have Sex With Men in Mainland China: Social App Capture-Recapture Method. JMIR Mhealth Uhealth 2020 Jan 24;8(1):e14800 [FREE Full text] [doi: 10.2196/14800] [Medline: 32012086]
10. Medina MM, Crowley C, Montgomery MC, Tributino A, Almonte A, Sowemimo-Coker G, et al. Disclosure of HIV Serostatus and Pre-exposure Prophylaxis Use on Internet Hookup Sites Among Men Who have Sex with Men. AIDS Behav 2019 Jul;23(7):1681-1688 [FREE Full text] [doi: 10.1007/s10461-018-2286-z] [Medline: 30267365]
11. Cruess DG, Burnham KE, Finitsis DJ, Cherry C, Grebler T, Goshe BM, et al. Online Partner Seeking and Sexual Risk Among HIV+ Gay and Bisexual Men: A Dialectical Perspective. Arch Sex Behav 2017 May;46(4):1079-1087. [doi: 10.1007/s10508-016-0833-0] [Medline: 27671781]
12. Aung T, Thein ST, McFarland W. Seroadaptive Behaviors of Men Who Have Sex with Men in Myanmar. AIDS Behav 2016 Dec;20(12):2827-2833. [doi: 10.1007/s10461-015-1216-6] [Medline: 26446976]
13. Khosropour CM, Dombrowski JC, Hughes JP, Manhart LE, Simoni JM, Golden MR. Operationalizing the Measurement of Seroadaptive Behaviors: A Comparison of Reported Sexual Behaviors and Purposely-Adopted Behaviors Among Men

who have Sex with Men (MSM) in Seattle. AIDS Behav 2017 Oct;21(10):2935-2944 [FREE Full text] [doi: 10.1007/s10461-017-1682-0] [Medline: 28097616]
14. Global AIDS Response Progress Reporting 2015. WHO Library Cataloguing-in-Publication Data. 2015. URL: https://www.unaids.org/sites/default/files/media_asset/JC2702_GARPR2015guidelines_en.pdf [accessed 2015-03-17]
15. Medina MM, Crowley C, Montgomery MC, Tributino A, Almonte A, Sowemimo-Coker G, et al. Disclosure of HIV Serostatus and Pre-exposure Prophylaxis Use on Internet Hookup Sites Among Men Who have Sex with Men. AIDS Behav 2019 Jul;23(7):1681-1688 [FREE Full text] [doi: 10.1007/s10461-018-2286-z] [Medline: 30267365]
16. Ko N, Tseng P, Huang Y, Chen Y, Hsu S. Seeking sex partners through the internet and mobile phone applications among men who have sex with men in Taiwan. AIDS Care 2016 Jul;28(7):927-931. [doi: 10.1080/09540121.2015.1131969] [Medline: 26754350]
17. Stahlman S, Grosso A, Ketende S, Mothopeng T, Taruberekera N, Nkonyana J, et al. Characteristics of men who have sex with men in southern Africa who seek sex online: a cross-sectional study. J Med Internet Res 2015 May 25;17(5):e129 [FREE Full text] [doi: 10.2196/jmir.4230] [Medline: 26006788]
18. Grov C, Breslow AS, Newcomb ME, Rosenberger JG, Bauermeister JA. Gay and bisexual men's use of the Internet: research from the 1990s through 2013. J Sex Res 2014;51(4):390-409 [FREE Full text] [doi: 10.1080/00224499.2013.871626] [Medline: 24754360]
19. Yang Z, Zhang S, Dong Z, Jin M, Han J. Prevalence of unprotected anal intercourse in men who have sex with men recruited online versus offline: a meta-analysis. BMC Public Health 2014 May 26;14:508 [FREE Full text] [doi: 10.1186/1471-2458-14-508] [Medline: 24885058]
20. Crittenden KS, Kaponda CPN, Jere DL, McCreary LL, Norr KF. Participation and diffusion effects of a peer-intervention for HIV prevention among adults in rural Malawi. Soc Sci Med 2015 May;133:136-144 [FREE Full text] [doi: 10.1016/j.socscimed.2015.03.055] [Medline: 25864150]
21. Alibayeva K, Saparbekov M, Baiserkin B, Abishev A, Tazhibaeva G, Kasymbekova S. Study of the possibility of introduction of Kazakhstan NGO-based rapid HIV testing procedures. HIV AIDS (Auckl) 2019;11:219-227 [FREE Full text] [doi: 10.2147/HIV.S212718] [Medline: 31564992]
22. Roth Y. Zero Feet Away: The Digital Geography of Gay Social Media. J Homosex 2016;63(3):437-442. [doi: 10.1080/00918369.2016.1124707] [Medline: 26643774]
23. Carballo-Diéguez A, Bauermeister J. "Barebacking": intentional condomless anal sex in HIV-risk contexts. Reasons for and against it. J Homosex 2004;47(1):1-16. [doi: 10.1300/J082v47n01_01] [Medline: 15189783]
24. Chow JY, Konda KA, Calvo GM, Klausner JD, Cáceres CF. Demographics, Behaviors, and Sexual Health Characteristics of High Risk Men Who Have Sex With Men and Transgender Women Who Use Social Media to Meet Sex Partners in Lima, Peru. Sex Transm Dis 2017 Mar;44(3):143-148 [FREE Full text] [doi: 10.1097/OLQ.0000000000000566] [Medline: 28178111]
25. Medina MM, Crowley C, Montgomery MC, Tributino A, Almonte A, Sowemimo-Coker G, et al. Disclosure of HIV Serostatus and Pre-exposure Prophylaxis Use on Internet Hookup Sites Among Men Who have Sex with Men. AIDS Behav 2019 Jul;23(7):1681-1688 [FREE Full text] [doi: 10.1007/s10461-018-2286-z] [Medline: 30267365]
26. Purcell D, Higa D, Mizuno Y, Lyles C. Quantifying the Harms and Benefits from Serosorting Among HIV-Negative Gay and Bisexual Men: A Systematic Review and Meta-analysis. AIDS Behav 2017 Oct;21(10):2835-2843. [doi: 10.1007/s10461-017-1800-z] [Medline: 28573378]
27. Badal HJ, Stryker JE, DeLuca N, Purcell DW. Swipe Right: Dating Website and App Use Among Men Who Have Sex With Men. AIDS Behav 2018 Apr;22(4):1265-1272. [doi: 10.1007/s10461-017-1882-7] [Medline: 28884248]
28. Underhill K. Intimacy, condom use, and pre-exposure prophylaxis (PReP) acceptability among men who have sex with men (MSM) in primary partnerships: a comment on Gamarel and Golub. Ann Behav Med 2015 Apr;49(2):151-153 [FREE Full text] [doi: 10.1007/s12160-014-9651-6] [Medline: 25245137]
29. Khan SI, Khan MNM, Hasan AR, Irfan SD, Horng LM, Chowdhury EI, et al. Understanding the reasons for using methamphetamine by sexual minority people in Dhaka, Bangladesh. Int J Drug Policy 2019 Nov;73:64-71. [doi: 10.1016/j.drugpo.2019.07.009] [Medline: 31344562]
30. Rawat S, Wilkerson JM, Lawler SM, Patankar P, Rosser BRS, Shukla K, et al. Recommendations for the Development of a Mobile HIV Prevention Intervention for Men Who Have Sex With Men and Hijras in Mumbai: Qualitative Study. JMIR Public Health Surveill 2018 May 03;4(2):e46 [FREE Full text] [doi: 10.2196/publichealth.9088] [Medline: 29724705]

Abbreviations

aOR: adjusted odds ratio
CBOs: community-based organizations
MSM: Male who have sex with male
VCT: Voluntary Counselling and Testing

Edited by P Sullivan, T Sanchez; submitted 29.10.20; peer-reviewed by J Wang, A Queiroz; comments to author 21.12.20; revised version received 23.02.21; accepted 15.06.21; published 02.09.21.

Please cite as:
Chen L, Chen W, Jiang T, Ni Z, Ma Q, Pan X
The Characteristics and Risk Factors of Web-Based Sexual Behaviors Among Men Who Have Sex With Men in Eastern China: Cross-sectional Study
JMIR Public Health Surveill 2021;7(9):e25360
URL: https://publichealth.jmir.org/2021/9/e25360
doi:10.2196/25360
PMID:34473066

Original Paper

Uncovering Clinical Risk Factors and Predicting Severe COVID-19 Cases Using UK Biobank Data: Machine Learning Approach

Kenneth Chi-Yin Wong[1], MSc; Yong Xiang[1], MBBS; Liangying Yin[1], MPhil; Hon-Cheong So[1,2,3,4,5,6,7], MBBS, PhD

[1]School of Biomedical Sciences, The Chinese University of Hong Kong, Hong Kong, China

[2]KIZ-CUHK Joint Laboratory of Bioresources and Molecular Research of Common Diseases, Kunming Institute of Zoology and The Chinese University of Hong Kong, Kunming, China

[3]CUHK Shenzhen Research Institute, Shenzhen, China

[4]Department of Psychiatry, The Chinese University of Hong Kong, Hong Kong, China

[5]Margaret K.L. Cheung Research Centre for Management of Parkinsonism, The Chinese University of Hong Kong, Hong Kong, China

[6]Brain and Mind Institute, The Chinese University of Hong Kong, Hong Kong, China

[7]Hong Kong Branch of the Chinese Academy of Sciences Center for Excellence in Animal Evolution and Genetics, The Chinese University of Hong Kong, Hong Kong, China

Corresponding Author:
Hon-Cheong So, MBBS, PhD
School of Biomedical Sciences, The Chinese University of Hong Kong
RM 520A, Lo Kwee Seong Biomedical Sciences Buildiing
Chinese University of Hong Kong
Hong Kong
China
Phone: 86 39439255
Email: hcso@cuhk.edu.hk

Abstract

Background: COVID-19 is a major public health concern. Given the extent of the pandemic, it is urgent to identify risk factors associated with disease severity. More accurate prediction of those at risk of developing severe infections is of high clinical importance.

Objective: Based on the UK Biobank (UKBB), we aimed to build machine learning models to predict the risk of developing severe or fatal infections, and uncover major risk factors involved.

Methods: We first restricted the analysis to infected individuals (n=7846), then performed analysis at a population level, considering those with no known infection as controls (ncontrols=465,728). Hospitalization was used as a proxy for severity. A total of 97 clinical variables (collected prior to the COVID-19 outbreak) covering demographic variables, comorbidities, blood measurements (eg, hematological/liver/renal function/metabolic parameters), anthropometric measures, and other risk factors (eg, smoking/drinking) were included as predictors. We also constructed a simplified (lite) prediction model using 27 covariates that can be more easily obtained (demographic and comorbidity data). XGboost (gradient-boosted trees) was used for prediction and predictive performance was assessed by cross-validation. Variable importance was quantified by Shapley values (ShapVal), permutation importance (PermImp), and accuracy gain. Shapley dependency and interaction plots were used to evaluate the pattern of relationships between risk factors and outcomes.

Results: A total of 2386 severe and 477 fatal cases were identified. For analyses within infected individuals (n=7846), our prediction model achieved area under the receiving-operating characteristic curve (AUC–ROC) of 0.723 (95% CI 0.711-0.736) and 0.814 (95% CI 0.791-0.838) for severe and fatal infections, respectively. The top 5 contributing factors (sorted by ShapVal) for severity were age, number of drugs taken (cnt_tx), cystatin C (reflecting renal function), waist-to-hip ratio (WHR), and Townsend deprivation index (TDI). For mortality, the top features were age, testosterone, cnt_tx, waist circumference (WC), and red cell distribution width. For analyses involving the whole UKBB population, AUCs for severity and fatality were 0.696 (95% CI 0.684-0.708) and 0.825 (95% CI 0.802-0.848), respectively. The same top 5 risk factors were identified for both outcomes, namely, age, cnt_tx, WC, WHR, and TDI. Apart from the above, age, cystatin C, TDI, and cnt_tx were among the top 10 across all 4 analyses. Other diseases top ranked by ShapVal or PermImp were type 2 diabetes mellitus (T2DM), coronary artery disease, atrial fibrillation, and dementia, among others. For the “lite” models, predictive performances were broadly similar, with estimated

AUCs of 0.716, 0.818, 0.696, and 0.830, respectively. The top ranked variables were similar to above, including age, cnt_tx, WC, sex (male), and T2DM.

Conclusions: We identified numerous baseline clinical risk factors for severe/fatal infection by XGboost. For example, age, central obesity, impaired renal function, multiple comorbidities, and cardiometabolic abnormalities may predispose to poorer outcomes. The prediction models may be useful at a population level to identify those susceptible to developing severe/fatal infections, facilitating targeted prevention strategies. A risk-prediction tool is also available online. Further replications in independent cohorts are required to verify our findings.

(JMIR Public Health Surveill 2021;7(9):e29544) doi:10.2196/29544

KEYWORDS

prediction; COVID-19; risk factors; machine learning; pandemic; biobank; public health; prediction models; medical informatics

Introduction

COVID-19 has resulted in a pandemic affecting more than a hundred countries worldwide [1-3]. More than 177 million confirmed cases and 3.8 million fatalities have been reported worldwide as of June 19, 2021 [4], while a large number of mild or asymptomatic cases may remain undetected. Given the extent of the pandemic, it is urgent to identify risk factors that may be associated with severe disease, and to gain deeper understanding into its pathophysiology. Accurate prediction of those at risk of developing severe diseases is also clinically important.

Machine learning (ML) approaches are powerful tools to predict disease outcomes and have been increasingly applied in biomedical research. In this study we employed boosted trees (with XGboost) to predict disease outcomes and identify risk factors. This ML approach can capture complex and nonlinear interactions between variables, hence leading to better predictive power in many circumstances. In view of the COVID-19 pandemic, many ML models have been developed for diagnostic or prognostic purposes. For instance, Bayat et al [5] developed a prediction model for COVID-19 infection based on 75,991 veteran patients who were tested for the virus. The prediction was based on boosted trees and predictors included vital signs, hematology measurements, and blood biochemistries. Knight et al [6] built a model to predict in-hospital mortality for patients hospitalized with COVID-19, based on demographics, comorbidities, vital signs, and blood test results. A variety of methods including XGboost, generalized additive model, and LASSO were employed. Chung et al [7] employed deep neural networks to predict the severity of COVID-19 infection based on basic patient information, comorbidities, vital signs, clinical symptoms, and complete blood count. Wynants et al [8] performed a systematic review of COVID-19–related prediction models up to July 1, 2020, covering 169 studies describing 232 prediction models. Several recent reviews have also summarized the applications of ML methods in the study of COVID-19 (eg, [8-11]).

Here we made use of the UK Biobank (UKBB) data to build ML models to predict severity and fatality from COVID-19, and evaluated the contributing risk factors. We built prediction models not only for patients infected but also at a general population level. While predictive performance is the main concern in most previous studies, we argue that ML models can also provide important insights into individual contributing factors and the pattern of complex relationships between risk factors and the outcome. While many have studied risk factors of COVID-19 susceptibility or severity in the UKBB [12-14] or other cohorts (eg, [8,15-18]), most relied on conventional linear models. As such, nonlinear effects and interactions between variables may be missed.

We note that in the UKBB clinical data were collected years before the outbreak of infection in 2020, which may be a limitation. Ideally, the predictors should be measured at the time when the model is intended to be applied (eg, at admission). However, we believe that building ML models with previously collected clinical data is useful for reasons detailed below. First, using previously collected clinical features may facilitate the identification of potential causal risk factors. As the predictors are collected prior to the outbreak, there is no concern about reverse causality. In practice, infection itself will lead to changes in many clinical parameters (eg, glucose, inflammatory markers, liver/renal functions); hence, it is often difficult to tell the direction of effect in cross-sectional studies. We hypothesize that this study will identify general or "baseline" risk factors or laboratory measurements that may be (causally) predictive of outcome. Second, the UKBB is a huge population-based sample (N=~500,000), and the rich clinical data collected previously enable ML models to be developed at the general population level. Importantly, there is a relative lack of such population-level ML prediction models to identify who may be at risk of developing severe COVID-19 infections. We hope this study will fill the gap, as this may have implications for prioritizing individuals for specific prevention strategies (eg, vaccination) and diagnostic testing under limited resources.

In this study we performed 4 sets of analysis. In the first 2 sets, we built ML models to predict the severity and mortality of COVID-19 among those who are tested positive for the virus. In this setting, predictive performance is of secondary concern (as predictors were not assessed at or during admission), but the predictive performance can shed light on to what extent *baseline* (prediagnostic) clinical characteristics contribute to severe infections. In the other 2 sets of analysis, we predicted severity and mortality of COVID-19 at the population level, considering individuals not known to be infected as "controls." Our objectives are twofold. The first is to build prediction models for severity and mortality from COVID-19. In addition, we will uncover how different risk factors and their interactions impact on disease severity.

Methods

UK Biobank Data

The UKBB is a large-scale prospective cohort comprising nearly 500,000 individuals aged 40-69 when they were recruited in 2006-2010. Given that the first case of COVID-19 in the UK was recorded on January 31, 2020, individuals with recorded mortality before January 31, 2020 (28,931 out of 502,524 individuals) were excluded. We also excluded from subsequent analyses a very small number of individuals (n=19) whose cause of mortality was COVID-19 (ICD code U07.1) but with negative test result(s) within 1 week. The current age of individuals included in our analyses ranged from 50 to 87 years, with 50.77% (255,170/502,524) being older than 70. This analysis was conducted under the project number 28732. For details of the UKBB data, please also refer to Sudlow et al [19].

COVID-19 Phenotypes

COVID-19 outcome data were downloaded from data portal provided by the UKBB. Details of data release are provided in [20]. Briefly, the latest COVID test results were extracted on December 30, 2020 (last update on December 14, 2020). The data set also included an indicator on whether the patient was an inpatient when the specimen was taken. We consider inpatient (hospitalization) status as a proxy for severity, as more sophisticated indicators of severity cannot be reliably derived yet. We noted that only 10.22% (468,235/4,581,006 infected cases, from [21] as of June 16, 2021) of patients were admitted in the UK; as such, it is likely that only the more severe cases were hospitalized. Hospitalization has also been considered as an outcome measure in many studies, including those of vaccination effectiveness [22-25], risk prediction [26,27], and genetic/clinical risk factors [28,29] underlying severe COVID-19.

In general, we required both test result and origin to be 1 (indicating positive test and inpatient origin, respectively) to qualify as an "inpatient" case. For a small number of individuals with inpatient origin=0 and result=1, but changed to origin=1 with result=0 within 2 weeks' time (based on the fact that median duration of viral persistence is nearly 2 weeks [30]), we still considered those as inpatient cases (ie, assume the hospitalization was related to the infection). All other patients with at least one positive SARS-CoV-2 test result were considered as "outpatient."

Data on mortality and cause of mortality were also extracted (with latest update on December 14, 2020). Individuals with recorded cause of mortality as "U07.1" were considered as having a fatal infection with laboratory-confirmed COVID-19 (please also refer to [31]). We defined a case as "severe COVID-19" if the individual is an inpatient or if the cause of mortality is U07.1.

Sets of Analysis

Four sets of analysis were performed. The first 2 sets were restricted to test-positive cases (n=7846). "Severe COVID-19" (n=2386) and death (n=477) due to COVID-19 were treated as outcomes. Because only prediagnostic clinical data were available, the main objective of this analysis was to identify baseline risk factors for severe/fatal illness among the infected. We then performed another 2 sets of analysis with the same outcomes, but the "unaffected" group was composed of the general population (n=465,728) that did not have a diagnosis of COVID-19 or were tested negative. The 4 sets of analysis were also referred to as cohorts A-D as shown in Table 1. We also constructed gender-specific prediction models.

Table 1. The four sets of analysis performed and predictive performances (full model and lite model).

Cohort	Group 1	Group 2	n (group 1)	n (group 2)	Area under the curve[a] (%)		95% CI (%)	
					Full	Lite	Full	Lite
A	Hospitalized or fatal cases	Nonhospitalized cases	2386	5460	72.3	71.6	71.1-73.6	70.3-72.9
B	Fatal cases	All other COVID-19 cases	477	7369	81.4	81.8	79.1-83.8	79.4-84.2
C	Hospitalized or fatal cases	UK Biobank patients without a COVID-19 diagnosis or tested negative	2386	465,728	69.6	69.6	68.4-70.8	68.4-70.7
D	Fatal cases	UK Biobank patients without a COVID-19 diagnosis or tested negative	477	465,728	82.5	83.0	80.2-84.8	80.8-85.3

[a]AUC was taken from the average of 5 folds of cross-validation.

Variables Included in Analysis

We extracted a total of 97 clinical variables of potential relevance based on the literature. For details, please refer to Table S1d in Multimedia Appendix 1 and the references therein. The prediction model using all 97 variables will be referred to as the "full" model, as opposed to a simplified model ("lite" model; see below) based on mainly demographic data and medical history that can be more readily obtained. Among the 97 variables, 21 were categorical and 76 were quantitative traits. The missing rates of variables were all below 20% (ranging from 0.0% to 19.9% for the 97 variables). We included a wide range of clinical features here, with an objective to uncover potential novel risk factors for the disease. The ML model we employed (XGboost) tends to have a low bias and high variance; however, with proper tuning of hyperparameters and regularization, overfitting can be largely avoided even when a large number of predictors are included [32].

The full list of variables is shown in Table S1b in Multimedia Appendix 1. Briefly, we included basic demographic variables (eg, age, sex, ethnic group, socioeconomic status as indicated

by the Townsend deprivation index [TDI]), comorbidities (eg, heart diseases, type 1 and 2 diabetes mellitus [T1DM/T2DM], hypertension [HT], asthma/chronic obstructive pulmonary disease [COPD], cancer, dementia, and psychiatric disorders), indicators of general health (number of medications taken [cnt_tx], number of illnesses, etc.), blood measurements (hematology, liver and renal function measures, metabolic parameters such as lipid levels, HbA1c), anthropometric measures (eg, waist circumference [WC], waist-to-hip ratio [WHR], body mass index), and lifestyle risk factors (eg, smoking, drinking habits). Disease traits were defined based on ICD-10 diagnoses (UKBB data-field 41270), self-reported illnesses (UKBB data-field 20002), and data from follow-ups. Individuals with no records of the relevant disease from either self-reports or ICD-10 diagnoses were regarded as having no history of the disease.

Imputation

Missing values of remaining features were imputed with the R package missRanger (R Foundation). The program is based on missForest [33], which is an iterative imputation approach based on random forest. It has been widely used and has been shown to produce low imputation errors and good performance in predictive models [34]. The main difference between missRanger and missForest is that the former uses the R package "ranger" to build random forests, which can lead to a large improvement in speed. Predictive mean matching (pmm) was also employed to avoid imputation with values not present in the original data. We employed the default parameters (pmm.k=3, num.trees=100) and default settings of ranger. Out-of-bag errors (in terms of classification errors or normalized root-mean-squared error) were computed which provides a guide to imputation accuracy.

We have also attempted to use multiple imputation by chained equation (MICE) for imputation. For our data set with nearly 500,000 individuals, MICE stopped after running for 6 hours due to memory overflow error (>64 GB), whereas missRanger finished the imputation within 3 hours successfully. We considered the computational burden of MICE as too high and therefore employed missRanger in our analyses.

Several studies have compared MissForest with MICE, and there are several advantages of missForest. For categorical variables, imputation accuracy of missForest is likely to be higher than that of MICE [35]. MissForest also runs considerably faster than MICE and is especially suitable for imputation settings where complex interactions and nonlinear relationships are likely [33]. Stekhoven et al [33] reported superior performance of missForest compared with MICE, with reduction in the proportion of falsely classified entries of up to 60%. In another comparison study, missForest and MICE performed similarly but it was reported that highly correlated variables may lead to significant problems with MICE [36].

XGboost Prediction Model

XGboost with gradient-boosted trees was employed for building prediction models. Analysis was performed by the R package "xgboost." We employed a fivefold nested cross-validation strategy to develop and test the model. To avoid overoptimistic results due to choosing the best set of hyperparameters based on test performance, the test sets were *not* involved in hyperparameter tuning.

In each iteration, we divided the data into 5 folds, among which one-fifth was reserved for testing only. For the remaining four-fifth of the data, we further sampled four-fifth for training and one-fifth for hyperparameter tuning. The best prediction model was applied to the test set. The process was repeated 5 times. A grid-search procedure was used to search for the best combination of hyperparameters (eg, tree depth, learning rate, regularization parameters for L1/L2 penalty). The full range of hyperparameters chosen for grid search is given in Table S6 in Multimedia Appendix 1.

Building a Simplified "Lite" Model

The "full" model described above covers a wide range of predictors but some features (such as blood biochemistries) may not be readily accessible. For easier implementation in practice, we also built a simplified prediction model (also referred to as the "lite" model) based on a reduced set of 27 predictors. The reduced set of variables were chosen based on the ease of being assessed or measured, which included comorbidities (see above), anthropometric measures (BMI, weight, WC), demographic variables (eg, age, sex, ethnic group), and general indicators of health (number of medications taken, number of illnesses).

Evaluating Predictive Performance and Calibration

To evaluate the predictive performance of the prediction models, we computed the area under the receiving-operating characteristic curve (AUC–ROC), which is very widely used in clinical prediction studies. We also calculated other measures including the area under the precision–recall curve (AUC–PRC), F1 score, accuracy, and Matthews correlation coefficient (MCC). The cutoff of predicted probability for calculating the latter 3 measures was determined by optimizing the geometric mean of sensitivity and specificity.

In addition to good ability to discriminate cases from noncases, it is also important that the predicted event probabilities match with the observed probabilities (also known as calibration of a model). We assessed calibration by several measures, including the Hosmer–Lemeshow test, expected calibration error (ECE), and maximum calibration error (MCE) [37-40] across 10 equally sized bins by discretizing the predicted probabilities. We also attempted 3 approaches to further improve calibration, including Platt scaling, isotonic regression, and beta calibration [41-44]. The objective is to rescale the predicted probabilities such that they are closer to the actual probabilities of the outcome [45].

Identifying and Quantifying the Effects of Important Predictors

In this work we primarily employed Shapley value (ShapVal) [46,47] to assess variable importance, which is a measure based on game theory to assess the contribution of each feature. ShapVal has been shown to represent a consistent and locally accurate contribution of each feature [48]. ShapVal enables local explanation of the model as it could be computed for each observation, but can also provide global importance measures.

By contrast, gain and split count may produce inconsistent estimates of global importance as shown by Lundberg et al [48].

Intuitively, the ShapVal of the *i*th feature (for individual *k*) is the contribution of this feature to the prediction of outcome for the individual, averaging over all possible orderings of the features (as the contribution may differ when variables enter the prediction algorithm in different orders). We ranked the global importance of features based on mean absolute ShapVal as described in previous studies [46,47]. We also attempted an alternative approach similar to "permutation importance" proposed in [49]. This method involves permuting the outcome vector to model the distribution of ShapVal under the null, and comparing the null ShapVals with the observed ShapVal. We derived a *P* value from permutation as an alternative indicator of feature importance. A total of 500 permutations were performed for each model. To verify the validity of the permutation procedure especially under imbalanced case–control data, we also carried out a small-scale simulation study. A data set with 50,000 individuals and 10 covariates (x_1, x_2, ..., x_{10}) were generated, where the first covariate x_1 was linearly correlated with the outcome. The control-to-case ratio was set at 976:1, same as that for cohort D. Type I error and power were assessed by repeating the entire permutation procedure for 100 randomly generated data sets (please see Multimedia Appendix 2 for details).

A related index is the Shapley *interaction* value [47], which computes the difference in Shapley value of feature *i* with and without another feature *j*. ShapVal were averaged across 5 folds. Besides, we included the "gain" measure for reference, which is the reduction of loss or impurity contributed by all splits by a specific variable.

An advantage of Shapley value is that it is calculated for each individual, so how each risk factor affects a specific person's risk of infection/severity can be estimated as well. To illustrate this concept, we also produced decision plots for individuals at the highest, median, and lowest risk of each cohort.

Cluster Analysis Based on Shapley Value

We also performed cluster analysis based on ShapVal to identify subgroup of patients who share similar clinical risk factors with respect to severity of infection. As introduced in [48], this approach may be considered a form of "supervised" clustering, as the outcome (severe/fatal disease) is also taken into account in the clustering process. Unlike a traditional clustering approach based on risk factors, this approach has important advantages. First, the clusters derived may be more clinically relevant as the *outcome* is also considered, reducing the chance that irrelevant features contribute to the subgrouping (an irrelevant feature will have relatively small variations in ShapVal and will not contribute substantially to clustering). Second, this approach essentially considers all features on the same "scale," as ShapVal is computed with respect to the outcome. Input features are often of different units and scales, but ShapVal considers feature contributions to the outcome as the unit of measure. Because of computational cost concerns, here we only performed clustering on cohorts A (nonsevere vs severe infection) and B (fatal vs nonfatal infection).

K-Means Sparse Clustering

Here we performed k-means sparse clustering to uncover underlying patient subgroups based on ShapVal of risk factors. As the number of features included is large but not all may contribute to the underlying subgroups, we employed *sparse* clustering which incorporates feature selection in the clustering process. The R package "sparcl" was employed. To perform sparse k-means clustering, we need to predetermine the number of clusters and tuning parameter (L1 penalty) for feature selection [50]. The optimal number of clusters was assumed to be the same as that in k-means clustering, which was determined by the silhouette index. The tuning parameter (L1 bound) was set to range between 2 and 6 with an interval of 0.4. Then the gap statistic [51] was used to determine the optimal tuning parameter.

Results

An overview of the sample sizes in each set of analysis is presented in Table 1. Please also refer to Table S1a and S1b in Multimedia Appendix 1 for a detailed summary of case counts and covariates.

Simulation Results for the Permutation Testing Approach

Simulation results for the validity of permutation *P* values are presented in Table S8 in Multimedia Appendix 1. We observed no inflation of type I error (false-positive rate) despite the imbalanced case-to-control ratio. At a *P* value threshold of 0.05, the proportion of results with $P<.05$ for x_2 to x_{10} (variables with null effect) remained less than 0.05 for different effect sizes of the predictor (please also refer to Multimedia Appendix 2).

Prediction Performance of the XGboost Model for Risk and Severity of Infection

AUC–ROC and Other Results

We performed 5-fold cross-validation and the average AUC under the ROC curve is given in Table 1 and Table S2a in Multimedia Appendix 1. Here we describe the results for the full models first. We observed better predictive performances in cohorts B (fatal cases vs outpatient cases) and D (fatal cases vs population with no known infection), where fatalities from COVID-19 were modeled. The corresponding mean AUC–ROC values were 0.814 (95% CI 0.791-0.838) and 0.825 (95% CI 0.802-0.848), respectively. The mean AUC–ROC for cohort A (hospitalized/fatal cases vs other cases) was 0.723 (95% CI 0.711-0.736) and that for cohort C (hospitalized/fatal cases vs population with no known infection) was 0.696 (95% CI 0.684-0.708).

As for the "lite" models which included a reduced set of predictors, the predictive performances in terms of AUC are broadly similar, with estimated AUC–ROC for cohorts A-D of 0.716, 0.818, 0.696, and 0.830, respectively.

The results of other predictive indices are listed in Table S2b in Multimedia Appendix 1. Estimates of AUC–PRC were the highest for cohorts A and B (0.535 and 0.171, respectively) and much lower for cohorts C and D (0.007 and 0.006, respectively).

This is expected due to the much higher prevalence of outcome in the first 2 cohorts. AUC–PRC may be approximated by the average precision (please refer to [52] for further details).

We also conducted sex-stratified analysis (Table S2a in Multimedia Appendix 1). The resulting AUC–ROC was similar to the overall analysis in males (except for cohort D), but generally lower in females. This may be partially explained by lower number of severe and fatal cases in females, which leads to greater difficulty in model training.

Proportion of Cases Explained by Individuals at the Top k% of Predicted Risk

We also computed the proportion of cases explained by individuals at the highest *k*% of predicted risks (Table 2). For example, considering the full model, for prediction of mortality among infected individuals (cohort B), individuals at the highest 5%, 10%, and 20% of predicted risks explain 17.4% (83/477), 32.7% (156/477), and 52.0% (248/477) of total fatalities, respectively. As for prediction in the population (cohort D), individuals at the highest 5%, 10%, and 20% of predicted risks explain 32.5% (155/477), 45.7% (218/477), and 63.5% (303/477) of total fatalities, respectively. For prediction of severe disease among the infected (cohort A), individuals at the highest 5%, 10%, and 20% of predicted risks explain 11.2% (267/2386), 21.6% (515/2386), and 38.2% (911/2386) of total cases, respectively, while more than half (1272/2386, 53.3%) of cases are explained by people at the top 30% of predicted risks. For prediction of severe cases in the population (cohort C), the corresponding figures were 19.7% (470/2386), 29.3% (700/2386), and 42.7% (1019/2386), respectively, and more than half (1260/2386, 52.8%) of cases are explained by people at the top 30% of predicted risks. Similar figures were observed for full and lite models in general.

These results showed in general a strong enrichment of cases among those predicted to have high risks, indicating good model discriminatory ability.

Table 2. Relative risk (RR) comparing subjects in the top and bottom k% of predicted risks and proportion of cases explained by those at top k% of predicted risk.

Full model					Lite model			
k	Risk in top k%[a,b]	Risk in bottom k%	RR	Proportion of cases explained by top k%	Risk in top k%[a,b]	Risk in bottom k%	RR	Proportion of cases explained by top k%
Cohort A								
5	0.676	0.148	4.56	0.112	0.691	0.158	4.37	0.113
10	0.654	0.138	4.74	0.216	0.644	0.157	4.10	0.211
20	0.579	0.145	4.00	0.382	0.581	0.153	3.79	0.381
30	0.540	0.148	3.65	0.533	0.533	0.152	3.50	0.526
40	0.489	0.152	3.20	0.644	0.479	0.158	3.03	0.630
50	0.443	0.166	2.67	0.730	0.439	0.170	2.59	0.720
Cohort B								
5	0.214	0.000	Infinity	0.174	0.212	0.003	84.27	0.174
10	0.200	0.001	158.20	0.327	0.216	0.008	28.38	0.352
20	0.171	0.008	22.42	0.562	0.188	0.008	24.59	0.618
30	0.148	0.009	16.57	0.727	0.155	0.008	19.21	0.763
40	0.127	0.009	14.21	0.830	0.131	0.009	14.23	0.866
50	0.111	0.010	10.94	0.916	0.111	0.011	10.37	0.912
Cohort C								
5	0.0201	0.0017	11.76	0.197	0.0210	0.0013	15.88	0.207
10	0.0149	0.0021	6.98	0.293	0.0158	0.0012	12.95	0.310
20	0.0109	0.0023	4.67	0.427	0.0118	0.0021	5.71	0.462
30	0.0090	0.0030	2.99	0.528	0.0097	0.0027	3.57	0.573
40	0.0075	0.0033	2.27	0.590	0.0084	0.0026	3.20	0.656
50	0.0069	0.0033	2.09	0.678	0.0074	0.0028	2.63	0.725
Cohort D								
5	0.0067	0.00000	Infinity	0.325	0.0068	0.00000	Infinity	0.333
10	0.0047	0.00002	218.02	0.457	0.0047	0.00006	73.67	0.463
20	0.0033	0.00011	30.30	0.635	0.0032	0.00009	36.75	0.616
30	0.0026	0.00014	18.74	0.746	0.0027	0.00011	23.38	0.784
40	0.0021	0.00016	13.17	0.828	0.0022	0.00013	16.68	0.874
50	0.0018	0.00022	8.35	0.893	0.0019	0.00015	13.03	0.929

[a]'Top k%' refers to top k% of *predicted* probability of outcome by XGboost.

[b]'Risk in top k%' refers to the actual probability of the outcome (severe disease or fatality) within the patients belonging to the highest k% of predicted risks.

Relative Risk of Actual Outcome Probabilities, Comparing Those at the Highest and Lowest k% of Predicted Risks

We also computed the relative risk (RR) of infection or severe disease by comparing individuals at the highest and lowest *k*% of predicted risks (Table 2). For example, considering the full model, if we compare the actual probability of outcome at the top decile (top 10%) against those at the bottom decile of predicted risks, the RR was 4.74, 158.2, 6.98, and 218.02, respectively, for cohorts A to D. If we compare the top 20% against the lowest 20% of predicted risks, the corresponding RRs were 4.00, 22.42, 4.67, and 30.30. The RRs for the lite model were similar for cohorts A and C, but were smaller for cohorts B and D when the comparison was made at the more extreme ends of predicted risks.

We observed large RRs for cohorts B and D, suggesting that the prediction models were able to discriminate individuals at the highest and lowest risks of fatality very well. RRs for cohorts B and D were much larger than those for cohorts A and C,

indicating that the model predicted fatality better than severe disease.

Calibration

As for calibration, please refer to Figures S6 and S7 in Multimedia Appendix 3. For full models, cohort A was well-calibrated (without using other methods for recalibration) with ECE of 0.022 and MCE of 0.044 only. For other models, the ECE and MCE were generally larger, probably due to large difficulty in calibration with a much lower probability of the outcome. The best ECEs (after recalibration by 1 of the 3 methods) were 0.11, 0.14, and 0.02, respectively, for cohorts B-D. The Hosmer–Lemeshow test was nonsignificant in cohorts C and D (P=.99 and .98, respectively). For the "lite" models, the best ECEs were 0.017, 0.043, 0.024, and 0.089, respectively, for cohorts A-D, with nonsignificant Hosmer–Lemeshow test results except for cohort B (Hosmer–Lemeshow P=.49, .003, .97, and .41 for cohorts A-D, respectively).

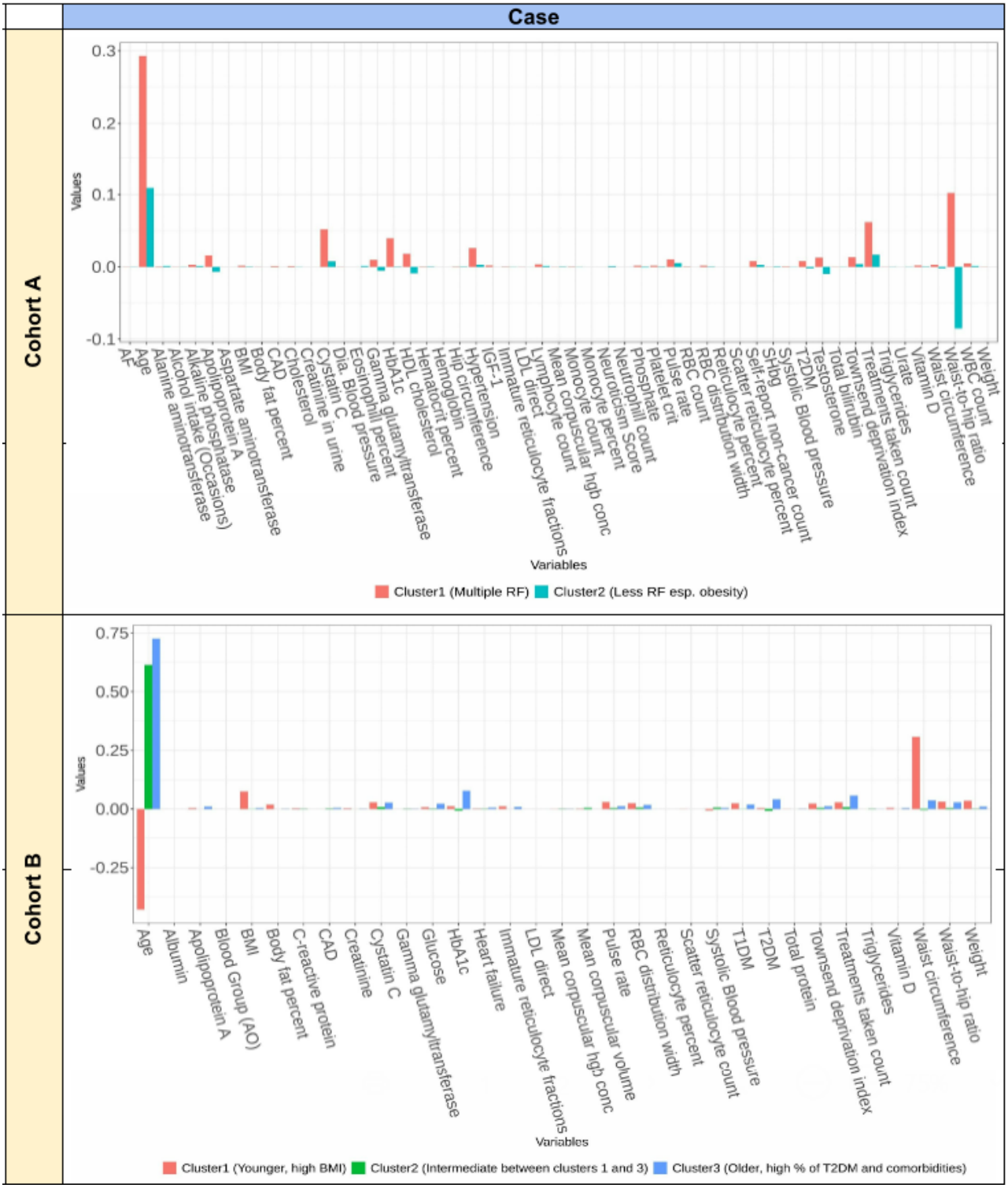
Results From Cluster Analysis Based on ShapVal

Figures 1 and S11 in Multimedia Appendix 3 show the results based on sparse k-means clustering. We performed clustering separately in cases and controls to uncover patient subgroups with different clinical background. Here we focus on clustering results within cases. As the number of variables is large, we only showed the variables that were statistically significant (P<.05 from t test or ANOVA) across the clusters in the figures.

For cohort A, we found 2 clusters as the optimal solution. The first cluster has higher ShapVal for most risk factors, especially age, but also cnt_tx, HbA1c, cystatin C, high-density lipoprotein (HDL)-cholesterol, and HT. ShapVal for WHR was positive for the first group but negative for the second group. The first cluster may represent a subgroup of severe cases with a larger number of clinical risk factors/comorbidities and advanced age, while the second cluster may be a distinct group with less conventional risk factors (especially obesity), yet is susceptible to severe infections perhaps due to other (unmeasured) factors, such as genetics.

Considering cohort B cases (fatal infections), the optimal solution comprised 3 clusters. Interestingly, the first and third clusters seemed to be markedly different with respect to their risk factor profiles. Mean ShapVal for age was largely negative for the first cluster but highly positive for the other 2 clusters. By contrast, mean ShapVal for WC was markedly higher and positive for the first cluster. The third cluster was characterized by the highest mean ShapVal for age, and higher (positive) ShapVal for mainly cnt_tx, HbA1c, and T2DM. The results suggest that there may exist pathophysiologically distinct subgroups of patients with fatal infection. The first cluster represents a subgroup with younger age but with higher proportion of obesity. The third cluster represents another subgroup with advanced age, more comorbidities, and higher proportion of glucose abnormalities or T2DM. The second cluster is in between.

Figure 1. Results of sparse k-means clustering based on Shapley values (ShapVal) in cohorts A (hospitalized cases) and B (fatal cases). The y-axis indicates the ShapVal and only those risk Factors with significant differences (P<.05 in t-test or ANOVA) across clusters were shown on the x-axis. AF: atrial fibrillation; CAD: coronary artery disease; Hb: hemoglobin; HbA1c: hemoglobin A1c; HDL: high-density lipoprotein; LDL: low-density lipoprotein; RBC: red blood cell; RF: risk factor; SHBG: sex hormone binding globulin; T1DM: type 1 diabetes; T2DM: type 2 diabetes.



Important Contributing Variables Identified

Overview

Here we primarily report the results of the full model as a more complete set of predictors is included. The Shapley dependence plots (ranked by mean absolute ShapVal) of the top 15 features (full model) are shown in Figure 2 and those of the top 6 features for the lite model are presented in Figure 3. For more complete plots (up to 30 variables) with ranking by mean abs(ShapVal) or permutation P values, please refer to Figures S1-S4 in Multimedia Appendix 3.

Full ShapVal analysis results on all variables are given in Tables S3a-c in Multimedia Appendix 1. The top 10 variables (ranked by either ShapVal or permutation P value) from the full model

are presented in Tables 3 and 4 while the top 5 from the lite model are presented in Tables 5 and 6. We also included variable importance by gain, and plots are presented in Figure S5a and S5b in Multimedia Appendix 3.

Figure 2. Shapley value dependence plots of the top 15 risk factors ranked by mean abs(shapley value) (full model) for cohorts A, B, C, and D, respectively. Shapley value (y-axis) is computed on a log-odds scale. Every unit increase of ShapVal corresponds to an odds ratio (OR) of exp(1)=2.72 compared with the baseline. Positive ShapVal indicates increase in the odds of the outcome and vice versa. CAD: coronary artery disease; COPD: chronic obstructive pulmonary disease; HDL: high-density lipoprotein; RBC: red blood cell; T2DM: type 2 diabetes mellitus.

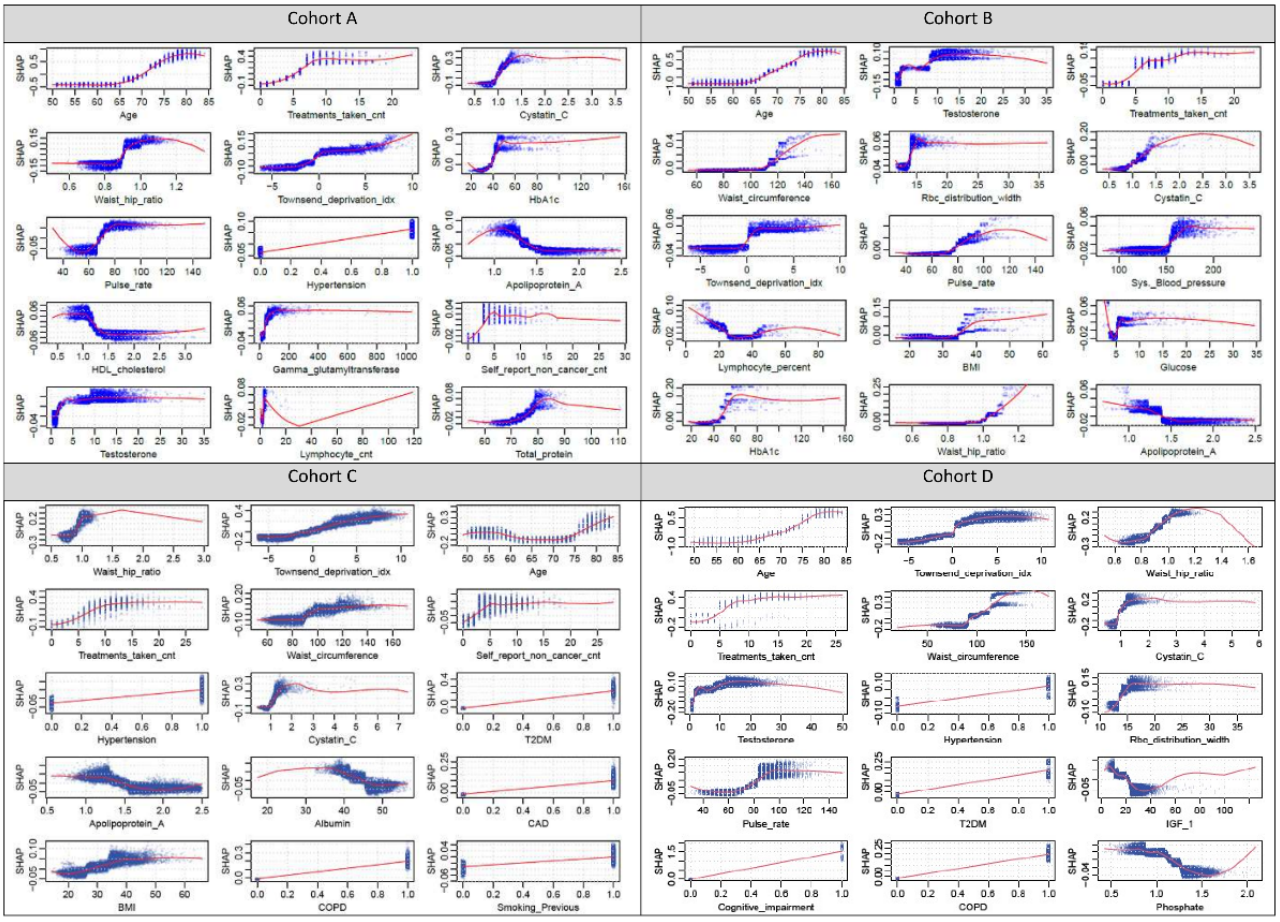


Figure 3. ShapVal dependence plots of the top 6 risk factors ranked by mean abs(shapley value) (lite model) for cohorts A, B, C, and D, respectively. T2DM: type 2 diabetes mellitus.

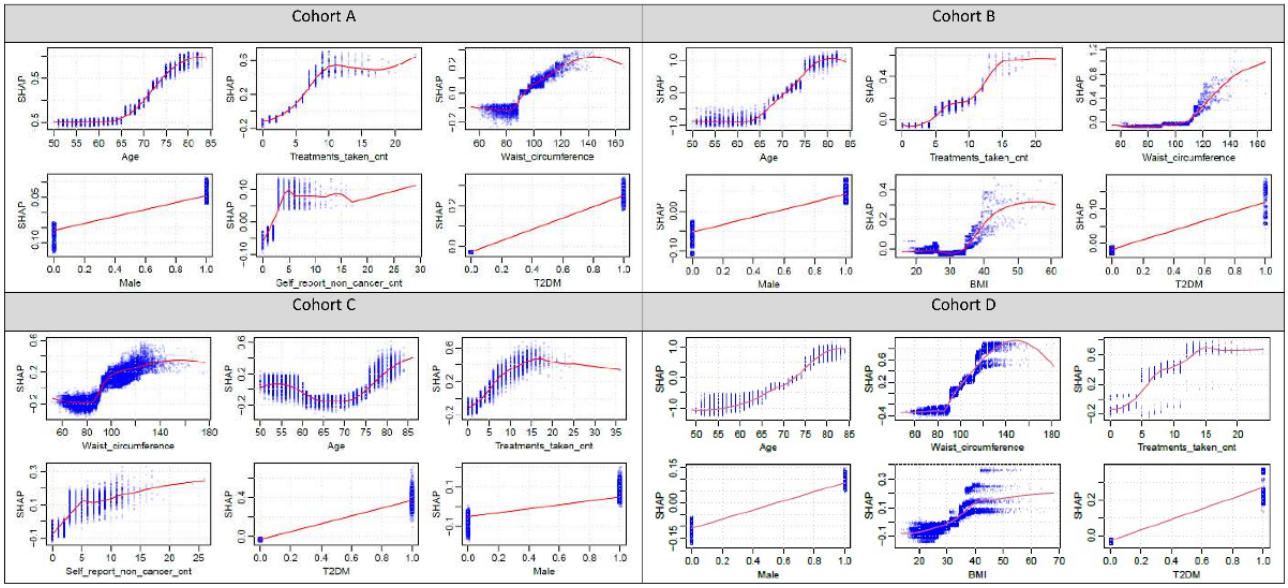


Table 3. Top 10 risk factors ranked by mean absolute Shapley value for cohorts A, B, C, and D (full model).

Risk factor	ShapVal	*P* value
Cohort A		
Age	0.442	.002
Treatments taken count	0.093	.002
Cystatin C	0.088	.002
Waist-to-hip ratio	0.085	.002
Townsend deprivation index	0.059	.004
HbA1c[a]	0.056	.002
Pulse rate	0.048	.002
Hypertension	0.048	.002
Apolipoprotein A	0.027	.016
HDL[b] cholesterol	0.026	.016
Cohort B		
Age	0.708	.002
Testosterone	0.069	.002
Treatments taken count	0.048	.002
Waist circumference	0.035	.002
RBC[c] distribution width	0.027	.002
Cystatin C	0.024	.002
Townsend deprivation index	0.023	.002
Pulse rate	0.019	.004
Systolic blood pressure	0.016	.002
Lymphocyte percentage	0.015	.004
Cohort C		
Waist-to-hip ratio	0.113	.002
Townsend deprivation index	0.096	.002
Age	0.088	.002
Treatments taken count	0.063	.002
Waist circumference	0.044	.002
Self-report: noncancer count	0.043	.002
Hypertension	0.036	.002
Cystatin C	0.030	.024
T2DM	0.030	.002
Apolipoprotein A	0.024	.052
Cohort D		
Age	0.519	.002
Townsend deprivation index	0.136	.002
Waist-to-hip ratio	0.131	.002
Treatments taken count	0.115	.002
Waist circumference	0.110	.002
Cystatin C	0.096	.002
Testosterone	0.086	.002

Risk factor	ShapVal	*P* value
Hypertension	0.061	.002
RBC distribution width	0.046	.002
Pulse rate	0.036	.006

[a]HbA1c: hemoglobin A1c.

[b]HDL: high-density lipoprotein.

[c]RBC: red blood cell.

[d]T2DM: type 2 diabetes mellitus.

Table 4. Top 10 risk factors ranked by P-value, listing only factors which are not yet included in for cohorts A, B, C, and D (full model).

Risk factor	*P* value	ShapVal
Cohort A		
T2DM[a]	.004	0.010
Self-report: noncancer	.008	0.018
Depression	.008	0.004
CAD[b]	.016	0.002
Cancer diagnosed by doctor	.026	0.000
Alcohol intake (occasions)	.028	0.002
AF[c]	.028	0.000
Smoking (current)	.036	0.000
γ-glutamyltransferase	.046	0.021
WBC[d] count	.046	0.014
Cohort B		
BMI	.002	0.015
Glucose	.002	0.015
HbA1c[e]	.002	0.014
Weight	.002	0.010
Mean platelet volume	.002	0.009
T2DM	.002	0.007
Sleep duration	.002	0.006
T1DM[f]	.002	0.003
Cognitive impairment	.002	0.003
CAD	.002	0.003
Cohort C		
COPD[g]	.002	0.015
Depression	.002	0.009
Cognitive impairment	.002	0.007
CAD	.004	0.017
Ethnic (Asian/Asian British)	.004	0.007
Heart failure	.004	0.007
AF	.004	0.006
Smoking (previous)	.006	0.015
Stroke	.012	0.001
Ethnic (Black/Black British)	.020	0.001
Cohort D		
T2DM	.002	0.026
Cognitive impairment	.002	0.024
COPD	.002	0.021
AF	.002	0.016
Heart failure	.002	0.007
CAD	.002	0.008
Ethnic (Black/Black British)	.004	0.004

Risk factor	*P* value	ShapVal
Stroke	.004	0.002
Alcohol drinker (current)	.004	0.001
Smoking (previous)	.006	0.003

[a]T2DM: type 2 diabetes mellitus.
[b]CAD: coronary artery disease.
[c]AF: atrial fibrillation.
[d]WBC: white blood cell.
[e]HbA1c: hemoglobin A1c.
[f]T1DM: type 1 diabetes mellitus.
[g]COPD: chronic obstructive pulmonary disease.

Table 5. Top 5 risk factors ranked by mean absolute Shapley value for cohorts A, B, C, and D (lite model).

Risk factor	ShapVal	*P* value
Cohort A		
Age	0.496	.002
Treatments taken count	0.121	.002
Waist circumference	0.085	.002
Male	0.058	.002
Self-report: noncancer count	0.054	.004
Cohort B		
Age	0.721	.002
Treatments taken count	0.079	.014
Waist circumference	0.071	.040
Male	0.048	.010
BMI	0.034	.242
Cohort C		
Waist circumference	0.153	.002
Age	0.120	.002
Treatments taken count	0.102	.002
Self-report: noncancer count	0.064	.002
T2DM[a]	0.050	.002
Cohort D		
Age	0.056	.002
Waist circumference	0.248	.002
Treatments taken count	0.154	.002
Male	0.098	.002
BMI	0.043	.036

[a]T2DM: type 2 diabetes mellitus.

Table 6. Top 5 risk factors ranked by *P* value, listing only factors which are not yet included in for cohorts A, B, C, and D (lite model).

Risk factor	*P* value	ShapVal
Cohort A		
T2DM[a]	.002	0.047
Smoking (current)	.004	0.026
Depression	.016	0.015
Alcohol drinker (current)	.020	0.013
CAD[b]	.022	0.010
Cohort B		
T2DM	.006	0.027
Cognitive impairment	.006	0.015
T1DM[c]	.020	0.009
Bipolar	.024	0.006
AF[d]	.036	0.011
Cohort C		
COPD[e]	.002	0.024
Ethnic (Asian/British Asian)	.002	0.016
Cognitive impairment	.002	0.008
Male	.004	0.049
CAD	.004	0.023
Cohort D		
T2DM	.002	0.043
COPD	.002	0.039
Cognitive impairment	.002	0.029
AF	.002	0.024
Ethnic (Black/Black British)	.002	0.016

[a]T2DM: type 2 diabetes mellitus.

[b]CAD: coronary artery disease.

[c]T1DM: type 1 diabetes mellitus.

[d]AF: atrial fibrillation.

[e]COPD: chronic obstructive pulmonary disease.

As for interaction analyses, top results are presented in Table 7 and full results in Tables S4 and S5 in Multimedia Appendix 1. Plots are presented in Figure 4 (top 2 interacting pairs from each model) and Figures S8 and S9 in Multimedia Appendix 3 (top 6 interacting pairs).

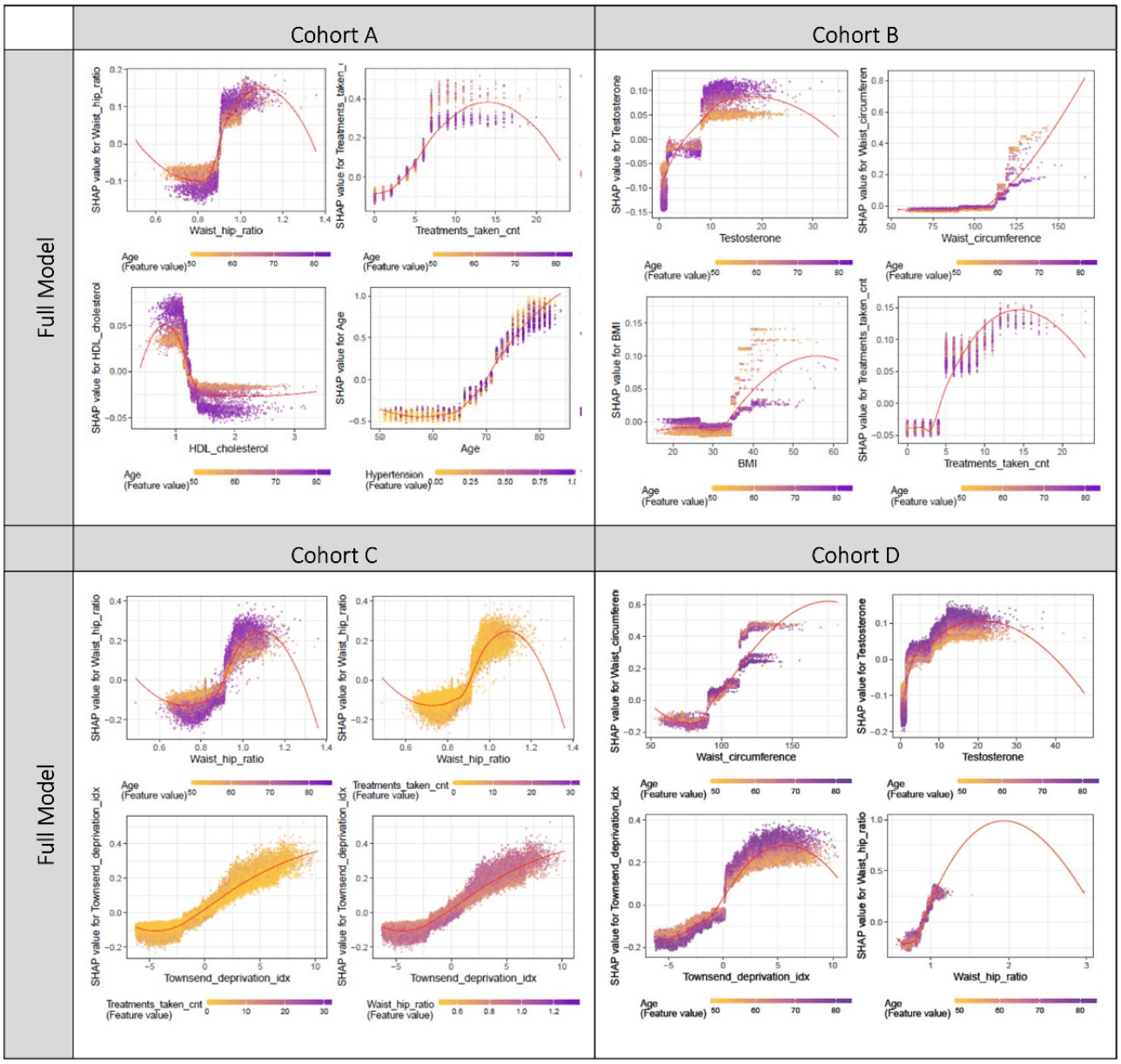
Note that ShapVal is measured on the log-odds scale. Every unit increase of ShapVal corresponds to an odds ratio of exp(1)=2.72. Positive ShapVal indicates increase in the odds of outcome and vice versa.

Table 7. Top interacting pairs of variables ranked by ShapVal (full model).

Risk factor 1	Risk factor 2	Value
Cohort A		
Waist-to-hip ratio	Age	150
Treatments taken count	Age	149
HDL[a] cholesterol	Age	86
Age	Hypertension	85
Cystatin C	Age	84
Cohort B		
Testosterone	Age	195
Waist circumference	Age	95
BMI	Age	82
Treatments taken count	Age	63
Pulse rate	Age	57
Cohort C		
Waist-to-hip ratio	Age	709
Waist-to-hip ratio	Treatments taken count	494
Townsend deprivation index	Treatments taken count	481
Townsend deprivation index	Waist-to-hip ratio	450
Albumin	Waist-to-hip ratio	407
Cohort D		
Waist circumference	Age	859
Testosterone	Age	780
Townsend deprivation index	Age	725
Waist-to-hip ratio	Age	603
Age	Hypertension	585

[a]HDL: high-density lipoprotein.

Figure 4. ShapVal interaction plots of the full model for the top 4 interacting pairs of cohorts A, B, C, and D, respectively.



Cohort A (Hospitalized/Fatal Cases vs Outpatient Cases)

The top 5 contributing features by ShapVal included age, number of medications received (cnt_tx), cystatin C, TDI, and WHR, followed by HbA1c. Higher levels of these risk factors generally lead to higher disease severity among the infected. Interestingly, Shapley dependence plots revealed potential *nonlinear* and "threshold" effects of risk factors on the outcome. For example, age of 65 or above was associated with a markedly increased risk of severe/fatal infection. Markedly elevated risks were also observed for HbA1c levels over 40 mmol/mol and 5 or more drugs received. Impaired renal function (IRF; raised cystatin C >1 mg/L) was also linked to worse outcomes. For WHR, levels of 0.9 or higher appeared to be associated with a marked increase in risks. For other features, please refer to Figure 2. We note that at the extreme ends of variables, the observations are often sparse, so the trend shown by the Loess curve may not be reliable (this also applies to other cohorts). Variable importance based on gain revealed similar patterns of important features (Figures S5a and S5b in Multimedia Appendix 3).

If we consider the "*P* value" or permutation importance (PermImp) measure, variables with top 10 (absolute) ShapVal also showed significant *P* values ($P<.05$ for all cases). T2DM was among the top 10 by PermImp but not by ShapVal. Depression and coronary artery disease (CAD) also showed low *P* values ($P<.02$), but were not listed among the top 30 by ShapVal.

Regarding interactions between variables, most of the top interacting pairs involved age (Figure 4 and Tables S4 and S5 in Multimedia Appendix 1). For example, younger individuals were observed to have more extreme ShapVal at similar ranges of cnt_tx. The effect of WHR on severity was more marked among the elderly, and the same was true for HDL-cholesterol (low HDL is a risk factor).

Model B (Fatal Cases vs Outpatient Cases)

The top 5 contributing variables by ShapVal included age, testosterone (which may reflect the effect of gender), cnt_tx, WC, and red blood cell distribution width (RDW), which were followed by cystatin C, TDI, pulse rate, systolic blood pressure (SBP), and percentage of lymphocytes. Again, certain nonlinear and "threshold" effects appeared to be present for many top-ranked features. For age, the risk for mortality was more marked beyond 65 years. Higher levels of all the above risk factors (RFs) (except percentage of lymphocytes, which showed a U-shaped relationship) were associated with higher mortality, but the effects were nonlinear. Regarding the top results based on PermImp, 8 out of 10 predictors ranked high by ShapVal also had the lowest *P* values (lowest *P* value of .002 since we performed 500 permutations). Other top-ranked features (*P*=.002) included HbA1c, type 1 and T2DM, weight, mean platelet volume, etc.

Variable importance based on gain yielded similar results (Figures S5a and S5b in Multimedia Appendix 3). As for interactions between the variables, again interactions were most prominent with age (Figure 4). For example, the effects of WC and BMI (when exceeding a threshold of around 110 cm and 35 kg/m^2, respectively) on mortality were more prominent among younger individuals. The effects of testosterone and HbA1c, however, were more marked in older individuals.

Model C (Hospitalized/Fatal Cases vs Population With No Known Infection)

Based on ShapVal, WHR was the top contributing variable and WC was ranked fifth, suggesting that central obesity may be a stronger predictor for severe disease than BMI alone (BMI was ranked 13th by ShapVal). As before, TDI and age were ranked among the top. For age, slightly unexpectedly, a U-shaped curve was observed, which suggests lowest risk at the age group of 65-70. Note that model C may also capture RFs related to susceptibility to infection. It is possible, for instance, that younger individuals had higher risks of exposure due to work or social interactions. Among the top 10, two are related to general multiple comorbidities (cnt_tx and cnt_noncancer). Increased cystatin C and lower apolipoprotein A were also associated with higher susceptibility to severe infections, and HT and T2DM were also among the top 10. Considering PermImp as the ranking criteria, COPD, depression, and dementia were observed to have the lowest permutation *P* values (*P*=.002) though not top listed by ShapVal.

The interaction plot (Figure 4) shows WHR may interact with age, with elderly individuals showing more prominent effects from changes in WHR.

Model D (Fatal Cases vs Population With No Known Infection)

Based on ShapVal, age was the top feature, followed by TDI, WHR, number of drugs taken, and WC. Other top features included cystatin C, testosterone, HT, RDW, and pulse rate. Higher levels of these features (or presence of comorbidity) generally lead to higher mortality risks. Based on PermImp, T2DM, dementia, and COPD were the most highly ranked (ignoring features that are already listed in the top 10 by ShapVal).

Shapley interaction analysis suggested that the top interacting pairs involved age and some of the top contributing features (Figure 4 and Figure S8 in Multimedia Appendix 3). The effects of testosterone (likely also reflects gender effects) and TDI were more prominent among the elderly, while the effect of BMI was larger in the younger age groups.

As for important variables from the sex-stratified analysis, the top variables were similar which included age, WC/WHR, cystatin C, number of medications received, socioeconomic status (as reflected by TDI), among others (Table S3c in Multimedia Appendix 1).

PermImp Compared With ShapVal

Overall speaking, the PermImp measure tends to rank binary traits higher than ShapVal. Of note, several diseases were consistently top listed by PermImp across the 4 cohorts (though some were not highlighted by ShapVal), including CAD, atrial fibrillation (AF), T2DM, and dementia, which were among the top 10 in at least three cohorts in Table 4. Other diseases that were listed at least twice included depression, COPD, stroke, and heart failure.

Results From the "Lite" Model

Here we highlight top contributing features for the "lite" models consisting of 27 predictors (Table S3b in Multimedia Appendix 1). Remarkably, the top 3 features (ranked by ShapVal) were consistent across all 4 cohorts. These features included age, cnt_tx, and WC (WHR was not included in the lite model as WC is easier to measure). Of note, sex and T2DM were ranked among the top 6 across all cohorts.

If we consider PermImp as the ranking criteria (further ranked by ShapVal if PermImp is equal), age, cnt_tx, and WC were still highly ranked and listed among the top 5 in at least three cohorts (Table S3b in Multimedia Appendix 1). T2DM was ranked among the top 5 in all cohorts. Other potential risk factors included dementia (top 10 across 3 cohorts) as well as AF, COPD, and CAD (top 10 across 2 cohorts).

Results From the Logistic Model

As discussed above, we primarily focused on the XGboost ML model as it can capture nonlinear relationships and interactions between predictors. Here we also performed our analyses with logistic regression (LR) for comparison. For prediction performance (Table S7a in Multimedia Appendix 1), the AUC–ROC of the full LR model was 0.728 (95% CI 0.715-0.741), 0.810 (95% CI 0.786-0.834), 0.712 (95% CI 0.701-0.724), and 0.833 (95% CI 0.810-0.856), respectively, for cohorts A-D. For the "lite" model (using 27 predictors only), the AUC–ROC of the LR approach was 0.722 (95% CI 0.709-0.735), 0.824 (95% CI 0.801-0.848), 0.697 (95% CI 0.685-0.709), and 0.834 (95% CI 0.812-0.857), respectively, for cohorts A-D (Table S7a in Multimedia Appendix 1). These figures were very close to those obtained by XGboost, although AUC–ROC using LR was slightly higher in general (median difference=0.005). If we compute the RR of individuals at the highest and lowest k% of predicted risks, the results were

generally similar (Table S7b in Multimedia Appendix 1). For cohort D and the full model of cohort B, XGboost performed better than LR at the extreme ends of predicted risks, with observed risk=0 (ie, no cases were observed) for those predicted at the lowest 5% of risk (Table 2).

While prediction is one of our goals, uncovering important contributing factors and their relationship to COVID-19 severity is a major objective of this study. In fact, the latter is considered our primary objective when considering the analyses within patients infected (cohorts A and B). As LR assumes linearity on a log-odds scale, it could not capture nonlinear relationships or "threshold effects" of variables on disease severity.

Individual Shapley Decision Plots and Online Calculator

We also showed individual Shapley decision plot for 3 individuals with the highest, median, and lowest predicted risks in each cohort (Figure S10 in Multimedia Appendix 3). The y-axis is based on a log-odds scale.

To facilitate further research and studies on risk-prediction models, we also constructed an online risk calculation tool (for "lite" model) [53]. The online tool can also construct a Shapley decision plot based on individual risk factors.

Discussion

Principal Findings

In this study we have performed 4 sets of analysis, predicting severe or fatal COVID-19 infection among affected individuals or in the population. We observed good predictive power from the XGboost ML models, especially for the prediction of mortality. We also identified risk factors for increased severity or mortality, and uncovered possible nonlinear effects of some features, which may be clinically relevant and shed light on disease mechanisms.

Prediction of Severity/Mortality

In general, our prediction models achieved reasonably good predictive power. The models predicted mortality (AUC 81%-83%) better than severity of disease. As discussed earlier, in the absence of better alternatives, hospitalization (test performed as inpatient) was used as a proxy for severity. However, reasons or criteria for hospitalization may vary across individuals or hospitals, and some tests may be performed in inpatients for surveillance or due to other confirmed/suspected cases in the ward. As a result, hospitalized patients could also include some with mild or moderate illnesses, which may also impair the prediction performance. By contrast, mortality from infection is a more objective outcome. Other studies (eg, [54-56]) have also defined "severe" or "critical" disease based on intensive care unit admission or need for ventilatory support. However, we could not find sufficiently detailed clinical data to support such a classification at the time of this analysis.

Discriminatory Power of the Models and Clinical Implications

By assessing the proportion of cases explained by those at the top k% of predicted risks, we observed in general a strong enrichment of cases among those with high predicted risks, indicating good discriminative ability of the models and suggesting the possibility to focus on the highest-risk group for targeted preventions or treatment. A similar strong enrichment was also observed for the lite model with fewer predictors. We also observed large RRs of the actual outcomes when comparing individuals at high and low percentiles of predicted risks. For example, for the prediction of mortality among the infected, the RR was up to 158 times (~20% vs 0.1%) when comparing and top and bottom deciles using the full model, and 28.38 times when considering the simplified model (~21% vs 0.8%). These results suggest that the prediction models may be used for risk stratification and prioritizing those at higher risks of deterioration, for early medical attention or admission. As the "lite" model only relies on demographic data and information on comorbidities, risk stratification may be conducted even at the start of the illness without other blood or imaging results.

Previous Relevant Works

A number of studies have focused on prediction of severity/mortality of COVID-19 (corresponding to our prediction in cohorts A and B) and were reviewed in [8]. For cohort A (prediction of severity among infected), the AUC is 72.3%, which is moderate but not as good as many previous ML models for severity prediction [8]. The AUC for prediction of mortality is much higher (AUC=81.4%), although we noted that some studies have reported higher predictive power from clinical symptoms, blood biochemistry on admission, and imaging features [8]. We understand that without access to the above features, predictive performance may be inferior. By contrast, due to heterogeneity of clinical samples, treatment approaches, model evaluation methods, and other features across studies, direct comparisons of predictive performance across studies may be difficult. Here we are not aiming at deriving a highly accurate prediction model; the main purpose is to identify general or "baseline" risk factors for severe disease, thereby gaining insight into disease pathophysiology. However, we also showed that such clinical features or blood measurements, even when collected much earlier in time, may still be highly predictive of outcomes and hence may be incorporated into existing prediction algorithms. The models here may also be useful when blood results or imaging are not available (eg, before admission) and the goal is to quickly classify a patient's risk.

For cohorts C and D, the general population (with no known infection) was treated as "controls." Compared with cohorts A and B, the identified risk factors may also increase the overall susceptibility to infection. The AUC for cohort C (severe/fatal disease) is about 70% but is much higher when mortality is considered as the outcome (AUC=~83%). To our knowledge, there are still very few predictive models built at a *generalpopulationlevel* to identify susceptible individuals; this work is among the first to employ an ML approach to predict the risk of COVID-19/severe infection at a population level. DeCaprio et al [57] proposed an ML model to assess the vulnerability to COVID-19 in the population. However, due to limited data, no actual COVID-19 patients were included and "proxy" outcomes were used instead. Models were built from mainly demographic and comorbidity data to predict

hospitalization due to acute respiratory distress syndrome, pneumonia, influenza, acute bronchitis, and other respiratory tract infections.

Another very recent study ("QCOVID" study) from the UK [58] utilized general practice records from 6.08 million adults (age 19 to 100) as the derivation cohort and 2.17 million adults as the validation set. Mortality from COVID-19 was the primary outcome and a survival model (subdistribution hazard model) [58] was used to predict mortalities. The predictors included demographic (eg, age, TDI, ethnicity), lifestyle (eg, BMI, smoking), and a large range of comorbid conditions. The resulting Harrell's C (comparable to AUC) was 0.928. However, we note that the QCOVID study included individuals of a much younger age range (19 or older), which will improve predictive performance, as age is by far the most important predictor of mortality, with markedly reduced risks in younger individuals. For example, if we refer to age-specific predictive performance (see Supplementary Table C in the study [58]), Harrell's C for mortality was 0.678, 0.831, 0.812, and 0.814 in 50-59, 60-69, 70-79, and 80+ year olds, respectively, for males in the first follow-up period (January 24 to April 30, 2020). For females, the corresponding numbers were 0.618, 0.77, 0.866, and 0.821. These numbers reflect lower predictive power when restricted to a narrower age range. One main difference between this work and the above study is that we employed an *XGboost ML* approach which is able to also capture nonlinear and more complex interaction effects. As shown in our Shapley dependence plots, the models were able to reveal nonlinear effects in a data-driven manner. We also included a number of blood measurements to shed light on potential new risk factors and mechanisms underlying the disease. The QCOVID study employed a survival model (subdistribution hazard) that accounts for time-to-event and competing risks; however, the proportional hazards assumption is required which may not hold due to restrictions/interventions introduced during the period (ie, time-dependent associations may be present).

A few other studies have investigated risk factors (especially comorbidities) for COVID-19 infection in the UKBB. For example, Atkins et al [12] studied elderly individuals (age >65) in UKBB, and found that HT, history of falls, CAD, T2DM, and asthma were the top comorbidities among hospitalized cases. The analysis was restricted to the elderly population, however. In a more recent work, McQueenie et al [13] studied the impact of multiple comorbidities and polypharmacy on infection risks. Having 2 or more long-term conditions, cardiometabolic disorders, and polypharmacy were associated with heightened risks of infection. Among individuals with multiple comorbidities, severe obesity and IRF may lead to increased risks. Another study of primary care patients in the UK revealed that deprivation, male sex, older age, ethnicity (being Black), and chronic renal disease were associated with higher risks of being tested positive [59]. Another large-scale British primary care study of more than 17 million individuals revealed similar risk factors as above [60]. There is also a relatively large literature on the study of risk factors associated with severe or fatal disease [15-18,61-64]. Some commonly reported risk factors included age, sex, obesity, T2DM, HT, renal, cardiometabolic, and respiratory disorders. As discussed above, an important difference between the above epidemiological studies and this work is that we employed XGboost, an ML approach that can uncover nonlinear and interaction effects, while other studies mostly employed regression models that assume linear and additive effects of covariates. We also performed a comprehensive analysis including 4 models covering different outcomes and both infected and population cohorts.

Comparison With Logistic Model

We have performed LR to compare with XGboost on cohorts A and B. The differences in predictive performance appeared to be small. The number of cases (especially fatalities) is relatively small in this data set, and this may limit the predictive performance of more complex models such as XGboost, which may be expected to improve with larger case numbers. An important advantage of XGboost is that it can detect nonlinear relationships when compared with LR. In addition, XGboost may handle multiple collinearity better than LR. Assuming 2 highly correlated features A and B, for each specific tree usually only 1 variable will be used and as the trees are sequential, the focus of the model will be usually on one but not on both features [65]. Hence, XGboost also handles multicollinearity well, which is important here as many clinical variables are correlated. XGboost also directly models interaction between variables. It is much more difficult for LR to model interactions due to the rapid increase in feature space when interaction terms are included.

Highlights of Potential Risk Factors

For the limit of space, we shall only highlight the top 5-10 risk factors ranked by ShapVal here. Across the 4 cohorts, age and cardiometabolic risk factors predominate the top risk factors. Age and WHR/WC were ranked among the top 5 across all 4 cohorts. The number of medications taken was among the top 5 across all cohorts, and cystatin C (reflecting renal function) was among the top 10 across all cohorts. HbA1c was a top 10 risk factor for cohort A, and T2DM was also highly ranked across multiple cohorts especially when PermImp was considered. TDI (reflecting socioeconomic status) was among the top 10 in most cohorts. As described above, results from the "lite" models were generally in line with those from the full models, with age, WC, and cnt_tx consistently ranked as the top 3.

Obesity has been observed to be a major risk factor for susceptibility or severity of infection in the UKBB [14,66] and in many other studies [67,68]. The observation that WC/WHR were highly ranked suggests that *central* obesity is a major risk factor and may be a better predictor of severity than BMI alone.

Another major risk factor we identified is IRF, as reflected by elevated risks with raised urea and cystatin C. Several studies also suggested that IRF increases risk of mortality [64,69,70], although it is probably not as widely recognized as cardiometabolic disorders as a major risk factor. Because COVID-19 itself may lead to renal failure, our findings specifically suggest that underlying or baseline IRF is an important risk factor. The high ranking of cystatin C also indicates that this measure may better reflect renal function than

urea or creatinine (which were also included in our analysis) [71,72], and may serve as a superior predictor for COVID-19 severity.

Other potential risk factors briefly highlighted below were less reported. As some were listed only once or twice among the top 10, and for some their ShapVal was close to other risk factors, further replications are required. For example, testosterone was top ranked by XGboost (for mortality), with higher levels associated with increased risk. This may partially reflect that males are at a higher risk of fatal infections, but it remains to be studied whether testosterone itself is involved in the pathophysiology of severe COVID-19, as the ML model chose this variable instead of sex. Studies have suggested that elevated or reduced testosterone levels may be associated with a more severe clinical course [73]. Besides, interestingly, 5-alpha-reductase inhibitors or androgen-deprivation therapy has been shown to be associated with a lower risk or severity of disease [74,75]. We also found a few hematological indices that may be potential risk factors. High RDW was associated with mortality in our study and was also identified in a recent meta-analysis of 3 studies as a risk factor [76]. Low lymphocyte percentage was a top 10 risk factor in cohort B, which may be related to immune functioning and response to infections. Lymphopenia was reported as a main hematological finding in those with severe illnesses [40,77]. Most previous studies considered hematological indices at admission or during hospitalization. Slightly surprisingly, this study suggested that high RDW or reduced lymphocyte percentage *prior to the diagnosis* may also be predictive of worse outcomes.

Comorbid Diseases Associated With Severity as Highlighted by PermImp

Among the diseases being included as covariates, T2DM is most consistently ranked among the top, no matter whether full or lite models are used, and regardless of ranking by ShapVal or PermImp (*P* value). T2DM has been shown in numerous studies to be associated with higher risk and severity of infection [78,79]. We noted some discrepancy between the ranked results based on ShapVal and those based on PermImp. In general, the latter measure favors binary variable, while ShapVal alone tends to rank continuous variables higher. We are unsure about the exact reason, but it may be an interesting topic for further methodology studies. If we employed a composite ranking criteria based on PermImp followed by ShapVal, then a few more diseases were ranked among the top 10, such as hypertension and COPD. For cohort D, T2DM, dementia, COPD, AF, heart failure, and CAD were also top ranked, suggesting that a range of chronic cardiovascular, respiratory, and neuropsychiatric conditions may be associated with increased mortality.

Full and Lite Prediction Models

We note that the simplified (lite) prediction model has very similar predictive performance (as assessed by AUC) to the "full" model with a larger panel of predictors. However, it is important to note that features associated with the outcome may not always improve predictive power. AUC is relatively insensitive to detecting changes in predictive performance when additional risk factors are added [80-82].

For example, Pencina et al [80] showed that in the prediction of cardiovascular disease risk in a study on women's health, adding extra established risk factors often result in minimal improvements in AUC. For instance, in a model with age, SBP, and smoking, adding any lipid measures result in only an increase of 0.01 in AUC from the baseline of 0.76. In the same vein, starting from a full prediction model [containing Ln(age), Ln(SBP), smoking, Ln(Total cholesterol), Ln(HDL)], deleting any one of these established risk factors (except age) resulted in a very small reduction in AUC of <0.02. In general, for a model with high baseline AUC from existing predictors (eg, age, sex, and obesity in the case of COVID-19), including additional predictors may not result in much improvement in discriminative power or AUC [83].

Nevertheless, it is still valuable to study variable importance (eg, ShapVal) from the ML model as it may shed light on the pathophysiology of the disease. For example, many factors such as age and T2DM may lead to poorer renal function (and higher cystatin C), which in turn may increase the severity of infection. Given that age, T2DM, and other main comorbidities are already modeled, adding cystatin C may not improve discriminative power of the model. However, its inclusion may still change the predicted probability of outcome, which will be reflected in ShapVal. The high ranking of cystatin C (based on ShapVal) may shed light on renal impairment as a potential mechanism associated with clinical deterioration.

Some limitations have been discussed above; for example, the use of hospitalization as a proxy for severity, and that the predictors were recorded prior to the pandemic. We briefly discuss other limitations here. The UKBB is a very large-scale study with detailed phenotypic data, but still the number of fatal cases is relatively small. In addition, the UKBB is not entirely representative of the UK population, as participants tend to be healthier and wealthier overall [84]. Further, it remains to be studied whether the findings are generalizable to other populations. Symptom measures and lung imaging features were not available at the time of analysis. Despite adjusting for a rich set of predictors and that all predictors were recorded prior to the outbreak, causality cannot be confirmed from this study, due to risk of residual confounding by unknown factors. This study was performed on a cohort with age over 50, and generalizability to younger individuals remains to be studied. In cohorts C and D, the population with no known infection was regarded as controls. It is expected that some may become infected in the future, and some may have been infected but not tested; however, the chance of missing cases of severe infection is probably not high. Since the UKBB represents a relatively healthy population with a low rate of severe COVID-19 cases so far (236/468,114, 0.50%), we expect the use of "unscreened" controls is unlikely to result in substantial bias.

Regarding the ML model, XGboost is a state-of-the-art method that has been consistently shown to be the best or one of the best ML methods in supervised learning tasks/competitions [85] (especially for tasks not involving computer vision or natural language processing). Nevertheless, other ML methods may still be useful or may uncover novel risk factors. Assessing variable importance is a long-standing problem in ML; here we

mainly employed ShapVal, which is both computationally fast and was shown to have good theoretical properties [46,47].

Conclusions

In conclusion, we identified a number of baseline risk factors for severe/fatal infection by an ML approach. Shapley dependence plots revealed possible nonlinear and "threshold" effects of risk factors on the risks of infection or severity. To summarize, age, central obesity, IRF, multiple comorbidities, cardiometabolic abnormalities or disorders (especially T2DM), and low socioeconomic status may predispose to poorer outcomes, among other risk factors. The prediction models (of cohorts C/D) may be useful at a population level to identify those susceptible to developing severe/fatal infections, thereby facilitating targeted prevention strategies. Further replication and validation in independent cohorts are required to confirm our findings.

Acknowledgments

This work was supported partially by the Lo Kwee Seong Biomedical Research Fund from The Chinese University of Hong Kong, the KIZ-CUHK Joint Laboratory of Bioresources and Molecular Research of Common Diseases, the Kunming Institute of Zoology, and The Chinese University of Hong Kong. We thank Professor Pak Sham for support on data access and analyses, and Ms Qiu Jinghong for formatting and editing of the manuscript.

Authors' Contributions

H-CS contributed to the conception and design, as well as supervised the study; H-CS and KC-YW were responsible for the analytic methodology. KC-YW (main), YX, LY, and H-CS performed data analysis. H-CS and KC-YW performed data interpretation. H-CS, with input from KC-YW, drafted the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplementary tables S1-S8.
[XLSX File (Microsoft Excel File), 2018 KB - publichealth_v7i9e29544_app1.xlsx]

Multimedia Appendix 2
Simulation experiment to verify the validity of permutation testing for rare outcomes.
[DOCX File , 16 KB - publichealth_v7i9e29544_app2.docx]

Multimedia Appendix 3
Supplementary figures.
[XLSX File (Microsoft Excel File), 14559 KB - publichealth_v7i9e29544_app3.xlsx]

References

1. Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, et al. Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus-Infected Pneumonia. N Engl J Med 2020 Mar 26;382(13):1199-1207 [FREE Full text] [doi: 10.1056/NEJMoa2001316] [Medline: 31995857]
2. Novel Coronavirus Pneumonia Emergency Response Epidemiology Team. [The epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (COVID-19) in China]. Zhonghua Liu Xing Bing Xue Za Zhi 2020 Feb 17;41(2):145-151. [doi: 10.3760/cma.j.issn.0254-6450.2020.02.003] [Medline: 32064853]
3. Guan W, Ni Z, Hu Y, Liang W, Ou C, He J, China Medical Treatment Expert Group for Covid-19. Clinical Characteristics of Coronavirus Disease 2019 in China. N Engl J Med 2020 Apr 30;382(18):1708-1720 [FREE Full text] [doi: 10.1056/NEJMoa2002032] [Medline: 32109013]
4. Johns Hopkins Coronavirus Resource Center. URL: https://coronavirus.jhu.edu/map.html [accessed 2021-06-19]
5. Bayat V, Phelps S, Ryono R, Lee C, Parekh H, Mewton J, et al. A SARS-CoV-2 Prediction Model from Standard Laboratory Tests. Clin Infect Dis 2020 Aug 12:ciaa1175 [FREE Full text] [doi: 10.1093/cid/ciaa1175] [Medline: 32785701]
6. Knight SR, Ho A, Pius R, Buchan I, Carson G, Drake TM, ISARIC4C investigators. Risk stratification of patients admitted to hospital with covid-19 using the ISARIC WHO Clinical Characterisation Protocol: development and validation of the 4C Mortality Score. BMJ 2020 Sep 09;370:m3339 [FREE Full text] [doi: 10.1136/bmj.m3339] [Medline: 32907855]
7. Chung H, Ko H, Kang WS, Kim KW, Lee H, Park C, et al. Prediction and Feature Importance Analysis for Severity of COVID-19 in South Korea Using Artificial Intelligence: Model Development and Validation. J Med Internet Res 2021 Apr 19;23(4):e27060 [FREE Full text] [doi: 10.2196/27060] [Medline: 33764883]

8. Wynants L, Van Calster B, Collins GS, Riley RD, Heinze G, Schuit E, et al. Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal. BMJ 2020 Apr 07;369:m1328 [FREE Full text] [doi: 10.1136/bmj.m1328] [Medline: 32265220]
9. Alballa N, Al-Turaiki I. Machine learning approaches in COVID-19 diagnosis, mortality, and severity risk prediction: A review. Inform Med Unlocked 2021;24:100564 [FREE Full text] [doi: 10.1016/j.imu.2021.100564] [Medline: 33842685]
10. Adamidi ES, Mitsis K, Nikita KS. Artificial intelligence in clinical care amidst COVID-19 pandemic: A systematic review. Comput Struct Biotechnol J 2021;19:2833-2850 [FREE Full text] [doi: 10.1016/j.csbj.2021.05.010] [Medline: 34025952]
11. Vaid A, Somani S, Russak AJ, De Freitas JK, Chaudhry FF, Paranjpe I, et al. Machine Learning to Predict Mortality and Critical Events in a Cohort of Patients With COVID-19 in New York City: Model Development and Validation. J Med Internet Res 2020 Nov 06;22(11):e24018 [FREE Full text] [doi: 10.2196/24018] [Medline: 33027032]
12. Atkins J, Masoli J, Delgado J, Pilling L, Kuo C, Kuchel G, et al. Preexisting Comorbidities Predicting COVID-19 and Mortality in the UK Biobank Community Cohort. J Gerontol A Biol Sci Med Sci 2020 Oct 15;75(11):2224-2230 [FREE Full text] [doi: 10.1093/gerona/glaa183] [Medline: 32687551]
13. McQueenie R, Foster HME, Jani BD, Katikireddi SV, Sattar N, Pell JP, et al. Correction: Multimorbidity, polypharmacy, and COVID-19 infection within the UK Biobank cohort. PLoS One 2021 May 6;16(5):e0251613 [FREE Full text] [doi: 10.1371/journal.pone.0251613] [Medline: 33956868]
14. Yates T, Razieh C, Zaccardi F, Davies MJ, Khunti K. Obesity and risk of COVID-19: analysis of UK biobank. Prim Care Diabetes 2020 Oct;14(5):566-567 [FREE Full text] [doi: 10.1016/j.pcd.2020.05.011] [Medline: 32493608]
15. Rod JE, Oviedo-Trespalacios O, Cortes-Ramirez J. A brief-review of the risk factors for covid-19 severity. Rev Saude Publica 2020;54:60 [FREE Full text] [doi: 10.11606/s1518-8787.2020054002481] [Medline: 32491116]
16. Romero Starke K, Petereit-Haack G, Schubert M, Kämpf D, Schliebner A, Hegewald J, et al. The Age-Related Risk of Severe Outcomes Due to COVID-19 Infection: A Rapid Review, Meta-Analysis, and Meta-Regression. Int J Environ Res Public Health 2020 Aug 17;17(16):5974 [FREE Full text] [doi: 10.3390/ijerph17165974] [Medline: 32824596]
17. Wingert A, Pillay J, Gates M, Guitard S, Rahman S, Beck A, et al. Risk factors for severity of COVID-19: a rapid review to inform vaccine prioritisation in Canada. BMJ Open 2021 May 13;11(5):e044684 [FREE Full text] [doi: 10.1136/bmjopen-2020-044684] [Medline: 33986052]
18. Wolff D, Nee S, Hickey NS, Marschollek M. Risk factors for Covid-19 severity and fatality: a structured literature review. Infection 2021 Feb 28;49(1):15-28 [FREE Full text] [doi: 10.1007/s15010-020-01509-1] [Medline: 32860214]
19. Sudlow C, Gallacher J, Allen N, Beral V, Burton P, Danesh J, et al. UK biobank: an open access resource for identifying the causes of a wide range of complex diseases of middle and old age. PLoS Med 2015 Mar;12(3):e1001779 [FREE Full text] [doi: 10.1371/journal.pmed.1001779] [Medline: 25826379]
20. Data for COVID-19 research. URL: http://biobank.ndph.ox.ac.uk/showcase/exinfo.cgi?src=COVID19 [accessed 2021-09-08]
21. The official UK government website for data and insights on coronavirus (COVID-19). URL: https://coronavirus.data.gov.uk/ [accessed 2021-09-08]
22. Lopez Bernal J, Andrews N, Gower C, Robertson C, Stowe J, Tessier E, et al. Effectiveness of the Pfizer-BioNTech and Oxford-AstraZeneca vaccines on covid-19 related symptoms, hospital admissions, and mortality in older adults in England: test negative case-control study. BMJ 2021 May 13;373:n1088 [FREE Full text] [doi: 10.1136/bmj.n1088] [Medline: 33985964]
23. Tenforde M, Olson SM, Self WH, Talbot HK, Lindsell CJ, Steingrub JS, HAIVEN Investigators. Effectiveness of Pfizer-BioNTech and Moderna Vaccines Against COVID-19 Among Hospitalized Adults Aged ≥65 Years - United States, January-March 2021. MMWR Morb Mortal Wkly Rep 2021 May 07;70(18):674-679 [FREE Full text] [doi: 10.15585/mmwr.mm7018e1] [Medline: 33956782]
24. Dagan N, Barda N, Kepten E, Miron O, Perchik S, Katz MA, et al. BNT162b2 mRNA Covid-19 Vaccine in a Nationwide Mass Vaccination Setting. N Engl J Med 2021 Apr 15;384(15):1412-1423 [FREE Full text] [doi: 10.1056/NEJMoa2101765] [Medline: 33626250]
25. Haas EJ, Angulo FJ, McLaughlin JM, Anis E, Singer SR, Khan F, et al. Impact and effectiveness of mRNA BNT162b2 vaccine against SARS-CoV-2 infections and COVID-19 cases, hospitalisations, and deaths following a nationwide vaccination campaign in Israel: an observational study using national surveillance data. Lancet 2021 May 15;397(10287):1819-1829 [FREE Full text] [doi: 10.1016/S0140-6736(21)00947-8] [Medline: 33964222]
26. Dashti H, Roche EC, Bates DW, Mora S, Demler O. SARS2 simplified scores to estimate risk of hospitalization and death among patients with COVID-19. Sci Rep 2021 Mar 02;11(1):4945 [FREE Full text] [doi: 10.1038/s41598-021-84603-0] [Medline: 33654180]
27. Karaismailoglu E, Karaismailoglu S. Two novel nomograms for predicting the risk of hospitalization or mortality due to COVID-19 by the naïve Bayesian classifier method. J Med Virol 2021 May;93(5):3194-3201 [FREE Full text] [doi: 10.1002/jmv.26890] [Medline: 33599308]
28. Hamer M, Kivimäki M, Gale C, Batty G. Lifestyle risk factors, inflammatory mechanisms, and COVID-19 hospitalization: A community-based cohort study of 387,109 adults in UK. Brain Behav Immun 2020 Jul;87:184-187 [FREE Full text] [doi: 10.1016/j.bbi.2020.05.059] [Medline: 32454138]

29. Pairo-Castineira E, Clohisey S, Klaric L, Bretherick AD, Rawlik K, Pasko D, GenOMICC Investigators, ISARIC4C Investigators, COVID-19 Human Genetics Initiative, 23andMe Investigators, BRACOVID Investigators, Gen-COVID Investigators, et al. Genetic mechanisms of critical illness in COVID-19. Nature 2021 Mar 11;591(7848):92-98. [doi: 10.1038/s41586-020-03065-y] [Medline: 33307546]
30. Walsh K, Jordan K, Clyne B, Rohde D, Drummond L, Byrne P, et al. SARS-CoV-2 detection, viral load and infectivity over the course of an infection. J Infect 2020 Sep;81(3):357-371 [FREE Full text] [doi: 10.1016/j.jinf.2020.06.067] [Medline: 32615199]
31. COVID-19 test results data. URL: http://biobank.ndph.ox.ac.uk/showcase/exinfo.cgi?src=COVID19_tests [accessed 2021-09-08]
32. Lever J, Krzywinski M, Altman N. Model selection and overfitting. Nat Methods 2016 Aug 30;13(9):703-704. [doi: 10.1038/nmeth.3968]
33. Stekhoven DJ, Bühlmann P. MissForest--non-parametric missing value imputation for mixed-type data. Bioinformatics 2012 Jan 01;28(1):112-118. [doi: 10.1093/bioinformatics/btr597] [Medline: 22039212]
34. Waljee AK, Mukherjee A, Singal AG, Zhang Y, Warren J, Balis U, et al. Comparison of imputation methods for missing laboratory data in medicine. BMJ Open 2013 Aug 01;3(8):e002847 [FREE Full text] [doi: 10.1136/bmjopen-2013-002847] [Medline: 23906948]
35. Shah A, Bartlett J, Carpenter J, Nicholas O, Hemingway H. Comparison of random forest and parametric imputation models for imputing missing data using MICE: a CALIBER study. Am J Epidemiol 2014 Mar 15;179(6):764-774 [FREE Full text] [doi: 10.1093/aje/kwt312] [Medline: 24589914]
36. Penone C, Davidson A, Shoemaker K, Di Marco M, Rondinini C, Brooks T, et al. Imputation of missing data in life-history trait datasets: which approach performs the best? Methods Ecol Evol 2014 Aug 08;5(9):961-970 [FREE Full text] [doi: 10.1111/2041-210x.12232]
37. Crowson CS, Atkinson EJ, Therneau TM. Assessing calibration of prognostic risk scores. Stat Methods Med Res 2016 Aug;25(4):1692-1706 [FREE Full text] [doi: 10.1177/0962280213497434] [Medline: 23907781]
38. Nixon J, Dusenberry M, Zhang L, Jerfel G, Tran D. Measuring Calibration in Deep Learning. CVPR Workshops. 2019. URL: https://openaccess.thecvf.com/content_CVPRW_2019/html/Uncertainty_and_Robustness_in_Deep_Visual_Learning/Nixon_Measuring_Calibration_in_Deep_Learning_CVPRW_2019_paper.html [accessed 2021-09-14]
39. Demler OV, Paynter NP, Cook NR. Tests of calibration and goodness-of-fit in the survival setting. Stat Med 2015 May 10;34(10):1659-1680 [FREE Full text] [doi: 10.1002/sim.6428] [Medline: 25684707]
40. Tan L, Wang Q, Zhang D, Ding J, Huang Q, Tang Y, et al. Correction: Lymphopenia predicts disease severity of COVID-19: a descriptive and predictive study. Signal Transduct Target Ther 2020 Apr 29;5(1):61 [FREE Full text] [doi: 10.1038/s41392-020-0159-1] [Medline: 33911071]
41. Song H, Diethe T, Kull M, Flach P. Distribution calibration for regression. 2019 Presented at: Proceedings of the 36th International Conference on Machine Learning; June 10-15, 2019; Long Beach, CA p. 5897-5906.
42. Niculescu-Mizil A, Caruana R. Predicting good probabilities with supervised learning. New York, NY: Association for Computing Machinery; 2005 Presented at: Proceedings of the 22nd international conference on Machine learning; August 7-11, 2005; Bonn, Germany p. 625-632. [doi: 10.1145/1102351.1102430]
43. Jiang X, Osl M, Kim J, Ohno-Machado L. Smooth isotonic regression: a new method to calibrate predictive models. AMIA Jt Summits Transl Sci Proc 2011;2011:16-20 [FREE Full text] [Medline: 22211175]
44. Steyerberg EW, Vergouwe Y. Towards better clinical prediction models: seven steps for development and an ABCD for validation. Eur Heart J 2014 Aug 01;35(29):1925-1931 [FREE Full text] [doi: 10.1093/eurheartj/ehu207] [Medline: 24898551]
45. Niculescu-Mizil A, Caruana R. Obtaining Calibrated Probabilities from Boosting. 2005 Presented at: 21st Conference on Uncertainty in Artificial Intelligence (UAI); July 26-29, 2005; Edinburgh, Scotland p. 413-420.
46. Lundberg S, Lee S. A unified approach to interpreting model predictions. Advances in neural information processing systems. In: Proceedings of the 31st International Conference on Neural Information Processing Systems. Red Hook, NY: Curran Associates; 2017 Presented at: 31st International Conference on Neural Information Processing Systems; December 4-9, 2017; Long Beach, CA p. 4768-4777.
47. Lundberg SM, Erion G, Chen H, DeGrave A, Prutkin JM, Nair B, et al. From Local Explanations to Global Understanding with Explainable AI for Trees. Nat Mach Intell 2020 Jan;2(1):56-67 [FREE Full text] [doi: 10.1038/s42256-019-0138-9] [Medline: 32607472]
48. Lundberg S, Erion G, Lee SI. Consistent individualized feature attribution for tree ensembles. arXiv 2018 [FREE Full text]
49. Altmann A, Toloşi L, Sander O, Lengauer T. Permutation importance: a corrected feature importance measure. Bioinformatics 2010 May 15;26(10):1340-1347. [doi: 10.1093/bioinformatics/btq134] [Medline: 20385727]
50. Witten DM, Tibshirani R. A framework for feature selection in clustering. J Am Stat Assoc 2010 Jun 01;105(490):713-726 [FREE Full text] [doi: 10.1198/jasa.2010.tm09415] [Medline: 20811510]
51. Tibshirani R, Walther G, Hastie T. Estimating the number of clusters in a data set via the gap statistic. Journal of the Royal Statistical Societyries B (Statistical Methodology) 2001;63(2):411-423. [doi: 10.1111/1467-9868.00293]

52. Boyd K, Eng K, Page C. Area under the Precision-Recall Curve: Point Estimates and Confidence Intervals. In: Machine Learning and Knowledge Discovery in Databases. Berlin, Germany: Springer; 2013:451-466.
53. Risk Estimation for Covid-19 - Online Prediction Tool. URL: https://labsocuhk.ddns.net:8890/covid19/ [accessed 2021-09-08]
54. Subudhi S, Verma A, Patel AB, Hardin CC, Khandekar MJ, Lee H, et al. Comparing machine learning algorithms for predicting ICU admission and mortality in COVID-19. NPJ Digit Med 2021 May 21;4(1):87 [FREE Full text] [doi: 10.1038/s41746-021-00456-x] [Medline: 34021235]
55. Patrício A, Costa RS, Henriques R. Predictability of COVID-19 Hospitalizations, Intensive Care Unit Admissions, and Respiratory Assistance in Portugal: Longitudinal Cohort Study. J Med Internet Res 2021 Apr 28;23(4):e26075 [FREE Full text] [doi: 10.2196/26075] [Medline: 33835931]
56. Yun K, Lee JS, Kim EY, Chandra H, Oh B, Oh J. Severe COVID-19 Illness: Risk Factors and Its Burden on Critical Care Resources. Front Med (Lausanne) 2020 Nov 19;7:583060 [FREE Full text] [doi: 10.3389/fmed.2020.583060] [Medline: 33330540]
57. DeCaprio D, Gartner J, McCall CJ, Burgess T, Garcia K, Kothari S, et al. Building a COVID-19 vulnerability index. J Med Artif Intell 2020 Dec;3:15-15. [doi: 10.21037/jmai-20-47]
58. Clift AK, Coupland CAC, Keogh RH, Diaz-Ordaz K, Williamson E, Harrison EM, et al. Living risk prediction algorithm (QCOVID) for risk of hospital admission and mortality from coronavirus 19 in adults: national derivation and validation cohort study. BMJ 2020 Oct 20;371:m3731 [FREE Full text] [doi: 10.1136/bmj.m3731] [Medline: 33082154]
59. de Lusignan S, Dorward J, Correa A, Jones N, Akinyemi O, Amirthalingam G, et al. Risk factors for SARS-CoV-2 among patients in the Oxford Royal College of General Practitioners Research and Surveillance Centre primary care network: a cross-sectional study. The Lancet Infectious Diseases 2020 Sep 07;20(9):1034-1042 [FREE Full text] [doi: 10.1016/S1473-3099(20)30371-6]
60. Williamson EJ, Walker AJ, Bhaskaran K, Bacon S, Bates C, Morton CE, et al. Factors associated with COVID-19-related death using OpenSAFELY. Nature 2020 Aug;584(7821):430-436. [doi: 10.1038/s41586-020-2521-4] [Medline: 32640463]
61. Noor FM, Islam MM. Prevalence and Associated Risk Factors of Mortality Among COVID-19 Patients: A Meta-Analysis. J Community Health 2020 Dec;45(6):1270-1282 [FREE Full text] [doi: 10.1007/s10900-020-00920-x] [Medline: 32918645]
62. Rahman A, Sathi N. Risk factors of the severity of COVID-19: A meta-analysis. Int J Clin Pract 2021 Jul;75(7):e13916 [FREE Full text] [doi: 10.1111/ijcp.13916] [Medline: 33372407]
63. Zhou Y, Chi J, Lv W, Wang Y. Obesity and diabetes as high-risk factors for severe coronavirus disease 2019 (Covid-19). Diabetes Metab Res Rev 2021 Feb 20;37(2):e3377 [FREE Full text] [doi: 10.1002/dmrr.3377] [Medline: 32588943]
64. Harrison SL, Fazio-Eynullayeva E, Lane DA, Underhill P, Lip GYH. Comorbidities associated with mortality in 31,461 adults with COVID-19 in the United States: A federated electronic medical record analysis. PLoS Med 2020 Sep 10;17(9):e1003321 [FREE Full text] [doi: 10.1371/journal.pmed.1003321] [Medline: 32911500]
65. Understand Your Dataset with Xgboost. XGBoost R Package. 2020. URL: https://xgboost.readthedocs.io/en/latest/R-package/discoverYourData.html [accessed 2021-09-08]
66. Hamer M, Gale CR, Kivimäki M, Batty GD. Overweight, obesity, and risk of hospitalization for COVID-19: A community-based cohort study of adults in the United Kingdom. Proc Natl Acad Sci U S A 2020 Sep 01;117(35):21011-21013 [FREE Full text] [doi: 10.1073/pnas.2011086117] [Medline: 32788355]
67. Popkin BM, Du S, Green WD, Beck MA, Algaith T, Herbst CH, et al. Individuals with obesity and COVID-19: A global perspective on the epidemiology and biological relationships. Obes Rev 2020 Nov;21(11):e13128 [FREE Full text] [doi: 10.1111/obr.13128] [Medline: 32845580]
68. Tamara A, Tahapary DL. Obesity as a predictor for a poor prognosis of COVID-19: A systematic review. Diabetes Metab Syndr 2020;14(4):655-659 [FREE Full text] [doi: 10.1016/j.dsx.2020.05.020] [Medline: 32438328]
69. Di Castelnuovo A, Bonaccio M, Costanzo S, Gialluisi A, Antinori A, Berselli N, COvid-19 RISkTreatments (CORIST) collaboration. Common cardiovascular risk factors and in-hospital mortality in 3,894 patients with COVID-19: survival analysis and machine learning-based findings from the multicentre Italian CORIST Study. Nutr Metab Cardiovasc Dis 2020 Oct 30;30(11):1899-1913 [FREE Full text] [doi: 10.1016/j.numecd.2020.07.031] [Medline: 32912793]
70. Uribarri A, Núñez-Gil IJ, Aparisi A, Becerra-Muñoz VM, Feltes G, Trabattoni D, HOPE COVID-19 Investigators. Impact of renal function on admission in COVID-19 patients: an analysis of the international HOPE COVID-19 (Health Outcome Predictive Evaluation for COVID 19) Registry. J Nephrol 2020 Aug;33(4):737-745 [FREE Full text] [doi: 10.1007/s40620-020-00790-5] [Medline: 32602006]
71. Hojs R, Bevc S, Ekart R, Gorenjak M, Puklavec L. Serum cystatin C as an endogenous marker of renal function in patients with mild to moderate impairment of kidney function. Nephrol Dial Transplant 2006 Jul;21(7):1855-1862. [doi: 10.1093/ndt/gfl073] [Medline: 16524933]
72. Shlipak MG, Mattes MD, Peralta CA. Update on cystatin C: incorporation into clinical practice. Am J Kidney Dis 2013 Sep;62(3):595-603 [FREE Full text] [doi: 10.1053/j.ajkd.2013.03.027] [Medline: 23701892]
73. Giagulli VA, Guastamacchia E, Magrone T, Jirillo E, Lisco G, De Pergola G, et al. Worse progression of COVID-19 in men: Is testosterone a key factor? Andrology 2021 Jan;9(1):53-64 [FREE Full text] [doi: 10.1111/andr.12836] [Medline: 32524732]

74. Cadegiani F, McCoy J, Wambier C, Goren A. 5-Alpha-Reductase Inhibitors Reduce Remission Time of COVID-19: Results From a Randomized Double Blind Placebo Controlled Interventional Trial in 130 SARS-CoV-2 Positive Men. medRxiv 2020. [doi: 10.1101/2020.11.16.20232512]
75. Montopoli M, Zumerle S, Vettor R, Rugge M, Zorzi M, Catapano C, et al. Androgen-deprivation therapies for prostate cancer and risk of infection by SARS-CoV-2: a population-based study (N = 4532). Ann Oncol 2020 Aug;31(8):1040-1045 [FREE Full text] [doi: 10.1016/j.annonc.2020.04.479] [Medline: 32387456]
76. Lippi G, Henry B, Sanchis-Gomar F. Red Blood Cell Distribution Is a Significant Predictor of Severe Illness in Coronavirus Disease 2019. Acta Haematol 2021 Aug 25;144(4):360-364 [FREE Full text] [doi: 10.1159/000510914] [Medline: 32841949]
77. Terpos E, Ntanasis-Stathopoulos I, Elalamy I, Kastritis E, Sergentanis TN, Politou M, et al. Hematological findings and complications of COVID-19. Am J Hematol 2020 Jul;95(7):834-847 [FREE Full text] [doi: 10.1002/ajh.25829] [Medline: 32282949]
78. Gupta R, Hussain A, Misra A. Diabetes and COVID-19: evidence, current status and unanswered research questions. Eur J Clin Nutr 2020 Jun 13;74(6):864-870 [FREE Full text] [doi: 10.1038/s41430-020-0652-1] [Medline: 32404898]
79. Apicella M, Campopiano MC, Mantuano M, Mazoni L, Coppelli A, Del Prato S. COVID-19 in people with diabetes: understanding the reasons for worse outcomes. The Lancet Diabetes & Endocrinology 2020 Sep;8(9):782-792. [doi: 10.1016/s2213-8587(20)30238-2]
80. Pencina M, D' Agostino R, D' Agostino R, Vasan R. Evaluating the added predictive ability of a new marker: From area under the ROC curve to reclassification and beyond. Statist. Med 2007 Jan 30;27(2):157-172 [FREE Full text] [doi: 10.1002/sim.2929]
81. Cook NR. Use and Misuse of the Receiver Operating Characteristic Curve in Risk Prediction. Circulation 2007 Feb 20;115(7):928-935. [doi: 10.1161/circulationaha.106.672402]
82. Ware JH. The limitations of risk factors as prognostic tools. N Engl J Med 2006 Dec 21;355(25):2615-2617. [doi: 10.1056/NEJMp068249] [Medline: 17182986]
83. Janssens A, Martens F. Reflection on modern methods: Revisiting the area under the ROC Curve. Int J Epidemiol 2020 Aug 01;49(4):1397-1403. [doi: 10.1093/ije/dyz274] [Medline: 31967640]
84. Fry A, Littlejohns T, Sudlow C, Doherty N, Adamska L, Sprosen T, et al. Comparison of Sociodemographic and Health-Related Characteristics of UK Biobank Participants With Those of the General Population. Am J Epidemiol 2017 Nov 01;186(9):1026-1034 [FREE Full text] [doi: 10.1093/aje/kwx246] [Medline: 28641372]
85. Nielsen D. Tree Boosting With XGBoost. Master thesis, Norwegian University of Science and Technology. 2016. URL: http://pzs.dstu.dp.ua/DataMining/boosting/bibl/Didrik.pdf [accessed 2021-09-08]

Abbreviations

AF: atrial fibrillation
AUC–PRC: area under the precision–recall curve
AUC–ROC: area under the receiving-operating characteristic curve
CAD: coronary artery disease
COPD: chronic obstructive pulmonary disease
ECE: expected calibration error
HDL: high-density lipoprotein
HT: hypertension
IRF: impaired renal function
LR: logistic regression
MCC: Matthews correlation coefficient
MCE: maximum calibration error
MICE: multiple imputation by chained equation
ML: machine learning
RDW: red blood cell distribution width
RF: risk factor
RR: relative risk
SBP: systolic blood pressure
T1DM: type 1 diabetes mellitus
T2DM: type 2 diabetes mellitus
TDI: Townsend deprivation index
UKBB: UK Biobank
WC: waist circumference
WHR: waist-to-hip ratio

Edited by Y Khader; submitted 12.04.21; peer-reviewed by D DeCapprio, T Lee, H Oyama; comments to author 12.05.21; revised version received 24.06.21; accepted 31.07.21; published 30.09.21.

Please cite as:
Wong KCY, Xiang Y, Yin L, So HC
Uncovering Clinical Risk Factors and Predicting Severe COVID-19 Cases Using UK Biobank Data: Machine Learning Approach
JMIR Public Health Surveill 2021;7(9):e29544
URL: https://publichealth.jmir.org/2021/9/e29544
doi:10.2196/29544
PMID:34591027

Original Paper

Logistics Workers Are a Key Factor for SARS-CoV-2 Spread in Brazilian Small Towns: Case-Control Study

Breno Bernardes-Souza[1], MD; Saulo Ricardo Costa Júnior[2]; Carolina Ali Santos[1], MD; Raimundo Marques Do Nascimento Neto[1], MD, PhD; Fernando De Carvalho Bottega[3], MD; Daiana Carolina Godoy[2]; Bruno Lourençoni Freitas[2]; Daniela Leite Garcia Silva[3], MPharm; Titus Josef Brinker[4], MD; Raiza Aranha Nascimento[5], MD; Unaí Tupinambás[3], MD, PhD; Alexandre Barbosa Reis[6,7], MPharm, PhD; Wendel Coura-Vital[6,7], MPharm, PhD

[1]School of Medicine, Federal University of Ouro Preto, Ouro Preto, Brazil

[2]School of Medicine, Federal University of Lavras, Lavras, Brazil

[3]Faculty of Medicine, Federal University of Minas Gerais, Belo Horizonte, Brazil

[4]German Cancer Research Center, Heidelberg, Germany

[5]School of Medicine, Jose do Rosario Vellano University, Belo Horizonte, Brazil

[6]School of Pharmacy, Federal University of Ouro Preto, Ouro Preto, Brazil

[7]National Institute of Science and Technology in Tropical Diseases, Brazilian National Council for Scientific and Technological Development, Brasília, Brazil

Corresponding Author:
Breno Bernardes-Souza, MD
School of Medicine
Federal University of Ouro Preto
Morro do Cruzeiro University Campus
Ouro Preto, 35400000
Brazil
Phone: 55 31 3559 1001
Email: brenoneps@gmail.com

Abstract

Background: Data on how SARS-CoV-2 enters and spreads in a population are essential for guiding public policies.

Objective: This study seeks to understand the transmission dynamics of SARS-CoV-2 in small Brazilian towns during the early phase of the epidemic and to identify core groups that can serve as the initial source of infection as well as factors associated with a higher risk of COVID-19.

Methods: Two population-based seroprevalence studies, one household survey, and a case-control study were conducted in two small towns in southeastern Brazil between May and June 2020. In the population-based studies, 400 people were evaluated in each town; there were 40 homes in the household survey, and 95 cases and 393 controls in the case-control study. SARS-CoV-2 serology testing was performed on participants, and a questionnaire was applied. Prevalence, household secondary infection rate, and factors associated with infection were assessed. Odds ratios (ORs) were calculated by logistic regression. Logistics worker was defined as an individual with an occupation focused on the transportation of people or goods and whose job involves traveling outside the town of residence at least once a week.

Results: Higher seroprevalence of SARS-CoV-2 was observed in the town with a greater proportion of logistics workers. The secondary household infection rate was 49.1% (55/112), and it was observed that in most households (28/40, 70%) the index case was a logistics worker. The case-control study revealed that being a logistics worker (OR 18.0, 95% CI 8.4-38.7) or living with one (OR 6.9, 95% CI 3.3-14.5) increases the risk of infection. In addition, having close contact with a confirmed case (OR 13.4, 95% CI 6.6-27.3) and living with more than four people (OR 2.7, 95% CI 1.1-7.1) were also risk factors.

Conclusions: Our study shows a strong association between logistics workers and the risk of SARS-CoV-2 infection and highlights the key role of these workers in the viral spread in small towns. These findings indicate the need to focus on this population to determine COVID-19 prevention and control strategies, including vaccination and sentinel genomic surveillance.

(JMIR Public Health Surveill 2021;7(9):e30406) doi:10.2196/30406

KEYWORDS

COVID-19; SARS-CoV-2; logistics workers; risk factors; household infection

Introduction

SARS-CoV-2 emerged in Wuhan, China in December 2019. The virus spread worldwide, resulting in the COVID-19 pandemic [1]. In Brazil, the first case was confirmed on February 25, 2020, and the country gradually became one of the most affected, sustaining an average of more than 40,000 new cases per day and 1000 deaths per day during the second quarter of 2020 [2,3].

As evidence mounted suggesting that a high proportion of individuals infected with SARS-CoV-2 are asymptomatic or oligosymptomatic [4], seroprevalence studies emerged as an important tool not only to see the real extension of the pandemic but also to help understand the dynamics and factors that contribute to viral spread. A national population-based study with samples from 133 large sentinel cities in Brazil conducted from May to June 2020 showed a marked variability in seroprevalence across Brazilian regions, ranging from below 1% in most cities in the south to up to 25% in the Amazon (north) region [5]. Seroprevalence was similar between different ages and sex but was higher among those with low socioeconomic status and among those living in households with greater numbers of people. The study estimated that there were 7 undetected SARS-CoV-2 cases for every detected case in Brazil.

This aforementioned national study included only large Brazilian cities because few cases had been reported in less populous areas at the time. In this context of few reported cases and lack of SARS-CoV-2 research studies in small Brazilian towns, our study aimed to verify the seroprevalence and underreporting of SARS-CoV-2 in these towns, to understand their dynamics of viral transmission, and to identify potential core groups that can serve as an initial source of infection to their general population as well as factors associated with higher risk of infection.

Methods

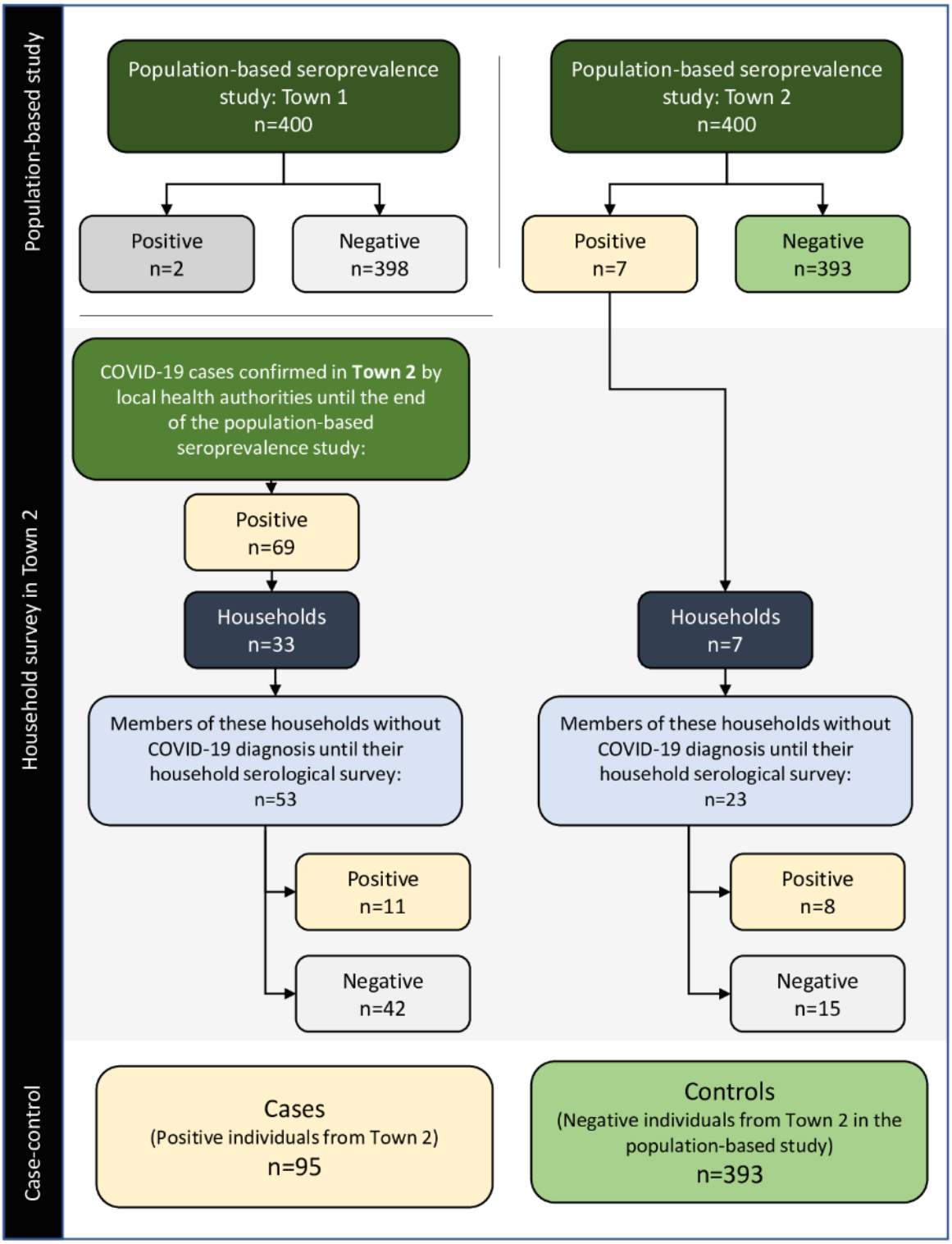
Study Design

Initially, a cross-sectional population-based seroprevalence study was conducted on May 30 and 31, 2020, in the urban area of a small Brazilian town called Nepomuceno (hereby entitled Town 1). Town 1 was chosen by convenience among small towns with no reported COVID-19 cases to verify if SARS-CoV-2 had already spread even in low densely populated Brazilian areas without confirmed COVID-19 cases. The study showed a low seroprevalence, and the identified cases were all related to logistics workers. To confirm the influence of these workers in the spread of the virus in the region, we conducted other studies in another nearby small town called Carmópolis and hereby entitled Town 2.

A similar population-based seroprevalence study was conducted in Town 2 on June 27 and 28, 2020. After the seroprevalence study, a household survey was conducted on June 29 and 30 in all residences of Town 2 that had at least one COVID-19 case confirmed by either our seroprevalence study or by the local health authorities until June 28. During this household survey, all residents were interviewed and serologically tested for COVID-19. After receiving the serological results from a specific household and after evaluating all its individual questionnaires, the interviewer returned to that household to inform them of the results and to conduct a joint interview with all its members aiming to define the index patient and the most likely source of infection to the household and to obtain information on the household's general COVID-19 prevention behaviors.

At the end, a case-control study was carried out with the information obtained from all participants in Town 2 to identify factors associated with COVID-19 diagnosis. In this study, all individuals with positive testing for COVID-19, identified during the cross-sectional seroprevalence study or by the household survey, were considered cases. All individuals with negative COVID-19 testing during the cross-sectional population-based study were considered as controls (Figure 1).

Figure 1. Study design of our population-based, household survey, and case-control study.



Sampling

The sample size for the cross-sectional population-based seroprevalence study was estimated using the online software OpenEpi (OpenEpi Project version 3.01) considering the total population of the urban area, a seroprevalence of 2% [5], and an absolute precision of 1.5%, resulting in a sample of approximately 400 participants in each town. Using maps and census data made available by the Brazilian Institute of Geography and Statistics [6], the total sample (n=400) from each town was divided between all urban census sectors proportionally to their population. Corners of these census sectors were randomly selected for the initial visit, from which a random route was established inside the sector. After the interview and blood collection in the first residence, 4 houses were skipped and a new interview was conducted in the fifth house (commercial properties such as stores, banks, and hotels were not considered), and in cases of refusal, the immediate

next house was selected. In the houses participating in this population-based survey, only the resident with the closest birthday was interviewed and serologically tested for COVID-19, and a previous COVID-19 diagnosis was not an exclusion criteria.

For the case-control study, considering the 95 cases and 393 controls, a type I error (α) of .05, and a frequency of exposure of 1% in controls and 8% in cases, the test power (1-β) was between 90% and 95%.

Study Area

Town 2 was chosen because it is a small town (*small* defined as total population less than 30,000 people) within a radius of 100 km from Town 1 that had the highest number of COVID-19–confirmed cases at the time. Both towns are located in the state of Minas Gerais, in southeastern Brazil, and they have a total population of 25,733 and 17,048 inhabitants, respectively. About 19,004 inhabitants live in the urban area of Town 1 and 11,739 in the urban area of Town 2 [6]. Their current estimated annual gross domestic product (GDP) per capita is US $4706 and US $5497, respectively, and the economy of both is similar, with the service (tertiary) sector comprising nearly 70% of their GDP, while the remaining percentage is mostly represented by coffee- and tomato-related agro-industrial activities [7].

Serological Testing of COVID-19

At the beginning of each visit, a sample of the participant's peripheral blood (3 mL) was collected by puncture of the brachiocephalic vein by a trained nurse and then transferred to a serum-separating tube. The tube was stored between 2 °C to 8 °C and transported within 2 hours to the public laboratory of the town Department of Health, where it was immediately centrifuged (2000xg for 10 minutes) and the separate serum was tested for SARS-CoV-2 antibodies using a lateral flow immunoassay according to the manufacturer's instructions (Hightop SARS-CoV-2 IgM/IgG Antibody Test, Qingdao Hightop Biotech Co, Ltd, China). The sample was considered positive if IgM or IgG antibodies were detectable. The Hightop kit was chosen because robust performance studies [8-11] were available showing that this kit has specificity of 100% for both IgM and IgG, without cross-reactivity even for human seasonal coronaviruses, and an IgG sensitivity of approximately 95% 20 days after the onset of symptoms.

Collection of Data

The interviews of the population-based seroprevalence study were conducted verbally just after the blood collection, and responses were saved on portable electronic devices using KoBoToolbox software (Harvard University). All interviewers were third- to sixth-year medical students who were centrally trained and were provided with personal protective equipment for each interview. The interviews sought information on the following: sociodemographic and economic characteristics; behavioral variables related to COVID-19; current and previous symptoms compatible with COVID-19; and general health condition, use of medications, and presence of comorbidities. COVID-19 prevention questions were not based on actual efficacious prevention but rather assessed what methods (regardless of effectiveness) people were using.

In Town 2, the subsequent household survey of all positive individuals of the town included serological testing of all household members without previous COVID-19 diagnosis and individual interviews with all household members using the same questionnaire from the population-based study (interview was not duplicated if the participant had already been interviewed during the population-based study). If the household still had members on quarantine or isolation at the date of the survey, the interview and serological test of all household members were postponed to 1 day after the end of that period.

Definitions: COVID-19 Confirmed Case, Index Case, Logistics Worker, and High-risk Group

For the household survey, the local health authorities gave us a list of all 69 COVID-19 cases confirmed in Town 2 until June 28, 2020, apart from those cases detected by our population-based seroprevalence study. Their definition of confirmed cases included patients with a positive SARS-CoV-2 reverse transcriptase–polymerase chain reaction (RT-PCR) or serology test (IgM or IgG).

The index patient was defined as the most likely first infected member of a household, and it was usually the household member who first presented COVID-19–compatible symptoms. The presence of patients with asymptomatic COVID-19 in the house, the type (RT-PCR or serology) and date of the first positive test of each patient, the history of previous symptoms compatible with COVID-19 (detailed history was particularly important for cases whose COVID-19 diagnosis was based on serology), and the contact tracing information of each household provided by the town Department of Health were also considered during definition of the index patient. For each household, the joint interview conducted with all of its members was also of pivotal importance for defining the index patient and the most likely source of infection to the household. The index date of each household was defined as the date of symptom onset for the index patient or as the date of the first COVID-19–positive test in cases of an asymptomatic index patient. All this information was also used to retrospectively create the probable SARS-CoV-2 transmission chain between different households.

For the purposes of this study, a logistics worker was defined as an individual with an occupation focused on the transportation of people or goods and whose job involves traveling outside the town of residence at least once a week.

An individual was considered as part of the COVID-19 high-risk group if they reported at least one of the following conditions: 60 years or older; chronic obstructive pulmonary disease; pulmonary fibrosis; asthma; heart failure, previous myocardial infarction, atrial fibrillation, coronary artery disease, or other severe heart disease; previous stroke; type 1 or type 2 diabetes mellitus; chronic kidney disease on dialysis or with glomerular filtration rate <60 mL/min; severe liver disease; severe neurologic conditions; chromosomal abnormalities; sickle cell anemia; HIV with a low CD4 cell count or not on HIV treatment; immunocompromised state from blood, bone marrow, or organ transplant; prolonged use of corticosteroids or other

immunosuppressant drug; current cancer; current smoker; or BMI of 35 kg/m^2 or higher.

Statistical Analysis

The data analysis was performed using STATA software version 14.0 (StataCorp). To calculate the household secondary infection rate, the number of household members with confirmed COVID-19 was divided by the total number of household members excluding the index case. The 95% CIs around the prevalence and secondary infection rates were calculated using the Wilson method.

To investigate the factors associated with the risk of catching COVID-19, case and controls were compared. A logistic regression model was used to evaluate the association between the dependent and independent variables. Occupation was categorized based on the level of essentiality of each occupation during the social restrictions and lockdown measures that had been implemented worldwide and in Brazil at the moment. Univariate analysis was performed for all variables collected, and those with a P<.25 were included in the initial multivariate model. The backward method [12] was subsequently adopted and only variables with P<.05 remained in the final multivariate model. Among variables that showed collinearity, only the one that was the best predictor (higher log likelihood) was retained.

Ethical Approval

The study was approved by the research ethics committee of Federal University of Ouro Preto, Brazil (protocol identification number: CAAE - 32267920.7.0000.5150). Informed consent was read and signed by all participants. In case of minors younger than 18 years, written consent was obtained from parents or legal guardians. Literate children and adolescents were also asked to read and sign an assent form.

Results

Characteristics of the Population of Town 1 and Town 2

The cross-sectional population-based study gave information about general characteristics of inhabitants from both towns (Table 1). The inhabitants in Town 1 had an average age of 47.2 (SD 20.3) years. The average number of people per household was 3.2 (SD 1.4), and the average number of rooms and bathrooms per house was 6.4 (SD 2.0) and 1.5 (SD 0.9), respectively. Thus, the average number of people per room in each housing unit was 0.5 (SD 0.3). It was also observed that in 38.7% of households there was at least one person 60 years or older.

In Town 2, inhabitants had an average age of 43.5 (SD 21.1) years. The average number of residents per household was 3.2 (SD 1.6), and the average number of rooms and bathrooms was 7.4 (SD 2.2) and 1.5 (SD 0.7), respectively. Thus, the average number of people per room in each housing unit was 0.4 (SD 0.2). In 36.5% of households, there was at least one person 60 years or older.

Other characteristics of the study participants from both towns are detailed in Table 1. Although there are minor differences in socioeconomic and demographic variables between both towns, their preventive behaviors for COVID-19 are similar.

Table 1. Cross-sectional population-based study: sociodemographic and behavioral characteristics of Town 1 (n=400) and Town 2 (n=400).

Variable	Town 1, n (%)	Town 2, n (%)	*P* value
Sex			.01
Male	156 (39.0)	196 (49.0)	
Female	244 (61.0)	204 (51.0)	
Race			.04
White	211 (52.8)	235 (58.7)	
Brown-skinned	112 (28.0)	117 (29.2)	
Black	70 (17.5)	40 (10.0)	
Other	7 (1.7)	8 (2.1)	
Age group (years)			.29
0-12	23 (5.8)	33 (8.2)	
13-18	17 (4.2)	22 (5.5)	
19-30	53 (13.2)	66 (16.5)	
31-45	81 (20.2)	78 (19.5)	
46-59	113 (28.3)	109 (27.2)	
≥60	113 (28.3)	92 (23.0)	
Occupation			.01
Homemaker/unemployed	69 (17.2)	49 (12.2)	
Retiree	84 (21.0)	54 (13.5)	
Student/teacher/professor	58 (14.5)	66 (16.5)	
Rural worker	28 (7.0)	23 (5.8)	
Storekeeper/clerk/local employee/independent worker	130 (32.5)	155 (38.7)	
Health care professional	15 (3.8)	13 (3.3)	
Logistics worker	16 (4.0)	40 (10.0)	
Smoking status			.36
Nonsmoker	252 (63.0)	271 (67.7)	
Former smoker	79 (19.7)	68 (17.0)	
Current smoker	69 (17.3)	61 (15.3)	
BCG[a] vaccinated?			.41
Yes	355 (88.7)	362 (90.5)	
No	45 (11.3)	38 (9.5)	
COVID-19 high-risk group?			.04
Yes	220 (55.0)	191 (47.8)	
No	180 (45.0)	209 (52.2)	
Did you meet someone exclusively for leisure/socializing purposes during the past 10 days?			.01
Yes	156 (39.0)	202 (50.5)	
No	244 (61.0)	198 (49.5)	
Do you wear mask at work?			.07
Yes, all the time	138 (34.6)	131 (32.7)	
Yes, most of the time	49 (12.2)	33 (8.2)	
Yes, only sometimes	25 (6.2)	15 (3.8)	
No	29 (7.2)	34 (8.5)	
Not applicable (do not work or home office)	159 (39.8)	187 (46.8)	

Variable	Town 1, n (%)	Town 2, n (%)	*P* value
Do you wear mask while walking on the streets?			.24
Yes, all the time	260 (65.0)	278 (69.5)	
Yes, most of the time	60 (15.0)	41 (10.3)	
Yes, only sometimes	34 (8.5)	37 (9.2)	
No	25 (6.3)	19 (4.7)	
Not applicable (do not leave the house)	21 (5.2)	25 (6.3)	
Do you pull the mask down to talk to someone?			.38
Yes, always	32 (8.0)	26 (6.5)	
Yes, sometimes	42 (10.5)	53 (13.3)	
No	326 (81.5)	321 (80.2)	
Are you regularly taking exclusively for COVID-19 prevention?			
Vitamin or mineral	23 (5.8)	30 (7.5)	.32
Hydroxychloroquine	0 (0)	1 (0.2)	.32
Herbal medicine	7 (1.8)	2 (0.5)	.09
Ivermectin	—[b]	23 (5.8)	N/A[c]

[a]BCG: Bacillus Calmette Guérin.

[b]Prophylactic use of ivermectin was not assessed in Town 1.

[c]N/A: not applicable.

Population-Based Seroprevalence and Underreporting

The prevalence of SARS-CoV-2 infection in Town 1 was 0.5% (95% CI 0.13%-1.80%), since two positive cases were found among the 400 participants evaluated in the population-based serological survey. Based on an urban population of 19,004 inhabitants, this prevalence estimate represents 95 people infected, which is 48-fold more than the number of confirmed cases at that moment (although there were no confirmed cases in the town while the study was being planned, 2 cases were reported by local health authorities just before the execution phase of our study). All 2 cases found in the seroprevalence survey and all other 2 cases already reported in the town were logistics workers or their household members.

In Town 2, a total of 7 positive cases were found among the 400 participants in the population-based seroprevalence study, which corresponds to a prevalence of 1.75% (95% CI 0.85-3.57). As the urban population is 11,739 inhabitants, this prevalence estimate represents 205 people infected, which is 3-fold more than the number of confirmed cases (69 cases had already been reported in the town). Most of the cases identified in the seroprevalence survey (4/7, 57.1%) were logistics workers or their household members. None of the cases found in the population-based survey had been previously detected by local health authorities.

Town 2 Household Survey of COVID-19 Cases

During the household survey of all COVID-19 cases from Town 2, a total of 40 residences were evaluated, 7 of which were residences of COVID-19 cases identified in our population-based seroprevalence study and 33 residences from COVID-19 cases independently confirmed by local health authorities. In these 40 households, there were 152 individuals in total, and the average number of residents per house was 3.8 (SD 1.5). Until the serological survey of all members of these 40 households, the average number of confirmed COVID-19 cases per house was 1.9 (SD 1.4), and this average increased to 2.4 (SD 1.5) after the serological survey (Figure 1). In 70% (28/40) of households, the index case was a logistics worker, and there was at least one logistics worker in 77.5% (31/40) of the households (Table 2).

Table 2. Characteristics of all households from Town 2 with at least one COVID-19 case (n=40).

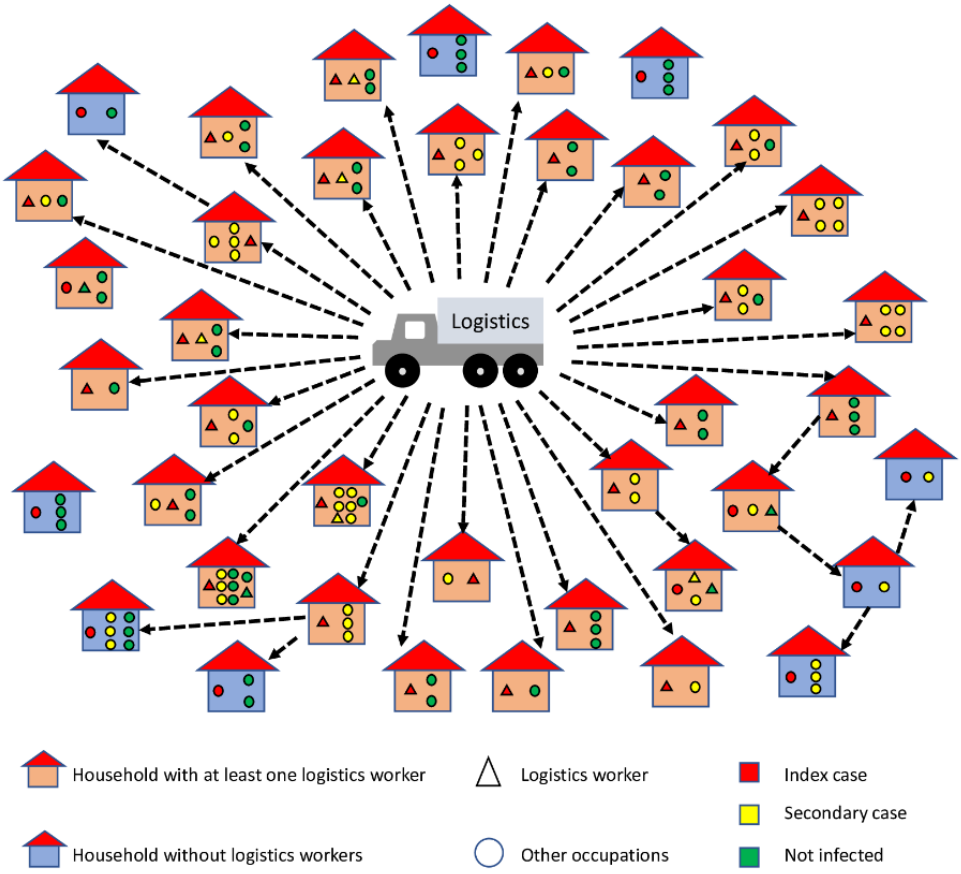
Variable	Households, n (%)
Did this household receive visitors in the 14-day period before the household index date?	
Yes	14 (35)
No	26 (65)
Was any celebration (eg, barbecue or dinner party) held in this household in the 14-day period before the household index date?	
Yes	4 (10)
No	36 (90)
Did the index case of this household attend any celebration in the 14-day period before the household index date?	
Yes	9 (22.5)
No	31 (77.5)
Is the index case a logistics worker?	
Yes	28 (70)
No	12 (30)
Is any member of this household a logistics worker?	
Yes	31 (78)
No	9 (23)
Measures taken to reduce viral transmission	
Sharing the same bed with the infected person was avoided	19 (48)
Sharing the same couch with the infected person was avoided	17 (42.5)
Sharing eating utensils with the infected person was avoided	16 (40)
The infected person washed his own sheets and other bedding	10 (25)
The infected person stayed in a separate room, walking out only when absolutely necessary	8 (20)
The infected person used a separate bathroom	6 (15)
How often did the household members perform hand hygiene while there was one active COVID-19 case in the house?	
Frequently	31 (78)
Sometimes	6 (15)
Rarely	3 (8)
Did the active COVID-19 case use to wear mask while near other people in shared areas of the house?	
No	27 (68)
Yes, always or almost always	12 (30)
Yes, only sometimes	1 (3)

Household Secondary Infection Rate and Contact Tracing

In Town 2, the secondary positive COVID-19 cases reported that symptoms started on average 5.7 (SD 3.2) days after the index date, with a minimum of 1 and a maximum of 12 days. Among the 112 individuals who lived with the index cases in the 40 households, 55 were also identified as confirmed COVID-19 cases until the end of our study, thus the secondary household infection rate in Town 2 was 49.1% (55/112, 95% CI 40.0-58.7).

Using the information about contact tracing provided by local health authorities and the information collected by our interviewers, we retrospectively constructed the probable SARS-CoV-2 transmission chain in all 40 households evaluated in our study from Town 2. It is possible to observe that, in most houses, the index case was a logistics worker (28/40, 70%). In addition, it was noted that the transmission route usually started at homes with logistics workers (Figure 2).

Figure 2. SARS-CoV-2 transmission chains in the first 40 households of Town 2 with COVID-19–confirmed cases. The arrows represent the probable transmission chains.



Factors Associated With Diagnosis of COVID-19

A comparison between cases (n=95) and controls (n=393) was performed by multivariate analysis using the variables obtained from the interviews. The results of the preliminary selection of the variables during univariate analysis (P<.25) are shown in Table 3. The variables retained in the final multivariate model (P<.05) were to be a logistics worker (odds ratio [OR] 18.0, 95% CI 8.4-38.7) or to live with a logistics worker (OR 6.9, 95% CI 3.3-14.5), to have close contact with a confirmed COVID-19 case (OR 13.4, 6.6-27.3), to live with four or more people (OR 2.7, 95% CI 1.4-5.4), and to be a current smoker (OR 0.2, 0.1-0.7; Table 4).

Table 3. Univariate analysis in the case-control study: distribution of COVID-19 cases (n=95) and controls (n=393) from Town 2 according to sociodemographic and behavioral characteristics.

Variables	Case, n (%)	Control, n (%)	Odds ratio (95% CI)	*P* value
Occupation				
Homemaker/unemployed	7 (7.4)	49 (12.0)	1.0 (reference)	N/A[a]
Retiree	7 (7.4)	55 (14.0)	0.9 (0.3-2.6)	.78
Student/teacher/professor	24 (25.3)	64 (16.3)	2.5 (1.0-6.3)	.05
Rural worker	0 (0)	23 (5.8)	N/A	N/A
Storekeeper/clerk/local employee/independent worker	19 (20.0)	153 (38.9)	0.8 (0.3-2.1)	.70
Health care professional	5 (5.3)	13 (3.3)	2.6 (0.7-9.5)	.15
Logistics worker	33 (34.7)	38 (9.7)	5.8 (2.3-14.6)	.01
How many people do you live with?				
Alone or with 1 person	11 (11.6)	122 (31.0)	1.0 (reference)	N/A
With 2 or 3 people	54 (56.8)	220 (56.0)	2.7 (1.4-5.4)	.01
With 4 or more people	30 (31.6)	51 (13.0)	6.5 (3.0-14.0)	.01
Number of rooms per person in the house				
>2	38 (40.0)	225 (57.3)	1.0 (reference)	N/A
≤2	57 (60.0)	168 (42.7)	2.0 (1.3-3.2)	.01
Do you live with or are you a logistics worker?				
No	17 (17.9)	305 (77.6)	1.0 (reference)	N/A
Yes, I live with a logistics worker	45 (47.4)	50 (12.7)	16.1 (8.6-30.4)	.01
Yes, I am a logistics worker	33 (34.7)	38 (9.7)	15.6 (7.9-30.6)	.01
Smoking status				
Nonsmoker	73 (76.8)	266 (67.7)	1.0 (reference)	N/A
Former smoker	16 (16.8)	66 (16.8)	0.9 (0.5-1.6)	.67
Current smoker	6 (6.3)	61 (15.5)	0.4 (0.1-0.9)	.02
Did you have close contact[b] with a COVID-19 case?				
No	46 (48.4)	369 (93.9)	1.0 (reference)	N/A
Yes	49 (51.6)	24 (6.1)	16.4 (9.2-29.1)	.01
Do you have frequent contact[c] with a logistics worker?				
No	33 (34.7)	285 (66.7)	1.0 (reference)	N/A
Yes	62 (65.3)	108 (33.3)	5.0 (3.1-8.0)	.01

[a]N/A: not applicable.

[b]Close contact was defined as being within 6 feet of a person who is infected for at least 15 minutes during a period starting from 2 days before illness onset until the end of isolation of the patient who is infected.

[c]Frequent contact was defined as having close contact at least once a week.

Table 4. Multivariate analysis of sociodemographic and behavioral factors associated with COVID-19 diagnosis: case-control study in Town 2.

Variables	Crude odds ratio (95% CI)	Adjusted odds ratio (95% CI)	*P* value
Do you live with or are you a logistics worker?			
No	1 (reference)	1 (reference)	N/A[a]
Yes, I live with a logistics worker	16.1 (8.6-30.4)	6.9 (3.3-14.5)	.01
Yes, I am a logistics worker	15.6 (7.9-30.6)	18.0 (8.4-38.7)	.01
Did you have close contact[b] with a COVID-19 case?			
No	1 (reference)	1 (reference)	N/A
Yes	16.4 (9.2-29.1)	13.4 (6.6-27.3)	.01
How many people do you live with?			
Alone or with 1 person	1 (reference)	1 (reference)	N/A
With 4 or more people	6.5 (3.0-14.0)	2.7 (1.1-7.1)	.04
Smoking status			
Nonsmoker	1 (reference)	1 (reference)	N/A
Current smoker	0.4 (0.1-0.9)	0.2 (0.1-0.7)	.01

[a]N/A: not applicable.

[b]Close contact was defined as being within 6 feet of a person who is infected for at least 15 minutes during a period starting from 2 days before illness onset until the end of isolation of the patient who is infected.

Discussion

Principal Findings

This study started as a seroprevalence survey in Town 1 (Brazil) to verify if SARS-CoV-2 had already spread even in Brazilian small towns without COVID-19–confirmed cases. The survey showed a low seroprevalence in that town (0.5%), but the identified cases shared a common denominator: they were all related to logistics workers. To confirm the influence of these workers in the spread of the virus in the region, we conducted both a seroprevalence survey and a case-control study in another nearby small town (Town 2) that already had a higher number of confirmed cases. This new survey showed a seroprevalence of 1.75% in the town, and 57.1% of the survey-identified cases were directly related to logistics workers. The case-control study showed that the occupation with the highest risk for COVID-19 are the ones related to logistics (risk higher than health care occupations) and that living with a logistics worker put inhabitants of the town at a high risk of acquiring COVID-19. In addition, we showed that the chain of transmission usually starts in households with logistics workers.

Our study took place between May and the end of June 2020, a time period when the virus was moving from bigger Brazilian cities and capitals toward small towns and rural areas [5]. This move was slow probably because, since April 2020, most cities in Brazil, including the two towns of this study, had already implemented many social contact restrictions and laws to mandate wearing a face mask [5,13]. So our study captures a screenshot of factors that allowed the expansion of the pandemic to low densely populated areas even in a scenario of gathering restrictions, face mask mandates, and other lockdown measures.

Throughout this pandemic, logistics workers kept *on the road* were of vital importance to maintain a continued supply of essential goods to allow people to *stay at home*. Besides that, medical supply chains are reliant on truck drivers and other logistics workers, and will continue to be as treatments and vaccines are approved, manufactured, and distributed [14]. As logistics workers strive to meet the unprecedented demands due to the current pandemic, their movement patterns and social interactions are unique and of foremost epidemiological significance [14,15].

As our study captures the moment of initial local viral transmission (as reflected by low seroprevalence in both towns), our results portray what triggers community transmission (ie, what allows transitioning from imported cases to community transmission). The identification of these triggers is important for slowing down the spread of a pathogen and is, thus, a strategy for public health security. Although imported cases are easier to manage, community transmissions are hard to trace, can grow quickly, and easily threaten local public health systems [16].

Logistics workers have been shown to spread infectious diseases such as HIV and syphilis across geographic lines, both locally and in distant areas [17]. The same seems to be true regarding SARS-CoV-2, and in fact, the transport sector was substantially hit during this pandemic to slow the spread of the virus. This hit on transportation was mainly focused on international travel, air transport, and tourism [18,19] while undermining the importance of essential local logistics workers. This underestimation is reflected by the lack of COVID-19 public health strategies and research studies focused in this group.

Our study shows that, in a scenario of lockdown and mask mandates in small Brazilian towns, essential local logistics workers and their household members had the highest risk of contracting COVID-19 during the initial phase of the local epidemic. Thus, these workers are an important core group that

spreads the infection to the general population, allowing the initiation of community transmissions. Noteworthy, all cases found in Town 1 during our study were likely imported cases, and at the time, there was no evidence of community transmission in that town.

Our study is among the first to show the peculiar role of these workers in the spread of SARS-CoV-2. To our knowledge, only one study from Uganda has pointed it out so far. The authors [20] reviewed the first 10 weeks of press releases from the Uganda Ministry of Health from the day when the first case was announced. At the end of these 10 weeks, 442 COVID-19 cases had been confirmed, most of which (71.8%) were truck drivers. Besides that, the majority of community cases identified have had contact with these drivers. They concluded that the epidemic in Uganda, a country that was in national lockdown during those 10 initial weeks, was literally being driven by truck drivers.

Considering our findings, one factor that probably explains why Town 2 had a seroprevalence almost four times higher than Town 1 is the fact that the population of Town 2 had a significantly higher proportion of logistics workers (Table 1). Another factor is that the study was done in Town 2 later than in Town 1, but this time gap alone likely does not explain the difference between the two towns because data from nearby cities indicate that seroprevalence in the area was stable and did not even double during this interval [5,21]. Apart from that, it should be observed that both towns have similar economies, are close to each other within the same state, and were taking the same lockdown measures in accordance with guidelines from their State Health Department. In addition, the population-based survey showed similar compliance with wearing a mask in both towns, with nearly all participants wearing masks when going out, which is similar to attitudes and practices toward COVID-19 in other countries at that time [22,23].

Our multivariate model showed that the risk of getting COVID-19 is almost three times higher in individuals who share their household with four or more members, compared to those who live alone or with only one person. We also found a household secondary infection rate of 49.1% (55/112), suggesting a high rate of intrafamily transmission. This rate is similar to rates found by other studies in western countries, such as 53% in the United States [24] and 43% in Italy [25], but it is higher than rates found in eastern countries, such as 30% in China [26] and 11.8% in South Korea [27], probably due to different culture and customs inside the household environment. For example, although one Chinese study [28] found that 93.5% of patients isolated at home with COVID-19 were fully compliant to wearing masks during family activities in shared areas of the house; only in 30% of households from our study did the confirmed case wear a mask in the same circumstance.

One variable that in our multivariate analysis was associated with lower risk of getting COVID-19 is smoking. The protective effect of smoking in COVID-19 has been a consistent finding across many published studies [29,30], but it should be viewed with caution because this protective effect is unlikely to outweigh the numerous proven adverse health effects of smoking. Besides that, although smokers may have a reduced chance of getting COVID-19, they have a higher risk of severe disease in case they are infected [31].

Our findings in this study are subject to a number of limitations. First, as our research was conducted only in two towns from the southern region of the state of Minas Gerais, our results may not be generalizable to other Brazilian states and even to other regions of the state of Minas Gerais. Second, regarding the calculated household secondary infection rate, although living in the same household might convey a high risk of acquiring infection, some infections might have originated outside the household, leading to a higher apparent secondary infection rate. Third, even though not all patients infected with SARS-CoV-2 will become IgM or IgG positive [32], we chose an antibody test kit that has a high sensitivity validated by many robust performance studies [8-11]. In addition, as our study is focused on the initial phase of local transmission, our results are unlikely to be affected by the fact that SARS-CoV-2 antibodies may become undetected in some individuals 3 months after recovery [33]. Fourth, recall bias and selection bias are intrinsic limitations of case-control studies. Recall bias was probably minimal in our study because we investigated variables that are easy to recollect (eg, occupation, COVID-19–related behavior, and contact tracing) especially because they are mostly related to a pandemic that impacted everyone's life, particularly in a small town with many implemented social contact restrictions and lockdown measures. Selection bias related to controls was probably minimal too because controls came from the initial population-based survey, so the control group is representative of the local population. In addition, we had more than 4 controls for each case, which is an optimal ratio to increase statistical power of a case-control study [34].

When it comes to cases, a source of selection bias is the fact that our case-control study also includes cases from Town 2 that were identified by local health authorities, and there may be biases in how they identified the cases. It is important to note that Brazil has a free and universal public health system and that COVID-19 testing in Brazil was scarce at the moment [35,36], so health authorities in Town 2 were testing only patients who were symptomatic, but no age or occupation was being prioritized. Under this scenario, it is not likely that our cases are biased toward a community segment, but they may be biased toward a group more likely to become symptomatic. Nevertheless, we think the probability of this bias in our main findings is low because, as already mentioned, the majority of cases detected in the population-based seroprevalence survey (which included participants regardless of symptoms) were also cases related to logistics workers.

Recent data from the Brazilian Ministry of Economy [37] has shown that truck drivers and bus drivers were the two occupations with the highest increase in job termination due to death (both with 407% increases) when compared with the first bimester of 2019 and 2021, which is three times higher than health care occupations. This data reinforces the validity of our results and indicates the need to focus on logistics workers to determine COVID-19 public policies, including prevention of the spread of novel variants.

Conclusions

Our study shows a strong association between being a logistics worker and the risk of SARS-CoV-2 infection, and points out the role of these workers as a core group that brings the virus to Brazilian small towns. These findings indicate the need to focus on these workers to determine COVID-19 prevention and control strategies, as they are important triggers for initiation of local community transmission and may be triggers for the spread of novel concerning variants in areas already under control. In light of this evidence, logistics workers should also be prioritized for SARS-CoV-2 vaccination and sentinel genomic surveillance, especially in areas similar to those of our study.

Acknowledgments

We would like to thank the Health Department of Nepomuceno (Town 1) and Carmópolis (Town 2) for their support in this study.

This study was supported by Federal University of Ouro Preto, Nepomuceno Town Health Department, and Carmópolis Town Health Department. The sponsors had no role in the study design; the collection, analysis, and interpretation of the data; the writing of the manuscript; and the decision to submit the paper for publication.

Authors' Contributions

BBS, ABR, and WCV conceptualized and designed the study, performed the statistical analysis, and wrote the manuscript. BBS, SRCJ, FCB, DCG, BLF, DLGS, and WCV coordinated the execution of the study, data collection, and data entry. SRCJ, CAL, RMNN, FCB, DCG, BLF, DLGS, TJB, RAN, and UT proofread the manuscript and contributed to the interpretation of the results. All authors declare responsibility for the data and findings presented, and have full access to the data set.

Conflicts of Interest

None declared.

References

1. Guan W, Ni Z, Hu Y, Liang W, Ou C, He J, et al. Clinical characteristics of coronavirus disease 2019 in China. N Engl J Med 2020 Apr 30;382(18):1708-1720. [doi: 10.1056/nejmoa2002032]
2. de Souza WM, Buss LF, Candido DDS, Carrera J, Li S, Zarebski AE, et al. Epidemiological and clinical characteristics of the COVID-19 epidemic in Brazil. Nat Hum Behav 2020 Aug;4(8):856-865. [doi: 10.1038/s41562-020-0928-4] [Medline: 32737472]
3. National Covid-19 surveillance report (week 40). Brazil Ministry of Health. 2020. URL: https://www.gov.br/saude/pt-br/media/pdf/2020/dezembro/11/boletim_epidemiologico_covid_40-1.pdf [accessed 2021-12-20]
4. Yanes-Lane M, Winters N, Fregonese F, Bastos M, Perlman-Arrow S, Campbell JR, et al. Proportion of asymptomatic infection among COVID-19 positive persons and their transmission potential: a systematic review and meta-analysis. PLoS One 2020;15(11):e0241536 [FREE Full text] [doi: 10.1371/journal.pone.0241536] [Medline: 33141862]
5. Hallal PC, Hartwig FP, Horta BL, Silveira MF, Struchiner CJ, Vidaletti LP, et al. SARS-CoV-2 antibody prevalence in Brazil: results from two successive nationwide serological household surveys. Lancet Glob Health 2020 Nov;8(11):e1390-e1398 [FREE Full text] [doi: 10.1016/S2214-109X(20)30387-9] [Medline: 32979314]
6. Map of the 12th Brazilian Demographic Census. Brazilian Institute of Geography and Statistics. 2010. URL: https://censo2010.ibge.gov.br/apps/mapa/ [accessed 2021-12-07]
7. Gross domestic product of Brazilian cities. Brazilian Institute of Geography and Statistics. 2017. URL: https://www.ibge.gov.br/estatisticas/economicas/contas-nacionais/9088-produto-interno-bruto-dos-municipios.html [accessed 2021-12-07]
8. Bond K, Nicholson S, Lim SM, Karapanagiotidis T, Williams E, Johnson D, et al. Evaluation of serological tests for SARS-CoV-2: implications for serology testing in a low-prevalence setting. J Infect Dis 2020 Sep 14;222(8):1280-1288 [FREE Full text] [doi: 10.1093/infdis/jiaa467] [Medline: 32761124]
9. Alger J, Cafferata ML, Alvarado T, Ciganda A, Corrales A, Desale H, et al. Using prenatal blood samples to evaluate COVID-19 rapid serologic tests specificity. Matern Child Health J 2020 Sep;24(9):1099-1103 [FREE Full text] [doi: 10.1007/s10995-020-02981-9] [Medline: 32671537]
10. Post-market validation of serological assays for COVID-19 - updated report. Australian Government Department of Health. 2020. URL: https://www.health.gov.au/resources/publications/post-market-validation-of-serological-assays-for-covid-19-updated-report [accessed 2021-12-07]
11. Brazilian task force for performance evaluation of coronavirus diagnostic kits. Brazilian Society of Clinical Analysis. 2020. URL: https://www.testecovid19.org/avaliacoes [accessed 2020-12-07]
12. Kleinbaum DG, Kupper LL, Nizam A, Rosenberg ES. Applied Regression Analysis and Other Multivariable Methods. Boston, MA: Cengage Learning; 2013.

13. Candido DS, Claro IM, de Jesus JG, Souza WM, Moreira FRR, Dellicour S, Brazil-UK Centre for Arbovirus Discovery, Diagnosis, Genomics and Epidemiology (CADDE) Genomic Network, et al. Evolution and epidemic spread of SARS-CoV-2 in Brazil. Science 2020 Sep 04;369(6508):1255-1260 [FREE Full text] [doi: 10.1126/science.abd2161] [Medline: 32703910]
14. Lemke M, Apostolopoulos Y, Gallos LK, Sönmez S. Commercial transport during a pandemic: network analysis to reconcile COVID-19 diffusion and vital supply chain resilience. J Occup Environ Med 2020 Sep;62(9):e537-e538. [doi: 10.1097/JOM.0000000000001940] [Medline: 32890226]
15. Lemke MK, Apostolopoulos Y, Sönmez S. A novel COVID-19 based truck driver syndemic? Implications for public health, safety, and vital supply chains. Am J Ind Med 2020 Aug;63(8):659-662 [FREE Full text] [doi: 10.1002/ajim.23138] [Medline: 32452556]
16. Godin A, Xia Y, Buckeridge DL, Mishra S, Douwes-Schultz D, Shen Y, et al. The role of case importation in explaining differences in early SARS-CoV-2 transmission dynamics in Canada-A mathematical modeling study of surveillance data. Int J Infect Dis 2021 Jan;102:254-259 [FREE Full text] [doi: 10.1016/j.ijid.2020.10.046] [Medline: 33115683]
17. Zhang X, Chow EP, Wilson DP, Sun X, Zhao R, Zhang J, et al. Prevalence of HIV and syphilis infections among long-distance truck drivers in China: a data synthesis and meta-analysis. Int J Infect Dis 2013 Jan;17(1):e2-e7 [FREE Full text] [doi: 10.1016/j.ijid.2012.07.018] [Medline: 23059625]
18. Muley D, Shahin M, Dias C, Abdullah M. Role of transport during outbreak of infectious diseases: evidence from the past. Sustainability 2020 Sep 08;12(18):7367. [doi: 10.3390/su12187367]
19. Ribeiro SP, Castro E Silva A, Dáttilo W, Reis AB, Góes-Neto A, Alcantara LCJ, et al. Severe airport sanitarian control could slow down the spreading of COVID-19 pandemics in Brazil. PeerJ 2020;8:e9446. [doi: 10.7717/peerj.9446] [Medline: 32617196]
20. Bajunirwe F, Izudi J, Asiimwe S. Long-distance truck drivers and the increasing risk of COVID-19 spread in Uganda. Int J Infect Dis 2020 Sep;98:191-193 [FREE Full text] [doi: 10.1016/j.ijid.2020.06.085] [Medline: 32615323]
21. Coura-Vital W, Cardoso DT, Ker FTDO, Magalhães FC, Bezerra JMT, Viegas AM, et al. Spatiotemporal dynamics and risk estimates of COVID-19 epidemic in Minas Gerais State: analysis of an expanding process. Rev Inst Med Trop Sao Paulo 2021;63:e21 [FREE Full text] [doi: 10.1590/S1678-9946202163021] [Medline: 33787741]
22. Zhong B, Luo W, Li H, Zhang Q, Liu X, Li W, et al. Knowledge, attitudes, and practices towards COVID-19 among Chinese residents during the rapid rise period of the COVID-19 outbreak: a quick online cross-sectional survey. Int J Biol Sci 2020;16(10):1745-1752 [FREE Full text] [doi: 10.7150/ijbs.45221] [Medline: 32226294]
23. Erfani A, Shahriarirad R, Ranjbar K, Mirahmadizadeh A, Moghadami M. Knowledge, attitude and practice toward the novel coronavirus (COVID-19) outbreak: a population-based survey in Iran. Bull World Health Organ 2020;30:A. [doi: 10.2471/blt.20.256651]
24. Grijalva CG, Rolfes MA, Zhu Y, McLean HQ, Hanson KE, Belongia EA, et al. Transmission of SARS-COV-2 infections in households - Tennessee and Wisconsin, April-September 2020. MMWR Morb Mortal Wkly Rep 2020 Nov 06;69(44):1631-1634. [doi: 10.15585/mmwr. mm6944e1] [Medline: 33151916]
25. Boscolo-Rizzo P, Borsetto D, Spinato G, Fabbris C, Menegaldo A, Gaudioso P, et al. New onset of loss of smell or taste in household contacts of home-isolated SARS-CoV-2-positive subjects. Eur Arch Otorhinolaryngol 2020 Sep;277(9):2637-2640 [FREE Full text] [doi: 10.1007/s00405-020-06066-9] [Medline: 32449021]
26. Wang Z, Ma W, Zheng X, Wu G, Zhang R. Household transmission of SARS-CoV-2. J Infect 2020 Jul;81(1):179-182 [FREE Full text] [doi: 10.1016/j.jinf.2020.03.040] [Medline: 32283139]
27. Park YJ, Choe YJ, Park O, Park SY, Kim Y, Kim J, COVID-19 National Emergency Response Center, Epidemiology and Case Management Team. Contact tracing during coronavirus disease outbreak, South Korea, 2020. Emerg Infect Dis 2020 Oct;26(10):2465-2468. [doi: 10.3201/eid2610.201315] [Medline: 32673193]
28. Li H, Peng Y, Lu J. Investigation and analysis of 108 cases of home isolated patients with mild COVID-19. Disaster Med Public Health Prep 2020 Aug 12:1-4 [FREE Full text] [doi: 10.1017/dmp.2020.296] [Medline: 32782040]
29. Usman M, Siddiqi TJ, Khan MS, Patel UK, Shahid I, Ahmed J, et al. Is there a smoker's paradox in COVID-19? BMJ Evid Based Med 2020 Aug 11:1. [doi: 10.1136/bmjebm-2020-111492] [Medline: 32788164]
30. Paleiron N, Mayet A, Marbac V, Perisse A, Barazzutti H, Brocq FX, et al. Impact of tobacco smoking on the risk of COVID-19: a large scale retrospective cohort study. Nicotine Tob Res 2021 Aug 04;23(8):1398-1404 [FREE Full text] [doi: 10.1093/ntr/ntab004] [Medline: 33420786]
31. Reddy RK, Charles WN, Sklavounos A, Dutt A, Seed PT, Khajuria A. The effect of smoking on COVID-19 severity: a systematic review and meta-analysis. J Med Virol 2021 Feb;93(2):1045-1056 [FREE Full text] [doi: 10.1002/jmv.26389] [Medline: 32749705]
32. Shahriarirad R, Sarkari B. COVID-19: clinical or laboratory diagnosis? A matter of debate. Trop Doct 2021 Jan;51(1):131-132. [doi: 10.1177/0049475520945446] [Medline: 32762302]
33. Long Q, Tang X, Shi Q, Li Q, Deng H, Yuan J, et al. Clinical and immunological assessment of asymptomatic SARS-CoV-2 infections. Nat Med 2020 Aug;26(8):1200-1204. [doi: 10.1038/s41591-020-0965-6] [Medline: 32555424]
34. Setia M. Methodology series module 2: case-control studies. Indian J Dermatol 2016;61(2):146-151 [FREE Full text] [doi: 10.4103/0019-5154.177773] [Medline: 27057012]

35. Thornton J. Covid-19: lack of testing in Brazil is a "major failure," says MSF. BMJ 2020 Jul 02;370:m2659. [doi: 10.1136/bmj.m2659] [Medline: 32616564]
36. Alves THE, de Souza TA, Silva SDA, Ramos NA, de Oliveira SV. Underreporting of death by COVID-19 in Brazil's second most populous state. Front Public Health 2020;8:578645. [doi: 10.3389/fpubh.2020.578645] [Medline: 33384978]
37. Gavras D. Essential and invisible worker is the main victim of the pandemic in Brazil. Folha de Sao Paulo. 2021. URL: https://www1.folha.uol.com.br/mercado/2021/06/trabalhador-essencial-e-invisivel-e-maior-vitima-da-pandemia-no-brasil.shtml [accessed 2021-06-28]

Abbreviations

GDP: gross domestic product
OR: odds ratio
RT-PCR: reverse transcriptase–polymerase chain reaction

Edited by T Sanchez, G Eysenbach; submitted 13.05.21; peer-reviewed by P Banik, D Laborde, R Shahriarirad; comments to author 07.06.21; revised version received 28.06.21; accepted 03.08.21; published 01.09.21.

Please cite as:
Bernardes-Souza B, Júnior SRC, Santos CA, Neto RMDN, Bottega FDC, Godoy DC, Freitas BL, Silva DLG, Brinker TJ, Nascimento RA, Tupinambás U, Reis AB, Coura-Vital W
Logistics Workers Are a Key Factor for SARS-CoV-2 Spread in Brazilian Small Towns: Case-Control Study
JMIR Public Health Surveill 2021;7(9):e30406
URL: https://publichealth.jmir.org/2021/9/e30406
doi:10.2196/30406
PMID:34388105

Original Paper

Estimation of COVID-19 Period Prevalence and the Undiagnosed Population in Canadian Provinces: Model-Based Analysis

Abdullah Hamadeh[1], PhD; Zeny Feng[2], PhD; Jessmyn Niergarth[2], PhD; William WL Wong[1], PhD

[1]School of Pharmacy, University of Waterloo, Kitchener, ON, Canada

[2]Department of Mathematics and Statistics, University of Guelph, Guelph, ON, Canada

Corresponding Author:
William WL Wong, PhD
School of Pharmacy
University of Waterloo
10A Victoria Street S
Kitchener, ON, N2G1C5
Canada
Phone: 1 519 888 4567 ext 21323
Email: wwlwong@uwaterloo.ca

Abstract

Background: The development of a successful COVID-19 control strategy requires a thorough understanding of the trends in geographic and demographic distributions of disease burden. In terms of the estimation of the population prevalence, this includes the crucial process of unravelling the number of patients who remain undiagnosed.

Objective: This study estimates the period prevalence of COVID-19 between March 1, 2020, and November 30, 2020, and the proportion of the infected population that remained undiagnosed in the Canadian provinces of Quebec, Ontario, Alberta, and British Columbia.

Methods: A model-based mathematical framework based on a disease progression and transmission model was developed to estimate the historical prevalence of COVID-19 using provincial-level statistics reporting seroprevalence, diagnoses, and deaths resulting from COVID-19. The framework was applied to three different age cohorts (< 30; 30-69; and ≥70 years) in each of the provinces studied.

Results: The estimates of COVID-19 period prevalence between March 1, 2020, and November 30, 2020, were 4.73% (95% CI 4.42%-4.99%) for Quebec, 2.88% (95% CI 2.75%-3.02%) for Ontario, 3.27% (95% CI 2.72%-3.70%) for Alberta, and 2.95% (95% CI 2.77%-3.15%) for British Columbia. Among the cohorts considered in this study, the estimated total number of infections ranged from 2-fold the number of diagnoses (among Quebecers, aged ≥70 years: 26,476/53,549, 49.44%) to 6-fold the number of diagnoses (among British Columbians aged ≥70 years: 3108/18,147, 17.12%).

Conclusions: Our estimates indicate that a high proportion of the population infected between March 1 and November 30, 2020, remained undiagnosed. Knowledge of COVID-19 period prevalence and the undiagnosed population can provide vital evidence that policy makers can consider when planning COVID-19 control interventions and vaccination programs.

(JMIR Public Health Surveill 2021;7(9):e26409) doi:10.2196/26409

KEYWORDS

COVID-19; prevalence; undiagnosed proportion; mathematical modeling; estimate; Canada; diagnosis; control; distribution; infectious disease; model; framework; progression; transmission

Introduction

The epidemiological information used to plan and evaluate strategies to prevent the spread of COVID-19 has undergone rapid changes since the start of the pandemic. As with many countries across the world, most Canadian provinces have enforced nonpharmaceutical interventions (NPIs) such as travel bans, school closures, and restrictions on nonessential businesses, workplaces, and social gatherings [1-4]. These measures, coupled with the highly uncertain and life-threatening nature of the disease, have resulted in profound societal and economic impacts [5].

With the high number of observed symptomless cases [3,4,6-12], there is now strong evidence that COVID-19 remains

asymptomatic in a significant proportion of the infected population. This feature of the disease has been hypothesized to be a main driver of the rapid spread of COVID-19 worldwide [1,2]. Studies have also demonstrated that the transmissibility of SARS-CoV-2, the causative agent of COVID-19 via asymptomatic and symptomatic individuals is similar [13,14].

With the emergence of new, more transmissible variants of SARS-CoV-2 [15] and given the age-dependence of the likelihood of transmission and hospitalization following infection [16,17], the development of a successful COVID-19 control strategy requires a thorough understanding of the trends in the geographic and demographic distribution of disease burden. Estimation of the undiagnosed population is crucial for the planning and allocation of resources needed to implement restrictions for preventing disease spread and, more importantly, for knowing when it is appropriate to relax such restrictions. In addition, knowledge of the size of the previously infected population is of importance for estimating the remaining susceptible population and for planning next-generation vaccination drives in response to emerging variants [18].

In Canada, data on COVID-19 prevalence that include the undiagnosed population are extremely limited. Estimates of prevalence of the disease have included seroprevalence studies [19-24]. These likely underestimate the true COVID-19 prevalence owing to small sample sizes and an undersampling of the groups that are most affected by COVID-19, such as lower socioeconomic status groups and immigrant groups [25,26]. Alternatively, COVID-19 prevalence and incidence can be inferred using a back-calculation approach [27,28], in which recently observed occurrences of COVID-19–related late-stage events (eg, COVID-19–related deaths) are mapped backward using a mathematical simulation model of the natural history of the disease. An important advantage of the back-calculation approach over others is its ability to include the undiagnosed population in the prevalence estimation.

Our objective is to estimate the period prevalence of COVID-19 between March 1 and November 30, 2020, and the proportion of the infected population that remained undiagnosed in the Canadian provinces of Quebec (QC), Ontario (ON), Alberta (AB), and British Columbia (BC) by using a model-based back-calculation framework. These estimates are derived for three different age cohorts (under 30; 30-69; and ≥70 years) in each of the provinces studied. These provinces are the four most populated in Canada and were selected because the vast majority of COVID-19 cases in Canada were observed in these geographic regions across the study period.

This study presents a framework for estimating the disease burden by region, demographics, and diagnosis status. A disease progression and transmission model is used to estimate the size and composition of the COVID-19 period prevalence by integrating the results of previous seroprevalence surveys with primary provincial observed data of health events related to COVID-19 and its sequelae, including COVID-19–related deaths. From these estimates, we derive the proportion of the infected population that remained undiagnosed during this period.

Methods

Overview

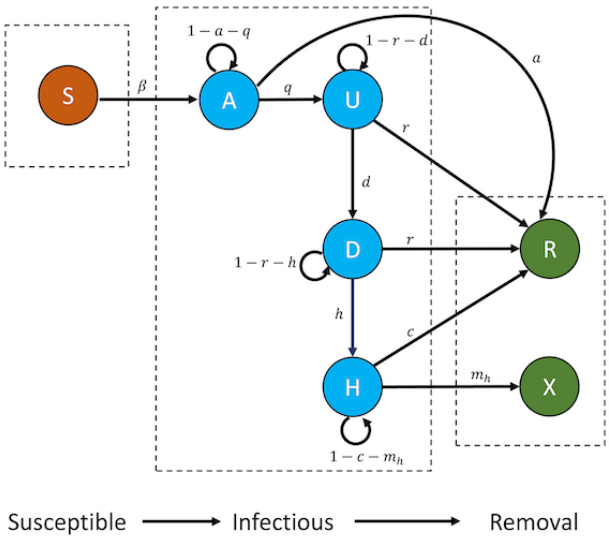
A mathematical framework based on a compartmental disease progression and transmission model was developed for the estimation of the period prevalence for a given population. The framework was applied to COVID-19 data from each of QC, ON, AB, and BC. For each province, a Markov chain Monte Carlo (MCMC)–based Bayesian state estimation algorithm [29] was used to construct joint posterior probability distributions for the unknown model parameters and the daily number of individuals in each COVID-19 health state. These probability distributions are constructed by iteratively comparing the model-generated mean estimates of the daily numbers of COVID-19–related health events and period prevalence against observed calibration targets. The calibration targets were obtained from provincial data collected between March 1 and November 30, 2020, that reported (1) daily cases of newly diagnosed COVID-19 [30-33], (2) daily new deaths attributed to COVID-19, and (3) COVID-19 seroprevalence [21-24]. An overview of our proposed method is presented in the following subsections. A detailed methodology section is included in Multimedia Appendix 1.

Disease Progression Model Assumptions

For each province, we develop an age-stratified "susceptible-infectious-removed" (SIR) compartmental framework to describe the progression through various disease states for individuals of the population. We stratified each population into three age cohorts: <30, 30 to 69, and ≥70 years. The model is structured based on the COVID-19 natural history model illustrated in Figure 1. The infectious state is subdivided into 4 health states: (1) state A, representing infected individuals who show no symptoms and are undiagnosed; (2) state U, representing symptomatic and undiagnosed individuals; (3) state D, representing individuals who are symptomatic and diagnosed; and (4) state H, representing hospitalized individuals. Individuals who recover (R) or die (X) are considered to be in the removal state.

We assume that individuals who reach state D do so by progressing through the states A → U → D. We also assume that the daily probability of recovery of an infected individual depends on their age cohort and whether they are in state A, state U or D, or state H. We assume all deaths due to COVID-19 are diagnosed and hospitalized prior to death. We assume that COVID-19–related mortality decreases gradually over time for all age groups as a result of better understanding of the disease and that the daily probability of diagnosing a COVID-19 infection has increased gradually since the start of the pandemic as a result of improved testing capacity.

Figure 1. COVID-19 model conceptual diagram. Health states: Susceptible (S); asymptomatic and undiagnosed (A); symptomatic and undiagnosed (U); symptomatic and diagnosed (D); hospitalized (H); recovered (R); and death (X).



β – mean number of daily new infections

q – daily probability of an asymptomatic infected individual developing symptoms

a – daily probability of recovery of an asymptomatic infected individual

r – daily probability of recovery of a non-hospitalized symptomatic infected individual

d – daily probability of diagnosis of an undiagnosed symptomatic infected individual

h – daily probability of hospitalization of a diagnosed infected individual

c – daily probability of recovery after hospitalization

m_h – daily probability of death after hospitalization

Disease Transmission Dynamics Assumptions

Within each province, we assume the disease to be transmissible across different age cohorts. We assume that the infectiveness of an infected individual will depend on whether they have been diagnosed (due to self-isolation following a diagnosis) and on whether they show symptoms [34]. Thus, the mean number of daily new infections caused by an infected individual will vary depending on their health state (A, U, or D).

Canadian Provinces have implemented NPIs to combat the spread of COVID-19. These interventions include travel bans, closure of schools and nonessential businesses, and limits on social gatherings. To reflect the effects of NPIs, seasonal effects on the transmissibility of SARS-CoV-2, and changes in public behavior, the infection rates K_A, K_U, and K_D are allowed to vary over 9 different periods: The first three periods (March 1-11, March 12- 29, and March 30 to June 1, 2020) reflect the periods of preimplementation, partial implementation, and full implementation of NPIs, respectively. The latter periods correspond to each of the months of June to November 2020. The daily probability of diagnosis of infected individuals is assumed to have increased gradually between March 1 and November 30, 2020, reflecting increases in testing capacity across this period.

Model Fitting

Health event data reporting the daily numbers of diagnosed cases and COVID-19–related deaths were collected for each province and age group for the study period. A summary of the cumulative diagnoses and COVID-19–related deaths as of November 30, 2020, is provided in Table 1.

Statistics on rates of recovery, testing, and hospitalization across the study period were also collected [30-33]. From these data, initial estimates of the mean values of the daily probabilities of hospitalization for diagnosed cases, as well as the daily probabilities of recovery and death for diagnosed and hospitalized cases, were calculated. Initial estimates of the mean daily probability of developing symptoms and of being discharged from the hospital were obtained from the literature [35,36]. The Metropolis-Hastings MCMC (MH-MCMC) algorithm was used to calibrate the remaining unknown parameters (Multimedia Appendix 2), and Kalman filtering was used to calibrate the daily number of individuals within each health state. The negative sum of the square of the weighted differences between (1) the expected and observed daily numbers of confirmed cases and deaths and (2) the expected and observed seroprevalence (Table 2) was used to approximate the log-likelihood function for computing the posterior distributions of unknown parameters and the unobserved daily numbers of individuals in each health state.

Table 1. Cumulative observed COVID-19 diagnoses and deaths as per data for Quebec, Ontario, Alberta, and British Columbia as of November 30, 2020.

Province and age cohort (years)	Population	Cumulative diagnoses as of November 30, 2020	Cumulative deaths as of November 30, 2020
Quebec			
<30	2,829,745	45,778	4
30-69	4,534,110	71,658	584
≥70	1,121,110	26,476	6467
Ontario			
<30	5,227,392	38,464	0
30-69	7,607,840	62,331	471
≥70	1,731,315	15,692	3084
Alberta			
<30	1,674,906	23,207	3
30-69	2,314,614	32,223	67
≥70	381,796	4013	491
British Columbia			
<30	1,681,252	12,054	0
30-69	2,747,468	18,624	67
≥70	642,616	3108	374

Table 2. Canadian provincial COVID-19 seroprevalence surveys conducted between March 2020 and July 2020 used for model fitting.

Province and survey date	Seroprevalence			Reference
	Age adjusted % (95% CI)	Total assays, n	Positive assays, n (%)	
Quebec				
July 9, 2020	2.23 (1.90-2.56)	7691	173 (2.25)	[22]
Ontario				
April 30, 2020	0.5 (0.1-1.5)	827	3 (0.36)	[21]
May 31, 2020	1.5 (0.7-2.2)	1061	15 (1.41)	[21]
June 18, 2020	0.96 (0.810-1.113)	19,839	189 (0.95)	[23]
June 30, 2020	1.1 (0.8-1.3)	7014	79 (1.12)	[21]
Alberta				
June 18, 2020	0.37 (0.182-0.552)	5644	24 (0.42)	[23]
British Columbia				
March 13, 2020	0.28 (0.03-0.95)	869	2 (0.23)	[24]
May 27, 2020	0.55 (0.15-1.37)	885	4 (0.45)	[24]
June 18, 2020	0.50 (0.304-0.694)	4962	29 (0.58)	[23]

Model Validation

The disease progression model was used to back-calculate each cohort's COVID-19 period prevalence based on the reported confirmed cases and deaths shown in Table 1, in addition to early provincial seroprevalence results as reported in Table 2. The fitted models generally showed close agreement with these data across the four provinces and three age cohorts. Multimedia Appendix 3 shows the fit of the models to the reported daily numbers of confirmed cases and deaths.

Table 3 summarizes the seroprevalence in Ontario for the months of July and August 2020 [19,20], which was reported by Public Health Ontario to be 1.1% (0.8%-1.3%). These two latter reported seroprevalences were not used as observed data in the model fitting but were instead used to validate the fitted model. Our calibrated model for Ontario showed close agreement with these latter seroprevalence survey results, with an estimated mean period prevalence of 1.13% as of July 31 (164,740 cases) and 1.20% (175,050 cases) as of August 31.

Table 3. Provincial COVID-19 seroprevalence surveys between July 2020 and August 2020 used for model validation in Ontario, Canada.

Date	Seroprevalence			Reference
	Age adjusted % (95% CI)	Total assays, n	Positive assays, n (%)	
July 31, 2020	1.1 (0.8-1.3)	7001	70 (0.99)	[20]
August 31, 2020	1.1 (0.8-1.3)	6789	72 (1.06)	[19]

Results

Prevalence and Total Incidence Estimates

The mean estimates of the COVID-19 period prevalence between March 1 and November 30, 2020, for each province are as follows: 4.73% (95% CI 4.42%-4.99%) for QC, 2.88% (95% CI 2.75%-3.02%) for ON; 3.27% (95% CI 2.72%-3.70%) for AB; and 2.95% (95% CI 2.77%-3.15%) for BC, as illustrated in Figure 2.

Figure 3 shows the observed and estimated cumulative total number of infections for each age cohort up to November 30, 2020. For that date, the median estimates of the cumulative total numbers of infected individuals were as follows: 135,407 (95% CI 126,380-143,185) for QC, 151,443 (95% CI 144,707-158,804) for ON, 55,596 (95% CI 45,892-63,063) for AB, and 50,356 (95% CI 47,318-53,912) for BC, among individuals aged under 30 years; 212,048 (95% CI 198,212-223,863) for QC, 218,446 (95% CI 208,519-228,609) for ON, 75,246 (95% CI 62,932-85,136) for AB, 80,915 (95% CI 76,063-86,605) for BC, among individuals aged between 30 and 69 years; and 53,549 (95% CI 50,462-56,298) for QC, 49,937 (95% CI 47,614-52,440) for ON, 11,932 (95% CI 9,961-13,445) for AB, 18,147 (95% CI 17,076-19,397) for BC, among individuals aged 70 years or above. Multimedia Appendix 4 shows the estimated distributions of the cumulative total number of individuals with COVID-19 infection and the reported cumulative total number of individuals diagnosed with COVID-19 infection. Summary statistics for the distributions are tabulated in Multimedia Appendix 5. These estimates include both the diagnosed and undiagnosed populations and they range between 2 and 6 times the reported diagnoses of the provinces as, illustrated in Figure 3.

Figure 2. Estimated COVID-19 period prevalence in Quebec, Ontario, Alberta, and British Columbia between March 1 and November 30, 2020.

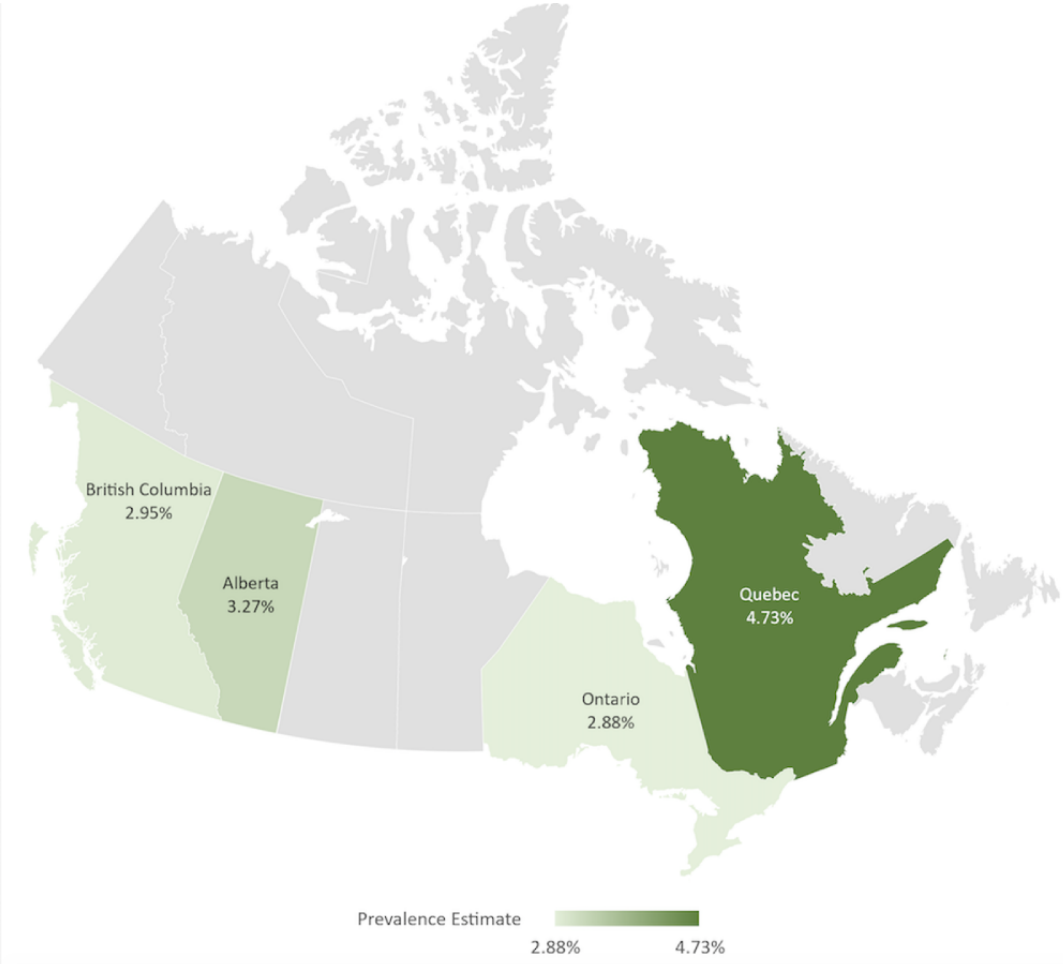
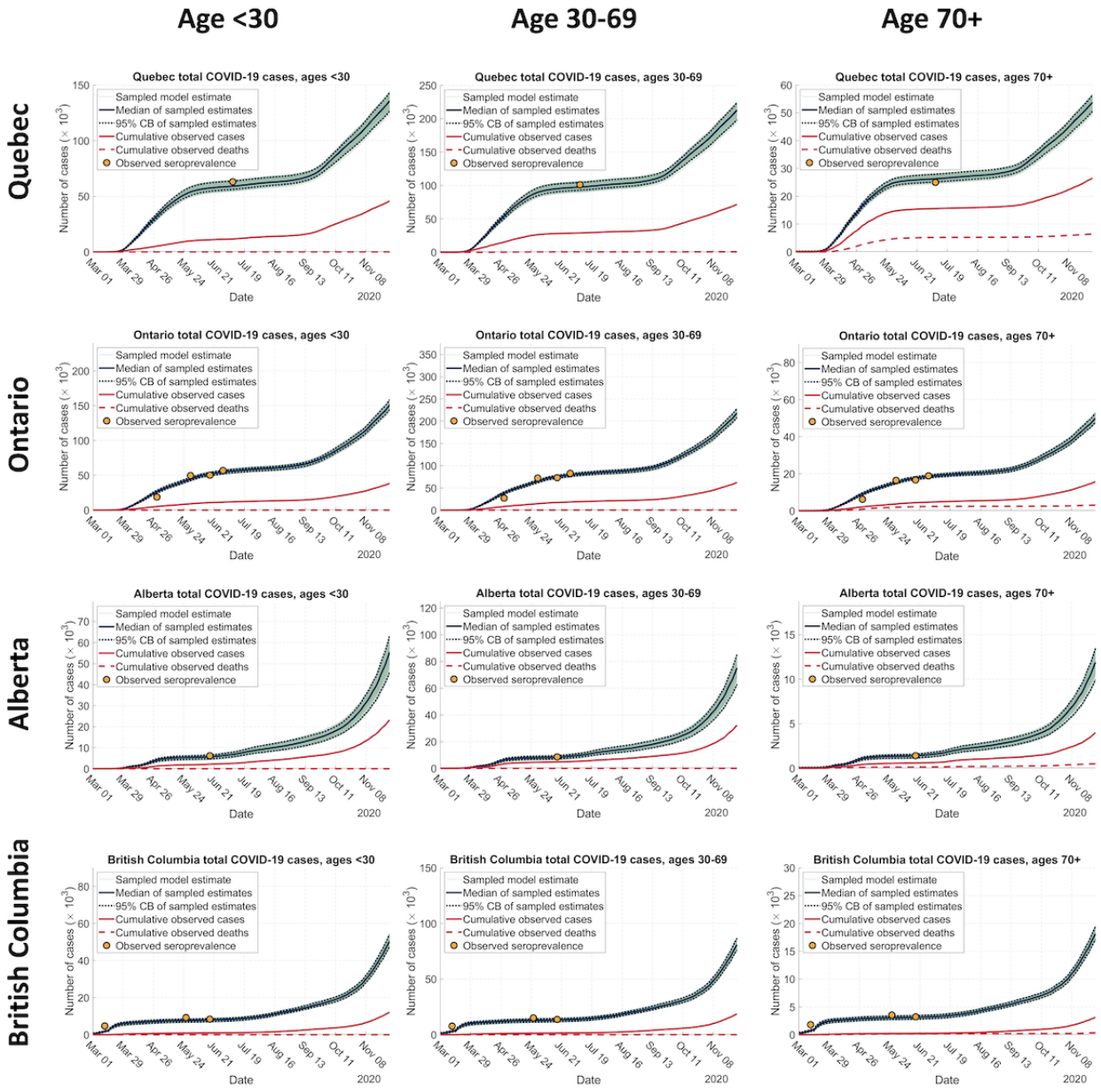


Figure 3. Estimated trajectories of cumulative total COVID-19 cases, cumulative reported COVID-19 diagnoses, and cumulative reported COVID-19 deaths in Quebec, Ontario, Alberta, and British Columbia between March 1 and November 30, 2020. CB: credible band.



Undiagnosed Proportion

Across the study period, the estimated proportion of the total infected population that was undiagnosed in each cohort and province was as follows: 66.19% (95% CI 63.78%-68.03%) for QC, 74.60% (95% CI 73.42%-75.78%) for ON, 58.26% (95% CI 49.43%-63.20%) for AB, and 76.06% (95% CI 74.53%-77.64%) for BC among individuals under 30 years; 66.21% (95% CI 63.85%-67.99%) for QC, 71.47% (95% CI 70.11%-72.73%) for ON, 57.18% (95% CI 48.80%-62.15%) for AB, and 76.98% (95% CI 75.52%-78.50%) for BC among individuals aged between 30 and 69 years; and 50.56% (95% CI 47.53%-52.97%) for QC, 68.58% (95% CI 67.04%-70.08%) for ON, 66.37% (95% CI 59.71%-70.15%) for AB, and 82.87% (95% CI 81.80%-83.98%) for BC among individuals aged 70 years and above.

Discussion

Principal Findings

We have combined our mathematical model with detailed province-level data to provide a comprehensive and robust estimate of the burden of COVID-19 infections in four large Canadian provinces between March 1 and November 30, 2020. Across all provinces and cohorts studied, our model-based prevalence estimates indicate that the period prevalence from March 1 to November 30, 2020, including both the diagnosed and undiagnosed populations, ranged between 2- to 6-fold the reported diagnosed period prevalence.

A variety of methods have previously been used to estimate the true prevalence of infectious diseases in Canada and around the world, including that of hepatitis C and HIV [37-41]. Common methods include seroprevalence surveys and model-based

approaches [39]. Our findings suggest that the prevalence of COVID-19 in Canada over the study period was significantly higher than estimates based on data reported by provinces. In comparison, our estimates are congruent with seroprevalence surveys [3,4,6,42,43] and model-based approaches [27,28] conducted elsewhere around the world. Specifically, Bajema et al [42] reported the results of a large-scale seroprevalence survey conducted in the United States and found that the seroprevalence of New York state can be as high as 23%, much higher than the reported cases. Rostami et al [43] reported a systematic review and meta-analysis of seroprevalence of 23 countries worldwide and concluded that over 263 million people had been exposed or infected with COVID-19 as of the end of August 2020, roughly 10 times more than the 25 million people reported [44]. Flaxman et al [27] generated a model-based prevalence estimate based on a back-calculation method for 11 European countries and concluded that there are considerably fewer COVID-19 cases detected than their model estimated due to the presence of asymptomatic or mild cases. Perkins et al [28] also used a mathematical modeling approach to estimate the unobserved incidence in the United States and reported that the number of detected symptomatic infections was less than 10% of the total infected population during the early stage of the pandemic. As testing capacity has increased over time, the daily probability of diagnosis of a given infected individual will also have increased. Consequently, it is to be expected that the ratio between the overall prevalence and estimates of prevalence based solely on diagnosis figures will be lower than what has been reported for earlier stages of the pandemic. Our 2- to 6-fold estimates reasonably reflect this fact.

In contrast to the cross-sectional "snapshots" of the pandemic offered by seroprevalence surveys, our model-based approach provides longitudinal estimates of the COVID-19 population, which unveils the trends in the true spread of the disease over time as well as insights into the medium- to long-term effectiveness of NPIs in limiting transmissions. On the other hand, our analysis is subject to certain limitations. First, accurately estimating the period prevalence depends on knowledge of key model parameters such as the transmission rates and probabilities of diagnosis. The initial values of these parameters that were used in our model may have inherited biases from the existing literature on the natural history of COVID-19. However, through the Bayesian approach, uncertainties in these parameters are ultimately reflected in the credible intervals of the final prevalence estimates. Second, our method can, in principle, be applied to Canadian regions not considered in this study as well as to other countries. However, our longitudinal estimates of the period prevalence require high-resolution time-series data on the number of confirmed cases and deaths in each region and age cohort under investigation.

Establishing a robust baseline estimate of the prevalence and undiagnosed proportion is critical, as it contains important information for decision makers to plan for the future regarding how many individuals are likely to require vaccination and how much extra screening effort is needed to diagnose unaware infected individuals to prevent transmission. Our study provided estimates from the period of March 1 to November 30, 2020. Towards the end of the study period, COVID-19 vaccines were on track for deployment around the globe [45]. In recent months, these vaccines have been proven to be highly effective [46]. At the same time, new SARS-CoV-2 variants have reversed downward trends in infections even in countries with good rates of vaccination coverage [15], where these rapidly changing circumstances have prompted a re-evaluation of plans to ease NPIs. Given the higher transmissibility of the novel SARS-CoV-2 variants, updated estimates of the prevalence and undiagnosed proportion will be necessary, as this information contains important indicators for decision-makers to plan for future interventions, such as the distribution of next-generation vaccines [18].

If testing costs and time continue to decrease, expanding the number of tests can increase the diagnosis rate and reduce potential asymptomatic transmission [47]. However, to determine the appropriate level of expansion, such as, for example, whether to target specific high-risk populations or to conduct a general population screening, a cost-effectiveness analysis and budget impact analysis would be required [48]. Our framework for the inference of COVID-19 prevalence would provide pivotal parameters and estimates for these analyses.

Conclusions

Our study provides a framework for estimating the prevalence of COVID-19 in Canada and indicates a substantial proportion of the population infected between March 1 and November 30, 2020, remained undiagnosed. The analysis we have presented provides a more complete picture of the pandemic than would be indicated from observations that only focus on COVID-19 diagnosis statistics. This information is critical for policy makers and public health officials when considering the implementation or relaxation of interventions for controlling COVID-19.

Acknowledgments

This work was partially supported by an Ontario Ministry of Research, Innovation, and Science Early Researcher Award that was awarded to WW. This work was also partially supported by Discovery Grants from the Natural Sciences and Engineering Research Council of Canada (NSERC) (1257369 to WW and 400095 to ZF).

Conflicts of Interest

None declared.

Multimedia Appendix 1

Detailed methodology section.
[DOCX File , 79 KB - publichealth_v7i9e26409_app1.docx]

Multimedia Appendix 2
Model parameters and their Bayesian estimates.
[DOCX File , 72 KB - publichealth_v7i9e26409_app2.docx]

Multimedia Appendix 3
Model validation results.
[DOCX File , 1259 KB - publichealth_v7i9e26409_app3.docx]

Multimedia Appendix 4
Distribution of the estimated cumulative total number of COVID-19 cases, reported cumulative diagnoses, and reported cumulative deaths.
[DOCX File , 494 KB - publichealth_v7i9e26409_app4.docx]

Multimedia Appendix 5
Estimated cumulative total COVID-19 infections as of November 30, 2020.
[DOCX File , 44 KB - publichealth_v7i9e26409_app5.docx]

References

1. Peeri NC, Shrestha N, Rahman MS, Zaki R, Tan Z, Bibi S, et al. The SARS, MERS and novel coronavirus (COVID-19) epidemics, the newest and biggest global health threats: what lessons have we learned? Int J Epidemiol 2020 Feb 22:717-726. [doi: 10.1093/ije/dyaa033] [Medline: 32086938]
2. Zhao H, Lu X, Deng Y, Tang Y, Lu J. COVID-19: asymptomatic carrier transmission is an underestimated problem. Epidemiol. Infect 2020 Jun 11;148:E116. [doi: 10.1017/s0950268820001235]
3. Sood N, Simon P, Ebner P, Eichner D, Reynolds J, Bendavid E, et al. Seroprevalence of SARS-CoV-2-Specific Antibodies Among Adults in Los Angeles County, California, on April 10-11, 2020. JAMA 2020 Jun 16;323(23):2425-2427 [FREE Full text] [doi: 10.1001/jama.2020.8279] [Medline: 32421144]
4. Goodman D, Rothfeld M. 1 in 5 New Yorkers May Have Had Covid-19, Antibody Tests Suggest. The New York Times. 2020. URL: https://www.nytimes.com/2020/04/23/nyregion/coronavirus-antibodies-test-ny.html [accessed 2021-08-31]
5. Antunes P, Stewart M. Economic Implications of Social Distancing to August. The Conference Board of Canada. 2020 Mar 23. URL: https://www.conferenceboard.ca/research/economic-implications-of-social-distancing?AspxAutoDetectCookieSupport=1 [accessed 2021-08-31]
6. Baggett TP, Keyes H, Sporn N, Gaeta JM. Prevalence of SARS-CoV-2 infection in residents of a large homeless shelter in Boston. JAMA 2020 Jul 02;323(21):2191-2192 [FREE Full text] [doi: 10.1001/jama.2020.6887] [Medline: 32338732]
7. Wong J, Abdul Aziz ABZ, Chaw L, Mahamud A, Griffith MM, Lo Y, et al. High proportion of asymptomatic and presymptomatic COVID-19 infections in air passengers to Brunei. J Travel Med 2020 Aug 20;27(5):taaa066 [FREE Full text] [doi: 10.1093/jtm/taaa066] [Medline: 32365178]
8. Hijnen D, Marzano AV, Eyerich K, GeurtsvanKessel C, Giménez-Arnau AM, Joly P, et al. SARS-CoV-2 transmission from presymptomatic meeting attendee, Germany. Emerg Infect Dis 2020 Aug;26(8):1935-1937 [FREE Full text] [doi: 10.3201/eid2608.201235] [Medline: 32392125]
9. Dong Y, Mo X, Hu Y, Qi X, Jiang F, Jiang Z, et al. Epidemiology of COVID-19 among children in China. Pediatrics 2020 Jun;145(6):e20200702 [FREE Full text] [doi: 10.1542/peds.2020-0702] [Medline: 32179660]
10. Yanes-Lane M, Winters N, Fregonese F, Bastos M, Perlman-Arrow S, Campbell JR, et al. Proportion of asymptomatic infection among COVID-19 positive persons and their transmission potential: A systematic review and meta-analysis. PLoS One 2020;15(11):e0241536 [FREE Full text] [doi: 10.1371/journal.pone.0241536] [Medline: 33141862]
11. Al-Sadeq DW, Nasrallah GK. The incidence of the novel coronavirus SARS-CoV-2 among asymptomatic patients: A systematic review. Int J Infect Dis 2020 Oct;98:372-380 [FREE Full text] [doi: 10.1016/j.ijid.2020.06.098] [Medline: 32623083]
12. He J, Guo Y, Mao R, Zhang J. Proportion of asymptomatic coronavirus disease 2019: A systematic review and meta-analysis. J Med Virol 2021 Feb;93(2):820-830 [FREE Full text] [doi: 10.1002/jmv.26326] [Medline: 32691881]
13. He D, Zhao S, Lin Q, Zhuang Z, Cao P, Wang MH, et al. The relative transmissibility of asymptomatic COVID-19 infections among close contacts. Int J Infect Dis 2020 May;94:145-147 [FREE Full text] [doi: 10.1016/j.ijid.2020.04.034] [Medline: 32315808]
14. Yin G, Jin H. Comparison of transmissibility of coronavirus between symptomatic and asymptomatic patients: reanalysis of the Ningbo COVID-19 data. JMIR Public Health Surveill 2020 May 28;6(2):e19464 [FREE Full text] [doi: 10.2196/19464] [Medline: 32442131]

15. Mahase E. Delta variant: What is happening with transmission, hospital admissions, and restrictions? BMJ 2021 Jul 15;373:n1513. [doi: 10.1136/bmj.n1513] [Medline: 34130949]
16. Mueller AL, McNamara MS, Sinclair DA. Why does COVID-19 disproportionately affect older people? Aging (Albany NY) 2020 May 29;12(10):9959-9981 [FREE Full text] [doi: 10.18632/aging.103344] [Medline: 32470948]
17. Davies NG, Klepac P, Liu Y, Prem K, Jit M, CMMID COVID-19 working group, et al. Age-dependent effects in the transmission and control of COVID-19 epidemics. Nat Med 2020 Aug;26(8):1205-1211. [doi: 10.1038/s41591-020-0962-9] [Medline: 32546824]
18. Abdool Karim SS, de Oliveira T. New SARS-CoV-2 variants — clinical, public health, and vaccine implications. N Engl J Med 2021 May 13;384(19):1866-1868. [doi: 10.1056/nejmc2100362]
19. COVID-19 Seroprevalence in Ontario: August 1 to August 31, 2020. Public Health Ontari0 - COVID-19 Serosurveillance Summary. URL: https://www.publichealthontario.ca/-/media/documents/ncov/epi/2020/10/covid-19-epi-seroprevalence-in-ontario-aug-31.pdf [accessed 2020-11-01]
20. COVID-19 Seroprevalence in Ontario: July 4 to July 31, 202. Public Health Ontario - COVID-19 Serosurveillance Summary. URL: https://www.publichealthontario.ca/-/media/documents/ncov/epi/2020/10/covid-19-epi-seroprevalence-in-ontario-july-31.pdf [accessed 2020-11-01]
21. COVID-19 Seroprevalence in Ontario: March 27, 2020 to June 30, 2020. Public Health Ontario - COVID-19 Serosurveillance Summary. URL: https://www.publichealthontario.ca/-/media/documents/ncov/epi/2020/07/covid-19-epi-seroprevalence-in-ontario.pdf?la=en [accessed 2020-11-01]
22. Étude de séroprévalence des anti-SRAS-COV-2 chez les donneurs de sang d'Héma-Québec, vers la fin de la première vague de COVID-19 – Étude no. ET-20-004, Projet COVID-20-02. Webpage in French. 2021 Jan 21. URL: https://www.hema-quebec.qc.ca/userfiles/file/coronavirus/COVID-20-02-rappot-final-20-02-2021.pdf [accessed 2021-08-31]
23. COVID-19 Seroprevalence Report – August 19, 2020. Canadian Blood Services. URL: https://www.blood.ca/sites/default/files/CBS_COVID-19_Seroprevalence_Public_Report_Aug272020.pdf [accessed 2020-11-01]
24. Skowronski D, Sekirov I, Sabaiduc S, Zou M, Morshed M, Lawrence D. Low SARS-CoV-2 sero-prevalence based on anonymized residual sero-survey before and after first wave measures in British Columbia, Canada, March-May 2020. medRxiv. Preprint posted online on July 15, 2020. [doi: 10.1101/2020.07.13.20153148]
25. Ng E. COVID-19 deaths among immigrants: Evidence from the early months of the pandemic. Statistics Canada. 2021 Jun 9. URL: https://www150.statcan.gc.ca/n1/pub/45-28-0001/2021001/article/00017-eng.htm [accessed 2021-06-15]
26. Clouston SA, Natale G, Link BG. Socioeconomic inequalities in the spread of coronavirus-19 in the United States: A examination of the emergence of social inequalities. Soc Sci Med 2021 Jan;268:113554 [FREE Full text] [doi: 10.1016/j.socscimed.2020.113554] [Medline: 33308911]
27. Flaxman S, Mishra S, Gandy A, Unwin HJT, Mellan TA, Coupland H, Imperial College COVID-19 Response Team, et al. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature 2020 Aug;584(7820):257-261. [doi: 10.1038/s41586-020-2405-7] [Medline: 32512579]
28. Perkins TA, Cavany SM, Moore SM, Oidtman RJ, Lerch A, Poterek M. Estimating unobserved SARS-CoV-2 infections in the United States. Proc Natl Acad Sci U S A 2020 Sep 08;117(36):22597-22602 [FREE Full text] [doi: 10.1073/pnas.2005476117] [Medline: 32826332]
29. Zarchan P, Musoff H. Fundamentals of Kalman Filtering: A Practical Approach, Fourth Edition. Reston, Virginia: American Institute of Aeronautics and Astronautics; Jan 2015.
30. COVID-19 vaccinations data. Government of Ontario. URL: https://covid-19.ontario.ca/data [accessed 2020-07-02]
31. Data on COVID-19 in Québec. Québec.ca - Official website of the Gouvernement du Québec. 2020 Jul 02. URL: https://www.quebec.ca/en/health/health-issues/a-z/2019-coronavirus/situation-coronavirus-in-quebec/ [accessed 2021-08-31]
32. BC COVID-19 Data. BC Center for Disease Control. URL: http://bccdc.ca/covid19data [accessed 2020-07-02]
33. COVID-19 Alberta Statistics. Government of Alberta. URL: https://covid19stats.alberta.ca [accessed 2020-07-02]
34. He X, Lau EHY, Wu P, Deng X, Wang J, Hao X, et al. Temporal dynamics in viral shedding and transmissibility of COVID-19. Nat Med 2020 May 15;26(5):672-675. [doi: 10.1038/s41591-020-0869-5] [Medline: 32296168]
35. Lauer SA, Grantz KH, Bi Q, Jones FK, Zheng Q, Meredith HR, et al. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. Ann Intern Med 2020 May 05;172(9):577-582 [FREE Full text] [doi: 10.7326/M20-0504] [Medline: 32150748]
36. Li L, Huang T, Wang Y, Wang Z, Liang Y, Huang T, et al. COVID-19 patients' clinical characteristics, discharge rate, and fatality rate of meta-analysis. J Med Virol 2020 Jun 23;92(6):577-583 [FREE Full text] [doi: 10.1002/jmv.25757] [Medline: 32162702]
37. Sweeting MJ, De Angelis D, Brant LJ, Harris HE, Mann AG, Ramsay ME. The burden of hepatitis C in England. J Viral Hepat 2007 Aug;14(8):570-576. [doi: 10.1111/j.1365-2893.2007.00851.x] [Medline: 17650291]
38. Deuffic-Burban S, Mathurin P, Valleron A. Modelling the past, current and future HCV burden in France: detailed analysis and perspectives. Stat Methods Med Res 2009 Jul 26;18(3):233-252. [doi: 10.1177/0962280208094697] [Medline: 19036916]
39. Hamadeh A, Feng Z, Krahn M, Wong WWL. A model-based framework for chronic hepatitis C prevalence estimation. PLoS One 2019 Nov 21;14(11):e0225366 [FREE Full text] [doi: 10.1371/journal.pone.0225366] [Medline: 31751393]

40. Trubnikov M, Yan P, Archibald C. Estimated prevalence of Hepatitis C Virus infection in Canada, 2011. Can Commun Dis Rep 2014 Dec 18;40(19):429-436 [FREE Full text] [doi: 10.14745/ccdr.v40i19a02] [Medline: 29769874]
41. Rosenberg PS, Biggar RJ, Goedert JJ, Gail MH. Backcalculation of the number with human immunodeficiency virus infection in the United States. Am J Epidemiol 1991 Mar 01;133(3):276-285. [doi: 10.1093/oxfordjournals.aje.a115872] [Medline: 2000845]
42. Bajema KL, Wiegand RE, Cuffe K, Patel SV, Iachan R, Lim T, et al. Estimated SARS-CoV-2 seroprevalence in the US as of September 2020. JAMA Intern Med 2021 Apr 01;181(4):450-460 [FREE Full text] [doi: 10.1001/jamainternmed.2020.7976] [Medline: 33231628]
43. Rostami A, Sepidarkish M, Leeflang MM, Riahi SM, Nourollahpour Shiadeh M, Esfandyari S, et al. SARS-CoV-2 seroprevalence worldwide: a systematic review and meta-analysis. Clin Microbiol Infect 2021 Mar;27(3):331-340 [FREE Full text] [doi: 10.1016/j.cmi.2020.10.020] [Medline: 33228974]
44. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis 2020 May;20(5):533-534 [FREE Full text] [doi: 10.1016/S1473-3099(20)30120-1] [Medline: 32087114]
45. Mahase E. Covid-19: Pfizer and BioNTech submit vaccine for US authorisation. BMJ 2020 Nov 20;371:m4552. [doi: 10.1136/bmj.m4552] [Medline: 33219049]
46. Iacobucci G. Covid-19: Two doses of Pfizer vaccine are "highly effective" against infection, hospital admission, and death, study finds. BMJ 2021 May 05;373:n1164. [doi: 10.1136/bmj.n1164] [Medline: 33952443]
47. Overview of Testing for SARS-CoV-2 (COVID-19). Centers for Disease Control and Prevention. URL: https://www.cdc.gov/coronavirus/2019-ncov/php/open-america/expanded-screening-testing.html [accessed 2021-08-31]
48. Appleby J. Tackling covid-19: are the costs worth the benefits? BMJ 2020 May 21;369:m1496. [doi: 10.1136/bmj.m1496] [Medline: 32317272]

Abbreviations

AB: Alberta
BC: British Columbia
MCMC: Markov chain Monte Carlo
MH-MCMC: Metropolis-Hastings Markov chain Monte Carlo
NPIs: nonpharmaceutical interventions
ON: Ontario
QC: Quebec
SIR: susceptible-infectious-removed

Edited by T Sanchez; submitted 12.12.20; peer-reviewed by R Shahriarirad, F Amer; comments to author 11.06.21; revised version received 17.06.21; accepted 22.06.21; published 09.09.21.

Please cite as:
Hamadeh A, Feng Z, Niergarth J, Wong WWL
Estimation of COVID-19 Period Prevalence and the Undiagnosed Population in Canadian Provinces: Model-Based Analysis
JMIR Public Health Surveill 2021;7(9):e26409
URL: https://publichealth.jmir.org/2021/9/e26409
doi:10.2196/26409
PMID:34228626

Original Paper

Associations Between the Perceived Severity of the COVID-19 Pandemic, Cyberchondria, Depression, Anxiety, Stress, and Lockdown Experience: Cross-sectional Survey Study

Lei Han[1]; Yanru Zhan[1]; Weizi Li[1]; Yuqing Xu[1]; Yan Xu[2*]; Jinzhe Zhao[2*]

[1]School of Psychology, Shandong Normal University, Ji'nan, Shandong, China

[2]Faculty of Psychology, Beijing Normal University, Beijing, China

[*]these authors contributed equally

Corresponding Author:
Jinzhe Zhao
Faculty of Psychology
Beijing Normal University
19 Xinjiekouwai Street Haidian District
Beijing, 100875
China
Phone: 86 19800356013
Email: sszbjz@163.com

Abstract

Background: The outbreak of the COVID-19 pandemic has caused great panic among the public, with many people suffering from adverse stress reactions. To control the spread of the pandemic, governments in many countries have imposed lockdown policies. In this unique pandemic context, people can obtain information about pandemic dynamics on the internet. However, searching for health-related information on the internet frequently increases the possibility of individuals being troubled by the information that they find, and consequently, experiencing symptoms of cyberchondria.

Objective: We aimed to examine the relationships between people's perceived severity of the COVID-19 pandemic and their depression, anxiety, and stress to explore the role of cyberchondria, which, in these relationship mechanisms, is closely related to using the internet. In addition, we also examined the moderating role of lockdown experiences.

Methods: In February 2020, a total of 486 participants were recruited through a web-based platform from areas in China with a large number of infections. We used questionnaires to measure participants' perceived severity of the COVID-19 pandemic, to measure the severity of their cyberchondria, depression, anxiety, and stress symptoms, and to assess their lockdown experiences. Confirmatory factor analysis, exploratory factor analysis, common method bias, descriptive statistical analysis, and correlation analysis were performed, and moderated mediation models were examined.

Results: There was a positive association between perceived severity of the COVID-19 pandemic and depression (β=0.36, t=8.51, P<.001), anxiety (β=0.41, t=9.84, P<.001), and stress (β=0.46, t=11.45, P<.001), which were mediated by cyberchondria (β=0.36, t=8.59, P<.001). The direct effects of perceived severity of the COVID-19 pandemic on anxiety (β=0.07, t=2.01, P=.045) and stress (β=0.09, t=2.75, P=.006) and the indirect effects of cyberchondria on depression (β=0.10, t=2.59, P=.009) and anxiety (β=0.10, t=2.50, P=.01) were moderated by lockdown experience.

Conclusions: The higher the perceived severity of the COVID-19 pandemic, the more serious individuals' symptoms of depression, anxiety, and stress. In addition, the associations were partially mediated by cyberchondria. Individuals with higher perceived severity of the COVID-19 pandemic were more likely to develop cyberchondria, which aggravated individuals' depression, anxiety, and stress symptoms. Negative lockdown experiences exacerbated the COVID-19 pandemic's impact on mental health.

(JMIR Public Health Surveill 2021;7(9):e31052) doi:10.2196/31052

KEYWORDS

COVID-19; cyberchondria; depression; anxiety; stress; ABC theory of emotions; lockdown experience; perceived severity; cross-sectional; online health information

Introduction

Background

Since 2020, hundreds of millions of people have been infected with COVID-19 and millions of people have died [1]. Due to its long incubation period, high infectiousness, and high risk of death if not treated promptly, COVID-19 has become a major public health emergency worldwide [2]. Public health emergencies, such as severe acute respiratory syndrome (SARS) in 2003 [3], Middle East respiratory syndrome in 2012 [4], and Ebola virus disease in 2014 [5] have significantly harmed people's lives, caused people to suffer economic losses, and caused severe psychological trauma. The impacts of these events on economic development may be alleviated in the short term, but their impacts on social stability and mental health may be long-term [6]. Studies have shown that, during the COVID-19 pandemic, people experienced varying degrees of depression, anxiety, and stress symptoms [7], which lasted over 4 weeks [8].

Previous studies [9,10] have found that the objective severity of the pandemic is negatively correlated with mental health (eg, depression, anxiety, worry, and dissatisfaction). In addition, knowledge and concerns about COVID-19 (eg, low confidence in doctors, low perceived likelihood of survival, and spending more time gathering health information) [11] and the perceived impact of the pandemic [12] were found to be positively correlated with depression, anxiety, and stress. In this study, we aimed to investigate the relationship between the perceived severity of the COVID-19 pandemic and depression, anxiety, and stress, as well as the mechanisms underlying these associations, with subjective assessments based on psychometric standards.

Hypothesis 1: Perceived Severity of the COVID-19 Pandemic Is Positively Associated With and Depression, Anxiety, and Stress

The ABC theory of emotions [13] suggests that stimulus events are only indirect causes that trigger individuals' emotions and behaviors as consequences, while the direct causes of such emotions and behaviors are the beliefs that result from an individual's perception and evaluation of the stimulus event. One study [14] examined the relationship between individuals' appraisals of SARS risk and their emotional and behavioral responses. Another study [15] found that the public's risk perception regarding the Ebola outbreak was positively correlated with fear, anger, anxiety, disgust, and sadness. According to the ABC theory of emotions [13], since the COVID-19 pandemic greatly threatens people's safety, individuals' subjective feelings and evaluations of this threat's severity significantly affect their physical and mental health. Individuals' mental states may be affected by the pandemic to different degrees depending on their perception of the severity of the COVID-19 pandemic, even while they experience the same event. If individuals perceive the pandemic to be more severe, they are more likely to exhibit negative mental states.

Hypothesis 2: Cyberchondria Mediates the Association Between Perceived Severity of the COVID-19 Pandemic and Depression, Anxiety, and Stress

With the advent of the digital age, health-related information can be easily and quickly accessed via the internet at little to no cost. Statistics published by the Office for National Statistics [16] show that from 2007 to 2016, the proportion of internet users searching for health-related information increased from 18% to 51%. After the outbreak of COVID-19, people could obtain information on pandemic dynamics on the internet. The unique period of home quarantine also promoted people to use the information found on the internet to diagnose their physical health. During the COVID-19 pandemic, individuals who perceive the pandemic to be more serious are more sensitive to the pandemic's development and their own health. They repeatedly search for information related to the pandemic to assess their risk of contracting COVID-19. Therefore, the higher individuals' perceived severity of the COVID-19 pandemic is, the more likely they are to show cyberchondria [17].

Cyberchondria has many negative effects on individuals' mental health. Research has found that there is a positive correlation between cyberchondria and anxiety during the pandemic [18], and cyberchondria is associated with an increase in searches for health information, which can lead to an individual having irrational thoughts, panicking unnecessarily, and paying excessive attention to health problems and can result in higher levels of depression [19,20]. In addition, after frequent exposure to various types of health-related information, individuals with cyberchondria become even more uncertain about COVID-19 and pay even more attention to their own physical conditions as well as to those of the people around them, which may cause even greater stress.

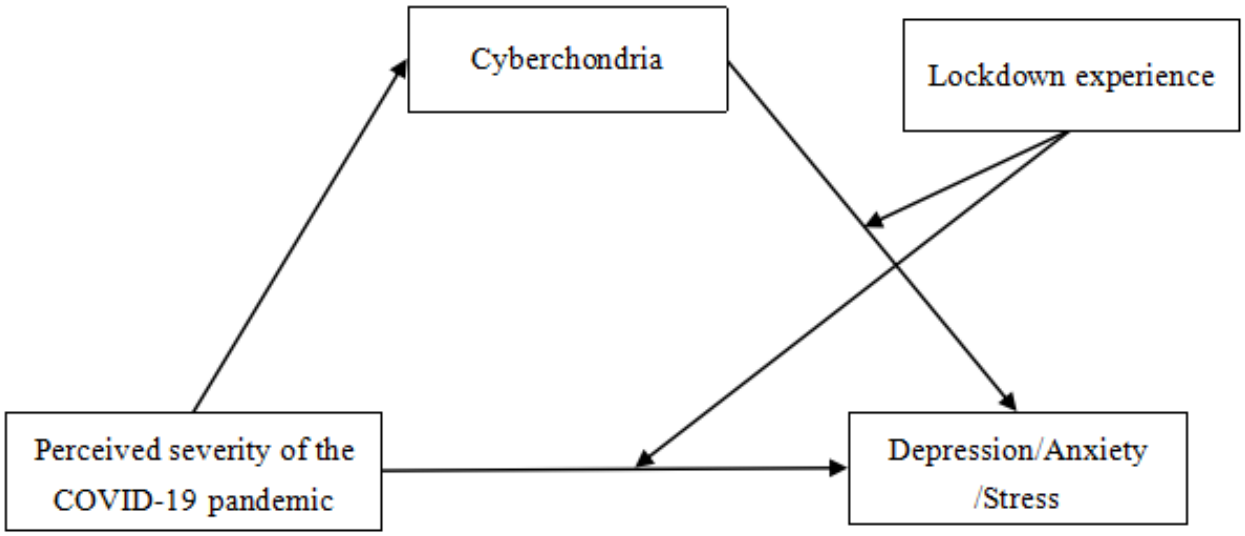
Hypothesis 3: Direct Effects and Indirect Effects Are Moderated by Lockdown Experience

To effectively control the spread of the COVID-19 pandemic and reduce the risk of public infection, many governments adopted public lockdown measures, which included school closures, travel restrictions, and public-gathering bans [21]. These measures effectively controlled the rate and scope of COVID-19 infections by reducing the risk of people becoming infected [22]. However, lockdown policies meant that most communication with the outside world occurred only through telephone or online. This type of social isolation and lack of traditional communication exerts negative psychological effects on people [23,24].

Individuals in quarantine may suffer from insomnia and show emotional reactions such as depression, anxiety, stress, anger, and confusion [23,25,26]. In addition, children and adolescents also experienced depression and anxiety during the lockdown—when children and adolescents experienced negative feelings and behaviors during lockdown periods, they were more likely to have symptoms of depression and anxiety, and their mental states were worse than those of children and adolescents without negative lockdown experience [27]. Negative experiences may further aggravate the negative mental state experienced by an individual caused by the COVID-19 pandemic. While individuals with no negative experience are

more receptive to lockdown policies and recognize the important role of lockdown measure has in controlling the spread of the pandemic. Thus, the direct effects of perceived severity of the COVID-19 pandemic on depression, anxiety, and stress, and the indirect effects of cyberchondria on depression, anxiety, and stress are moderated by lockdown experience (Figure 1).

Figure 1. Theoretical model: a moderated mediation model.



Methods

Study Design and Participants

From late January to late February 2020, we used a web-based platform to administer questionnaires. A total of 539 participants completed the questionnaires, and 486 participants (137 males and 349 females) were selected, yielding a qualified rate of 90.17%. Participants' ages ranged from 14 to 50 years (mean 22.94, SD 5.68).The research was approved by the Ethics Committee of the School of Psychology, Shandong Normal University; anonymous testing was used, and the instructions indicated that the data would be used only for scientific research. A small fee was paid to all participants via the internet for their participation.

Measures

Perceived Severity of the COVID-19 Pandemic Questionnaire

We used a self-designed questionnaire to measure the participants' subjective feelings about the severity of the COVID-19 pandemic. While preparing the questionnaire, we first interviewed 18 people from COVID-19 pandemic areas via web-based videoconference. According to the interview results, perceived severity of the COVID-19 pandemic is divided into 3 dimensions: health risk, emotion, and behavior. Second, we compiled items based on web-based interview results to measure individuals' perceived severity of the COVID-19 pandemic. Two psychometrics professors were invited to evaluate the questionnaire items and to modify any unclear or ambiguous questions, forming a 26-item preliminary version of the perceived severity of the COVID-19 pandemic questionnaire. Third, 174 participants were recruited and tested using the preliminary questionnaire. The Kaiser-Meyer-Olkin value was 0.83, and Bartlett test of sphericity was significant (P<.001), indicating that the data were suitable for factor analysis. Subsequently, we conducted exploratory factor analysis, and items with commonality less than 0.3, factor loadings less than 0.4, and cross-loadings (factor loadings greater than 0.4 in 2 or more dimensions and the difference of factor loadings less than 0.3) were deleted; finally, 14 items remained. Then, confirmatory factor analysis was performed using data from 486 participants. The results showed that the construct validity of the questionnaire was good (model fit index: χ^2/df=3.57, comparative fit index 0.93; Tucker–Lewis index 0.92; root mean square error of approximation 0.07; standardized root mean squared residual 0.06). The questionnaire was based on the 3 dimensions: health risk (eg, "I suspect that anyone may be infected by COVID-19"), emotion (eg, "Because of COVID-19 pandemic, I feel distressed and irritable"), and behavior (eg, "Only after thoroughly disinfecting purchased goods can I use them with peace of mind"). Items were rated on a 5-point scale from 1 (strongly disagree) to 5 (strongly agree); the higher the total score on the questionnaire, the higher perceived severity of the COVID-19 pandemic. Cronbach α=.88, which indicated that the reliability of the questionnaire was good.

Lockdown Experience Questionnaire

We used a self-designed questionnaire to measure lockdown experience. While preparing the questionnaire, we first interviewed 16 people from areas in lockdown via web-based videoconference during the COVID-19 pandemic. Based on the interview results, we divided lockdown experience into 3 dimensions: feeling, behavior, and economic situation. Second, we compiled items based on the web-based interview results to measure individuals' lockdown experiences. Two psychometrics professors were invited to evaluate the questionnaire items and to modify any unclear or ambiguous questions, which formed a 30-item preliminary version of the lockdown experience questionnaire. Third, 174 participants were recruited and tested

using the preliminary questionnaire. The Kaiser-Meyer-Olkin value was 0.78, and Bartlett test of sphericity was significant (P<.001), indicating that the data were suitable for factor analysis. Subsequently, exploratory factor analysis was carried out, and items with commonality less than 0.3, factor loadings less than 0.4, and cross-loadings were deleted, after which, 11 items remained. Then, confirmatory factor analysis was performed, which included 486 participants. The results showed that the construct validity of the questionnaire was good (model fit index: χ^2/df=2.96, comparative fit index 0.94; Tucker–Lewis index 0.92; root mean square error of approximation 0.06, standardized root mean squared residual 0.05). The questionnaire was based on 3 dimensions: feeling (eg, "During the lockdown period, I feel oppressed"), behavior (eg, "During the lockdown period, my work and learning efficiency decreased"), and economic situation (eg, "I think the lockdown policy has put a lot of pressure on me economically"). Items were rated on a 5-point scale from 1 (strongly disagree) to 5 (strongly agree); higher total scores indicated a more negative lockdown experience. Cronbach α=.77, which indicated that the reliability of the questionnaire is good.

When Liu et al [27] investigated the relationship between lockdown experience and depression and anxiety, they defined and examined the variable of lockdown experience from 2 aspects: feeling and behavior. Based on our interview results, we study divided the dimensions of the lockdown experience into feelings, behavior, and economic situation.

Depression Anxiety Stress Scale

Depression, anxiety, and stress were measured using the 21-item Depression Anxiety Stress Scale [28], which is divided into 3 dimensions: depression (eg, "I could see nothing in the future to be hopeful about"), anxiety (eg, "I was worried about situations in which I might panic and make a fool of myself"), and stress (eg, "I found it difficult to relax"). Each dimension contains 7 items, each rated on a 4-point scale from 0 (disagree) to 3 (strongly agree). Higher scores indicate higher levels of depression, anxiety, and stress. During the COVID-19 pandemic, the psychometric properties of the 21-item Depression Anxiety Stress Scale have been verified in samples from different countries [29-38]. In this study, Cronbach α=0.86, 0.85, and 0.90 for the depression, anxiety, and stress subscales, respectively, which indicated that subscale reliability was good.

Cyberchondria Scale

To assess cyberchondria, we used the Cyberchondria Scale [39], which is divided into 2 dimensions: impulse and excess (eg, "I spend a lot of time searching for health-related information on the internet"); worry and fear (eg, "When there are different explanations for disease symptoms on the internet, I tend to believe the more serious explanations"). The Cyberchondria Scale consists of 13 items rated on a 4-point scale from 1 (never) to 4 (always), with higher score indicating more serious cyberchondria. Cronbach α=.93, which indicated that the reliability of the scale was good.

Statistical Analysis

AMOS software (version 7.0; IBM Corp) was used for confirmatory factor analysis. SPSS software (version 24.0; IBM Corp) was used for exploratory factor analysis, common method bias, descriptive statistical analysis, and correlation analysis. SPSS PROCESS macro (version 3.5) was used to verify the moderated mediation models [40]. All regression coefficients were tested using the bias-corrected percentile bootstrap method. The theoretical model was tested by estimating the 95% confidence intervals of the mediation and moderating effects with 5000 repeated samples. An effect was considered significant if the confidence interval did not include 0.

Results

Common Method Bias

Because a questionnaire method was used to collect data, which can lead to common method bias, we used the Harman 1-factor test to detect common method bias [41]. The results of principal component factor analysis without rotation showed 14 factors with eigenvalues greater than 1, among which, the variation explained by the first factor was only 26.65%, which is less than the critical standard of 40%. Thus, there was no substantial common method bias in this study.

Descriptive Statistics and Correlations

We found that perceived severity of the COVID-19 pandemic was positively correlated with depression, anxiety, stress, and cyberchondria and negatively associated with lockdown experience (Table 1). Cyberchondria was positively correlated with depression, anxiety, and stress and negatively associated with lockdown experience. Lockdown experience was negatively associated with depression, anxiety, and stress.

Table 1. Means, standard deviations, and correlations among key variables.

Variables	Mean (SD)	Variables					
		Perceived severity	Depression	Anxiety	Stress	Cyberchondria	Lockdown experience
Perceived severity	53.66 (8.90)						
r		1	0.36	0.41	0.46	0.36	0.51
P value		—[a]	<.001	<.001	<.001	<.001	<.001
Depression	6.68 (7.55)						
r		0.36	1	0.84	0.84	0.38	0.52
P value		<.001	—	<.001	<.001	<.001	<.001
Anxiety	6.20 (7.57)						
r		0.41	0.84	1	0.85	0.38	0.50
P value		<.001	<.001	—	<.001	<.001	<.001
Stress	9.57 (9.60)						
r		0.46	0.84	0.85	1	0.39	0.54
P value		<.001	<.001	<.001	—	<.001	<.001
Cyberchondria	31.64 (8.20)						
r		0.36	0.38	0.38	0.39	1	0.33
P value		<.001	<.001	<.001	<.001	—	<.001
Lockdown experience	33.30 (7.06)						
r		0.51	0.52	0.50	0.54	0.33	1
P value		<.001	<.001	<.001	<.001	<.001	—

[a]Not applicable.

Mediating Effects

In the absence of cyberchondria, the positive predictive effects of perceived severity of the COVID-19 pandemic on depression (β=0.36, *t*=8.51, *P*<.001), anxiety (β=0.41, *t*=9.84, *P*<.001), and stress (β=0.46, *t*=11.45, *P*<.001) were significant (Multimedia Appendix 1). Thus, hypothesis 1 was supported.

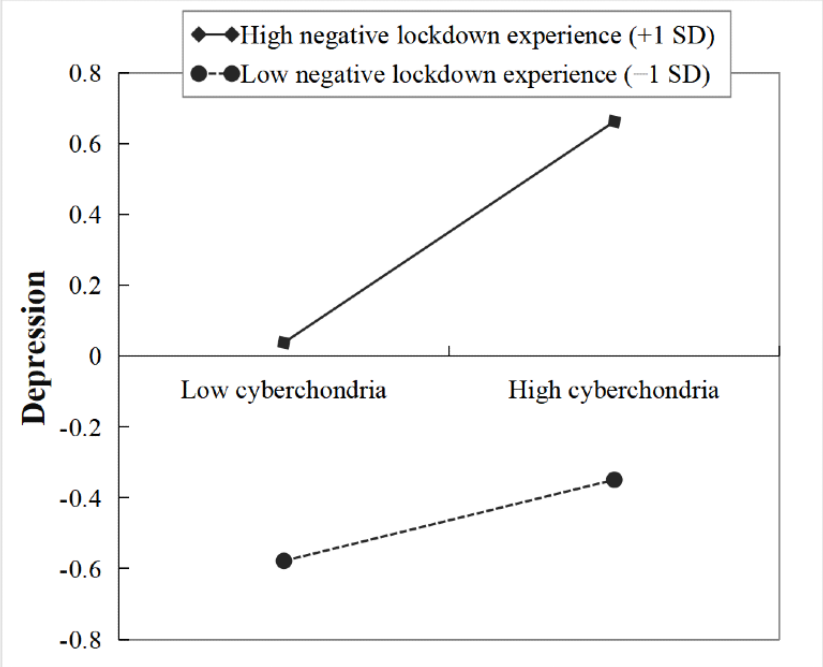
When cyberchondria was added to the analysis as a mediator, the direct relationships between perceived severity of the COVID-19 pandemic and depression (β=0.26, *t*=5.85, *P*<.001), anxiety (β=0.31, *t*=7.24, *P*<.001), and stress (β=0.37, *t*=8.83, *P*<.001) were also significant. Perceived severity of the COVID-19 pandemic had a positive predictive effect on cyberchondria (β=0.36, *t*=8.59, *P*<.001). The positive predictive effects of cyberchondria on depression (β=0.29, *t*=6.66, *P*<.001), anxiety (β=0.27, *t*=6.24, *P*<.001), and stress (β=0.26, *t*=6.14, *P*<.001) were also significant.

The results suggested that cyberchondria partially mediated the link between perceived severity of the COVID-19 pandemic and depression (indirect effect 0.11, 95% CI 0.07-0.15). This indirect effect accounted for 30.56% of the total effect. In addition, cyberchondria partially mediated the link between perceived severity of the COVID-19 pandemic and anxiety (indirect effect 0.10, 95% CI 0.06-0.14). This indirect effect accounted for 24.39% of the total effect. Finally, cyberchondria partially mediated the link between perceived severity of the COVID-19 pandemic and anxiety (indirect effect 0.09, 95% CI 0.06-0.14). This indirect effect accounted for 19.57% of the total effect. Thus, hypothesis 2 was supported.

Moderated Mediation

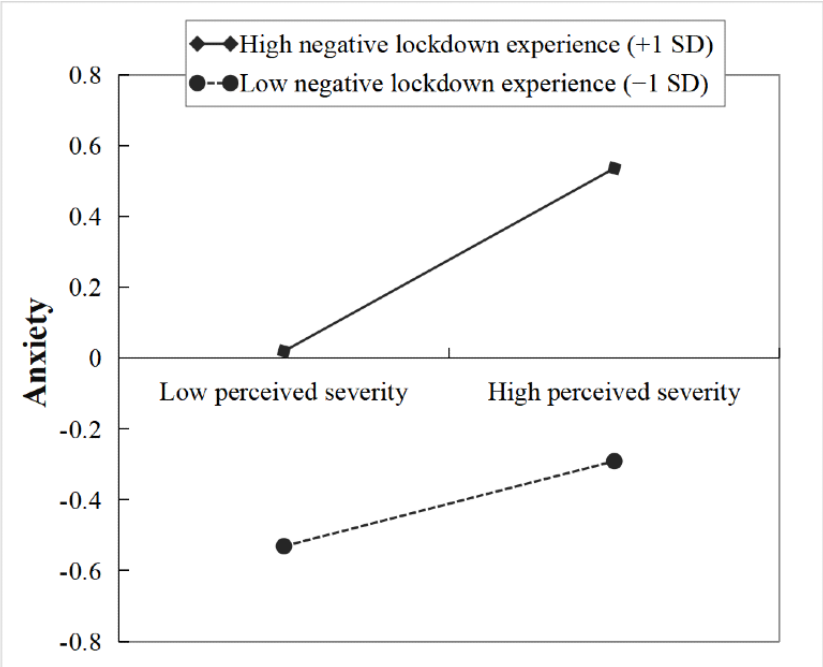
After lockdown experience (Multimedia Appendix 2) was entered into the model, the product of cyberchondria and lockdown experience had a significant predictive effect on depression (β=0.10, *t*=2.59, *P*=.009), but the product of perceived severity of the COVID-19 pandemic and lockdown experience had no significant predictive effect on depression (β=0.05, *t*=1.38, *P*=.17). Further simple slope analysis (Figure 2) showed that the association between cyberchondria and depression was stronger for individuals with high negative lockdown experience (1 SD above the mean: β=0.31, *t*=5.74, *P*<.001) than that for individuals with low negative lockdown experience (1 SD below the mean: β=0.11, *t*=2.02, *P*=.04).

Figure 2. The moderation of the relationship between cyberchondria and depression by lockdown experience.



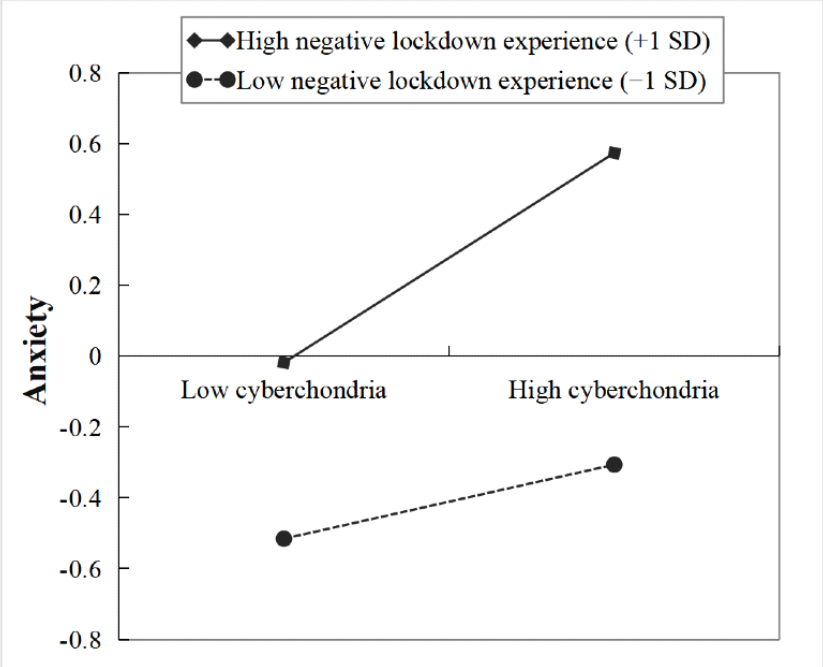
The product of perceived severity of the COVID-19 pandemic and lockdown experience (β=0.07, *t*=2.01, *P*=.045) and the product of cyberchondria and lockdown experience (β=0.10, *t*=2.50, *P*=.01) had significant predictive effects on anxiety. Further simple slope analysis (Figure 3) showed that the association between perceived severity of the COVID-19 pandemic and anxiety was stronger for individuals with high negative lockdown experience (1 SD above the mean: β=0.26, *t*=4.15, *P*<.001) than that for individuals with low negative lockdown experience (1 SD below the mean: β=0.12, *t*=2.33, *P*=.02).

Figure 3. The moderation of the relationship between perceived severity of the COVID-19 pandemic and anxiety by lockdown experience.



Similarly, simple slope analysis (Figure 4) indicated that the association between cyberchondria and anxiety was stronger for individuals with high negative lockdown experiences (1 SD above the mean: β=0.30, *t*=5.43, *P*<.001) than that for individuals with low negative lockdown experience (1 SD below the mean: β=0.10, *t*=1.84, *P*=.07).

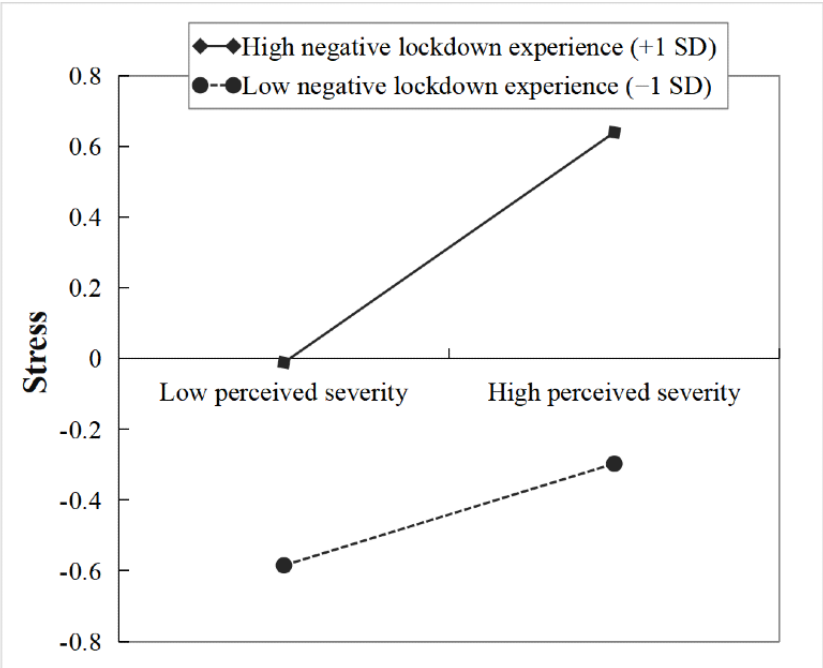
Figure 4. The moderation of the relationship between cyberchondria and anxiety by lockdown experience.



The product of perceived severity of the COVID-19 pandemic and lockdown experience had a significant predictive effect on stress (β=0.09, *t*=2.75, *P*=.006), but the product of cyberchondria and lockdown experience had no significant predictive effect on stress (β=0.05, *t*=1.44, *P*=.15). Further simple slope analysis (Figure 5) showed that the association between perceived severity of the COVID-19 pandemic and stress was stronger for individuals with high negative lockdown experience (1 SD above the mean: β=0.33, *t*=5.46, *P*<.001) than that for individuals with low negative lockdown experience (1 SD below the mean: β=0.14, *t*=2.91, *P*=.004).

These results indicated that individuals' higher negative lockdown experience strengthened the positive effect of perceived severity of the COVID-19 pandemic on anxiety and stress and the positive effect of cyberchondria on depression and anxiety. Thus, hypothesis 3 was partially supported.

Figure 5. The moderation of the relationship between perceived severity of the COVID-19 pandemic and stress by lockdown experience.



Discussion

Principal Findings

In this study, we found that perceived severity of the COVID-19 pandemic was positively associated with depression, anxiety, and stress. The higher individuals' perceived severity of the COVID-19 pandemic, the higher their levels of depression, anxiety, and stress. The severity of cyberchondria partly mediated the relationship between perceived severity of the COVID-19 pandemic and depression, anxiety, and stress. Individuals with high perceived severity of the COVID-19 pandemic were more likely to suffer from cyberchondria, and the higher the severity of cyberchondria, the higher their depression, anxiety, and stress levels. The direct effect of perceived severity of the COVID-19 pandemic on anxiety and stress and the indirect effect of cyberchondria on depression and anxiety were moderated by the lockdown experience. Individuals with high negative lockdown experience had stronger relationships between perceived severity of the COVID-19 pandemic and anxiety/stress and between cyberchondria and depression/anxiety.

Perceived Severity of the COVID-19 Pandemic and Depression, Anxiety, and Stress

Perceived severity of the COVID-19 pandemic had a significant positive predictive effect on depression (P<.001), anxiety (P<.001), and stress (P<.001), which is consistent with the findings of previous studies [9,10] on the objective severity of the COVID-19 pandemic and supports the ABC theory of emotions [13]. This finding indicates that the COVID-19 pandemic has prompted a series of emotional reactions that increase with perceived severity of the COVID-19 pandemic. When individuals thought that the pandemic was very serious and were not able to deal with it well, the negative impact of the pandemic increased.

Specifically, in the COVID-19 public health emergency, individuals with higher perceived severity of the COVID-19 pandemic perceived a greater threat to their safety; therefore, they were worried and panicked about the spread of the pandemic for an extended time period, which increased their depression, anxiety, and stress levels. In contrast, individuals with lower perceived severity of the COVID-19 pandemic thought that the spread of the pandemic could be effectively controlled; therefore, they did not worry too much about their safety, which allowed their depression, anxiety, and stress levels to be lower.

The Mediating Role of Cyberchondria

Cyberchondria moderated the association between perceived severity of the COVID-19 pandemic and depression (P<.001), anxiety (P<.001), and stress (P<.001), which is consistent with previous findings. Laato et al [42] found that individuals' cyberchondria worsened as individuals' perceived severity of the COVID-19 pandemic increased. According to the ABC theory of emotions [13], individuals with higher perceived severity of the COVID-19 pandemic would continue to pay attention to the pandemic and believe that they were at high risk of contracting COVID-19, and they would repeatedly search for information related to the COVID-19 pandemic. Moreover, excessive or repetitive internet searches for health-related information are one of the main causes of cyberchondria. Many people's concerns about illness are not alleviated by searching for related information, but instead, are further aggravated [43]. Therefore, individuals with higher perceived severity of the COVID-19 pandemic have a higher degree of cyberchondria than individuals with lower perceived severity of the COVID-19 pandemic.

In this study, we found that individuals with higher perceived severity of the COVID-19 pandemic had higher levels of depression, anxiety, and stress when they showed higher levels of cyberchondria. Consistent with the findings of previous studies [44,45], individuals searching the internet for health-related information did not reduce their concerns about illness but rather increased their levels of depression and anxiety. We further explored the relationship between cyberchondria and stress. The results support the hypothesis that one's stress level is higher when one's cyberchondria is more severe. Specifically, when individuals were worried about their illness, they searched for health-related information to eliminate their worries. However, individuals with severe cyberchondria often think that the reliability of health-related information obtained via internet search is very low, and they still worry about their illness after the search [46,47]. During the outbreak of the COVID-19 pandemic, the internet searching behavior of individuals with higher severity of cyberchondria continued for an extended amount of time. Their chronic negative state of fear that they were infected with COVID-19 increased their levels of depression, anxiety, and stress.

The Moderating Role of Lockdown Experience

We found that lockdown experience moderated the direct effects of perceived severity of the COVID-19 pandemic on anxiety (P=.045) and stress (P=.006). Our findings are consistent with those of a previous study [27] that showed that lockdown measures are usually associated with a negative mental state. During lockdown, people remained in their homes for an extended period of time, had to abandon their daily routines, and rarely had social contact with others, which caused them to suffer from feelings of boredom, frustration, and isolation [23]. Individuals who were affected by lockdown measures may have experienced life problems and had more serious negative experiences for example, they may have believed that the lockdown measures affected their quality of life and economic resources, which aggravated their anxiety and stress caused by their perceived severity of the COVID-19 pandemic. In contrast, for individuals with a less negative lockdown experience, this measure did not affect them as negatively, and they were more likely to recognize the important role of lockdown measures in controlling the COVID-19 pandemic. Therefore, the anxiety and stress caused by perceived severity of the COVID-19 pandemic could be alleviated.

The findings of our study also suggested that lockdown experience moderated the negative effects of cyberchondria on depression (P=.009) and anxiety (P=.01). During the COVID-19 pandemic, everyone was subject to the lockdown policy, but compared to individuals with a high degree of negative

lockdown experience, individuals with a low degree of negative lockdown experience usually thought that the lockdown policy implemented by the government could effectively control the spread of the pandemic and help reduce the likelihood that they would be infected with COVID-19. Therefore, a low degree of negative lockdown experience could reduce the depression and anxiety caused by cyberchondria.

Implications and Limitations

The public should be guided to calmly seek pandemic-related knowledge, to prevent a series of negative emotional reactions. Countries and governments should also promptly control the spread of the COVID-19 pandemic and curb the spread of false or exaggerated information related to the pandemic, which will help alleviate cyberchondria and reduce depression, anxiety, and stress levels. Simultaneously, lockdown experiences' impact on individuals' psychological states should also be considered. Therefore, in implementing a lockdown policy, the government should reduce the public's degree of negative lockdown experience as much as possible by issuing unemployment benefits and wage subsidies and providing accommodations. These approaches can help the government control the COVID-19 pandemic and alleviate people's negative mental states and psychological problems due to the outbreak of the pandemic. In addition, previous studies have shown that the most evidence-based treatment for psychiatric symptoms during COVID-19 is cognitive behavioral therapy [48]. In particular, internet cognitive behavioral therapy can effectively treat individuals' symptoms of depression, anxiety, and cyberchondria and can also reduce insomnia [49-51]. Therefore, internet cognitive behavioral therapy can be used to treat people's psychiatric symptoms during the COVID-19 pandemic, which can provide people with convenient, fast, and effective psychological assistance during the lockdown period [52].

This study also had several limitations. The COVID-19 pandemic was found to cause hemodynamic changes in the brain [53]. This study mainly used self-reported questionnaires to measure psychiatric symptoms and did not make a clinical diagnosis. The gold standard for establishing psychiatric diagnosis involves a structured clinical interview and functional neuroimaging [54-56]. In the future, more technical means, combined with clinical diagnostic criteria, must be adopted to investigate the impact of major public health emergencies (such as the COVID-19 pandemic) on mental health. In addition, this study was cross-sectional in design and could not identify causal relationships among the variables. Moreover, data were collected during the high-incidence stage of China's pandemic, which means that the results reflect only the mental health status of the Chinese public during this stage of the disease but do not reveal the dynamic changes in the relationships between the variables. A longitudinal study should be used to explore the COVID-19 pandemic's continuous impact on people's psychology.

Conclusions

This study showed that the higher individuals' perceived severity of the COVID-19 pandemic was, the higher their levels of depression, anxiety, and stress. Cyberchondria partially mediated the relationships between perceived severity of the COVID-19 pandemic and depression, anxiety, and stress. Individuals with higher perceived severity of the COVID-19 pandemic were more likely to develop cyberchondria and had higher depression, anxiety and stress levels. The lockdown experience moderated the direct effect of perceived severity of the COVID-19 pandemic on anxiety/stress and the indirect effects of cyberchondria on depression/anxiety. A high degree of negative lockdown experience could exacerbate the negative influence of perceived severity of the COVID-19 pandemic on anxiety/stress as well as the negative influence of cyberchondria on depression/anxiety.

Acknowledgments

We want to express our sincere gratitude to all participants. This work was supported by the National Natural Science Foundation of China (62077034, 31671160), the Major Project of National Social Science Foundation (19ZDA363), and Shandong Provincial Social Science Planning Project (20CJYJ16).

Authors' Contributions

LH contributed to the conception, methodology, supervision, and resources. YZ contributed to the conceptualization, formal analysis, validation, original draft, and final manuscript. WL and Yuqing X contributed to the formal analysis. Yan X contributed to the supervision, validation, resources, and critical revision. JZ contributed to the software, investigation, writing revisions, and editing.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Mediating effect analysis.
[DOC File , 47 KB - publichealth_v7i9e31052_app1.doc]

Multimedia Appendix 2

Mediating effect analysis with moderation.
[DOC File , 18 KB - publichealth_v7i9e31052_app2.doc]

References

1. Coronavirus (COVID-19) data. World Health Organization. URL: https://www.who.int/data#reports [accessed 2021-09-12]
2. Coronavirus disease 2019 (COVID-19) situation report – 5. World Health Organization. 2020 Mar 11. URL: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200311-sitrep-51-covid-19.pdf?sfvrsn=1ba62e57_10 [accessed 2020-03-15]
3. Chowell G, Abdirizak F, Lee S, Lee J, Jung E, Nishiura H, et al. Transmission characteristics of MERS and SARS in the healthcare setting: a comparative study. BMC Med 2015 Sep 03;13:210 [FREE Full text] [doi: 10.1186/s12916-015-0450-0] [Medline: 26336062]
4. Kucharski A, Althaus C. The role of superspreading in Middle East respiratory syndrome coronavirus (MERS-CoV) transmission. Euro Surveill 2015 Jun 25;20(25):14-18 [FREE Full text] [doi: 10.2807/1560-7917.es2015.20.25.21167] [Medline: 26132768]
5. Breban R, Riou J, Fontanet A. Interhuman transmissibility of Middle East respiratory syndrome coronavirus: estimation of pandemic risk. Lancet 2013 Aug 24;382(9893):694-699 [FREE Full text] [doi: 10.1016/S0140-6736(13)61492-0] [Medline: 23831141]
6. van Gelder N, Peterman A, Potts A, O'Donnell M, Thompson K, Shah N, Gender and COVID-19 working group. COVID-19: Reducing the risk of infection might increase the risk of intimate partner violence. EClinicalMedicine 2020 Apr 11;21:100348 [FREE Full text] [doi: 10.1016/j.eclinm.2020.100348] [Medline: 32292900]
7. Wang C, Pan R, Wan X, Tan Y, Xu L, Ho CS, et al. Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. Int J Environ Res Public Health 2020 Mar 06;17(5):1729 [FREE Full text] [doi: 10.3390/ijerph17051729] [Medline: 32155789]
8. Wang C, Pan R, Wan X, Tan Y, Xu L, McIntyre RS, et al. A longitudinal study on the mental health of general population during the COVID-19 epidemic in China. Brain Behav Immun 2020 Jul;87:40-48 [FREE Full text] [doi: 10.1016/j.bbi.2020.04.028] [Medline: 32298802]
9. Le K, Nguyen M. The psychological burden of the COVID-19 pandemic severity. Econ Hum Biol 2021 May;41:100979 [FREE Full text] [doi: 10.1016/j.ehb.2021.100979] [Medline: 33497964]
10. Lu W, Wang H, Lin Y, Li L. Psychological status of medical workforce during the COVID-19 pandemic: a cross-sectional study. Psychiatry Res 2020 Jun;288:112936 [FREE Full text] [doi: 10.1016/j.psychres.2020.112936] [Medline: 32276196]
11. Wang C, Chudzicka-Czupała A, Tee ML, Núñez MIL, Tripp C, Fardin MA, et al. A chain mediation model on COVID-19 symptoms and mental health outcomes in Americans, Asians and Europeans. Sci Rep 2021 Mar 19;11(1):6481 [FREE Full text] [doi: 10.1038/s41598-021-85943-7] [Medline: 33742072]
12. Wang C, Tee M, Roy AE, Fardin MA, Srichokchatchawan W, Habib HA, et al. The impact of COVID-19 pandemic on physical and mental health of Asians: a study of seven middle-income countries in Asia. PLoS One 2021 Feb 11;16(2):e0246824 [FREE Full text] [doi: 10.1371/journal.pone.0246824] [Medline: 33571297]
13. Ellis A. Reason and Emotion in Psychotherapy. New York, NY: Lyle Stewart; 1962.
14. Dorfan NM, Woody SR. Danger appraisals as prospective predictors of disgust and avoidance of contaminants. J Soc Clin Psychol 2011 Feb;30(2):105-132. [doi: 10.1521/jscp.2011.30.2.105]
15. Yang J, Chu H. Who is afraid of the Ebola outbreak? The influence of discrete emotions on risk perception. J Risk Res 2016 Oct 28;21(7):834-853. [doi: 10.1080/13669877.2016.1247378]
16. Internet access – households and individuals, Great Britain: 2016. Office for National Statistics. 2016 Aug 04. URL: https://www.ons.gov.uk/peoplepopulationandcommunity/householdcharacteristics/homeinternetandsocialmediausage/bulletins/internetaccesshouseholdsandindividuals/2016 [accessed 2020-03-05]
17. Starcevic V, Berle D. Cyberchondria: towards a better understanding of excessive health-related internet use. Expert Rev Neurother 2013 Feb;13(2):205-213. [doi: 10.1586/ern.12.162] [Medline: 23368807]
18. Jungmann SM, Witthöft M. Health anxiety, cyberchondria, and coping in the current COVID-19 pandemic: which factors are related to coronavirus anxiety? J Anxiety Disord 2020 Jun;73:102239 [FREE Full text] [doi: 10.1016/j.janxdis.2020.102239] [Medline: 32502806]
19. Barke A, Bleichhardt G, Rief W, Doering BK. The Cyberchondria Severity Scale (CSS): German validation and development of a short form. Int J Behav Med 2016 Oct 1;23(5):595-605. [doi: 10.1007/s12529-016-9549-8] [Medline: 26931780]
20. Bessière K, Pressman S, Kiesler S, Kraut R. Effects of internet use on health and depression: a longitudinal study. J Med Internet Res 2010 Feb 28;12(1):e6 [FREE Full text] [doi: 10.2196/jmir.1149] [Medline: 20228047]
21. Variation in government responses to COVID-19. Blavatnik School. 2021 Mar 24. URL: https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19 [accessed 2021-04-12]
22. Li H, Chen X, Huang H. The novel coronavirus outbreak: what can be learned from China in public reporting? Glob Health Res Policy 2020 Mar 09;5:9 [FREE Full text] [doi: 10.1186/s41256-020-00140-9] [Medline: 32166128]

23. Brooks SK, Webster RK, Smith LE, Woodland L, Wessely S, Greenberg N, et al. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. Lancet 2020 Mar 14;395(10227):912-920. [doi: 10.1016/S0140-6736(20)30460-8] [Medline: 32112714]
24. Shankar A, Hamer M, McMunn A, Steptoe A. Social isolation and loneliness: relationships with cognitive function during 4 years of follow-up in the English Longitudinal Study of Ageing. Psychosom Med 2013 Feb;75(2):161-170. [doi: 10.1097/PSY.0b013e31827f09cd] [Medline: 23362501]
25. Jeong H, Yim HW, Song YJ, Ki M, Min JA, Cho J, et al. Mental health status of people isolated due to Middle East Respiratory Syndrome. Epidemiol Health 2016 Nov 05;38:e2016048. [doi: 10.4178/epih.e2016048] [Medline: 28196409]
26. Khan AH, Sultana S, Hossain S, Hasan MT, Ahmed HU, Sikder T. The impact of COVID-19 pandemic on mental health & wellbeing among home-quarantined Bangladeshi students: a cross-sectional pilot study. J Affect Disord 2020 Dec 01;277:121-128 [FREE Full text] [doi: 10.1016/j.jad.2020.07.135] [Medline: 32818775]
27. Liu Y, Yue S, Hu X, Zhu J, Wu Z, Wang J, et al. Associations between feelings/behaviors during COVID-19 pandemic lockdown and depression/anxiety after lockdown in a sample of Chinese children and adolescents. J Affect Disord 2021 Apr 01;284:98-103. [doi: 10.1016/j.jad.2021.02.001] [Medline: 33592433]
28. Lovibond PF, Lovibond SH. The structure of negative emotional states: comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. Behav Res Ther 1995 Mar;33(3):335-343. [doi: 10.1016/0005-7967(94)00075-u] [Medline: 7726811]
29. Burke T, Berry A, Taylor LK, Stafford O, Murphy E, Shevlin M, et al. Increased psychological distress during COVID-19 and quarantine in Ireland: a national survey. J Clin Med 2020 Oct 28;9(11):3481 [FREE Full text] [doi: 10.3390/jcm9113481] [Medline: 33126707]
30. Hao F, Tan W, Jiang L, Zhang L, Zhao X, Zou Y, et al. Do psychiatric patients experience more psychiatric symptoms during COVID-19 pandemic and lockdown? A case-control study with service and research implications for immunopsychiatry. Brain Behav Immun 2020 Jul;87:100-106 [FREE Full text] [doi: 10.1016/j.bbi.2020.04.069] [Medline: 32353518]
31. Kaya H, Ayık B, Tasdelen R, Ercis M, Ertekin E. Social support promotes mental health during the COVID-19 outbreak: a cross-sectional study from Turkey. Psychiat Danub 2021 Jun 25;33(2):217-224. [doi: 10.24869/psyd.2021.217]
32. Le HT, Lai AJX, Sun J, Hoang MT, Vu LG, Pham HQ, et al. Anxiety and depression among people under the nationwide partial lockdown in Vietnam. Front Public Health 2020;8:589359 [FREE Full text] [doi: 10.3389/fpubh.2020.589359] [Medline: 33194995]
33. Ranieri J, Guerra F, Perilli E, Passafiume D, Maccarone D, Ferri C, et al. Prolonged COVID 19 outbreak and psychological response of nurses in Italian healthcare system: cross-sectional study. Front Psychol 2021 Apr 6;12:608413 [FREE Full text] [doi: 10.3389/fpsyg.2021.608413] [Medline: 33889106]
34. Tee ML, Tee CA, Anlacan JP, Aligam KJG, Reyes PWC, Kuruchittham V, et al. Psychological impact of COVID-19 pandemic in the Philippines. J Affect Disord 2020 Dec 01;277:379-391 [FREE Full text] [doi: 10.1016/j.jad.2020.08.043] [Medline: 32861839]
35. Wang C, Chudzicka-Czupała A, Grabowski D, Pan R, Adamus K, Wan X, et al. The association between physical and mental health and face mask use during the COVID-19 pandemic: a comparison of two countries with different views and practices. Front Psychiatry 2020 Sep 9;11:569981 [FREE Full text] [doi: 10.3389/fpsyt.2020.569981] [Medline: 33033485]
36. Wang C, Fardin M, Shirazi M, Pan R, Wan X, Tan Y, et al. Mental health of the general population during the 2019 coronavirus disease (COVID-19) pandemic: a tale of two developing countries. Psychiatry International 2021 Mar 09;2(1):71-84. [doi: 10.3390/psychiatryint2010006]
37. Wang C, López-Núñez MI, Pan R, Wan X, Tan Y, Xu L, et al. The impact of the COVID-19 pandemic on physical and mental health in China and Spain: cross-sectional study. JMIR Form Res 2021 May 21;5(5):e27818 [FREE Full text] [doi: 10.2196/27818] [Medline: 33900933]
38. Wang C, Tripp C, Sears SF, Xu L, Tan Y, Zhou D, et al. The impact of the COVID-19 pandemic on physical and mental health in the two largest economies in the world: a comparison between the United States and China. J Behav Med 2021 Jun 14:1-19 [FREE Full text] [doi: 10.1007/s10865-021-00237-7] [Medline: 34128179]
39. Ding J. The Characteristics and Influential Factors Research of Cyberchondria. Beijing: Beijing Forestry University; 2016.
40. Hayes AF. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. New York, NY: Guildford Press; 2013.
41. Podsakoff PM, MacKenzie SB, Lee J, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Psychol 2003 Oct;88(5):879-903. [doi: 10.1037/0021-9010.88.5.879] [Medline: 14516251]
42. Laato S, Islam AKMN, Islam MN, Whelan E. What drives unverified information sharing and cyberchondria during the COVID-19 pandemic? Eur J Inf Syst 2020 Jun 07;29(3):288-305. [doi: 10.1080/0960085x.2020.1770632]
43. Starcevic V. Cyberchondria: challenges of problematic online searches for health-related information. Psychother Psychosom 2017 May 11;86(3):129-133 [FREE Full text] [doi: 10.1159/000465525] [Medline: 28490037]

44. McMullan RD, Berle D, Arnáez S, Starcevic V. The relationships between health anxiety, online health information seeking, and cyberchondria: systematic review and meta-analysis. J Affect Disord 2019 Feb 15;245:270-278. [doi: 10.1016/j.jad.2018.11.037] [Medline: 30419526]
45. Vismara M, Caricasole V, Starcevic V, Cinosi E, Dell'Osso B, Martinotti G, et al. Is cyberchondria a new transdiagnostic digital compulsive syndrome? A systematic review of the evidence. Compr Psychiatry 2020 May;99:152167 [FREE Full text] [doi: 10.1016/j.comppsych.2020.152167] [Medline: 32146315]
46. Eastin MS, Guinsler NM. Worried and wired: effects of health anxiety on information-seeking and health care utilization behaviors. Cyberpsychol Behav 2006 Aug;9(4):494-498. [doi: 10.1089/cpb.2006.9.494] [Medline: 16901253]
47. Muse K, McManus F, Leung C, Meghreblian B, Williams JMG. Cyberchondriasis: fact or fiction? A preliminary examination of the relationship between health anxiety and searching for health information on the internet. J Anxiety Disord 2012 Jan;26(1):189-196. [doi: 10.1016/j.janxdis.2011.11.005] [Medline: 22137465]
48. Ho CSH, Chee CYI, Ho RCM. Mental health strategies to combat the psychological impact of COVID-19 beyond paranoia and panic. Ann Acad Med Singap 2020 Mar 16;49(3):155-160 [FREE Full text] [Medline: 32200399]
49. Newby JM, McElroy E. The impact of internet-delivered cognitive behavioural therapy for health anxiety on cyberchondria. J Anxiety Disord 2020 Jan;69:102150. [doi: 10.1016/j.janxdis.2019.102150] [Medline: 31739276]
50. Shabahang R, Aruguete MS, McCutcheon L. Video-based cognitive-behavioral intervention for COVID-19 anxiety: a randomized controlled trial. Trends Psychiatry Psychother 2021 May 21;43(2):141-150 [FREE Full text] [doi: 10.47626/2237-6089-2020-0056] [Medline: 34043898]
51. Soh HL, Ho RC, Ho CS, Tam WW. Efficacy of digital cognitive behavioural therapy for insomnia: a meta-analysis of randomised controlled trials. Sleep Med 2020 Nov;75:315-325. [doi: 10.1016/j.sleep.2020.08.020] [Medline: 32950013]
52. Zhang MWB, Ho RCM. Moodle: the cost effective solution for internet cognitive behavioral therapy (I-CBT) interventions. Technol Health Care 2017 Feb 21;25(1):163-165. [doi: 10.3233/thc-161261]
53. Olszewska-Guizzo A, Mukoyama A, Naganawa S, Dan I, Husain SF, Ho CS, et al. Hemodynamic response to three types of urban spaces before and after lockdown during the COVID-19 pandemic. Int J Environ Res Public Health 2021 Jun 06;18(11):6118 [FREE Full text] [doi: 10.3390/ijerph18116118] [Medline: 34204034]
54. Ho CSH, Lim LJH, Lim AQ, Chan NHC, Tan RS, Lee SH, et al. Diagnostic and predictive applications of functional near-infrared spectroscopy for major depressive disorder: a systematic review. Front Psychiatry 2020 May 6;11:378 [FREE Full text] [doi: 10.3389/fpsyt.2020.00378] [Medline: 32477179]
55. Husain SF, Tang TB, Yu R, Tam WW, Tran B, Quek TT, et al. Cortical haemodynamic response measured by functional near infrared spectroscopy during a verbal fluency task in patients with major depression and borderline personality disorder. EBioMedicine 2020 Jan 01;51:102586 [FREE Full text] [doi: 10.1016/j.ebiom.2019.11.047] [Medline: 31877417]
56. Husain SF, Yu R, Tang T, Tam WW, Tran B, Quek TT, et al. Validating a functional near-infrared spectroscopy diagnostic paradigm for major depressive disorder. Sci Rep 2020 Jun 16;10(1):9740 [FREE Full text] [doi: 10.1038/s41598-020-66784-2] [Medline: 32546704]

Edited by G Eysenbach; submitted 08.06.21; peer-reviewed by X Hu, R Ho; comments to author 09.07.21; revised version received 06.08.21; accepted 16.08.21; published 16.09.21.

Please cite as:
Han L, Zhan Y, Li W, Xu Y, Xu Y, Zhao J
Associations Between the Perceived Severity of the COVID-19 Pandemic, Cyberchondria, Depression, Anxiety, Stress, and Lockdown Experience: Cross-sectional Survey Study
JMIR Public Health Surveill 2021;7(9):e31052
URL: https://publichealth.jmir.org/2021/9/e31052
doi:10.2196/31052
PMID:34478402

Original Paper

Determinants of Shielding Behavior During the COVID-19 Pandemic and Associations With Well-being Among National Health Service Patients: Longitudinal Observational Study

Patrik Bachtiger[1,2], MBBS, MSc, MPH; Alexander Adamson[1], MSc; William A Maclean[1], MPhil; Mihir A Kelshiker[1,2], BA, MBBS; Jennifer K Quint[1,2], PhD; Nicholas S Peters[1,2], MD

[1]National Heart and Lung Institute, Imperial College London, London, United Kingdom

[2]Imperial College Healthcare NHS Trust, London, United Kingdom

Corresponding Author:
Nicholas S Peters, MD
National Heart and Lung Institute
Imperial College London
Hammersmith Hospital
Du Cane Road
London, W12 0HS
United Kingdom
Phone: 44 020 7589 5111
Email: n.peters@imperial.ac.uk

Abstract

Background: The UK National Health Service (NHS) classified 2.2 million people as clinically extremely vulnerable (CEV) during the first wave of the 2020 COVID-19 pandemic, advising them to “shield” (to not leave home for any reason).

Objective: The aim of this study was to measure the determinants of shielding behavior and associations with well-being in a large NHS patient population for informing future health policy.

Methods: Patients contributing to an ongoing longitudinal participatory epidemiology study (Longitudinal Effects on Wellbeing of the COVID-19 Pandemic [LoC-19], n=42,924) received weekly email invitations to complete questionnaires (17-week shielding period starting April 9, 2020) within their NHS personal electronic health record. Question items focused on well-being. Participants were stratified into four groups by self-reported CEV status (qualifying condition) and adoption of shielding behavior (baselined at week 1 or 2). The distribution of CEV criteria was reported alongside situational variables and univariable and multivariable logistic regression. Longitudinal trends in physical and mental well-being were displayed graphically. Free-text responses reporting variables impacting well-being were semiquantified using natural language processing. In the lead up to a second national lockdown (October 23, 2020), a follow-up questionnaire evaluated subjective concern if further shielding was advised.

Results: The study included 7240 participants. In the CEV group (n=2391), 1133 (47.3%) assumed shielding behavior at baseline, compared with 633 (13.0%) in the non-CEV group (n=4849). CEV participants who shielded were more likely to be Asian (odds ratio [OR] 2.02, 95% CI 1.49-2.76), female (OR 1.24, 95% CI 1.05-1.45), older (OR per year increase 1.01, 95% CI 1.00-1.02), living in a home with an outdoor space (OR 1.34, 95% CI 1.06-1.70) or three to four other inhabitants (three: OR 1.49, 95% CI 1.15-1.94; four: OR 1.49, 95% CI 1.10-2.01), or solid organ transplant recipients (OR 2.85, 95% CI 2.18-3.77), or have severe chronic lung disease (OR 1.63, 95% CI 1.30-2.04). Receipt of a government letter advising shielding was reported in 1115 (46.6%) CEV participants and 180 (3.7%) non-CEV participants, and was associated with adopting shielding behavior (OR 3.34, 95% CI 2.82-3.95 and OR 2.88, 95% CI 2.04-3.99, respectively). In CEV participants, shielding at baseline was associated with a lower rating of mental well-being and physical well-being. Similar results were found for non-CEV participants. Concern for well-being if future shielding was required was most prevalent among CEV participants who had originally shielded.

Conclusions: Future health policy must balance the potential protection from COVID-19 against our findings that shielding negatively impacted well-being and was adopted in many in whom it was not indicated and variably in whom it was indicated. This therefore also requires clearer public health messaging and support for well-being if shielding is to be advised in future pandemic scenarios.

(JMIR Public Health Surveill 2021;7(9):e30460) doi:10.2196/30460

KEYWORDS

COVID-19; shielding; well-being; personal health record; determinant; behavior; protection; longitudinal; observational; health policy; mental health; epidemiology; public health

Introduction

At the start of the first wave of the COVID-19 pandemic, the UK National Health Service (NHS) identified 2.2 million people as clinically extremely vulnerable (CEV), and they were assumed to be at high risk of severe COVID-19 infection [1]. CEV status was conferred by the severity, history, and treatment levels of specific conditions [2]. These individuals were notified by a postal letter (March 25, 2020, onwards) to enter an unprecedented period of shielding; a voluntary action that, at the time, instructed "stay at home at all times and avoid all face-to-face contact for at least 12 weeks" [3]. CEV individuals were also advised to practice social distancing with those in the household not required to shield and to only have in-person encounters for health or social care reasons.

Whether the action of shielding reduced the risk of exposure to COVID-19 in the UK is particularly difficult to measure for the first wave, given largely absent at-home or community testing [4,5]. Acknowledging the potentially negative impact the original policy was having on general well-being, the shielding policy was revised after 4 months, such that CEV patients could, if they wished, meet as a group of up to six people outdoors and form a "support bubble" with another household (July 6, 2020, onwards) [6]. Ubiquitous government messaging had by then established the notion of "shielding" among health care professionals and the wider British public [7]. The prevalence of shielding behavior among patients in whom it is not indicated and its potential harm remain unknown. More broadly, there is inadequate understanding of the determinants for adopting shielding behavior or the potential trade-off in well-being when doing so [8].

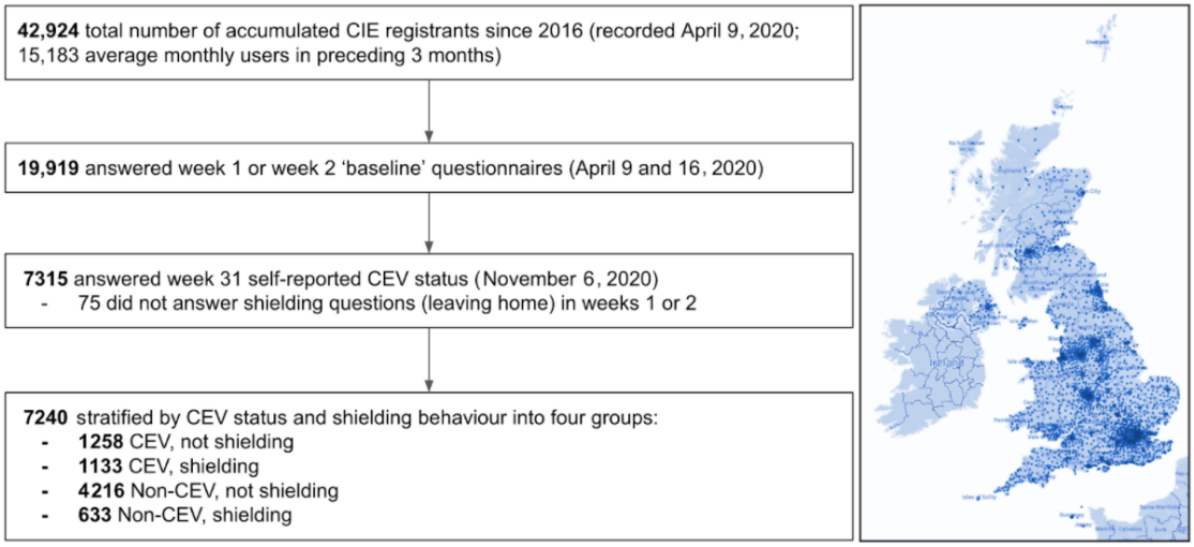
Therefore, the aim of our study was to explore the determinants of adopting shielding behavior and its relationship with well-being. Our study is informed by the likelihood that (1) shielding behavior is likely to impact well-being, and (2) the decision to shield is influenced by the anticipated impacts on well-being, with implications for adherence to public health advice. Our study specifically examines how demographic and lifestyle factors may impact both the choices to shield and associated outcomes of shielding. The intention was to test a hypothesis that shielding behavior in the first wave was determined by variables beyond CEV status and was overall detrimental to well-being.

Methods

Study Design

The Longitudinal Effects on Wellbeing of the COVID-19 Pandemic (LoC-19) study began inviting registrants of the Care Information Exchange (CIE) (Imperial College Healthcare NHS Trust, UK) to complete a weekly questionnaire as a direct care tool for self-monitoring their well-being, starting ("week 1") April 9, 2020. The CIE is the NHS's largest patient personal electronic health record with UK-wide registrants (Figure 1). Patients can access their digital health records within the CIE after an index encounter (eg, blood test, outpatient appointment, and inpatient admission) triggers creation of a record. Starting from 2016, on April 9, 2020, the CIE had accumulated 42,924 registrants, with a mean average number of 15,183 monthly active users (defined by at least one login) in the 3 months preceding the beginning of the LoC-19 study. LoC-19 participants would receive a weekly email notification to complete questionnaires within their CIE record, where responses were retained as a direct care tool for self-monitoring well-being during the pandemic. The subsequent online community of participants was also provided with regular feedback on how responses were being used to also inform local and national health policy.

Figure 1. Study inclusion diagram. Left: participant selection and stratification based on responses to baseline (week 1 and 2) and CEV status (week 31) questionnaires. Right: map of CIE registrants by UK postcode. CEV: clinically extremely vulnerable; CIE: Care Information Exchange.



Questionnaire Items and Outcome Measures

Applying recommendations for questionnaire design [9,10], question items were developed by a collaboration of experts in qualitative research at Imperial College London, encompassing public health, respiratory epidemiology, and digital health, and were also informed by previous studies [11,12]. Question items were externally peer reviewed and tested on lay persons (n=5) before being included. The themes covered included mental and physical well-being, situational variables (eg, home setting), and COVID-19 testing and symptoms. Receipt of government letters advising shielding (weeks 1 and 2) and CEV status (week 31, November 6, 2020, to capture the latest additions to the CEV list after week 2) were also recorded. Due to the weekly nature of the questionnaires, it was important to minimize bias introduced by respondent fatigue [13]; therefore, question items for mood and well-being were simplified to a Likert scale (1 to 10). Participants were also asked (week 14, July 10, 2020) to submit free-text responses to a question on the most difficult aspect of lockdown. A further question item posed in a separate questionnaire (week 29, October 23, 2020) evaluated prospective attitudes toward the need to assume shielding in the face of a further national lockdown. The questionnaires sent out in weeks 1 and 2 were almost identical and were used to define the baseline population. If participants answered both weeks, week 1 responses were used to baseline shielding behavior. A detailed description of variables captured by questionnaires used in this study is presented in Multimedia Appendix 1.

Ethical Approval

The weekly questionnaire was a direct care tool for patients to self-monitor their well-being during the COVID-19 pandemic. Participants were not paid or otherwise compensated for completing questionnaires. Upon review, the Imperial College Healthcare NHS Trust Data Protection Office advised that ethical approval for data analysis and publication was not required. Participants gave informed consent within the CIE, were free to opt out of receiving questionnaires at any time, and were informed prior to completing their responses that these would be fully anonymized and stored securely.

Participant Selection

We considered participants aged 18 years or above and those who answered questionnaires relevant to the analysis (Figure 1). Responses submitted later than 4 days from the release day of each weekly questionnaire were excluded.

Stratification of Study Groups

To align with the government's official definition of shielding behavior, participants who exclusively answered "I am not leaving my home" in response to what activity they were leaving home for (eg, "commute to work," "essential shopping," "exercise," and "other") were categorized as exhibiting shielding behavior. Classification of CEV or non-CEV status was defined by participants' responses to a question item listing clinical conditions conferring CEV status, which included being given clinical advice to shield. This classification gave rise to the following four participant groups: CEV and not shielding, CEV and shielding, non-CEV and not shielding, and non-CEV and shielding.

Data Analysis

Shielding behavior was compared within CEV and non-CEV groups separately, as these two patient groups were characteristically different, and it was not deemed appropriate to combine them. Groups were stratified in this way rather than through the use of an interaction term to ease interpretability of the analysis. Persistent shielding was defined as shielding at baseline, week 9, and week 15.

Descriptive statistics are reported alongside odds ratios (ORs) from univariable and multivariable logistic regression for the association with shielding behavior. ORs will not approximate relative risks as the outcome becomes more common and as ORs diverge further from 1. Variables included in the multivariable regression were selected a priori for their clinical relevance and to avoid multicollinearity from similar explanatory variables. Differences in categorical variables were assessed by chi-square tests or Fisher exact tests where chi-square test assumptions were violated, and differences in continuous variables were assessed using *t* tests. *P* values <.05 were considered statistically significant.

The 10-point scale measurements of "how do you feel today" in relation to "physically" and "mood" (1=worst, 10=best) were assessed using linear mixed effects regression, with "mood" and "physically" included as continuous outcome variables and patient included as the clustering variable. Week was centered and included as an explanatory variable in the model with a quadratic term. Week was included as a random effect, with the effect of week on the outcome allowed to vary by patient. The null model included week in the model only, univariable analyses added shielding into the model as an explanatory variable, and multivariable analyses added the same variables used when assessing associations with shielding behavior. Differences across time for each group are represented by mean values for each participant group on a longitudinal plot across all weeks.

Free-text responses (n=6300) were labeled in a multilabel supervised machine learning setting for efficiency. Responses were vectorized, and a logistic regression model was trained on 3000 manually labeled responses. Three researchers first independently manually labeled 100 responses each and reached a consensus on categories for labeling the remaining 2700. The remaining 3300 were labeled with this model, and every label was verified by sight and altered if necessary. Results are displayed as a stacked bar chart. All analyses were carried out in R version 3.6.2 or Python version 3.7.

Data Sharing

Imperial College Healthcare NHS Trust is the data controller. The data sets analyzed in this study are not publicly available, but can be shared for scientific collaboration subject to meeting the requirements of the institution's data protection policy.

Results

Baseline Characteristics

The study sample included 7240 participants. In the CEV group (n=2391), 1133 (47.3%) assumed shielding behavior at baseline,

compared with 633 (13.0%) in the non-CEV group (n=4849). The average number of questionnaires completed by participants did not differ by group, with participants completing an average 75% of the first 17 weekly questionnaires. Baseline characteristics and ORs from univariable and multivariable analyses are shown for the four groups in Table 1. Similarly, information for situational variables is presented in Table 2, and information for qualifying CEV status distribution is presented in Table 3. Among those initially shielding, 29.0% (329/1133) in the CEV group and 17.7% (112/633) in the non-CEV group were still doing so at week 15.

Table 1. Patient characteristics and questionnaire responses grouped by baseline demographics.

Characteristic	CEV[a], not shielding (N=1258)	CEV, shielding (N=1133)	CEV (univariable), OR[b] (95% CI)	*P* value	CEV (multivariable), OR[b] (95% CI)	*P* value	Non-CEV, not shielding (N=4216)	Non-CEV, shielding (N=633)	Non-CEV (univariable), OR[b] (95% CI)	*P* value	Non-CEV (multivariable), OR[b] (95% CI)	*P* value
Questionnaires completed (out of 17 possible), mean (SD)	12.8 (2.6)	12.7 (2.8)	0.99 (0.96-1.01)	.33	N/A[c]	N/A	12.8 (2.6)	12.6 (2.8)	0.98 (0.95-1.01)	.17	N/A	N/A
Age (years)[d], mean (SD)	58.5 (13.0)	60.2 (13.3)	1.01 (1.00-1.02)	.002	1.02 (1.01-1.03)	<.001	57.5 (13.7)	60.8 (14.4)	1.02 (1.01-1.03)	<.001	1.02 (1.01-1.03)	<.001
Sex, n (%)												
Male	608 (48.3)	488 (43.1)	N/A	N/A	N/A	N/A	1954 (46.3)	264 (41.7)	N/A	N/A	N/A	N/A
Female	650 (51.7)	645 (56.9)	1.24 (1.05-1.45)	.01	1.33 (1.09-1.62)	.004	2262 (53.7)	369 (58.3)	1.21 (1.02-1.43)	.03	1.43 (1.18-1.74)	<.001
Ethnicity, n (%)												
White	898 (71.4)	758 (66.9)	N/A	N/A	N/A	N/A	3160 (75.0)	416 (65.7)	N/A	N/A	N/A	N/A
Asian	72 (5.7)	123 (10.9)	2.02 (1.49-2.76)	<.001	2.10 (1.51-2.95)	<.001	206 (4.9)	68 (10.7)	2.51 (1.86-3.34)	<.001	2.65 (1.94-3.58)	<.001
Black	48 (3.8)	32 (2.8)	0.79 (0.50-1.24)	.31	0.79 (0.48-1.30)	.37	102 (2.4)	12 (1.9)	0.89 (0.46-1.57)	.72	1.06 (0.53-1.93)	.86
Mixed	14 (1.1)	6 (0.5)	0.51 (0.18-1.27)	.17	0.43 (0.15-1.15)	.11	59 (1.4)	13 (2.1)	1.67 (0.87-2.98)	.10	2.14 (1.11-3.87)	.02
Other	56 (4.5)	47 (4.1)	0.99 (0.66-1.48)	.98	1.13 (0.73-1.74)	.57	167 (4.0)	39 (6.2)	1.77 (1.22-2.52)	.002	2.15 (1.45-3.12)	<.001
Prefer not to say	18 (1.4)	13 (1.1)	0.86 (0.41-1.75)	.67	0.84 (0.38-1.84)	.66	24 (0.6)	7 (1.1)	2.22 (0.88-4.91)	.07	2.81 (1.00-6.80)	.03
Missing	152 (12.1)	154 (13.6)	N/A	N/A	N/A	N/A	498 (11.8)	78 (12.3)	N/A	N/A	N/A	N/A
Smoking status, n (%)												
Never smoker	707 (56.2)	653 (57.6)	N/A	N/A	N/A	N/A	2512 (59.6)	411 (64.9)	N/A	N/A	N/A	N/A
Exsmoker	465 (37.0)	417 (36.8)	0.97 (0.82-1.15)	.73	0.95 (0.78-1.17)	.63	1430 (33.9)	195 (30.8)	0.83 (0.69-1.00)	.05	0.83 (0.67-1.01)	.07
Smoker	82 (6.5)	63 (5.6)	0.83 (0.59-1.17)	.30	0.98 (0.65-1.47)	.92	264 (6.3)	25 (3.9)	0.58 (0.37-0.87)	.01	0.70 (0.43-1.09)	.14
Missing	4 (0.3)	N/A	N/A	N/A	N/A	N/A	10 (0.2)	2 (0.3)	N/A	N/A	N/A	N/A

[a]CEV: clinically extremely vulnerable.

[b]Odds ratios (ORs) represent the likelihood of adopting shielding behavior, expressed with associated 95% CIs.

[c]N/A: not applicable.

[d]Age showed a linear association with shielding behavior and was included as a linear continuous variable, with ORs representing a +1 increase in yearly age.

Table 2. Patient characteristics and questionnaire responses grouped by situational variables.

Situational variable	CEV[a], not shielding (N=1258)	CEV, shielding (N=1133)	CEV (univariable), OR[b] (95% CI)	*P* value	CEV (multivariable), OR (95% CI)	*P* value	Non-CEV, not shielding (N=4216)	Non-CEV, shielding (N=633)	Non-CEV (univariable), OR (95% CI)	*P* value	Non-CEV (multivariable), OR (95% CI)	*P* value
Key worker, n (%)												
No	1083 (86.1)	1010 (89.1)	N/A[c]	N/A	N/A	N/A	3641 (86.4)	567 (89.6)	N/A	N/A	N/A	N/A
Yes	163 (13.0)	112 (9.9)	0.74 (0.57-0.95)	.02	0.74 (0.54-1.01)	.06	556 (13.2)	54 (8.5)	0.62 (0.46-0.83)	.002	0.63 (0.44-0.87)	.007
Missing	12 (1.0)	11 (1.0)	N/A	N/A	N/A	N/A	19 (0.5)	12 (1.9)	N/A	N/A	N/A	N/A
Outdoor space, n (%)												
No outdoor space	197 (15.7)	136 (12.0)	N/A	N/A	N/A	N/A	696 (16.5)	81 (12.8)	N/A	N/A	N/A	N/A
Outdoor space	902 (71.7)	834 (73.6)	1.34 (1.06-1.70)	.02	1.20 (0.92-1.57)	.19	3011 (71.4)	470 (74.2)	1.34 (1.05-1.73)	.02	1.33 (1.02-1.76)	.04
Missing	159 (12.6)	163 (14.4)	N/A	N/A	N/A	N/A	509 (12.1)	82 (13.0)	N/A	N/A	N/A	N/A
Household members, n (%)												
1	320 (25.4)	250 (22.1)	N/A	N/A	N/A	N/A	980 (23.2)	119 (18.8)	N/A	N/A	N/A	N/A
2	562 (44.7)	480 (42.4)	1.09 (0.89-1.34)	.40	0.87 (0.68-1.10)	.24	1825 (43.3)	293 (46.3)	1.32 (1.06-1.66)	.02	1.25 (0.98-1.61)	.08
3	175 (13.9)	204 (18.0)	1.49 (1.15-1.94)	.003	1.32 (0.97-1.79)	.08	665 (15.8)	114 (18.0)	1.41 (1.07-1.86)	.01	1.49 (1.09-2.03)	.01
4	112 (8.9)	130 (11.5)	1.49 (1.10-2.01)	.01	1.33 (0.91-1.93)	.14	479 (11.4)	66 (10.4)	1.13 (0.82-1.56)	.44	1.19 (0.81-1.73)	.37
5+	76 (6.0)	63 (5.6)	1.06 (0.73-1.54)	.76	1.00 (0.63-1.58)	.99	236 (5.6)	33 (5.2)	1.15 (0.75-1.72)	.50	1.39 (0.85-2.21)	.17
Missing	13 (1.0)	6 (0.5)	N/A	N/A	N/A	N/A	31 (0.7)	8 (1.3)	N/A	N/A	N/A	N/A
Letter advising shielding, n (%)												
Not received	836 (66.5)	424 (37.4)	N/A	N/A	N/A	N/A	4063 (96.4)	574 (90.7)	N/A	N/A	N/A	N/A
Received	414 (32.9)	701 (61.9)	3.34 (2.82-3.95)	<.001	3.57 (2.96-4.32)	<.001	128 (3.0)	52 (8.2)	2.88 (2.04-3.99)	<.001	2.73 (1.83-4.00)	<.001
Missing	8 (0.6)	8 (0.7)	N/A	N/A	N/A	N/A	25 (0.6)	7 (1.1)	N/A	N/A	N/A	N/A
Shielding behavior (week 9), n (%)	159 (14.5)	523 (53.2)	6.66 (5.42-8.24)	<.001	N/A	N/A	129 (3.5)	216 (39.9)	18.33 (14.36-23.49)	<.001	N/A	N/A
Shielding behavior (week 15), n (%)	76 (7.4)	255 (29.0)	5.10 (3.89-6.75)	<.001	N/A	N/A	65 (1.9)	92 (17.7)	11.13 (8.00-15.59)	<.001	N/A	N/A

Situational variable	CEV[a], not shielding (N=1258)	CEV, shielding (N=1133)	CEV (univariable), OR[b] (95% CI)	*P* value	CEV (multivariable), OR (95% CI)	*P* value	Non-CEV, not shielding (N=4216)	Non-CEV, shielding (N=633)	Non-CEV (univariable), OR (95% CI)	*P* value	Non-CEV (multivariable), OR (95% CI)	*P* value
Any health care utilization, n (%)	1175 (93.4)	1065 (94.0)	1.11 (0.80-1.54)	.55	N/A	N/A	3277 (77.7)	518 (81.8)	1.29 (1.05-1.61)	.02	N/A	N/A
Emergency department attendance, n (%)	111 (8.8)	131 (11.6)	1.35 (1.04-1.77)	.03	N/A	N/A	304 (7.2)	52 (8.2)	1.15 (0.84-1.55)	.37	N/A	N/A
GP[d] in-person consultation, n (%)	428 (34.0)	376 (33.2)	0.96 (0.81-1.14)	.67	N/A	N/A	1115 (26.4)	158 (25.0)	0.93 (0.76-1.12)	.43	N/A	N/A
GP remote consultation, n (%)	852 (67.7)	832 (73.4)	1.32 (1.10-1.57)	.002	N/A	N/A	2354 (55.8)	376 (59.4)	1.16 (0.98-1.37)	.09	N/A	N/A
Admitted to hospital without COVID-19 symptoms, n (%)	82 (6.5)	112 (9.9)	1.57 (1.17-2.12)	.003	N/A	N/A	155 (3.7)	35 (5.5)	1.53 (1.04-2.21)	.03	N/A	N/A
Admitted to hospital with COVID-19 symptoms, n (%)	7 (0.6)	18 (1.6)	2.89 (1.25-7.45)	.02	N/A	N/A	14 (0.3)	<5[e]	1.43 (0.33-4.39)	.58	N/A	N/A
Hospital clinic in-person, n (%)	605 (48.1)	578 (51.0)	1.12 (0.96-1.32)	.15	N/A	N/A	1140 (27.0)	167 (26.4)	0.97 (0.80-1.17)	.73	N/A	N/A
Hospital clinic remote, n (%)	824 (65.5)	808 (71.3)	1.31 (1.10-1.56)	.002	N/A	N/A	1788 (42.4)	303 (47.9)	1.25 (1.05-1.47)	.01	N/A	N/A
COVID-19–positive result, n (%)	21 (1.7)	37 (3.3)	1.99 (1.17-3.47)	.01	N/A	N/A	82 (1.9)	15 (2.4)	1.22 (0.67-2.07)	.48	N/A	N/A
Persistent shielding[f], n (%)	N/A	202 (25.2)	N/A	N/A	N/A	N/A	N/A	67 (14.4)	N/A	N/A	N/A	N/A
COVID-19 symptoms, n (%)	352 (28.0)	368 (32.5)	1.24 (1.04-1.48)	.02	N/A	N/A	995 (23.6)	163 (25.8)	1.12 (0.92-1.36)	.24	N/A	N/A
Development of COVID-19 symptoms over the 17 weeks in those without symptoms at baseline, n (%)	216 (17.6)	231 (21.1)	1.26 (1.02-1.55)	.03	N/A	N/A	611 (14.7)	77 (12.5)	0.83 (0.64-1.06)	.15	N/A	N/A

[a]CEV: clinically extremely vulnerable.

[b]Odds ratios (ORs) represent likelihood of adopting shielding behavior, expressed with associated 95% CI.

[c]N/A: not applicable.

[d]GP: general practitioner.

[e]We state "<5" where there are five or fewer patients within the criteria in question in order to preserve patient anonymity.

[f]Persistent shielding defined as shielding at baseline, week 9, and week 15.

Table 3. Patient characteristics and questionnaire responses grouped by clinically extremely vulnerable qualifying criteria.

CEV[a] qualifying criteria	CEV, not shielding (N=1258), n (%)	CEV, shielding (N=1133), n (%)	OR[b] (95% CI) (univariable)	*P* value
Solid-organ transplant	82 (6.5)	188 (16.6)	2.85 (2.18-3.77)	<.001
Cancer (active chemotherapy)	38 (3.0)	42 (3.7)	1.24 (0.79-1.94)	.35
Cancer (lung, active radiotherapy)	<5[c]	<5	1.11 (0.21-6.01)	.90
Cancer (blood/bone)	76 (6.0)	84 (7.4)	1.25 (0.90-1.72)	.18
Cancer (immunotherapy)	83 (6.6)	57 (5.0)	0.75 (0.53-1.06)	.10
Bone marrow transplant	<5	7 (0.6)	1.95 (0.59-7.46)	.29
Severe respiratory illness	156 (12.4)	212 (18.7)	1.63 (1.30-2.04)	<.001
Rare disease	77 (6.1)	97 (8.6)	1.44 (1.05-1.96)	.02
Immunosuppression	380 (30.2)	372 (32.8)	1.13 (0.95-1.34)	.17
Down syndrome[d]	N/A[e]	<5	N/A	N/A
Chronic kidney disease (on dialysis)[d]	32 (2.5)	17 (1.5)	0.58 (0.32-1.04)	.08
Pregnancy with heart disease	<5	N/A	N/A	N/A
Expert clinical advice[f]	445 (35.4)	285 (25.2)	0.61 (0.51-0.73)	<.001

[a]CEV: clinically extremely vulnerable.

[b]Odds ratios (ORs) represent likelihood of adopting shielding behavior, expressed with associated 95% CI.

[c]We state "<5" where there are five or fewer patients within the criteria in question in order to preserve patient anonymity.

[d]Clinical conditions appended to the original CEV list after week 2.

[e]N/A: not applicable.

[f]Expert clinical advice refers to the patient receiving advice to shield despite not being a member of an at-risk group according to the CEV criteria.

Associations With Adopting Shielding Behavior

For CEV participants, multivariable analysis showed an independent association between shielding and being female, being Asian, an increase in yearly age, and receiving a letter advising the participant to shield. Similar associations were observed in the non-CEV group. Among CEV participants, living in a home with outdoor space was significant only in univariable analysis, but it was maintained in multivariable analysis in the non-CEV group. Likewise, being in a household consisting of three members (compared to a household with one member) was positively associated with shielding behavior in the univariable analysis in both the CEV and non-CEV groups; however, in the multivariable analysis, the CIs crossed 1 for the CEV group but did not in the non-CEV group. Overall, 30.5% of participants were CEV on the basis of clinical judgement rather than specific morbidity, and such an attribution was associated with being less likely to shield. Among qualifying CEV conditions, adopting shielding behavior was associated with being a solid organ transplant recipient, or having a severe respiratory illness or rare disease (Table 3).

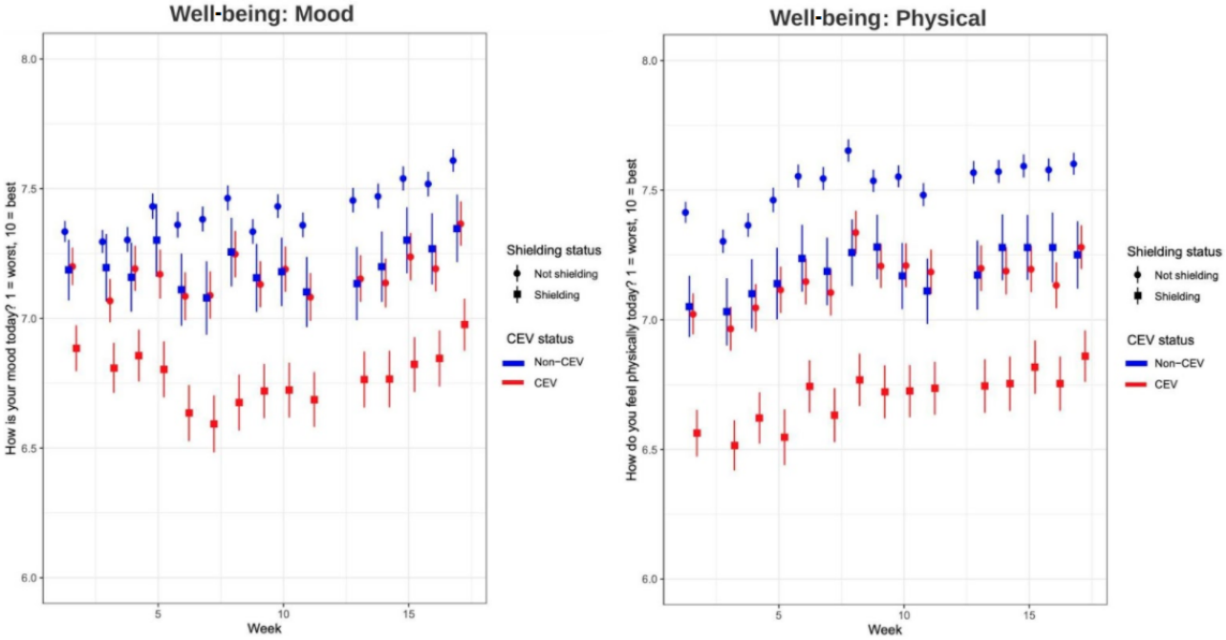
The persistence of shielding behavior was more prevalent in the CEV group than in the non-CEV group (202/802, 25.2% vs 67/464, 14.4%). Receipt of a government letter advising shielding was reported in 3.7% (180/4849) of non-CEV participants and was associated with adoption of shielding behavior (OR 2.88, 95% CI 2.04-3.99).

During the study period, the total number of participants who tested positive for COVID-19 was low in both the CEV (n=58, 2.4%) and non-CEV (n=97, 4.4%) cohorts. In the CEV group, there was a significant association between shielding behavior and testing positive for COVID-19 (OR 1.99, 95% CI 1.17-3.47). In the non-CEV group, there was no significant association between shielding behavior and testing positive for COVID-19. The subjective reporting of new symptoms attributable to COVID-19 infection was associated with shielding behavior in the CEV group, with no difference observed between those adopting shielding and those not adopting shielding in the non-CEV group.

Longitudinal Associations Between Shielding and Well-being

Longitudinal analysis of physical and mental well-being is displayed in Figure 2. Mental and physical well-being showed a quadratic relationship with time across the 17 weeks in both CEV and non-CEV patients (Multimedia Appendix 2 and Multimedia Appendix 3). In those who were CEV, shielding at baseline was associated with a lower rating of mental well-being (adjusted β −0.40, 95% CI −0.26 to −0.55) and physical well-being (adjusted β −0.51, 95% CI −0.37 to −0.66). Similar results were found for non-CEV patients (mental well-being: adjusted β −0.23, 95% CI −0.35 to −0.10; physical well-being: adjusted β −0.34, 95% CI −0.21 to −0.47). Unadjusted and adjusted results, along with coefficients for all variables included in the model, can be found in Multimedia Appendix 2 and Multimedia Appendix 3.

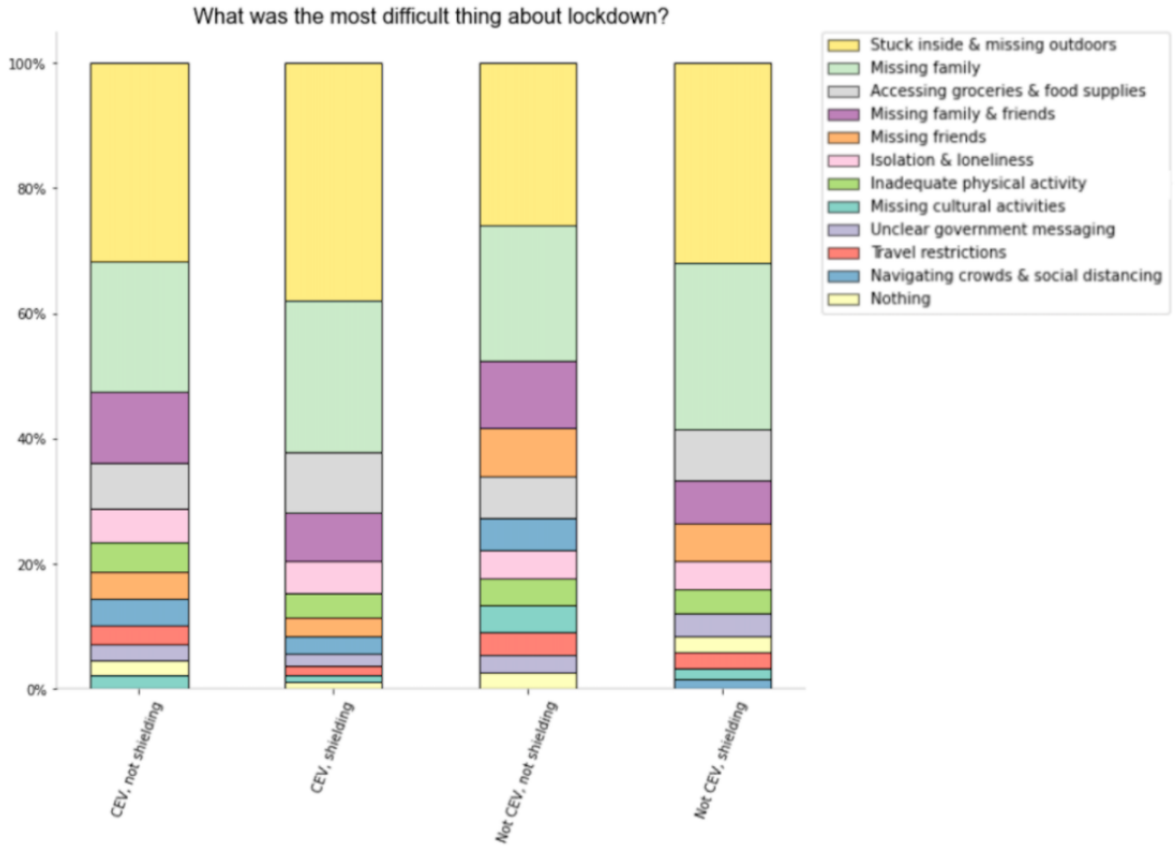
Figure 2. Longitudinal (17 weeks; April 9, 2020, to July 31, 2020) trends showing changes related to mood and physical well-being. CEV: clinically extremely vulnerable.



Thematic Analysis of the Most Challenging Elements of Lockdown

Across all groups, the most frequently occurring theme was feeling "stuck inside & missing outdoors," followed by "missing family" (Figure 3). Prevalent in all four groups was the concern around accessing food and grocery supplies.

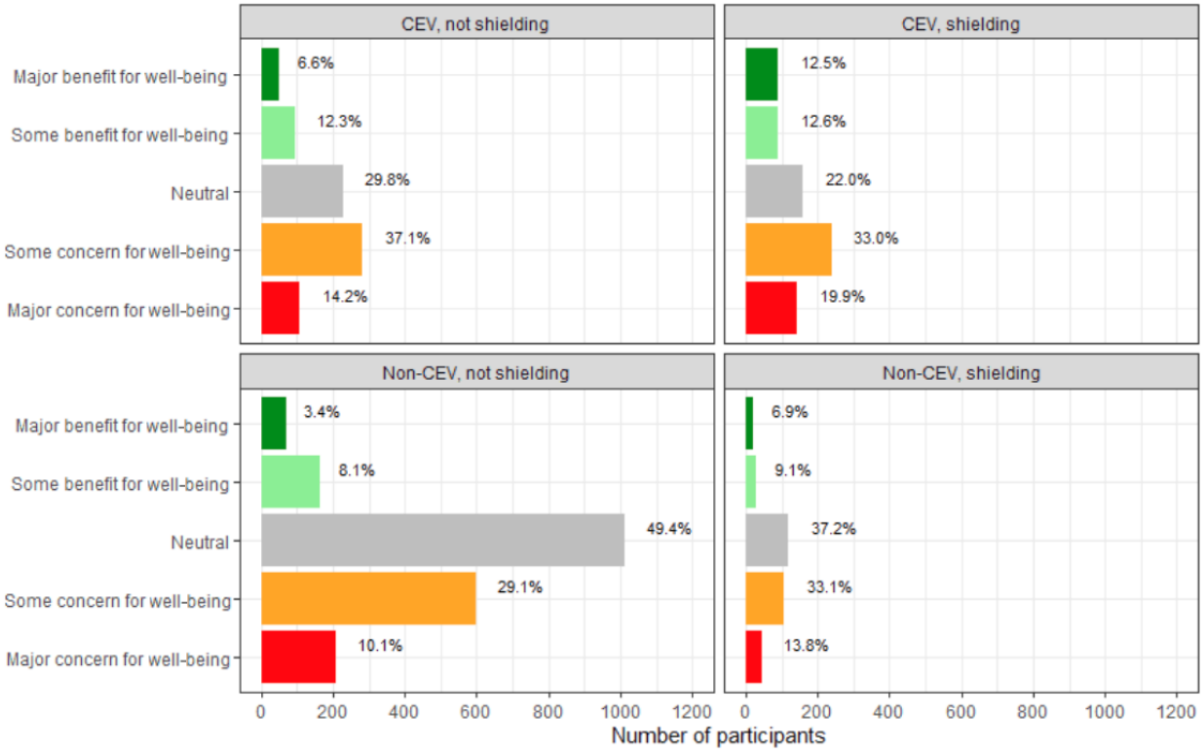
Figure 3. Week 14 questionnaire item posing a free-text question on the "most difficult thing about lockdown" (N=6300). CEV: clinically extremely vulnerable.



Concern for the Need to Shield Again

Across all groups, responses were skewed toward "some" or "major" concern for well-being should the requirement for further shielding arise (Figure 4). In the CEV group that adopted shielding behavior, 25.1% of participants projected that a requirement to shield again in anticipation of a second national lockdown would benefit their well-being, compared with 18.9% among those who did not adopt shielding behavior (P<.001).

Figure 4. Week 29 questionnaire item measuring the level of concern for well-being if, in anticipation of a second UK national lockdown, advice is to assume shielding again (N=3818). CEV: clinically extremely vulnerable.



Discussion

Main Findings

This longitudinal study of over 7000 NHS patients measured the determinants of shielding behavior and the impact on well-being throughout the first wave (17 weeks) of the UK's COVID-19 pandemic. We found that approximately half of our sample's CEV patients adopted shielding behavior ("staying at home at all times") as per the advice at the time. This behavior was also reported by 15% of non-CEV participants. Our findings highlight that shielding behavior was associated with worse mental and physical well-being in both CEV and non-CEV cohorts, suggesting that the adoption of such behavior when not indicated may have resulted in avoidable detriments to physical and mental health.

The percentage of the UK public with "high anxiety" over COVID-19 peaked during the time of the week 1 questionnaire [14], which may explain why many decided to assume the behavior of being a "shielder," despite not meeting the criteria. A survey of patients with arthritis who reported they were shielding (many of whom were non-CEV) suggested only 25% had received a government letter advising them to do so [15]. The timing of the baseline questionnaires also aligned with the first widespread reports that certain ethnic minorities were overrepresented among COVID-19 deaths [16,17], possibly explaining our observed positive association between shielding behavior and Asian ethnicity.

We found that only 50% of our sample's CEV population reported receiving a government letter. This is of concern given our observed positive association between letter receipt and adoption of shielding behavior. Though such letters may empower patients to make informed decisions about shielding, our study also suggests some misattributions of CEV status, where subsequent receipt of advice to shield was associated with unnecessary adoption of shielding behavior. Conversely, it has also been reported that some patients initially advised to shield were later informed by text message of no longer needing to do so, fueling uncertainty on what advice to follow. The positive association with increasing age reflects widespread misunderstanding about who shielding advice applied to, with some headlines calling on the government to "set free" healthy individuals aged over 70 years [18].

The hyperinflammatory features of severe COVID-19 have led to the suggestion that some CEV patients are in fact protected by virtue of taking immunosuppressants, for example, oral steroids for rheumatoid arthritis [19], and that following the advice given to the general population may have been adequate. Early epidemiological descriptions of COVID-19 identified underrepresentation of people with chronic respiratory disease [20], with subsequent studies suggesting a protective effect from inhaled corticosteroid therapy [20-22]. Here, our findings indicate the possibility of confounding by behavior, namely that those with severe respiratory illness were among the most likely to shield during the early stages of the pandemic, allowing the

first inference that shielding may have had a protective effect in this group.

The early months of the pandemic also exposed substantial inequalities and insecurities in food supply [23,24], with results from our qualitative analysis suggesting this was particularly marked among those shielding. Despite this, in the run up to the second national lockdown, a quarter of those CEV participants who originally shielded indicated "some" or "major" anticipated benefit to their well-being if further shielding was advised, suggesting negative impacts were far from universal.

Our findings are best interpreted in the context of their limitations. Though the LoC-19 participant cohort is large and uniquely rich (compared with less timely surveys on shielding from the Office of National Statistics [25]), covers the entire United Kingdom, and includes the spectrum of CEV patients, it is not fully representative of the general NHS patient population, particularly those traditionally underrepresented (eg, ethnic minorities). Notably, the digital divide that historically excludes older participants when using online survey tools for epidemiology studies is not represented here. However, the generalizability of the results is limited by this population having elected in the first instance to monitor their well-being using the provided tool. Participants completed, on average, 75% of the questionnaires in the first 17 weeks. Though this is a high response rate, our analyses did not account for potential biases from differential responses/retention rates on a weekly basis. As has been a common theme for COVID-19, the positive association with household outdoor space suggests the ability to shield (particularly for non-CEV individuals) may also follow a social gradient. Our study did not capture all possible social determinants, such as the need to sustain income and provide care to others [26]. Validated multiquestion instruments would have been preferable for evaluating mood and physical well-being; however, these were less suitable for this longitudinal study owing to the risk of biases, including responder fatigue. CEV status was captured at week 31 and not by baseline (week 1 or 2) questionnaires. The CEV list went through several iterations, and conditions, such as Down syndrome and chronic kidney disease on dialysis, were added later [27], such that recording CEV status in week 31 enabled comprehensive capture. However, this resulted in a lower number of participants eligible for inclusion in the analysis. Recall bias is unlikely to have been an issue for capturing self-reported CEV status by qualifying the clinical condition in week 31, though this time point may explain our result that CEV status determined by clinical advice was associated with being less likely to shield. These participants may have been uninformed of their CEV status until several weeks/months into the pandemic and therefore were initially not shielding at receipt of the baseline questionnaires. All participants, regardless of CEV status or shielding behavior, completed >75% of the sequential weekly questionnaires. Our data set nonetheless contains a variable level of weekly nonresponse, somewhat ameliorated by the large sample size.

Our finding that overall shielding negatively impacted both mental and physical well-being has also been observed in small studies focusing on specific disease groups such as cystic fibrosis [28] and complex dermatology [29]. Nonetheless, the ongoing pandemic led to an improved understanding of what determines the highest risk from COVID-19, with subsequent development and adoption of predictive risk modeling [30] that identified and extended shielding advice to a further 1.7 million people during the third national lockdown (February 2021) [31]. However, this was not informed by evidence that shielding is any more protective than established advice for the rest of the population. The lack of community testing during the first months of the COVID-19 pandemic means we are unable to definitively comment on whether the act of shielding was associated with lower incidence of COVID-19. In fact, our results suggest both positive COVID-19 testing and new symptoms indicative of COVID-19 were positively associated with shielding behavior; however, this may also be related to, as we observed, more health and social care encounters in this group. Therefore, beyond intuition, evaluating whether the shielding policy of the first wave of the pandemic in the United Kingdom achieved its primary objective of reducing cases of COVID-19 will remain challenging, but this study gives the first indication that the act of shielding precipitated a trade-off with well-being, and that unclear messaging may have driven inconsistencies in how shielding behavior was adopted. Ultimately, a partnership needs to be achieved with those we believe are at increased risk from COVID-19 to empower them to reduce their risk through consistent communication, openness about uncertainty, and respect for personal autonomy.

Conclusion

Future health policy must balance the as yet unproven benefit of shielding for protection from COVID-19 against our findings that shielding negatively impacted well-being and was adopted by many in whom it was not indicated and variably in whom it was indicated. Our findings highlight the need for clearer public health messaging and support for well-being if shielding is to be advised in future pandemic scenarios.

Acknowledgments

We are grateful to colleagues from the Faculty of Medicine, School of Public Health, and Institute of Global Health Innovation at Imperial College London for help with the questionnaires, and to the project team of Imperial NHS Care Information Exchange, including Felicia Opoku and John Kelly. Funding was received from Imperial Health Charity, Imperial Biomedical Research Centre of the National Institute of Health Research, British Heart Foundation, Pfizer Independent Grants, NHSX, and Rosetrees Foundation.

Authors' Contributions

PB contributed to the study design, data collection, literature review, data analysis, figures, and writing of the paper. AA contributed to the study design, literature review, figures, data analysis, and writing. MAK and WAM contributed to the figures, data analysis, and writing. JKQ contributed to the study design, literature review, data analysis, figures, and writing. NSP contributed to the study design, data collection, literature review, data analysis, figures, and writing. NSP is the guarantor. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted. The lead author affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Question items included in Care Information Exchange questionnaires.
[DOCX File , 18 KB - publichealth_v7i9e30460_app1.docx]

Multimedia Appendix 2
Mixed effects linear regression for the association between shielding and mood and physical rating (clinically extremely vulnerable).
[DOCX File , 17 KB - publichealth_v7i9e30460_app2.docx]

Multimedia Appendix 3
Mixed effects linear regression for the association between shielding and mood and physical rating (nonclinically extremely vulnerable).
[DOCX File , 17 KB - publichealth_v7i9e30460_app3.docx]

References

1. Dunn P, Allen L, Cameron G, Alderwick H. COVID-19 policy tracker 2020. The Health Foundation. URL: https://www.health.org.uk/news-and-comment/charts-and-infographics/covid-19-policy-tracker [accessed 2021-01-07]
2. Guidance on protecting people who are clinically extremely vulnerable from COVID-19. GOV.UK. 2021. URL: https://www.gov.uk/government/publications/guidance-on-shielding-and-protecting-extremely-vulnerable-persons-from-covid-19/guidance-on-shielding-and-protecting-extremely-vulnerable-persons-from-covid-19 [accessed 2021-01-10]
3. Letter template for GPs to circulate to patients at highest risk during COVID-19 pandemic. Department of Health and Social Care. URL: https://www.health-ni.gov.uk/publications/letter-template-gps [accessed 2020-12-30]
4. Peto J, Alwan NA, Godfrey KM, Burgess RA, Hunter DJ, Riboli E, et al. Universal weekly testing as the UK COVID-19 lockdown exit strategy. The Lancet 2020 May 02;395(10234):1420-1421 [FREE Full text] [doi: 10.1016/S0140-6736(20)30936-3] [Medline: 32325027]
5. Iacobucci G. Covid-19: What is the UK's testing strategy? BMJ 2020 Mar 26;368:m1222. [doi: 10.1136/bmj.m1222] [Medline: 32217754]
6. Press release: Plans to ease guidance for over 2 million shielding. GOV.UK. URL: https://www.gov.uk/government/news/plans-to-ease-guidance-for-over-2-million-shielding [accessed 2020-12-01]
7. Coronavirus lockdown: set free healthy over-70s, say doctors. The Sunday Times. 2020. URL: https://www.thetimes.co.uk/article/coronavirus-lockdown-set-free-healthy-over-70s-say-doctors-lxhvf8vzb [accessed 2021-01-20]
8. Sullivan K. New study to evaluate how well shielding against COVID-19 works. Swansea University Press Office. 2021. URL: https://www.swansea.ac.uk/press-office/news-events/news/2021/03/new-study-to-evaluate-how-well-shielding-against-covid-19-works-.php [accessed 2021-05-01]
9. Edwards P. Questionnaires in clinical trials: guidelines for optimal design and administration. Trials 2010 Jan 11;11:2 [FREE Full text] [doi: 10.1186/1745-6215-11-2] [Medline: 20064225]
10. McColl E, Jacoby A, Thomas L, Soutter J, Bamford C, Steen N, et al. Design and use of questionnaires: a review of best practice applicable to surveys of health service staff and patients. Health Technol Assess 2001;5(31):1-256 [FREE Full text] [doi: 10.3310/hta5310] [Medline: 11809125]
11. Bachtiger P, Adamson A, Chow J, Sisodia R, Quint JK, Peters NS. The Impact of the COVID-19 Pandemic on the Uptake of Influenza Vaccine: UK-Wide Observational Study. JMIR Public Health Surveill 2021 Apr 14;7(4):e26734 [FREE Full text] [doi: 10.2196/26734] [Medline: 33651708]
12. Bachtiger P, Adamson A, Quint JK, Peters NS. Belief of having had unconfirmed Covid-19 infection reduces willingness to participate in app-based contact tracing. NPJ Digit Med 2020 Nov 06;3(1):146 [FREE Full text] [doi: 10.1038/s41746-020-00357-5] [Medline: 33299071]

13. Lavrakas P. Encyclopedia of Survey Research Methods. Thousand Oaks, CA: Sage Publications; 2008.
14. Varga TV, Bu F, Dissing AS, Elsenburg LK, Bustamante JJH, Matta J, et al. Loneliness, worries, anxiety, and precautionary behaviours in response to the COVID-19 pandemic: A longitudinal analysis of 200,000 Western and Northern Europeans. Lancet Reg Health Eur 2021 Mar;2:100020 [FREE Full text] [doi: 10.1016/j.lanepe.2020.100020] [Medline: 33870246]
15. New research reveals shielding experiences of millions with arthritis. Versus Arthritis Charity. 2020. URL: https://www.versusarthritis.org/news/2020/july/new-research-reveals-shielding-experiences-of-millions-with-arthritis/ [accessed 2021-01-05]
16. Georghiou T, Appleby J. Are more black, Asian and minority ethnic people dying with Covid-19 than might be expected? Nuffield Trust. 2020. URL: https://www.nuffieldtrust.org.uk/news-item/are-more-black-asian-and-minority-ethnic-people-dying-with-covid-19-than-might-be-expected [accessed 2021-09-05]
17. Khunti K, Singh AK, Pareek M, Hanif W. Is ethnicity linked to incidence or outcomes of covid-19? BMJ 2020 Apr 20;369:m1548. [doi: 10.1136/bmj.m1548] [Medline: 32312785]
18. Bradley SH, Kirby E, Wheatstone P. Managing individual and population risk from covid-19. BMJ 2020 Jun 01;369:m2098. [doi: 10.1136/bmj.m2098] [Medline: 32482684]
19. Amani L, Warraich R, Patel N, Tahir H. COVID-19 and rheumatology: is shielding really necessary? Br J Hosp Med (Lond) 2020 Jun 02;81(6):1-3 [FREE Full text] [doi: 10.12968/hmed.2020.0284] [Medline: 32589537]
20. Schultze A, Walker AJ, MacKenna B, Morton CE, Bhaskaran K, Brown JP, et al. Risk of COVID-19-related death among patients with chronic obstructive pulmonary disease or asthma prescribed inhaled corticosteroids: an observational cohort study using the OpenSAFELY platform. The Lancet Respiratory Medicine 2020 Nov;8(11):1106-1120 [FREE Full text] [doi: 10.1016/S2213-2600(20)30415-X] [Medline: 32979987]
21. Rogliani P, Lauro D, Di Daniele N, Chetta A, Calzetta L. Reduced risk of COVID-19 hospitalization in asthmatic and COPD patients: a benefit of inhaled corticosteroids? Expert Rev Respir Med 2021 Apr;15(4):561-568 [FREE Full text] [doi: 10.1080/17476348.2021.1850275] [Medline: 33183113]
22. Singh D, Halpin DMG. Inhaled corticosteroids and COVID-19-related mortality: confounding or clarifying? The Lancet Respiratory Medicine 2020 Nov;8(11):1065-1066 [FREE Full text] [doi: 10.1016/S2213-2600(20)30447-1] [Medline: 32979985]
23. Cummins S, Berger N, Cornelsen L, Eling J, Er V, Greener R, et al. COVID-19: impact on the urban food retail system and dietary inequalities in the UK. Cities & Health 2020 Aug 03:1-4 [FREE Full text] [doi: 10.1080/23748834.2020.1785167]
24. Power M, Doherty B, Pybus K, Pickett K. How Covid-19 has exposed inequalities in the UK food system: The case of UK food and poverty. Emerald Open Res 2020 Apr 3;2:11. [doi: 10.35241/emeraldopenres.13539.1]
25. Gibbs T. Coronavirus and shielding of clinically extremely vulnerable people in England: 28 May to 3 June 2020. Office for National Statistics. 2020. URL: https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/bulletins/coronavirusandshieldingofclinicallyextremelyvulnerablepeopleinengland/28mayto3june2020 [accessed 2021-02-10]
26. Michie S, West R, Rogers MB, Bonell C, Rubin GJ, Amlôt R. Reducing SARS-CoV-2 transmission in the UK: A behavioural science approach to identifying options for increasing adherence to social distancing and shielding vulnerable people. Br J Health Psychol 2020 Nov;25(4):945-956 [FREE Full text] [doi: 10.1111/bjhp.12428] [Medline: 32428385]
27. Update on guidance for clinically extremely vulnerable individuals and actions for acute trusts. NHS England. URL: https://www.england.nhs.uk/coronavirus/wp-content/uploads/sites/52/2020/03/C0830-ii-trust-update-clinically-extremely-vulnerable-2nov.pdf [accessed 2021-03-05]
28. Westcott KA, Wilkins F, Chancellor A, Anderson A, Doe S, Echevarria C, et al. The impact of COVID-19 shielding on the wellbeing, mental health and treatment adherence of adults with cystic fibrosis. Future Healthc J 2021 Mar;8(1):e47-e49 [FREE Full text] [doi: 10.7861/fhj.2020-0205] [Medline: 33791475]
29. Khan SS, Marshall CL, Stylianou KA, McMullen E, Griffiths CEM, Warren RB, et al. An evaluation of dermatology patients shielding during the COVID-19 outbreak. Clin Exp Dermatol 2021 Jan;46(1):193-194. [doi: 10.1111/ced.14489] [Medline: 33098712]
30. Clift AK, Coupland CAC, Keogh RH, Diaz-Ordaz K, Williamson E, Harrison EM, et al. Living risk prediction algorithm (QCOVID) for risk of hospital admission and mortality from coronavirus 19 in adults: national derivation and validation cohort study. BMJ 2020 Oct 20;371:m3731 [FREE Full text] [doi: 10.1136/bmj.m3731] [Medline: 33082154]
31. Wise J. Covid-19: Extra 1.7 million people in England are asked to shield. BMJ 2021 Feb 17;372:n467. [doi: 10.1136/bmj.n467] [Medline: 33597119]

Abbreviations

CEV: clinically extremely vulnerable
CIE: Care Information Exchange
NHS: National Health Service
OR: odds ratio

Edited by T Sanchez; submitted 15.05.21; peer-reviewed by C Robb, S Six; comments to author 14.06.21; revised version received 04.07.21; accepted 15.07.21; published 20.09.21.

Please cite as:
Bachtiger P, Adamson A, Maclean WA, Kelshiker MA, Quint JK, Peters NS
Determinants of Shielding Behavior During the COVID-19 Pandemic and Associations With Well-being Among National Health Service Patients: Longitudinal Observational Study
JMIR Public Health Surveill 2021;7(9):e30460
URL: https://publichealth.jmir.org/2021/9/e30460
doi:10.2196/30460
PMID:34298499

Original Paper

The Influence of Social Distancing Behaviors and Psychosocial Factors on Physical Activity During the COVID-19 Pandemic: Cross-sectional Survey Study

Troy J Cross[1,2], PhD; Jennifer M J Isautier[1,2], MSc; Sarah J Morris[1], BMus(Hons); Bruce D Johnson[2], PhD; Courtney M Wheatley-Guy[3], PhD; Bryan J Taylor[4], PhD

[1]Sydney School of Health Sciences, Faculty of Medicine and Health, The University of Sydney, Camperdown, Australia

[2]Department of Cardiovascular Diseases, Mayo Clinic, Rochester, MN, United States

[3]Department of Cardiovascular Diseases, Mayo Clinic, Scottsdale, AZ, United States

[4]Department of Cardiovascular Diseases, Mayo Clinic, Jacksonville, FL, United States

Corresponding Author:
Troy J Cross, PhD
Sydney School of Health Sciences
Faculty of Medicine and Health
The University of Sydney
Camperdown Campus
Camperdown, 2006
Australia
Phone: 61 2 9351 2222
Email: troy.cross@sydney.edu.au

Abstract

Background: The COVID-19 pandemic has arguably facilitated a shift toward increased sedentariness and reduced physical activity. Moreover, there is mounting evidence that mental health has also declined during the pandemic. However, it remains unknown to what extent social distancing (SD) behaviors and mental health have affected the physical activity levels of the general population.

Objective: The purpose of this study was to determine the influence of SD behaviors and prevailing mental health on the odds of being physically active during the early COVID-19 pandemic response.

Methods: A total of 4819 adults (2474/4819, 51.3%, female) from the US population with a median age of 46 (IQR 35-59) completed an online survey during the early pandemic response (April-June 2020). The survey included questions on adherence to 11 SD behaviors, and validated questionnaires which assessed self-reported physical activity, depression, anxiety, and mental well-being. Respondents were categorized into 2 physical activity groups: inactive (0-599 metabolic equivalent of task [MET]-minutes/week) and active (≥600 MET-minutes/week). A logistic generalized additive model (GAM) was used to determine which SD factors and mental health outcomes were associated with physical activity level.

Results: The GAM analysis revealed that wearing a facemask in public (odds ratio [OR] 1.46, 95% CI 1.14-1.79; *P*=.003), limiting the use of public transport (OR 1.47, 95% CI 1.19-1.83; *P*=.001), and restricting travel outside the house (OR 1.56, 95% CI 1.19-2.05; *P*=.002) were SD behaviors associated with higher odds of being more physically active. Conversely, avoiding physical activity outside the house was associated with higher odds of being inactive (OR 0.52, 95% CI 0.46-0.63; *P*<.001). Leaving the house more frequently, and a higher mental well-being were associated with increasing odds of being physically active (*P*<.001). Engaging with a moderate number of SD behaviors (3-7 total) was positively associated with physical activity, whereas a very high SD vigilance (ie, engaging with ≥10 total behaviors) decreased the odds of being active during the early pandemic response.

Conclusions: Based on the findings of our study, we suggest that future public health messaging of SD guidelines should include (1) a clear portrayal of the benefits of regular exercise on mental health; and (2) a specific focus on how to be physically active outdoors in a COVID-safe manner.

(JMIR Public Health Surveill 2021;7(9):e31278) doi:10.2196/31278

KEYWORDS

physical activity; COVID-19; mental health; social distancing; public health; pandemic; physical health; exercise

Introduction

The COVID-19 outbreak was officially declared a pandemic on March 11, 2020, by the World Health Organization (WHO). During the first year of the COVID-19 pandemic response, no effective pharmaceutical therapies existed to prevent or contain the spread of the novel coronavirus. Consequently, many countries around the world began to rapidly implement nonpharmaceutical interventions to mitigate community transmission of COVID-19. These public health interventions included rules or guidelines for personal hygiene, respiratory etiquette, and social distancing (SD) [1-4]. On this latter point, SD is a broad term that encompasses many social behaviors designed to minimize interpersonal contact within the community, including but not limited to self-quarantine, working from home, school closures, restrictions on mass gatherings and travel outside the home, and minimum separation distance between persons in public spaces. In some circumstances, these public health measures have led governing authorities to enforce closure of local gymnasiums, sporting and recreational facilities, in addition to suspending organized team sports and other physical activities that would otherwise incur close interpersonal contact (dance classes, yoga, etc).

It follows from the above that SD guidelines and restrictions have reduced the opportunities for the public to engage in physical activity during the early COVID-19 pandemic. There is mounting evidence to suggest that physical activity has decreased since the beginning of the COVID-19 outbreak [5-10]. This shift toward sedentariness is especially alarming, seeing that sedentariness and physical inactivity are both well-known risk factors for long-term outcomes such as cardiovascular disease and premature mortality [11,12]. Physical inactivity had already been identified as a global pandemic itself prior to the COVID-19 outbreak [13]. Physical inactivity is the fourth leading risk factor for global mortality [14], and is perhaps of greater importance for the older rather than younger population during the current pandemic [15]. While SD is a necessary measure to minimize community transmission of COVID-19, it is important to also understand its collateral adverse effects such as reduced engagement in physical activity. In so doing, we may identify key areas for improving the messaging of SD guidelines in a way that ensures public safety, yet facilitates and encourages a healthy, active lifestyle as the pandemic continues.

It is noteworthy that opportunities for socialization through physical activity (eg, gym classes, team sports) have decreased during the COVID-19 pandemic. Moreover, SD measures are, by nature, a collection of behaviors specifically designed to minimize interpersonal contact, further diminishing opportunities for social interaction. Certainly, these fewer interactions may contribute to growing feelings of social isolation and loneliness during the pandemic [16]. The prolonged experience of social isolation may precipitate a poor state of mental health [17] which, in turn, may explain the increased symptoms of depression, anxiety, or reduced mental well-being reported during the pandemic [18-21]. It must be remembered that physical activity and mental health are related via a bidirectionally causal relationship [22,23]. As such, it is important that any investigation into the effects of SD behavior on physical activity during the COVID-19 pandemic is interpreted with consideration of the mental health status of the population under study.

We conducted a large, online cohort study among US residents. The principal aim of this study was to examine whether SD behaviors were associated with physical activity participation during the early phase of the COVID-19 pandemic (April to June 2020). A secondary aim was to examine the independent effects of mental health status on physical activity. We hypothesized that engaging in more SD behaviors, and having poorer mental health, would be associated with lower odds of meeting the minimum WHO recommendations for physical activity during the early COVID-19 pandemic response.

Methods

Study Design, Sampling, and Participant Recruitment

The data used in this study were drawn from a larger, longitudinal cohort study that commenced in April 2020: the COVID-19 Physical Activity and Well-being Survey (PAWS). The primary aim of the broader PAWS project is to examine temporal trends in physical activity and mental health throughout the COVID-19 pandemic in the United States. Data for this study were obtained from the first round of the PAWS. Participants were invited to complete the first round of the PAWS between April 27 and June 8, 2020. Survey responses were collected via the Qualtrics online platform. Participants were recruited via word of mouth, and social media campaigns (Facebook and Twitter) that were targeted using paid advertisements to recruit men and women across a wide range of ages. Participants were eligible to participate if they were aged 18 years or older, could read and understand English, and were able to provide a valid zip code as evidence of residing in the United States.

Ethical Approval and Informed Consent

This study was approved by the Mayo Clinic Institutional Review Board (#20-003709). Participants were provided with an information sheet on the landing page of the online survey. Participants were only allowed to continue participating if they acknowledged that they had read the information sheet, and agreed to the following statement “I give consent to participate in this study”.

Definition of Variables

Outcome

The outcome variable in this study was self-reported physical activity. Moderate-to-vigorous physical activity (MVPA) was determined using the Global Physical Activity Questionnaire (GPAQ) [24]. The GPAQ assesses the weekly volume of MVPA (minutes/week) in the domains of work, recreation, and

transport. Data obtained from the GPAQ were cleaned and subsequently analyzed using the guidelines outlined by the WHO [25]. Weekly MVPA was expressed as an intensity-weighted volume (ie, metabolic equivalent of task [MET]-minutes/week) by multiplying moderate and vigorous activities by the corresponding metabolic equivalents of tasks (METs) of 4.0 and 8.0, respectively [24,25]. Total weekly MVPA (MET-minutes/week) was taken as the sum of all domain-specific MVPA, and was used to categorize participants into the following 2 groups: inactive (0-599 MET-minutes/week) and active (≥600 MET-minutes/week). These demarcations are based on the lower threshold of the minimum requirement outlined in the 2020 WHO physical activity guidelines [26].

Exposures

The 2 exposures of this study were linked to our primary and secondary aims: SD behaviors and mental health.

Social Distancing

SD behavior was assessed by asking participants to indicate if they were presently engaging in one (or any) SD behavior at the time of the survey (11 different behaviors in total; Textbox 1). The total number of SD behaviors (sum of SD1–SD11) was taken as an index of SD vigilance.

Textbox 1. Questions designed to assess participant engagement with social distancing behaviors at the time of the survey.

Social distancing behaviors

"Regardless of whether specific guidelines/rules for social distancing have been issued by authorities in the place where you live, please indicate whether you are currently performing any of the following behaviors listed below. Please check all behaviors that apply."

SD1: Wearing a face mask in public

SD2: Avoiding close contact with others in your social circle

SD3: Avoiding places where many people gather

SD4: Working from home

SD5: Limiting time spend outside of your residence

SD6: Limiting your use of public transport

SD7: Self-quarantine/isolation

SD8: Restricting your travel outside the house

SD9: Avoiding physical activity outside the house

SD10: Avoiding physical contact with others (ie, handshaking, hugging)

SD11: Reducing the time or number of trips to shop for food/supplies/etc

Mental Health

Mental health was evaluated by assessing participant's symptoms of depression, anxiety, and mental well-being using the following tools: the 9-item Patient Health Questionnaire (PHQ-9) [27], the 7-item Generalized Anxiety Disorder scale (GAD-7) [28], and the 5-item World Health Organization Well-Being (WHO-5) Index [29,30], respectively.

Covariates

Pandemic Burden and Fear

We assessed the zip code–level burden of the COVID-19 pandemic by obtaining the number of deaths, and the confirmed and recovered cases attributed to the disease. These data were obtained from an up-to-date, online repository of COVID-19–related information [31]. Using this repository, we were able to obtain case numbers for each respondent's US state using zip code provided by the participant and the date the survey was completed. The difference between confirmed and recovered COVID-19 cases was taken as the number of active cases in the area. Deaths and case numbers were expressed per capita of the state in which the participant resided. Furthermore, we calculated the duration of time that SD guidelines/restrictions had been imposed by taking the difference between the survey response date and the first date in which the "stringency index" [32] of the participant's state was greater than 0. The "stringency index" is a novel score indicating the stringency with which a local government is responding to the COVID-19 pandemic. It is computed from a weighted average of 9 metrics used to characterize the strictness of containment and closure policies of the area. Participants were also asked to indicate their current level of fear associated with being infected by, or unknowingly spreading COVID-19.

Sedentary and Self-Monitoring Behavior

Data on sedentary behavior (minutes/day) were obtained directly from the GPAQ [24,25]. These data were used to categorize participants into 2 groups defined around an approximate threshold associated with increased cardiovascular morbidity (≥8 hours/day) in harmonized pooled studies [33]. Participants were asked to indicate whether they currently used a wearable device to track their physical activity.

Socioeconomic Status and Physical Health

Socioeconomic status [34,35], physical health [36-38], and chronic disease [39,40] are known to influence physical activity. Accordingly, sociodemographic variables, including age, gender, height, weight, educational, and employment status were collected, in addition to self-reported chronic disease and overall health status. Breathlessness, a hallmark symptom of many

chronic diseases, was assessed using the Medical Research Council (MRC) dyspnea scale [41].

Statistical Analyses

Differences in proportions between physical activity groups (inactive vs. active) were assessed using the Fisher exact test. The differences in means for count variables (eg, number of chronic conditions, number of SD behaviors) between physical activity groups were assessed using Tweedie regression. The odds of scoring higher on an ordinal scale variable was assessed using a cumulative link regression [42]. Post hoc comparisons of proportions within a given ordinal level of these models were evaluated using estimated marginal means [43]. A generalized additive model (GAM) was used to determine the effect of engaging with SD behaviors on the likelihood of performing a sufficient amount of MVPA [26]. The dependent (outcome) variable in our GAM was the binary variable indicating whether a participant's total MVPA was 600 or more MET-minutes/week (eg, inactive vs. active). The covariates used in the GAM were selected using a gradient boosting scheme as outlined in Multimedia Appendix 1. All statistical comparisons were considered significant if $P<.05$.

Results

Overall Sample Characteristics

The descriptive characteristics of survey respondents are reported in Table 1. The descriptive characteristics of the entire cohort indicate that our participants were a relatively healthy, educated, and affluent sample of the general population. There was a roughly equal distribution of male and female, middle-aged respondents in both activity groups.

Table 1. Descriptive characteristics by physical activity group.

Characteristics	Inactive (n=1864)	Active (n=2955)	Total (N=4819)
Demographics			
Age (years), median (IQR)	46 (36-59)	45 (34-59)	46 (35-59)
Gender, n (%)			
Female	947 (50.8)	1527 (51.7)	2474 (51.3)
Male	917 (49.2)	1428 (48.3)	2345 (48.7)
BMI (kg/m^2), median (IQR)	28.3 (24.8-33.4)	25.8 (23.1-29.8)[a]	26.7 (23.6-31.0)
Physical health, median (IQR)			
Number of chronic health conditions	1 (0-2)	0 (0-1)[a]	1 (0-2)
Breathlessness (Medical Research Council score)	1 (1-2)	1 (1-1)[a]	1 (1-2)
Self-reported general health, n (%)			
Poor	8 (0.4)	4 (0.1)[a]	12 (0.2)
Fair	166 (8.9)	55 (1.9)[a]	207 (4.3)
Good	597 (32.0)	490 (16.6)[a]	1006 (20.9)
Very good	882 (47.3)	1579 (53.4)[a]	2319 (48.1)
Excellent	211 (11.3)	827 (28.0)[a]	1275 (26.5)
Socioeconomic status, n (%)			
Educational attainment			
Less than high school	5 (0.3)	8 (0.3)[a]	13 (0.3)
High school	91 (4.9)	75 (2.5)[a]	166 (3.4)
Some college no degree	320 (17.2)	289 (9.8)[a]	609 (12.6)
Associate degree, n (%)	168 (9.0)	245 (8.3)[a]	413 (8.6)
Bachelor’s degree	639 (34.3)	1072 (36.3)[a]	1711 (35.5)
Master’s degree	444 (23.8)	827 (28.0)[a]	1271 (26.4)
Doctoral/professional degree	197 (10.6)	439 (14.9)[a]	636 (13.2)
Household income, n (%)			
Less than US $20,000	119 (6.4)	105 (3.6)[a]	224 (4.6)
US $20,000 to US $39,000	223 (12.0)	230 (7.8)[a]	453 (9.4)
US $40,000 to US $59,000	265 (14.2)	386 (13.1)[a]	651 (13.5)
US $60,000 to US $79,000	291 (15.6)	444 (15.0)[a]	735 (15.3)
US $80,000 to US $99,000	193 (10.4)	374 (12.7)	567 (11.8)
US $100,000 to US $149,000	325 (17.4)	632 (21.4)[a]	957 (19.9)
US $150,000 or more	240 (12.9)	548 (18.5)[a]	788 (16.4)
Prefer not to say	208 (11.2)	236 (8.0)[a]	444 (9.2)
Employment status			
Not working, n (%)	701 (37.6)	915 (31.0)[a]	1616 (33.5)
Working, n (%)	1163 (62.4)	2040 (69.0)[a]	3203 (66.5)
Household size (number of persons), median (IQR)	2 (2-4)	2 (2-4)	2 (2-4)

[a]Significantly different from the corresponding value (or proportion) of the inactive group, $P<.05$.

Physical Activity

The self-reported levels of MVPA within the work, transport, and recreational domains are reported in Table 2. Unsurprisingly, respondents who were physically active reported higher amounts of recreational work and thus higher total MVPA than their inactive counterparts ($P<.001$); 61.31% (2955/4819) of our cohort were meeting the minimum WHO recommendations for weekly MVPA at the time of the survey.

Table 2. Physical activity and mental health during the early COVID-19 pandemic response.

Variable	Inactive (n=1864)	Active (n=2955)	Total (N=4819)
Physical activity			
MVPA[a] by GPAQ[b] domain (MET[c]-minutes/week), median (IQR)			
Recreation	0 (0-0)	2160 (960-4080)[d]	720 (0-2760)
Work	0 (0-0)	0 (0-120)[d]	0 (0-0)
Transport	0 (0-0)	0 (0-480)[d]	0 (0-0)
Total	0 (0-120)	3060 (1680-5040)[d]	1320 (0-3840)
Sedentary behavior			
Sitting time (minutes/day), median (IQR)	480 (360-660)	420 (300-600)[d]	420 (300-600)
At-risk sitting time (≥480 minutes/day), n (%)	1110 (59.5)	1429 (48.4)[d]	2539 (52.7)
Self-monitoring behavior, n (%)			
Wearable device	403 (21.6)	1556 (52.7)[d]	1959 (40.7)
Mental health			
Depression (PHQ-9[e]), median (IQR)			
Score	6 (3-11)	4 (2-8)[d]	5 (2-9)
Symptom category, n (%)			
None (0-4)	748 (40.1)	1533 (51.9)[d]	2281 (47.3)
Mild (5-9)	565 (30.3)	873 (29.5)[d]	1438 (29.8)
Moderate (10-14)	277 (14.9)	328 (11.1)[d]	605 (12.6)
Moderately severe (15-19)	159 (8.5)	146 (4.9)[d]	305 (6.3)
Severe (20-27)	115 (6.2)	75 (2.5)[d]	190 (3.9)
Anxiety (GAD-7[f], median (IQR)			
Score	6 (2-10)	4 (1-8)[d]	5 (2-9)
Symptom category, n (%)			
None (0-4)	820 (44.0)	1502 (50.8)[d]	2322 (48.2)
Mild (5-9)	500 (26.8)	848 (28.7)[d]	1348 (28.0)
Moderate (10-14)	303 (16.3)	356 (12.0)[d]	659 (13.7)
Severe (15-21)	241 (12.9)	249 (8.4)[d]	190 (3.9)
Well-being (WHO-5[g]), median (IQR)			
Score	10 (5-16)	14 (10-18)[d]	13 (8-17)
Symptom category, n (%)			
Okay (13-25)	727 (39.0)	1764 (59.7)[d]	2491 (51.7)
Poor (0-12)	1137 (61.0)	1191 (40.3)[d]	2328 (48.3)

[a]MVPA: moderate-to-vigorous physical activity.

[b]GPAQ: Global Physical Activity Questionnaire.

[c]MET: metabolic equivalent of task.

[d]Significantly different from the corresponding value (or proportion) of the inactive group, $P<.05$.

[e]PHQ-9: 9-item Patient Health Questionnaire Scale.

[f]GAD-7: 7-item Generalized Anxiety Disorder Scale.

[g]WHO-5: 5-item World Health Organization Well-Being Index

Social Distancing

The SD behaviors reported by the cohort are presented in Table 3. The active group was roughly 70% more likely to leave the house more frequently than their physically inactive counterparts (odds ratio [OR] 1.70, 95% CI 1.53-1.90; *P*<.001). Moreover, respondents in the active group were more likely to engage in a greater total number of SD behaviors (OR 1.10, 95% CI 1.09-1.12; *P*<.001). Specifically, physically active participants were significantly more likely (*P*<.001) to wear a face mask in public (SD1), avoid close and physical contact with others (SD2 and SD10), avoid places where people gather (SD3), work from home (SD4), limit their use of public transport (SD6), restrict their travel outside the house (SD8), and to reduce their time/number of trips to shops to obtain food and supplies (SD11). Conversely, respondents in the physically *inactive* group were more likely (*P*<.001) to avoid physical activity outside of the house (SD9).

Table 3. Pandemic burden, social distancing behaviors, and perceptions of fear associated with coronavirus by physical activity group during the early COVID-19 pandemic response.

Variable	Inactive (n=1864)	Active (n=2955)	Total (N=4819)
Pandemic burden at time of survey			
Confirmed cases in the state (per 100,000 persons), median (IQR)	229 (168-447)	222 (166-421)	225 (167-430)
Recovered cases in the state (per 100,000 persons), median (IQR)	0 (0-94)	29 (0-98)[a]	0 (0-97)
Active cases in the state (per 100,000 persons), median (IQR)	186 (93-350)	180 (87-304)[a]	182 (88-321)
Deaths in the state (per 100,000 persons), median (IQR)	10.1 (7.2-23.1)	9.7 (7.3-19.4)	9.9 (7.2-20.7)
Duration of social distancing guidelines/restriction (weeks), median (IQR)	10.7 (10.0-14.2)	10.6 (9.8-13.8)[a]	10.6 (9.8-14.0)
Government stringency index, median (IQR)	73.2 (70.8-76.9)	73.2 (70.8-76.9)	73.2 (70.8-76.9)
Active authority-mandated lockdown/shelter-in-place/etc, n (%)	1342 (72.0)	2338 (79.1)[a]	3680 (76.4)
SD[b] behaviors			
Frequency of leaving the house, n (%)			
Less than once per week	183 (9.8)	110 (3.7)[a]	291 (6.0)
Once per week	274 (14.7)	278 (9.4)[a]	552 (11.5)
A few times per week	634 (34.0)	926 (31.3)[a]	1560 (32.4)
Once per day	436 (23.4)	1042 (35.3)[a]	1478 (30.7)
Multiple times per day	337 (18.1)	599 (20.3)[a]	936 (19.4)
SD1: Wearing a face mask in public, n (%)	1371 (73.6)	2542 (86.0)[a]	3913 (81.2)
SD2: Avoid close contact with others in social circle, n (%)	1420 (76.2)	2605 (88.2)[a]	4025 (83.5)
SD3: Avoid places where many people gather, n (%)	1478 (79.3)	2702 (91.4)[a]	4180 (86.7)
SD4: Working from home, n (%)	970 (52.0)	1779 (60.2)[a]	2749 (57.0)
SD5: Limiting time spent outside of house, n (%)	1112 (59.7)	1840 (62.3)	2952 (61.3)
SD6: Limiting the use of public transport, n (%)	1377 (73.9)	2546 (86.2)[a]	3923 (81.4)
SD7: Currently undergoing self-isolation/quarantine, n (%)	1015 (54.5)	1581 (53.5)	2596 (53.9)
SD8: Restricting travel outside of the house, n (%)	1233 (66.1)	2175 (73.6)[a]	3408 (70.7)
SD9: Avoiding physical activity outside of the house, n (%)	664 (35.6)	546 (18.5)[a]	1210 (25.1)
SD10: Avoid physical contact with others, n (%)	1511 (81.1)	2789 (94.4)[a]	4300 (89.2)
SD11: Reducing time/number of trips to shops for food/supplies/etc, n (%)	1410 (75.6)	2631 (89.0)[a]	4041 (83.9)
Total number of SD behaviors (sum SD1-11), median (IQR)	9 (6-10)	9 (7-10)[a]	9 (7-10)
Perceived fears of COVID-19[c], median (IQR)			
Afraid of being infected with COVID-19	5 (4-6)	5 (4-6)	5 (4-6)
Afraid of unknowingly spreading COVID-19	6 (5-7)	6 (5-7)	6 (5-7)

[a]Significantly different from corresponding value (or proportion) of the inactive group, $P<.05$.

[b]SD: social distancing.

[c]Likert-type item (1=strongly disagree; 7=strongly agree).

Mental Health

The prevailing mental health of participants in the sampled cohort is reported in Table 2. Raw scores for depression and anxiety were lower for the physically active compared with the inactive group ($P<.001$). In support of these observations, respondents in the physically active group displayed lower odds of reporting more severe symptoms of depression (OR 0.72, 95% CI 0.69-0.74; $P<.001$) and anxiety (OR 0.81, 95% CI 0.76-0.86; $P<.001$). The raw score for mental well-being was overall higher for participants in the active compared with the

inactive group (P<.001). There were also lower odds of the respondents' well-being score falling below 13 (ie, "poor well-being") [30] for those participants in the physically active group (OR 0.43, 95% CI 0.38-0.49; P<.001).

Pandemic Burden and Fear

Indicators of the burden of the pandemic and fears associated with COVID-19 are reported in Table 3. Overall, SD rules/guidelines had been active for approximately 2-3 months at the time of survey for the entire cohort—this duration was slightly lower in the physically active group (P=.003). The number of recovered COVID-19 cases (per 100,000 persons) was higher (P=.002), whereas the number of active cases was marginally lower (P=.005) in the active compared with the inactive group. The burden of deaths due to COVID-19 was similar between physical activity groups. There was a marginally higher proportion of respondents under an authority-mandated "lockdown" at the time of the survey in the active group (P<.001). The perceived fear of becoming infected with COVID-19 and the fear associated with unknowingly spreading the virus were similar between groups.

Sedentary and Self-Monitoring Behavior

Sedentary behavior (minutes/day) was slightly lower in the active group (P<.001; Table 3). In addition, the proportion of participants who reported that time spent sitting/reclining exceeded 8 hours per day was marginally lower in the physically active group (P<.001; Table 3). There was a greater proportion of respondents using a wearable device to track their physical activity in the active compared with the inactive group (P<.001; Table 3).

Socioeconomic Status and Physical Health

The cohort indicators of socioeconomic status and physical health are reported in Table 1. There was a greater proportion of respondents who were employed at the time of the survey in the active group (P<.001). Moreover, there were higher (P<.001) odds of possessing a higher level of educational attainment (OR 1.58, 95% CI 1.42-1.75) and household income (OR 1.16, 95% CI 1.09-1.23) for the active group. BMI, the number of chronic conditions, and the experience of breathlessness (MRC score) during daily activities were slightly higher in the inactive compared with the physically active group (P<.001). Lastly, there were greater odds of self-reporting better general health (OR 3.15, 95% CI 2.81-3.53; P<.001).

Logistic Generalized Additive Modeling

Tables 4 and 5 show the results of the logistic GAM parametric and smooth terms, respectively, used to determine the likelihood of engaging in higher amounts of physical activity. The coefficient of determination, R^2, for the logistic GAM was 0.37 and there was a significant improvement over an intercept-only (null) model (P<.001) [44]. The variance of the random effect of US state was not significant ($\sigma^2=1.16 \times 10^{-13}$; 95% CI -5.47×10^{-7} to 8.92×10^{-7}; P=.62). The use of a wearable device to track physical activity (ie, self-monitoring behavior), wearing a facemask in public (SD1), limiting the use of public transport and the number of trips to the shops (SD6 and SD11), and avoiding close physical contact with others were all positively associated with greater odds of performing sufficient (≥600 MET-minutes/week) amounts of MVPA during the early COVID-19 pandemic (P<.005). Avoiding physical activity outside the house was negatively associated with the odds of being physically active (P<.002). The nonlinear trends in ORs for all smooth terms are illustrated in Figure 1. The odds of being physically active (total MVPA ≥600 MET-minutes/week) tended to rise with greater self-reported general health (Figure 1A), higher levels of educational attainment (Figure 1C), increasing mental well-being (Figure 1F), and higher frequencies of leaving the house (Figure 1G). Conversely, the odds of being sufficiently active during the early pandemic decreased with increasing breathlessness (Figure 1B) and BMI (Figure 1E). Importantly, the effect of engaging with a higher number of SD behaviors on the odds of performing sufficient MVPA during the pandemic was seemingly biphasic (Figure 1H). For example, participating in 3-8 total SD behaviors was coupled with greater odds, whereas engaging with 10 or more SD behaviors was associated with lower odds of performing sufficient MVPA.

Table 4. Factors influencing physical activity level during the COVID-19 pandemic as determined by logistic generalized additive modeling (N=4819).[a]

Parametric terms	Statistics[b]		
	OR	95% CI	*P* value
Intercept	*0.24*	*0.19-0.32*	*<.001*
"At-risk" sedentary behavior (reference = less than 8 hours/day)	*0.71*	*0.62-0.83*	*<.001*
Wearable device	*3.27*	*2.82-3.79*	*<.001*
SD1: Wearing a facemask in public	*1.43*	*1.14-1.79*	*.003*
SD2: Avoiding close contact with others	1.20	0.91-1.59	.199
SD3: Avoiding places where many people gather	1.26	0.91-1.73	.193
SD6: Limiting the use of public transport	*1.47*	*1.19-1.83*	*.001*
SD9: Avoiding physical activity outside the house	*0.52*	*0.43-0.63*	*<.001*
SD10: Avoiding physical contact with others	*1.79*	*1.26-2.56*	*.002*
SD11: Reducing time/number of trips to shops for supplies	*1.56*	*1.19-2.05*	*.002*

[a]Parameter estimates for the parametric (linear) terms in the model are reported as the exponentiated log-odds ratio (ie, OR) and corresponding 95% CI. The OR indicates the odds of meeting the World Health Organization's minimum physical activity recommendations (≥600 MET-minutes/week) per unit change in the respective covariate. The Benjamini–Hochberg method was used to adjust *P* values to reduce the false discovery rate.

[b]Significant values are in italic.

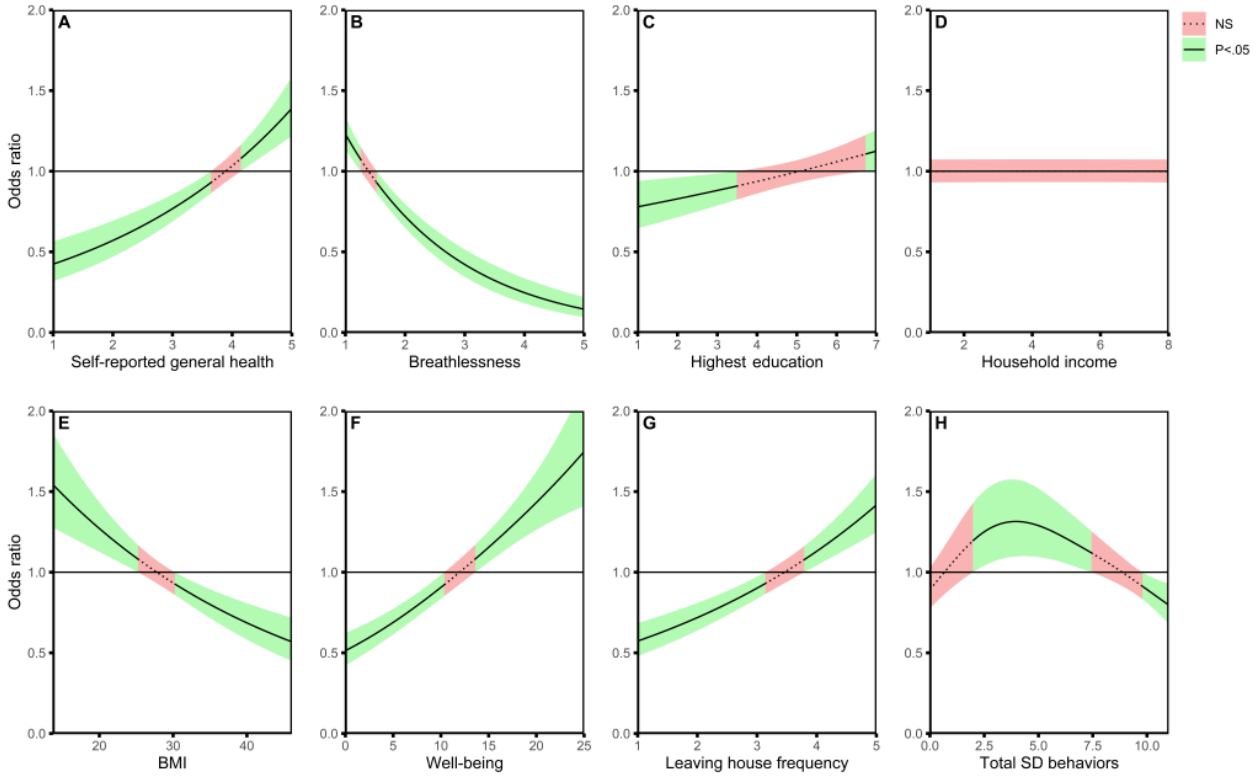
Table 5. Smooth terms influencing physical activity level during the COVID-19 pandemic as determined by logistic generalized additive modeling (N=4819).[a]

Smooth terms	Statistics[b]	
	edf	*P* value
BMI	*0.85*	*<.001*
Highest level of educational attainment	*0.65*	*.001*
Household income	*0.01*	*.023*
Number of chronic health conditions	0.00	.197
Self-reported general health	*0.90*	*<.001*
Breathlessness	*0.96*	*<.001*
Frequency of leaving the house	*0.91*	*<.001*
Total number of SD behaviors	*1.23*	*<.001*
Well-being	*1.19*	*<.001*

[a]The smooth terms included in the generalized additive model are summarized by their estimated degrees of freedom (*edf*). The Benjamini–Hochberg method was used to adjust *P* values to reduce the false discovery rate.

[b]Significant values are in italic.

Figure 1. Nonlinear effects of physical and mental health, and social distancing vigilance on the odds of meeting WHO recommendations for physical activity during the early COVID-19 pandemic response. The solid lines indicate the nonlinear trend in the odds of meeting WHO recommendations for physical activity for the corresponding covariate. The green-shaded regions denote the range of values of a covariate where the odds ratio for meeting WHO recommendations for physical activity is significantly different (P<.05) from 1.00 (ie, equivocal odds). Conversely, the red-shaded regions indicate the values of the respective covariate where the odds ratio is not different from 1.00. Note that self-reported general health (panel A), highest level of educational attainment (panel B), and household income (panel D) were input into the generalized additive model as ordinal variables. As such, the integer values correspond to the ordinal categorical levels of each covariate in order of lowest to highest category (eg, self-reported general health: 1=very poor; 5=excellent). NS: not significant; SD: social distancing.



Discussion

Principal Findings

The principal findings of this study were threefold: (1) physically active respondents were more likely to engage in SD behaviors; (2) the influence of engaging with SD behaviors on physical activity during the early pandemic was nonlinear; and (3) higher scores for mental well-being were a positive mediator of physical activity participation. These findings highlight the complex nature by which SD vigilance and mental health have impacted on the physical activity habits of the general population during the early COVID-19 pandemic.

Did Social Distancing Affect Physical Activity During the Early Pandemic Response?

We originally hypothesized that engaging in more SD behaviors would increase the likelihood of being *physically inactive* during the early pandemic response. Our findings only partly confirm this hypothesis. For example, participants who minimized their public exposure by leaving the house less than "once per day" were less likely to be physically active (Figure 1G). Furthermore, respondents were less likely to meet the minimum WHO recommendations for weekly MVPA if they reported that they were "avoiding physical activity outside the house" (SD9) at the time of the survey (Tables 4 and 5). However, the relationship between the total number of SD behaviors and physical activity was much less straightforward (Figure 1H). Certainly, individuals engaging with 10 or more of the surveilled SD behaviors (highly vigilant) were at lower odds of being physically active during the pandemic. Interestingly, however, it appeared that if a participant engaged with a moderate number of SD behaviors (3-7 total), they were at higher odds of meeting the minimum WHO recommendations for weekly MVPA. This nonlinear relationship between SD vigilance and physical activity is novel, insofar as it describes a potential "tipping point" phenomenon: too much is bad, yet a moderate amount is good. But which of the SD behaviors are specifically associated with being physically active?

The cross-sectional analyses of SD behaviors within our cohort (Table 3) appear to suggest that those individuals who were *physically active* during the early pandemic were more frequently wearing a facemask in public (SD1), avoiding close and physical contact with others (SD2 and SD10), avoiding places where people gather (SD3), working from home (SD4), and more often limiting their public exposure by restricting their use of public transport and travel outside the house (SD6, SD8, and SD11). These observations are complemented by the logistic GAM analysis (Tables 4 and 5), whereby SD1, SD6, SD10, and SD11 were all associated with significantly higher odds of

meeting the minimum WHO requirements for weekly MVPA at the time of the survey. The following question arises: why does engaging in *some* but not *all* SD measures appear to be positively associated with physical activity? It is difficult to offer any substantive explanation for these observations given the data at hand. Notwithstanding this point, it is known that physical activity level is positively associated with health literacy [45-47]. Thus, it is at least conceivable that participants who regularly engaged in more physical activity may have been better informed and aware of public health initiatives and were thus more likely to follow SD guidelines. The opposite is also plausible: those respondents who engaged with a moderate number of SD behaviors may also be more likely to heed other public health advice, such as recommendations for physical activity. However, this positive effect is only apparent up until the individual engages in nearly all (≥10) of the surveilled SD behaviors, after which it is likely that simultaneously engaging in these behaviors becomes prohibitive to accumulating sufficient weekly MVPA. It will be of great interest to assess whether vigilance with SD behaviors remains nonlinearly associated with physical activity level at our planned follow-up survey rounds.

Did Mental Health Affect Physical Activity During The Early Pandemic Response?

It is becoming clear that extended periods of social isolation, as imposed by public health measures, have negatively impacted on mental health during the COVID-19 pandemic [18-21]. This point is particularly concerning given that mental health may affect physical activity, and vice versa [22,23]. Indeed, cross-sectional analysis of our cohort tended to corroborate the above findings, whereby respondents in the *physically active* group reported higher well-being scores, and less symptoms of depression and anxiety compared with those in the inactive group (Table 2). However, among the 3 indicators of mental health, it was only the raw score for mental well-being (ie, WHO-5) that was selected as a covariate in the boosted GAM model (see Multimedia Appendix 1 for details). Specifically, we observed that raw scores for mental well-being greater than 13 were associated with meeting the WHO recommendations for weekly MVPA. However, participants with raw WHO-5 scores below this value (ie, "poor well-being") [30] were more likely to be *physically inactive* during the early pandemic response. Overall, the above findings support our secondary hypothesis that poorer mental health was associated with less physical activity during the early pandemic response.

What Other Factors Influenced Physical Activity in Our Cohort?

Respondents were more likely to be *physically active* if they were sedentary for less than 8 hours per day (Tables 4 and 5). This observation is perhaps not surprising given that daily hours are finite, and less time spent engaging with one behavior (ie, sitting) affords more time for another behavior (ie, physical activity) [48]. Those participants who reported that they used a wearable device to monitor their own physical activity were also more likely to accumulate sufficient weekly MVPA during the early pandemic response (Tables 4 and 5). This finding is consistent with the idea that objective self-monitoring, using wearable technologies, is a behavior change tool that is effective in reducing sedentary time and increasing physical activity in adults [49,50].

Methodological Considerations

Many investigators have argued that SD policies for minimizing spread of COVID-19 may worsen an existing global health crisis, that is, the physical inactivity pandemic [13,51]. Emerging research has vindicated these concerns by illustrating that physical activity of the public has declined during the COVID-19 pandemic [5-10]. Given that extending the recall period of the GPAQ to far beyond the past 7 days is likely to confound data with recall bias [52], we have not reported MVPA of our participants from a time before the pandemic began. As such, our data do not allow us to comment on whether physical activity truly declined during the early pandemic period in our cohort. For similar reasons, we are unable to directly comment on whether mental health status, as assessed via the GAD-7, WHO-5, and PHQ-9, worsened during the early pandemic in our cohort. A further consideration is that while our cohort was large, it is unlikely that our sample is representative of the greater US population. Our cohort was a convenience sample recruited via social media, a method of sampling known to recruit greater proportions of adults with higher levels of educational attainment than the general population [53]. Indeed, our cohort was a highly educated and affluent sample of the general population. We therefore emphasize that our findings may not apply to a more representative sample of a larger US population with greater socioeconomic diversity than that observed in this study.

Implications of Our Findings

Given that SD has arguably encouraged a public shift toward sedentariness, it is essential that we identify those factors of a person's "pandemic experience" which have contributed to this decline in physical activity. Our findings offer 4 major insights into the potential mediators of physical activity during the early pandemic response. First, we report that individuals with poor mental well-being were likely to be *physically inactive* during the early pandemic. Second, our data provide strong evidence that "getting outside" the house encourages sufficient weekly MVPA, notwithstanding any SD guidelines/restrictions that may be active at the time. Third, individuals demonstrating self-monitoring behavior via wearable activity trackers were more likely to accumulate sufficient weekly MVPA. Lastly, the extent to which SD vigilance impacts on physical activity is complex, insofar as engaging in a moderate number of SD behaviors (3-7 total) was associated with being physically active, while engaging in too many SD behaviors (≥10 total) was seemingly detrimental to engaging in adequate amounts of physical activity. This last observation may be telling of the challenges faced by the public when regulating their own vigilance with SD behaviors. We speculate that this finding may be a symptom of the belief that either (1) adhering to all SD behaviors takes priority over all other health promoting behaviors during the pandemic or (2) one cannot safely perform SD while being physically active, particularly outside the house.

In light of these findings, we suggest that public health messaging of SD guidelines may be improved to promote

physical activity during the pandemic by including specific advice outlining how to be physically active "outdoors" in a COVID-safe manner (eg, targeted infographics) [54,55], and by clearly portraying the benefits of regular exercise on mental health [56-58]. In such messaging, it would be worth mentioning that evidence suggests being physically fit confers a degree of immunity protection [59], and may reduce morbid outcomes associated with COVID-19, such as hospitalizations [60,61]. Lastly, our data indicate there may be value in specifically encouraging the use of wearable devices to self-monitor physical activity levels.

Conclusions

The recent availability of COVID-19 vaccines has marked the beginning of our recovery from this global pandemic [62]. However, until vaccination rates approach levels that confer "herd immunity" against the virus, SD measures will remain part of our COVID-normal existence for the foreseeable future. If we fail to recognize the impact that SD bears on physical activity, we may yet observe a "final wave" of chronic lifestyle diseases once the pandemic recedes. The findings of our investigation support the viewpoint that physical activity promotion should be more heavily integrated into the public health messaging of physical/SD guidelines during this current pandemic, and that any of these may precipitate in the future.

Acknowledgments

We thank all respondents for their time and effort in participating in the study. TC was supported by an Irene Diamond/American Federation for Aging Research Postdoctoral Transition Award. This research was supported by the Sydney Informatics Hub, a Core Research Facility of the University of Sydney. We also thank Dr Emmanuel Stamatakis for his guidance and advice during the preparation of this manuscript. This publication was supported in full by Mayo Clinic Arizona Cardiovascular Clinical Research Center (MCA CV CRC). We are thankful for their generous support. Contents of this publication are solely the responsibility of the authors and do not necessarily represent the official views of the MCA CV CRC.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Methodological approach.
[DOCX File , 24 KB - publichealth_v7i9e31278_app1.docx]

References

1. Centers for Disease Control and Prevention. Social Distancing - Keep a Safe Distance to Slow the Spread. 2020. URL: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html [accessed 2021-01-15]
2. Honein MA, Christie A, Rose DA, Brooks JT, Meaney-Delman D, Cohn A, CDC COVID-19 Response Team. Summary of Guidance for Public Health Strategies to Address High Levels of Community Transmission of SARS-CoV-2 and Related Deaths, December 2020. MMWR Morb Mortal Wkly Rep 2020 Dec 11;69(49):1860-1867 [FREE Full text] [doi: 10.15585/mmwr.mm6949e2] [Medline: 33301434]
3. World Health Organiziation. Coronavirus Disease (COVID-19) Advice for the Public. URL: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public [accessed 2021-09-20]
4. UK Government. Guidance: Coronavirus (COVID-19): Meeting With Others Safely (Social Distancing). URL: https://www.gov.uk/government/publications/coronavirus-covid-19-meeting-with-others-safely-social-distancing/coronavirus-covid-19-meeting-with-others-safely-social-distancing?priority-taxon=774cee22-d896-44c1-a611-e3109cce8eae [accessed 2021-09-20]
5. Lesser IA, Nienhuis CP. The Impact of COVID-19 on Physical Activity Behavior and Well-Being of Canadians. Int J Environ Res Public Health 2020 May 31;17(11):3899 [FREE Full text] [doi: 10.3390/ijerph17113899] [Medline: 32486380]
6. Meyer J, McDowell C, Lansing J, Brower C, Smith L, Tully M, et al. Changes in Physical Activity and Sedentary Behavior in Response to COVID-19 and Their Associations with Mental Health in 3052 US Adults. Int J Environ Res Public Health 2020 Sep 05;17(18):6469 [FREE Full text] [doi: 10.3390/ijerph17186469] [Medline: 32899495]
7. Tison GH, Avram R, Kuhar P, Abreau S, Marcus GM, Pletcher MJ, et al. Worldwide Effect of COVID-19 on Physical Activity: A Descriptive Study. Ann Intern Med 2020 Nov 03;173(9):767-770 [FREE Full text] [doi: 10.7326/M20-2665] [Medline: 32598162]
8. Qin F, Song Y, Nassis GP, Zhao L, Dong Y, Zhao C, et al. Physical Activity, Screen Time, and Emotional Well-Being during the 2019 Novel Coronavirus Outbreak in China. Int J Environ Res Public Health 2020 Jul 17;17(14):5170 [FREE Full text] [doi: 10.3390/ijerph17145170] [Medline: 32709003]
9. Wilke J, Mohr L, Tenforde AS, Edouard P, Fossati C, González-Gross M, et al. A Pandemic within the Pandemic? Physical Activity Levels Substantially Decreased in Countries Affected by COVID-19. Int J Environ Res Public Health 2021 Feb 24;18(5):2235 [FREE Full text] [doi: 10.3390/ijerph18052235] [Medline: 33668262]

10. Caputo EL, Reichert FF. Studies of Physical Activity and COVID-19 During the Pandemic: A Scoping Review. J Phys Act Health 2020 Nov 03;17(12):1275-1284. [doi: 10.1123/jpah.2020-0406] [Medline: 33152693]
11. Lavie CJ, Ozemek C, Carbone S, Katzmarzyk PT, Blair SN. Sedentary Behavior, Exercise, and Cardiovascular Health. Circ Res 2019 Mar;124(5):799-815. [doi: 10.1161/CIRCRESAHA.118.312669] [Medline: 30817262]
12. Stamatakis E, Gale J, Bauman A, Ekelund U, Hamer M, Ding D. Sitting Time, Physical Activity, and Risk of Mortality in Adults. J Am Coll Cardiol 2019 Apr 30;73(16):2062-2072 [FREE Full text] [doi: 10.1016/j.jacc.2019.02.031] [Medline: 31023430]
13. Kohl HW, Craig CL, Lambert EV, Inoue S, Alkandari JR, Leetongin G, et al. The pandemic of physical inactivity: global action for public health. Lancet 2012 Jul 21;380(9838):294-305. [doi: 10.1016/S0140-6736(12)60898-8] [Medline: 22818941]
14. World Health Organization. Global Health Risks: Mortality and Burden of Disease Attributable to Selected Major Risks. Geneva, Switzerland: World Health Organization; 2009.
15. Jiménez-Pavón D, Carbonell-Baeza A, Lavie CJ. Physical exercise as therapy to fight against the mental and physical consequences of COVID-19 quarantine: Special focus in older people. Prog Cardiovasc Dis 2020;63(3):386-388 [FREE Full text] [doi: 10.1016/j.pcad.2020.03.009] [Medline: 32220590]
16. Banerjee D, Rai M. Social isolation in Covid-19: The impact of loneliness. Int J Soc Psychiatry 2020 Sep;66(6):525-527 [FREE Full text] [doi: 10.1177/0020764020922269] [Medline: 32349580]
17. Killgore WDS, Cloonan SA, Taylor EC, Dailey NS. Loneliness: A signature mental health concern in the era of COVID-19. Psychiatry Res 2020 Aug;290:113117 [FREE Full text] [doi: 10.1016/j.psychres.2020.113117] [Medline: 32480121]
18. Vindegaard N, Benros ME. COVID-19 pandemic and mental health consequences: Systematic review of the current evidence. Brain Behav Immun 2020 Oct;89:531-542 [FREE Full text] [doi: 10.1016/j.bbi.2020.05.048] [Medline: 32485289]
19. Pierce M, Hope H, Ford T, Hatch S, Hotopf M, John A, et al. Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population. The Lancet Psychiatry 2020 Oct;7(10):883-892. [doi: 10.1016/s2215-0366(20)30308-4]
20. Xiong J, Lipsitz O, Nasri F, Lui LMW, Gill H, Phan L, et al. Impact of COVID-19 pandemic on mental health in the general population: A systematic review. J Affect Disord 2020 Dec 01;277:55-64 [FREE Full text] [doi: 10.1016/j.jad.2020.08.001] [Medline: 32799105]
21. Dubey S, Biswas P, Ghosh R, Chatterjee S, Dubey MJ, Chatterjee S, et al. Psychosocial impact of COVID-19. Diabetes Metab Syndr 2020;14(5):779-788 [FREE Full text] [doi: 10.1016/j.dsx.2020.05.035] [Medline: 32526627]
22. Steinmo S, Hagger-Johnson G, Shahab L. Bidirectional association between mental health and physical activity in older adults: Whitehall II prospective cohort study. Prev Med 2014 Sep;66:74-79 [FREE Full text] [doi: 10.1016/j.ypmed.2014.06.005] [Medline: 24945691]
23. Azevedo Da Silva M, Singh-Manoux A, Brunner EJ, Kaffashian S, Shipley MJ, Kivimäki M, et al. Bidirectional association between physical activity and symptoms of anxiety and depression: the Whitehall II study. Eur J Epidemiol 2012 Jul;27(7):537-546 [FREE Full text] [doi: 10.1007/s10654-012-9692-8] [Medline: 22623145]
24. Armstrong T, Bull F. Development of the World Health Organization Global Physical Activity Questionnaire (GPAQ). J Public Health 2006 Mar 2;14(2):66-70. [doi: 10.1007/s10389-006-0024-x]
25. World Health Organization. WHO STEPS Surveillance Manual: The WHO STEPwise Approach to Chronic Disease Risk Factor Surveillance. Geneva, Switzerland: World Health Organization; 2005.
26. Bull FC, Al-Ansari SS, Biddle S, Borodulin K, Buman MP, Cardon G, et al. World Health Organization 2020 guidelines on physical activity and sedentary behaviour. Br J Sports Med 2020 Dec 25;54(24):1451-1462 [FREE Full text] [doi: 10.1136/bjsports-2020-102955] [Medline: 33239350]
27. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. J Gen Intern Med 2001 Sep;16(9):606-613 [FREE Full text] [doi: 10.1046/j.1525-1497.2001.016009606.x] [Medline: 11556941]
28. Spitzer RL, Kroenke K, Williams JBW, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med 2006 May 22;166(10):1092-1097. [doi: 10.1001/archinte.166.10.1092] [Medline: 16717171]
29. Topp CW, Østergaard SD, Søndergaard S, Bech P. The WHO-5 Well-Being Index: a systematic review of the literature. Psychother Psychosom 2015;84(3):167-176 [FREE Full text] [doi: 10.1159/000376585] [Medline: 25831962]
30. World Health Organization. Wellbeing Measures in Primary Health Care - The DepCare Project. Geneva, Switzerland: Regional Office for Europe; 1998.
31. Guidotti E, Ardia D. COVID-19 Data Hub. JOSS 2020 Jul;5(51):2376. [doi: 10.21105/joss.02376]
32. Hale T, Angrist N, Goldszmidt R, Kira B, Petherick A, Phillips T, et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Hum Behav 2021 Apr 08;5(4):529-538. [doi: 10.1038/s41562-021-01079-8] [Medline: 33686204]
33. Ekelund U, Brown WJ, Steene-Johannessen J, Fagerland MW, Owen N, Powell KE, et al. Do the associations of sedentary behaviour with cardiovascular disease mortality and cancer mortality differ by physical activity level? A systematic review and harmonised meta-analysis of data from 850 060 participants. Br J Sports Med 2019 Jul 10;53(14):886-894. [doi: 10.1136/bjsports-2017-098963] [Medline: 29991570]

34. Eime RM, Charity MJ, Harvey JT, Payne WR. Participation in sport and physical activity: associations with socio-economic status and geographical remoteness. BMC Public Health 2015 Apr 29;15:434 [FREE Full text] [doi: 10.1186/s12889-015-1796-0] [Medline: 25928848]
35. Gidlow C, Johnston LH, Crone D, Ellis N, James D. A systematic review of the relationship between socio-economic position and physical activity. Health Education Journal 2016 Jul 27;65(4):338-367. [doi: 10.1177/0017896906069378]
36. Martínez-González MA, Martínez JA, Hu F, Gibney M, Kearney J. Physical inactivity, sedentary lifestyle and obesity in the European Union. Int J Obes Relat Metab Disord 1999 Nov 11;23(11):1192-1201. [doi: 10.1038/sj.ijo.0801049] [Medline: 10578210]
37. Rütten A, Abel T, Kannas L, von Lengerke T, Lüschen G, Diaz JA, et al. Self reported physical activity, public health, and perceived environment: results from a comparative European study. J Epidemiol Community Health 2001 Feb;55(2):139-146 [FREE Full text] [doi: 10.1136/jech.55.2.139] [Medline: 11154254]
38. Opdal IM, Larsen LS, Hopstock LA, Schirmer H, Lorem GF. A prospective study on the effect of self-reported health and leisure time physical activity on mortality among an ageing population: results from the Tromsø study. BMC Public Health 2020 Apr 28;20(1):575 [FREE Full text] [doi: 10.1186/s12889-020-08681-x] [Medline: 32345261]
39. Booth FW, Roberts CK, Thyfault JP, Ruegsegger GN, Toedebusch RG. Role of Inactivity in Chronic Diseases: Evolutionary Insight and Pathophysiological Mechanisms. Physiol Rev 2017 Oct 01;97(4):1351-1402 [FREE Full text] [doi: 10.1152/physrev.00019.2016] [Medline: 28814614]
40. Booth FW, Roberts CK, Laye MJ. Lack of exercise is a major cause of chronic diseases. Compr Physiol 2012 Apr;2(2):1143-1211 [FREE Full text] [doi: 10.1002/cphy.c110025] [Medline: 23798298]
41. Fletcher C, Elmes P, Fairbairn A, Wood C. The significance of respiratory symptoms and the diagnosis of chronic bronchitis in a working population. Br Med J Aug 29 1959;2(5147):257-266. [doi: 10.1136/bmj.2.5147.257] [Medline: 13823475]
42. Christensen R. ordinal—Regression Models for Ordinal Data. 2019. URL: https://CRAN.R-project.org/package=ordinal [accessed 2021-09-20]
43. Lenth R. emmeans—Estimated Marginal Means, aka Least-Squares Means. 2021. URL: https://CRAN.R-project.org/package=emmeans [accessed 2021-09-20]
44. Nagelkerke NJD. A note on a general definition of the coefficient of determination. Biometrika 1991;78(3):691-692. [doi: 10.1093/biomet/78.3.691]
45. Cajita M, Denhaerynck K, Dobbels F, Berben L, Russell C, De Geest S. Adequate Health Literacy Is Associated with Sufficient Physical Activity: Findings from the BRIGHT Study. The Journal of Heart and Lung Transplantation 2016 Apr;35(4):S90. [doi: 10.1016/j.healun.2016.01.247]
46. Valatkaitytė V, Česnaitienė VJ. Relationship Between Health Literacy, Physical Activity, Motivation and Barriers of People Aged 30–50 Years. BJSHS 2019 Jul 22;2(113):787. [doi: 10.33607/bjshs.v2i113.787]
47. Buja A, Rabensteiner A, Sperotto M, Grotto G, Bertoncello C, Cocchio S, et al. Health Literacy and Physical Activity: A Systematic Review. J Phys Act Health 2020 Oct 31;17(12):1259-1274. [doi: 10.1123/jpah.2020-0161] [Medline: 33129198]
48. Mekary RA, Willett WC, Hu FB, Ding EL. Isotemporal substitution paradigm for physical activity epidemiology and weight change. Am J Epidemiol 2009 Aug 15;170(4):519-527 [FREE Full text] [doi: 10.1093/aje/kwp163] [Medline: 19584129]
49. Compernolle S, DeSmet A, Poppe L, Crombez G, De Bourdeaudhuij I, Cardon G, et al. Effectiveness of interventions using self-monitoring to reduce sedentary behavior in adults: a systematic review and meta-analysis. Int J Behav Nutr Phys Act 2019 Aug 13;16(1):63 [FREE Full text] [doi: 10.1186/s12966-019-0824-3] [Medline: 31409357]
50. Laranjo L, Ding D, Heleno B, Kocaballi B, Quiroz JC, Tong HL, et al. Do smartphone applications and activity trackers increase physical activity in adults? Systematic review, meta-analysis and metaregression. Br J Sports Med 2021 Apr 21;55(8):422-432. [doi: 10.1136/bjsports-2020-102892] [Medline: 33355160]
51. Hall G, Laddu DR, Phillips SA, Lavie CJ, Arena R. A tale of two pandemics: How will COVID-19 and global trends in physical inactivity and sedentary behavior affect one another? Prog Cardiovasc Dis 2021;64:108-110 [FREE Full text] [doi: 10.1016/j.pcad.2020.04.005] [Medline: 32277997]
52. Cross TJ, Isautier JMJ, Stamatakis E, Morris SJ, Johnson BD, Wheatley-Guy C, et al. Self-reported physical activity before a COVID-19 'lockdown': is it just a matter of opinion? BMJ Open Sport Exerc Med 2021 May 06;7(2):e001088 [FREE Full text] [doi: 10.1136/bmjsem-2021-001088] [Medline: 34192013]
53. Thornton L, Batterham PJ, Fassnacht DB, Kay-Lambkin F, Calear AL, Hunt S. Recruiting for health, medical or psychosocial research using Facebook: Systematic review. Internet Interv 2016 May;4:72-81 [FREE Full text] [doi: 10.1016/j.invent.2016.02.001] [Medline: 30135792]
54. Wedig IJ, Duelge TA, Elmer SJ. Infographic. Stay physically active during COVID-19 with exercise as medicine. Br J Sports Med 2021 Mar;55(6):346-347 [FREE Full text] [doi: 10.1136/bjsports-2020-103282] [Medline: 33097523]
55. Fitzpatrick J, Castricum A, Seward H, Tulloh L, Dawson E. Infographic. COFIT-19: let's get moving through the COVID-19 pandemic!. Br J Sports Med 2020 Nov 19;54(22):1360-1361. [doi: 10.1136/bjsports-2020-102661] [Medline: 32561519]
56. Petruzzello SJ, Landers DM, Hatfield BD, Kubitz KA, Salazar W. A meta-analysis on the anxiety-reducing effects of acute and chronic exercise. Outcomes and mechanisms. Sports Med 1991 Mar;11(3):143-182. [doi: 10.2165/00007256-199111030-00002] [Medline: 1828608]

57. DeBoer LB, Powers MB, Utschig AC, Otto MW, Smits JAJ. Exploring exercise as an avenue for the treatment of anxiety disorders. Expert Rev Neurother 2012 Aug;12(8):1011-1022 [FREE Full text] [doi: 10.1586/ern.12.73] [Medline: 23002943]
58. Chekroud S, Gueorguieva R, Zheutlin A, Paulus M, Krumholz H, Krystal J, et al. Association between physical exercise and mental health in 1·2 million individuals in the USA between 2011 and 2015: a cross-sectional study. The Lancet Psychiatry 2018 Sep;5(9):739-746. [doi: 10.1016/s2215-0366(18)30227-x]
59. Laddu DR, Lavie CJ, Phillips SA, Arena R. Physical activity for immunity protection: Inoculating populations with healthy living medicine in preparation for the next pandemic. Prog Cardiovasc Dis 2021;64:102-104 [FREE Full text] [doi: 10.1016/j.pcad.2020.04.006] [Medline: 32278694]
60. Brawner CA, Ehrman JK, Bole S, Kerrigan DJ, Parikh SS, Lewis BK, et al. Inverse Relationship of Maximal Exercise Capacity to Hospitalization Secondary to Coronavirus Disease 2019. Mayo Clin Proc 2021 Jan;96(1):32-39 [FREE Full text] [doi: 10.1016/j.mayocp.2020.10.003] [Medline: 33413833]
61. Lavie CJ, Sanchis-Gomar F, Arena R. Fit Is It in COVID-19, Future Pandemics, and Overall Healthy Living. Mayo Clin Proc 2021 Jan;96(1):7-9 [FREE Full text] [doi: 10.1016/j.mayocp.2020.11.013] [Medline: 33413836]
62. Centers for Disease Control and Prevention - National Center for Health Statistics. Trends in Number of COVID-19 Cases and Deaths in the US Reported to CDC. 2021. URL: https://covid.cdc.gov/covid-data-tracker/#trends_dailytrendscases [accessed 2021-03-05]

Abbreviations

GAD-7: 7-item Generalized Anxiety Disorder Scale
GAM: generalized additive model
GPAQ: Global Physical Activity Questionnaire
MET: metabolic equivalent of task
MRC: Medical Research Council
MVPA: moderate-to-vigorous physical activity
OR: odds ratio
PAWS: Physical Activity and Well-being Survey
PHQ-9: 9-item Patient Health Questionnaire
SD: social distancing
WHO: World Health Organization

Edited by Y Khader; submitted 16.06.21; peer-reviewed by R Menhas, C Lavie, M Rusll; comments to author 09.08.21; revised version received 16.08.21; accepted 16.08.21; published 24.09.21.

Please cite as:
Cross TJ, Isautier JMJ, Morris SJ, Johnson BD, Wheatley-Guy CM, Taylor BJ
The Influence of Social Distancing Behaviors and Psychosocial Factors on Physical Activity During the COVID-19 Pandemic: Cross-sectional Survey Study
JMIR Public Health Surveill 2021;7(9):e31278
URL: https://publichealth.jmir.org/2021/9/e31278
doi:10.2196/31278
PMID:34509976

Viewpoint

Morocco's National Response to the COVID-19 Pandemic: Public Health Challenges and Lessons Learned

Abdelaziz Barkia[1], MPH; Hammou Laamrani[2], PhD; Abdelmounaim Belalia[3], PhD; Abderrahman Benmamoun[4], MD; Yousef Khader[5], SCD

[1]Epidemic Diseases Service, Ministry of Health, Rabat, Morocco

[2]Water, Energy, Food Security and Climate Change Nexus, Economic Sector, League of Arab States, Cairo, Egypt

[3]Ministry of Health, Rabat, Morocco

[4]Ministry of Health, Mohammadia, Morocco

[5]Department of Public Health, Jordan University of Science and technology, Irbid, Jordan

Corresponding Author:
Yousef Khader, SCD
Department of Public Health
Jordan University of Science and technology
Alramtha-Amman street
Irbid, 22110
Jordan
Phone: 962 796802040
Email: yskhader@just.edu.jo

Abstract

This report aimed to provide an overview of the epidemiological situation of COVID-19 in Morocco and to review the actions carried out as part of the national response to this pandemic. The methodology adopted was based on literature review, interviews with officials and actors in the field, and remote discussion workshops with a multidisciplinary and multisectoral working group. Morocco took advantage of the capacities already strengthened within the framework of the application of the provisions of the International Health Regulations (IHR) of 2005. A SWOT analysis made it possible to note that an unprecedented political commitment enabled all the necessary means to face the pandemic and carry out all the response activities, including a campaign of relentless communication. Nevertheless, and despite the efforts made, the shortage of human resources, especially those qualified in intensive care and resuscitation, has been the main drawback to be addressed. The main lesson learned is a need to further strengthen national capacities to prepare for and respond to possible public health emergencies and to embark on a process overhaul of the health system, including research into innovative tools to ensure the continuity of the various disease prevention and control activities. In addition, response to a health crisis is not only the responsibility of the health sector but also intersectoral collaboration is needed to guarantee an optimal coordinated fight. Community-oriented approaches in public health have to be strengthened through more participation and involvement of nongovernmental organizations (NGOs) and civil society in operational and strategic planning.

(JMIR Public Health Surveill 2021;7(9):e31930) doi:10.2196/31930

KEYWORDS

COVID-19; public health; challenges; prevention; control; infectious disease

Introduction

Background

Morocco, like all countries of the world, is facing an unprecedented situation of a global pandemic due to COVID-19 [1]. Since the announcement of the first alerts by the World Health Organization (WHO) relating to the emergence and spread of this new disease [2], the Moroccan government deployed a national monitoring and response plan adopting a spirit of solidarity and involving the public authorities and the whole of society.

A few days after the declaration of this first case on March 2, 2020 in Morocco and the notification of other cases, the “State of health emergency” was declared and a series of measures including containment was implemented to contain the spread of the virus [3]. Morocco has a population of around 36 million and is considered a middle-income country with limited health

care capacity compared to many other countries in the region. However, the country has accumulated several experiences in the field of public health emergency management and has prepared relatively well to deal with the emergence of sanitary risks related to the new virus, especially through training programs and strengthening organizational and managerial capacities.

Although the crisis continues to be a challenge to society as a whole, much can be learned from the actions already undertaken so far. Therefore, evaluation and review of the implementation of the various health interventions must be considered as a continuous process [4]. This would make it possible to assess the effectiveness of the actions implemented as well as their coherence, consistency, and alignment with the International Health Regulations (IHR) 2005 and guidelines [5,6].

Objectives

The main objective of this paper was to assess the actions undertaken in Morocco during the response to COVID-19 in order to draw lessons and identify good practices to capitalize on for better management of a potential new wave or future epidemics. Moreover, this study aimed to review and discuss the different interventions implemented as part of the national response plan against COVID-19; conduct an analysis of the strengths, weaknesses, opportunities, and threats (SWOT) of national preparedness and response to the COVID-19 pandemic; and discuss the main lessons learned from the national preparation and response to the pandemic.

Methodological Approach

The present work was based on 3 research processes, namely a review of key documents published; interviews with managers, actors, and resource persons; and remote discussions with a multidisciplinary and multisectoral working group set up for this purpose. Raw data were collected by analyzing memos and epidemiological bulletins and by regularly consulting the website of the Ministry of Health. A daily follow-up of press articles and statements from various officials of the Ministry of Health and members of the government was further carried out. The research process begun with the announcement of the COVID-19 pandemic in late December 2019 and ended by October 2020.

The discussion group was made up of 12 participants including 4 former officials at the level of the Ministry of Health, 4 former managers and health professionals including 2 Field Epidemiology Training Program (FETP) graduates, 2 medical journalists, and 2 biomedical research professors. This discussion group focused on the SWOT analysis through 3 workshops organized remotely to collect opinions regarding the operational implementation of the actions planned on the ground within the framework of the national COVID-19 monitoring and response plan. The principal investigator facilitated the workshops.

For each theme, a direct question was asked about strengths and weaknesses; then, participants were asked to suggest the opportunities to strengthen the response to the pandemic and also the threats that may hamper its control.

The Epidemiological Situation of COVID-19 in Morocco

The first case of COVID-19 in Morocco was detected on March 2, 2020. The first case was a 39-year-old man, originally from and living in Casablanca, who traveled to a European country and returned to Morocco on February 27, 2020. The first COVID-19–associated death was announced on March 12, 2020, and the first case of local transmission was recorded on March 13, 2020 [7,8].

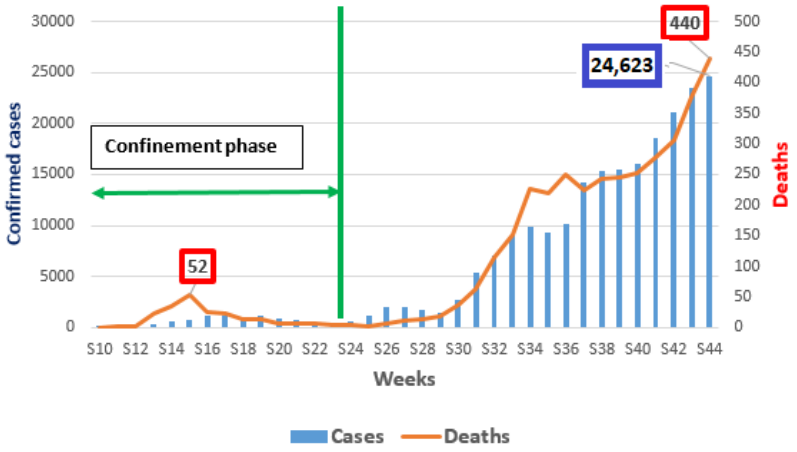
Between March 2, 2020 and October 31, 2020, a cumulative 219,084 confirmed cases was recorded (ie, an average of 898 cases per day). The total number of deaths was 3695 with an average of 8 deaths per day. The case fatality rate at the end of October was 1.7%. The weekly evolution of cases and deaths (Figure 1) shows a gradual increase and then an exacerbation in the number of confirmed cases and deaths. The epidemiological situation of the disease evolved in 3 stages of development of the epidemic. The first phase was marked by control of the situation with few cases and deaths (phase corresponding to the lockdown period). The second phase, corresponding with the first gradual lifting of confinement, was marked by a significant, steady increase in the number of cases. The third phase, corresponding with a relatively generalized lifting of lockdown, was marked by an exacerbation in the number of new cases and deaths.

Thus, the evolution of the number of cases followed a geometric progression from the 3rd phase of the epidemic. Just after the feast of the sacrifice (Eid El Adha), a new situation was marked by an increase in the number of deaths and patients in intensive care and resuscitation unit with very strong pressure on the health care system. The highest number of cases and deaths was recorded in the last week of October 2020 (week 44 of the year) with 24,623 confirmed cases and 440 deaths.

Regarding the spatial distribution of cases, all 12 regions of Morocco were affected, with variable attack rates ranging from 5 per 100,000 inhabitants in the Fes-Meknes Region to 6 per 100,000 inhabitants in the region of Dakhla-Oued Eddahab located in the extreme south of Morocco. The cumulative incidence in the Casablanca-Settat region, which recorded the highest number of cases, was 3 per 100,000 inhabitants, while the national average was 4 per 100,000 inhabitants.

According to data made public by the Ministry of Health, among the cases detected from March 2, 2020 to September 21, 2020, asymptomatic cases on admission represented 74.9%, mild cases represented 14.1%, moderate cases represented 9.6%, severe cases represented 1%, and critical cases represented 0.4% [9].

Figure 1. Weekly evolution of the number of COVID-19 cases and deaths in Morocco from March 2, 2020 to October 31, 2020.



National Preparation and Response

Preparedness and Coordination of the National Response

With few exceptions, the same structures responsible for coordinating the response against the influenza A (H1N1) 2009 pandemic have been reactivated to lead the response operations against COVID-19. A national plan for monitoring and responding to infection was officially launched on January 27, 2020. A high-level commission chaired by the head of government has been set up to take political, diplomatic, regulatory, cooperation, and response orientation decisions. The Ministry of Health has set up a steering committee for the health component of the response. The tasks of epidemiological monitoring and coordination have been entrusted to the National Public Health Emergency Operations Center as part of the operationalization of the actions included in the National Health Security Plan 2018-2022 [10].

A special fund for the management of the coronavirus pandemic "The COVID-19 Fund" has been created. This fund is earmarked to upgrade the medical services in terms of infrastructure and resources in an emergency, and it also aims to support the national economy. This Special Trust Account is open to any contribution from individuals as well as from legal, public, and private persons and entities. At the end of August 2020, this fund had reached more than US $3 billion, most of which was dedicated to support of economic activities (US $2.4 billion), while the rest went to the Ministry of Health for acquisition of medical equipment.

Detection and Testing, Contact Tracing, and Isolation

In order to detect any cases from abroad at an early stage, a monitoring and surveillance system was set up at the start of the crisis in January 2020 at all entry points for international traffic. All passengers were systematically subjected to a temperature measurement by thermal camera and infrared thermometer in addition to a visual examination. Any traveler meeting the case definition had to be rushed to hospital for isolation and a sample for reverse transcription polymerase chain reaction (RT-PCR) examination. The case definition has been regularly updated to adapt to the evolving epidemiological situation. It takes into account symptoms for suspected cases and the real-time PCR test results for confirmed cases.

The capacity of PCR testing was initially limited to 3 laboratories and then has been gradually expanded to 38 laboratories. Two mobile laboratories under the INH were also mobilized, and 5 PCR laboratory platforms were installed in ships to provide tests for travelers between Morocco and European countries after reopening the borders to Moroccan citizens residing in foreign countries. A new circular from the Ministry of Health dated September 26, 2020 announced the availability of molecular screening tests by qRT-PCR for COVID-19 in all private laboratories in Morocco that meet the criteria in technical specifications.

As a result, the number of tests, which was very limited at the beginning, has gradually increased from around 100 per day to more than 160,000 tests per week.

Currently, home isolation is required for the majority of contacts especially for those without obvious symptoms. The duration of follow-up and isolation is set at 14 days from the last contact with a confirmed COVID-19 case [6].

Organization of Case Management

The organization of the national response to COVID-19 has taken a series of rigorous measures concerning the management of cases affected by the disease. Among these measures is the management of all cases in a hospital environment. Thus, any case meeting the criteria of "possible case" or "confirmed case" was hospitalized in an isolation room. Severe cases were placed in an intensive care unit. Hospitalization capacity, which was very limited at the start, has been gradually increased through the establishment of field hospitals and capacity building of hospitals responsible for handling COVID cases.

Following the National Scientific, Technical and Advisory Committee's recommendations, Morocco has decided to treat all patients with COVID-19 with hydroxychloroquine (HCQ) or chloroquine (CQ), combined with azithromycin (AZM) as first-line treatment and according to a standardized treatment regimen, in a systematic and structured manner. Thus, each confirmed case, even asymptomatic, received first-line treatment for 10 days [6]. The duration of first-line treatment can be extended by 5 days, before considering second-line treatment.

Second-line treatment consisted of combination lopivinar/ritonavir for 10 days. Antibiotic therapy was prescribed only in case of a secondary bacterial infection. First-line treatment (HCQ or CQ + AZM) has been in effect in Morocco since the detection of the first cases, and it is still used now. These drugs are still available in pharmacies following the intervention of the Moroccan government with a subsidiary of the multinational producer.

Transfer to intensive care is done for severe cases according to pre-established criteria and after observation of the seriousness of the condition by the health care team.

At the beginning of September 2020, the Ministry of Health took new measures in the form of a memo [11] so that the treatment of potential cases can start as quickly as possible even before the release of PCR test results. Home care for asymptomatic or mild cases without risk factors has also been part of the treatment policy.

Communication, Information, and Social Mobilization

Since the announcement of the epidemic in China, the Moroccan government has deployed an institutional and risk-based communication strategy. Different government officials, depending on their position and field of intervention, have followed one another to provide information on the epidemiological situation or measures taken. As soon as the first case was announced in Morocco, a daily press briefing on the situation linked to the epidemic was broadcasted live through national public television channels. With the increase in the number of positive cases later, the Ministry of Health reduced the frequency of the press briefing to 1 every 2 weeks.

Officials at the regional level as well as resource persons including scientists were also involved, in particular by appearing on official TV and radio channels during news bulletins and television or radio broadcasts.

Multiple awareness-raising spots on preventive measures have been produced and distributed continuously to raise awareness to avoid the risk of contamination. Leaflets have been prepared to educate travelers at points of entry.

Lockdown and Lockdown Lifting

Given the exceptional nature of the situation related to COVID-19 and in accordance with the national constitution and regulations in force, Morocco declared a “state of health emergency” on March 19, 2020, allowing it to set up a series of preventive measures including lockdown with restriction of the movement of people and closure of national borders. In this context, the wearing of a mask was made mandatory. Reduction of the restrictive measures taken was later decided through a gradual lockdown lifting plan.

SWOT Analysis

A SWOT analysis [12] was conducted to determine the strengths, weaknesses, opportunities, and threats related to the interventions carried out.

Main Strengths

In this context, 9 major strengths deserve to be highlighted.

Preparation That Took Into Consideration the Lessons Learned From Other Public Health Emergencies of International Concern (PHEIC)

A pandemic preparedness and response plan was drawn up on the basis of the elements and orientation of the 2018-2022 National Health Security Plan that was implemented following the Joint External Assessment of the capacities required by the IHR (2005) and taking into account other response plans such as pandemic influenza, MERS-CoV, and Ebola disease.

The existence of know-how in the management of health crises and an awareness of the importance of developing the responsiveness of the health system in the face of a PHEIC was present, as recommended by the IHR (2005).

A risk assessment was established early by the Ministry of Health in the aftermath of the first signals of the COVID-19 epidemic that stressed that Morocco was at risk of being rapidly exposed to the disease. All interventions were carried out following precise knowledge of the level and origin of the risk.

Guidelines and procedures were gradually developed or revised, while adapting them to new scientific knowledge and the national epidemiological context and largely complying with WHO recommendations and guidelines.

Anticipated Reaction for Both Health and Financial Factors

A government action plan covering health, economic, and social aspects was implemented. A special fund was created at the initiative of the king of the country for the management of the pandemic. Programming and coordination of the actions of stakeholders were conducted to control the spread of the virus and its impact on economic and social life. All bodies of state and civil society were mobilized to ensure compliance with the measures recommended in the framework of the national response plan and the government action plan. Diplomatic missions were coordinated for exchange of expertise with the countries where the pandemic initially appeared. Financial aid measures were provided for vulnerable households and small businesses.

Proactive Epidemiological Surveillance and Notification of Cases Using an Electronic Platform

A fairly well-structured epidemiological surveillance system covering the entire national territory was present through structures dedicated to this function at national, regional, provincial, and prefectural levels and at border posts.

A pandemic surveillance system was established, which has benefited from the experience within the framework of the seasonal influenza surveillance system implemented gradually since 1996, which includes both clinical surveillance and virological surveillance of syndromes. An event-based surveillance system has been in place since 2018. A clear case definition has been constantly revised to adapt to the evolving epidemiological situation. Three telephone platforms were established for the management of alerts and referral of suspected cases. An interoperable and interconnected real-time electronic COVID case notification system was implemented, allowing data entry, analysis, and sharing at all levels.

Presence of Well-Trained Rapid Response Teams

Multidisciplinary and multisectoral teams were established for contact follow-up, coordinated by field epidemiologists or health professionals trained in epidemiology and rapid intervention. Contact tracing procedures were updated, with a view to their adaptation for the evolving epidemiological situation. The contact tracking system was reinforced with a mobile application called "Wiqaytna" based on Bluetooth technology, which allows notification of exposure to SARS-CoV2. Relentless contact tracing support has been provided by local and security authorities.

Increase in the Supply of Infrastructure, Equipment, and Health Products

Equipment was made available at all entry points, with modern temperature detection equipment (thermal cameras and remote thermometers). Hospital capacities were increased and reorganized, and patient reception conditions in the various COVID hospitals were improved. Military and civilian field hospitals were deployed to strengthen the health system in beds and equipment for intensive care and resuscitation. There was a significant increase in resuscitation beds and equipment. Production and industrial manufacture of masks, hydroalcoholic gel, and other disinfectant products were developed or reallocated, with price regulation. Capacity building of the laboratory system was conducted: Morocco had 4 laboratories at a biosafety level 3, which were used at the start of the epidemic and were subsequently reinforced until a good capacity was reached, including 30 laboratories with PCR platforms, 6 of which are mobile laboratories. Stocks of drugs, products, and personal protective equipment were constituted.

Patient Care in Accordance With Established Protocols

Management protocols were developed in collaboration with the Scientific, Technical and Advisory Committee of the Ministry of Health for the management of COVID-19 and were regularly updated based on new knowledge about the disease. Medicines and other pharmaceutical products were mobilized very early, and treatment services were integrated into all care structures and offered at home when the indication is justified. The organization of the care system and patient circuit were adapted in response to the new intervention logic. Free access to health care has been ensured for all suspected or confirmed cases. Psychologists were mobilized to provide psychological help to people weakened by illness and isolation. Several remote platforms were established to provide psychological support and counseling services to health professionals and citizens who develop certain disorders in the form of distress, depression, or acute panic disorders resulting from fear or confinement.

Solidarity Implication for Private Corporations

There has been exemplary compliance with barrier measures during the confinement period at the start of the crisis. Companies from the public and private sectors have supported the development of hospital services and consultation centers. There has been responsible involvement of certain private clinics in the management of COVID cases and in the management of other pathologies in the sense of relieving public hospitals and university hospitals. There have been massive amounts of participation by nongovernmental organizations (NGOs) and civil society organizations (CSOs) in various actions to fight COVID-19. Hotels and catering units have volunteered to offer reception rooms and catering services to convalescent patients or health personnel. University researchers were involved in the development of mathematical models to predict the spread of COVID-19 in Morocco. Manufacturers were involved in the production of masks and respirators. The ministry in charge of industry mobilized many companies within new business models that enable better production capacity.

Appropriate Governance and Coordination

Political commitment is present at the highest level of the state hierarchy (Royal commitment and of the whole government). There is a model of organization and coordination of the response that integrates all key sectors and takes into account all levels of intervention (central, regional, and local). There is a clear definition of the role and responsibilities of each ministerial department and other stakeholders including the business sector, the private sector, and civil society. The recently created Centre National des Opérations d'Urgence de Santé Publique (CNOUSP; National Public Health Emergency Operations Center) as part of the capacity building required by the IHR (2005) played a role as a focal points. Morocco already has a significant body of legislation and regulations to manage health crises in compliance with the law, which has been expanded during the COVID-19 pandemic. Ethical aspects were integrated in the policy and practices in terms of preparedness and response to the pandemic.

A Particular Interest of all Sectors in the Continuity of Essential Services

All sectors have an interest in maintaining vitally important activities during the confinement period based on all available staff resources and volunteers as well as regular monitoring of the supply or refueling of the markets by the availability of all necessities, food, hygiene products, or energy. Digitization of certain ministerial departments made it possible to guarantee the continuity of essential services by resorting to teleworking and by limiting the physical exchange of documents and administrative letters. Strengthening online banking services and the creation of a series of new digital services aimed to reduce the exchange of paper documents, thus limiting the risk of transmission of COVID-19. Practical manuals on teleworking in companies were published.

Main Weaknesses

Governance and Leadership Were Sometimes Overtaken by Events

Decision making was sometimes contested by the population and public opinion. Examples are decisions to confine certain towns in the following 6 hours, which precipitated part of the population towards an increased risk of accidents on overcrowded roads, or the decision to celebrate Eid El Adha (feast of sacrifice), which entailed a double risk of creating hotbeds of infection (contacts in uncontrollable cattle markets followed by extended family gatherings). There was a lack of collegial and socially appropriate decision making involving elected officials and the community. The multidisciplinary

expertise that must characterize the composition and members of the scientific committee in a period of health crisis involving health, psychological, and social determinants was not considered with rigor. There was a lack of a clear strategy or procedures for involving NGOs. Directives and measures in the field of occupational health were implemented late and remained insufficient given the delay in strengthening this component.

Insufficient and Exhausted Human Resources

There was a lack of human resources even before the onset of COVID-19. It was difficult to fill the gaps in doctors and nurses, in particular for certain specialties and for resuscitators. It was also difficult to maintain and consolidate the commitment of health personnel due to the lack of clear motivation and a skills development program. The resources of the private sector, where nearly 50% of the physician workforce works, are underutilized to deal with the pandemic.

Delay in Communicating the Results of Diagnostic Tests

Despite the strengthening effort, the laboratory network was not large enough, and the results of biological tests were communicated with some delay. This had a negative impact on the surveillance process (test, trace, isolate) and precocity of treatment. Primary health care establishments (ESSP) were involved late in the management of COVID cases.

Management of Serious Cases Stifled by a Lack of a Sufficient and Quality Technical Platform

Cases admitted to intensive care units had high mortality. Conditions of stay in public hospitals were strongly criticized by patients. There were difficult working conditions in some hospitals.

Insufficient Communication to Increase the Confidence of the Population

Complex information management, given the impressive flow, was present, but there was also a considerable amount of fake news associated with the pandemic (very apparent infodemic). There was low perception of the seriousness of the epidemic by certain categories of the population. There has been a gradual decrease in compliance with the instructions transmitted relating to the application of barrier measures by a good segment of the population. Compliance with barrier measures has not been as strong as might have been hoped for given the quantity and intensity of preventive and incentive messages around COVID-19. Certain individuals wear unsuitable protective masks.

Difficulties in Managing the Business Continuity of Other Health Programs

There is a lack of a clear business continuity strategy for health programs in the context of the pandemic. Several basic health care structures have partially closed. There has been exclusive concentration of certain hospital services on COVID-19 as well as a significant reduction in health services and in the performance of other health programs.

Opportunities

Morocco has all the assets to be able to take advantage of the current crisis linked to the COVID-19 pandemic by operating several levers at the same time while boosting public-private partnership and international cooperation with a view to reshaping the health system and ensure its resilience. Several opportunities are therefore offered and must be seized upon because of the lessons learned from the impact of the pandemic and the way it was managed.

Restructure the health system for strength and resilience as recommended in several initiatives and planning documents. Reconsider certain priorities of the health system and implement a new model of health development by giving more attention to the in-depth reform of the governance and functioning of the various health services.

Accelerate the implementation of the actions planned within the framework of the national health security plan including the establishment of a public health agency accompanied by a public health law as well as the development of a multirisk plan for management of all public health emergencies and humanitarian disasters. Take advantage of the reigning enthusiasm for effective strengthening of public-private partnerships. Seize the opportunities offered for the promotion of digital technology, teleworking, and telemedicine.

Threats

The pandemic is much more than a health crisis: It is also an unprecedented socioeconomic crisis that has already had devastating social, economic, and political effects that will leave deep scars that will be slow to fade. Its threats to the health system and health security in general are numerous, 4 of which can have a lasting impact on the health system:

1. Risk of amplification of public health problems linked to other communicable diseases and noncommunicable diseases
2. Risk of a more acute installation of resistance to the directives and instructions of the authorities because of the “infodemic” that surrounds the pandemic via rumors and false information with no borders and is propagated at great speed by social media
3. Risk of loss of human resources due to contamination by the virus
4. Risk of a deep and uncontrollable saturation of case management structures

Lessons Learned

During the first phases of the COVID-19 pandemic, Moroccans showed solemn commitment and collectively mobilized to face this PHEIC. The spirit that marked the whole society was animated by sincere patriotism, the spirit of sacrifice, as well as solidarity and loyalty. The response to the pandemic was distinguished by a strong political commitment and a mobilization of all segments of society: COVID-19 has revived a huge surge of solidarity.

The main lesson learned is a need to further strengthen national capacities to prepare for and respond to possible public health emergencies and to embark on a process overhaul of the health system, including research into innovative tools to ensure the continuity of the various disease prevention and control activities. In addition, the response to a health crisis is not the only responsibility of the health sector, and intersectoral collaboration is the guarantee of an optimal coordinated fight. Community-oriented approaches in public health have to be strengthened through more participation and involvement of NGOs and civil society in operational and strategic planning. Teleworking, telemedicine, and digitization emerged as one of the priority areas to be developed.

Conclusion

Morocco is considered among the countries that got the virus under control early on, but when economic and social restrictions were eased, the number of cases increased considerably. The impact of the pandemic on the lives of citizens was obvious from all standpoints. One of the crucial lessons that can be learned is that the response to a health crisis not only is the responsibility of the health sector but also intersectoral collaboration is the guarantee of an optimal coordinated fight. Community-oriented approaches in public health have to be strengthened through more participation and involvement of NGOs and civil society in operational and strategic planning.

Acknowledgments

The authors would like to acknowledge the Global Health Development Eastern Mediterranean Public Health Network (GHD EMPHNET) for their technical support.

Conflicts of Interest

None declared.

References

1. Amouch M, Karim N. Modeling the dynamic of COVID-19 with different types of transmissions. Chaos Solitons Fractals 2021 Sep;150:111188 [FREE Full text] [doi: 10.1016/j.chaos.2021.111188] [Medline: 34183873]
2. Guidance for After Action Review. World Health Organization. 2019. URL: https://extranet.who.int/iris/restricted/bitstream/handle/10665/311537/WHO-WHE-CPI-2019.4-eng.pdf;jsessionid=E71989C2EC51EFC2D4F1791CE103084A?sequence=1 [accessed 2021-09-06]
3. Policy responses to COVID-19. The International Monetary Fund. 2021. URL: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 [accessed 2021-09-06]
4. Monitoring and evaluation framework for COVID-19 response activities in the EU/EEA and the UK. European Centre for Disease Prevention and Control (ECDC). 2020 Jun 17. URL: https://www.ecdc.europa.eu/sites/default/files/documents/covid-19-framework-monitor-responses.pdf [accessed 2021-09-06]
5. COVID-19: Guide de gestion des contacts. Ministry of Health. URL: http://www.covidmaroc.ma/Documents/2020/coronavirus/PS/Guide_gestion_contact.pdf [accessed 2021-09-06]
6. Daily COVID-19 report. Morocco Ministry of Health. URL: https://www.sante.gov.ma/sites/Ar/Pages/activites.aspx?activiteID=241 [accessed 2020-05-30]
7. COVID-19 Public Health Emergency Bulletin, March 4, 2020. Ministry of Health. 2020 Mar 04. URL: https://tinyurl.com/3zuzbfme [accessed 2021-09-06]
8. COVID-19 epidemic in Morocco, Progress report as of March 31, 2020. Ministry of Health. 2020 Apr 10. URL: https://tinyurl.com/25w27ab3 [accessed 2021-09-06]
9. Fantoni Quinton S. Implication des services de santé au travail dans la lutte contre l'épidémie de COVID-19: nouvelles possibilités de prescription des arrêts de travail, report de certaines visites, participation active à la lutte…. Archives des Maladies Professionnelles et de l'Environnement 2020 May;81(3):209-211. [doi: 10.1016/j.admp.2020.04.010]
10. Plan d'Action National de Sécurité Sanitaire (PANSS) 2018-2022. Ministry of Health. 2018. URL: https://extranet.who.int/sph/sites/default/files/NBW%20Morocco_Final%20Report.pdf [accessed 2020-05-30]
11. Update of the protocol for the management of cases of SARS-Cov-2 infection. Ministry of Health. 2020. URL: https://www.maroc.ma/en/news/covid-19-implementation-home-treatment-protocol-asymptomatic-patients [accessed 2021-09-06]
12. Puyt R, Lie FB, De Graaf FJ, Wilderom CP. Origins of SWOT Analysis. Proceedings 2020 Aug;2020(1):17416 [FREE Full text] [doi: 10.5465/ambpp.2020.132]

Abbreviations

AZM: azithromycin
CNOUSP: Centre National des Opérations d'Urgence de Santé Publique
CQ: chloroquine
CSO: civil society organization

FETP: Field Epidemiology Training Program
HCQ: hydroxychloroquine
IHR: International Health Regulations
NGO: nongovernmental organization
PHEIC: Public Health Emergencies of International Concern
RT-PCR: reverse transcription polymerase chain reaction
WHO: World Health Organization

Edited by M Alyahya, T Sanchez; submitted 09.07.21; peer-reviewed by A El Rifay, S Azadnajafabad; comments to author 21.07.21; revised version received 03.08.21; accepted 09.08.21; published 17.09.21.

Please cite as:
Barkia A, Laamrani H, Belalia A, Benmamoun A, Khader Y
Morocco's National Response to the COVID-19 Pandemic: Public Health Challenges and Lessons Learned
JMIR Public Health Surveill 2021;7(9):e31930
URL: https://publichealth.jmir.org/2021/9/e31930
doi:10.2196/31930
PMID:34388104

Original Paper

Clinical, Laboratory, and Imaging Features of COVID-19 in a Cohort of Patients: Cross-Sectional Comparative Study

Rami Qaisieh[1], MD; Mohammad Al-Tamimi[2], MD, PhD; Naser El-Hammuri[1], MD; Marwan Shalabi[3], MD; Muna M Kilani[3], MD; Hana Taha[2,4,5], PhD; Abdallah Al-Muhtaseb[2], MD; Ibrahim Alfarrajin[2], MD; Marwan Abu Shaqra[2], MD; Almothana Hamdan[2], MD

[1]Department of General and Special Surgery, Faculty of Medicine, Hashemite University, Zarqa, Jordan

[2]Department of Basic Medical Sciences, Faculty of Medicine, Hashemite University, Zarqa, Jordan

[3]Department of Pediatrics and Neonatology, Faculty of Medicine, Hashemite University, Zarqa, Jordan

[4]Global Health Development/Eastern Mediterranean Public Health Network, Amman, Jordan

[5]Department of Neurobiology, Care Sciences and Society, Karolinska Institute, Stockholm, Sweden

Corresponding Author:
Mohammad Al-Tamimi, MD, PhD
Department of Basic Medical Sciences
Faculty of Medicine
Hashemite University
Damascus Highway
Zarqa
Jordan
Phone: 962 5 3903333
Fax: 962 5 3826613
Email: mohammad.altamimi@hu.edu.jo

Abstract

Background: The clinical, laboratory, and imaging features of COVID-19 disease are variable. Multiple factors can affect the disease progression and outcome.

Objective: This study aimed to analyze the clinical, laboratory, and imaging features of COVID-19 in Jordan.

Methods: Clinical, laboratory, and imaging data were collected for 557 confirmed COVID-19 patients admitted to Prince Hamzah Hospital (PHH), Jordan. Analysis was performed using appropriate statistical tests with SPSS version 24.

Results: Of the 557 COVID-19 polymerase chain reaction (PCR)-positive cases admitted to PHH, the mean age was 34.4 years (SD 18.95 years; range 5 weeks to 87 years), 86.0% (479/557) were male, 41% (29/70) were blood group A+, and 57.1% (93/163) were overweight or obese. Significant past medical history was documented in 25.9% (144/557), significant surgical history in 12.6% (70/557), current smoking in 14.9% (83/557), and pregnancy in 0.5% (3/557). The mean duration of hospitalization was 16.4 (SD 9.3; range 5 to 70) days; 52.6% (293/557) were asymptomatic, and 12.9% (72/557) had more than 5 symptoms, with generalized malaise and dry cough the most common symptoms. Only 2.5% (14/557) had a respiratory rate over 25 breaths/minute, and 1.8% (10/557) had an oxygen saturation below 85%. Laboratory investigations showed a wide range of abnormalities, with lymphocytosis and elevated C-reactive protein (CRP), erythrocyte sedimentation rate (ESR), and D-dimer the most common abnormalities. Ground glass opacity was the most common imaging finding. Men had a significantly higher frequency of symptoms, incidence of smoking, reduced hemoglobin, increased monocyte %, elevated creatinine levels, and intensive care unit admissions compared with women (P<.05). Hospitalization duration was associated with increased age, male gender, symptom score, history of smoking, elevated systolic blood pressure, elevated respiratory rate, and elevated monocyte %, CRP, ESR, creatinine, and D-dimer (P<.05).

Conclusions: Most COVID-19 cases admitted to PHH were asymptomatic. Variabilities in symptoms, signs, laboratory results, and imaging findings should be noted. Increased age, male gender, smoking history, and elevated inflammatory markers were significantly associated with longer duration of hospitalization.

(JMIR Public Health Surveill 2021;7(9):e28005) doi:10.2196/28005

KEYWORDS

COVID-19; gender; clinical; laboratory; imaging; SARS-CoV2; Jordan

Introduction

In December 2019, an outbreak of pneumonia of unknown etiology was identified in Wuhan city, China [1]. Later, it was found that the causative pathogen was severe acute respiratory syndrome coronavirus 2 (SARS-CoV2) [1]. The routes of transmission of this virus are mainly droplets and direct contact with patients, and the main source of the disease at present is patients with COVID-19 [2]. On March 11, 2020, the World Health Organization declared COVID-19 a pandemic due to its exponential spread all over the globe [3].

Studies have shown that COVID-19 is a systemic disease where different systems are affected differently; therefore, the clinical manifestations of the disease vary from patient to patient, with fever (78%-87%) and cough (57%-68%) being the most common manifestations in adults. Other manifestations like dyspnea (23%-24%), myalgia (17%-24%), and fatigue (31%-39%) are present to a lesser extent [4,5]. A small percentage of patients develop gastrointestinal symptoms such as nausea (6.0%-6.5%), vomiting (4.0%-6.5%), and diarrhea (8%-10%) [4,5]. The least prevalent symptoms are ophthalmological (2%-4%) and neurological (0%-14%) [4,5]. The severity of the disease varies among patients, with the elderly and patients with comorbidities being affected the most [6]. There are many complications of the disease such as acute respiratory distress syndrome, acute cardiac injury, acute kidney injury, and shock [7]. Patients are also at increased risk of hypercoagulability and thromboembolism [8].

X-ray imaging studies showed that bilateral involvement is more common than unilateral, and the most common lesion is a ground glass appearance followed by consolidation [4]. Computed tomography (CT) scans also confirmed these findings [9]. The most prevalent laboratory findings are decreased albumin, high C-reactive protein (CRP), lymphopenia, increased platelets, increased lactate dehydrogenase, and a high erythrocyte sedimentation rate (ESR) [10].

Although the prevalence of COVID-19 is equal between men and women, the disease is more severe in men [11]. Some studies attributed this to a higher expression of angiotensin-converting enzyme 2 (ACE2), the receptor for SARS-CoV2, in men than in women in pathological conditions [12]. Furthermore, it has been found that ACE2 expression is higher in current and ex-smokers, and smoking is more common in men than in women. Thus, the disease is more severe in men [13]. Patients with hypertension or chronic obstructive pulmonary disease (COPD) tend to have more severe COVID-19 disease. Children have less severe disease than adults, and these differences are possibly due to having different expression levels of ACE2 receptors [14]. While this disease involves mainly the respiratory tract, different organ systems can become involved.

Researchers have dug into massive gene expression datasets to show that other potential target cells that also produce ACE2 and TMPRSS2 are scattered throughout the body, which could explain the systemic nature of this disease [14]. While multiple studies have reported greater disease severity and mortality in men infected with COVID-19, no comparative studies have been conducted regarding the differences in clinical, laboratory, and imaging findings according to gender [11-13,15].

The first case of COVID-19 in Jordan was registered on March 2, 2020 in a Jordanian citizen who came back from Italy [16], and the number of cases as of December 12, 2020 exceeded 250,000 [3,16,17]. Even though there is a tremendous number of studies worldwide regarding COVID-19 patients' clinical features, laboratory findings, and imaging findings, there are only a few in our region (the Middle East), and no study has yet been done in Jordan. Clinical, laboratory, and imaging findings are widely variable according to geographic location, disease severity, SARS-CoV2 strains, population demographics, immunity, and other factors [2,10]. The aim of this study was to describe the clinical manifestations, laboratory findings, and imaging findings of COVID-19 patients in Jordan with an emphasis on gender-related differences.

Methods

Study Population

A total of 557 confirmed COVID-19 cases admitted to Prince Hamzah Hospital (PHH) during the period from March 1, 2020 to August 1, 2020 were recruited prospectively to this study after giving formal voluntary consent, and they were followed daily for clinical, paraclinical, and outcome parameters. All COVID-19 cases were confirmed by at least one positive COVID-19 reverse transcription (RT)-PCR test performed by an accredited referral lab. All COVID-19 recovery cases were confirmed by complete clinical and laboratory resolution, including 2 negative COVID-19 RT-PCR tests within 2 days. The government of Jordan had a policy at the time of the study to admit all COVID-19–positive patients to the hospital for isolation regardless of symptom severity.

The study protocol was approved by the institutional review board (IRB) at the Hashemite University (No: 1⁄5⁄2019⁄2020) and the Jordanian Ministry of Health/PHH IRB (No: 1/1631).

Demographic, Clinical, and Laboratory Data From COVID-19 Patients in Jordan

Confirmed COVID-19 patients' demographics; clinical, social, and medical history; and laboratory and imaging data were obtained directly from patients, relatives, or medical records of patients admitted to PHH, Amman, Jordan (the main COVID-19 isolation and management center in Jordan). Data were recorded on the first day of admission and daily during follow-ups. Demographic data included age, gender, weight, height, BMI, and blood group. Clinical data included symptoms reported by patients, vital signs, medical and surgical history, and duration of hospitalization. Laboratory data included all laboratory tests performed for patients during their admission. Imaging data assessed by an accredited radiology specialist were extracted for the 135 patients who had imaging studies (questionnaire in

Multimedia Appendix 1 and primary data file in Multimedia Appendix 2 are provided as supplementary material).

Statistical Analysis

Descriptive statistical analysis was used for determination of demographic, clinical, laboratory, and imaging findings. Percentages and means (SD) were calculated to describe the distributions of categorical and continuous variables, respectively. Chi-square and Fisher exact tests were used to assess the association between the study participants' age, gender, BMI, and duration of hospitalization with their clinical, laboratory, and imaging data. The level of statistical significance was set at $P \leq .05$. Data were analyzed using Microsoft Excel 2010 and SPSS version 24.0.

Results

Demographics and Clinical Features of COVID-19 in Jordan

Of the 557 COVID-19 cases who were admitted to PHH, the gender distribution was 86.0% (479/557) men and 14.0% (78/557) women. Among these patients, the mean age was 34.4 years (SD 18.95 years; range 5 weeks to 87 years), and the largest age group was 21-40 years old (190/557, 34.1%). BMI was documented in 163 patients: 8.0% (13/163) were underweight, 35.0% (57/163) were normal weight, 29.4% (48/163) were overweight, and 27.6% (45/163) were obese (Table 1). Blood groups were determined for 70 patients (70/557, 12.6%) with blood group A+ (29/70, 41%) and O+ (19/70, 27%) being the most common. Significant past medical history was documented in 25.9% (144/557) of patients, significant surgical history in 12.6% (70/557), current smoking in 14.9% (83/557), a history of allergies in 1.8% (10/557), and pregnancy in 0.5% (3/557). The mean duration of hospitalization was 16.4 (SD 9.3) days, ranging from 5 days to 70 days (Table 1).

Table 1. Demographic and clinical data of COVID-19 patients admitted to Prince Hamzah Hospital (PHH; n=557).

Variable	Number of participants	Relative percentage	Absolute percentage
Age (years)			
<1	10	1.8	1.8
1-20	152	27.3	27.3
21-40	190	34.1	34.1
41-60	154	27.6	27.6
61-80	48	8.6	8.6
>80	3	0.5	0.5
Gender			
Male	479	86.0	86.0
Female	78	14.0	14.0
BMI			
Underweight >18.5 kg/m^2	13	8.0	2.3
Normal 18.5-24.9 kg/m^2	57	35.0	10.2
Overweight 25-29.9 kg/m^2	48	29.4	8.6
Obese >30 kg/m^2	45	27.6	8.1
ND[a]	394	N/A[b]	70.7
Blood group			
A+	29	41.4	5.2
B+	13	18.6	2.3
AB+	2	2.9	0.4
O+	19	27.1	3.4
A-	1	1.4	0.2
B-	1	1.4	0.2
O-	5	7.1	0.9
ND	487	N/A	87.4
Admission duration (days)			
5-14	336	60.3	60.3
15-30	177	31.8	31.8
31-46	33	5.9	5.9
47-70	11	2.0	2.0
Symptoms			
Generalized malaise	120	21.5	21.5
Headache	75	13.5	13.5
Loss of smell	70	12.6	12.6
Diarrhea	57	10.2	10.2
Loss of taste	60	10.8	10.8
Chills/rigors	77	13.8	13.8
Myalgia	61	11.0	11.0
Nasal congestion	72	12.9	12.9
Dry cough	121	21.7	21.7
Fever	108	19.4	19.4

Variable	Number of participants	Relative percentage	Absolute percentage
Rhinorrhea	57	10.2	10.2
Sweating	35	6.3	6.3
Wet cough	44	7.9	7.9
Shortness of breath	56	10.1	10.1
Abdominal pain	33	5.9	5.9
Chest pain	29	5.2	5.2
Palpitations	12	2.2	2.2
Hemoptysis	5	0.9	0.9
Others	48	8.6	8.6
Symptom scores			
Asymptomatic	293	52.6	52.6
Mild: 1-5	192	34.5	34.5
Moderate: 6-10	50	9.0	9.0
Severe: 11-17	22	3.9	3.9
Past medical history			
Asthma	8	1.4	1.4
Hypertension	25	4.5	4.5
Diabetes	19	3.4	3.4
Diabetes and hypertension	60	10.9	10.9
Pregnancy	3	0.5	0.5
Others	33	6	6
No	408	73.9	73.2
ND	5	N/A	0.9
Past surgical history			
Yes	70	12.6	12.6
No	487	87.4	87.4
Allergic history			
Yes	10	2.6	1.8
No	377	97.4	67.7
ND	170	N/A	30.5
Smoking			
Past smoker	12	3.6	2.2
Current smoker	83	25.2	14.9
Never smoked	234	71.1	42.0
ND	228	N/A	40.9
Heart rate (/minute)			
<60	2	0.4	0.4
60-80	257	48.5	46.1
81-128	271	51.1	48.7
ND	27	N/A	4.8
Systolic blood pressure (mm Hg)			
<120	243	47.8	43.6
120-139	241	47.4	43.3

Variable	Number of participants	Relative percentage	Absolute percentage
140-159	21	4.1	3.8
≥160	3	0.6	0.5
ND	49	N/A	8.8
Diastolic blood pressure (mm Hg)			
<80	374	73.6	67.1
80-89	115	22.6	20.6
90-99	16	3.1	2.9
≥100	3	0.6	0.5
ND	49	N/A	8.8
Respiratory rate (/minutes)			
<12	0	0.0	0.0
12-25	493	97.2	88.5
>25	14	2.8	2.5
ND	50	N/A	9.0
Oxygen saturation (%)			
<80	4	0.8	0.7
80-84	6	1.2	1.1
85-94	52	10.0	9.3
95-100	458	88.1	82.2
ND	37	N/A	6.6

[a]ND: not determined.

[b]N/A: not applicable.

The patients complained of a variety of symptoms; nevertheless, most of the patients (293/557, 52.6%) were asymptomatic, while 34.5% (192/557) had 1-5 symptoms, 9.0% (50/557) had 6-10 symptoms, and 3.9% (22/557) had more than 11 symptoms. Among the symptomatic patients, generalized malaise and dry cough were the most common symptoms, and they were documented in 21.5% (120/557) and 21.7% (121/557) of the patients, respectively. These were followed by fever (108/557, 19.4%), chills and rigors (77/557, 13.8%), headache (75/557, 13.5%), nasal congestion (72/557, 12.9%), loss of smell (70/557, 12.6%), myalgia (61/557, 11.0%), loss of taste (60/557, 10.8%), rhinorrhea (57/557, 10.2%), and shortness of breath (56/557, 10.1%). Gastrointestinal symptoms were less frequently documented with diarrhea (57/557, 10.2%) and abdominal pain (33/557, 5.9%) being most prevalent. The least reported symptoms were chest pain (29/557, 5.2%), palpitations (12/557, 2.2%), and hemoptysis (5/557, 0.9%; Table 1). Regarding the vital signs of admitted COVID-19 patients, about 50% (271/557, 48.7%) of patients had a heart rate >80 beats per minute and systolic blood pressure ≥120 mm Hg (265/557, 47.6%), while nearly 25% had a diastolic pressure ≥80 mm Hg (134/557, 24.1%). Only 2.5% (14/557) had a respiratory rate over 25 per minute, with about 2% having an oxygen saturation below 85% (10/557, 1.8%; Table 1).

Laboratory Data for COVID-19

Laboratory investigations for COVID-19 patients admitted to PHH (Table 2 and Table 3) showed low hemoglobin and hematocrit in 9.9% (55/557) and 7.7% (43/557) of patients, respectively. Total white blood cell count was low in 7.2% (40/557) and high in 4.8% (27/557) of patients. Differential count showed that the neutrophil percentage was low in 14.2% (79/557), the lymphocyte percentage was low in 12.6% (70/557) and high in 28.7% (160/557), the basophil percentage was low in 44.9% (250/557), the eosinophil percentage was low in 43.4% (242/557), and the monocyte percentage was high in 26.2% (146/557). Platelet count was low in 6.6% (37/557), with high prothrombin time, international normalized ratio, and D-dimer found in 2.3% (13/557), 3.6% (20/557), and 13.1% (73/557), respectively. Inflammatory markers including CRP and ESR were elevated in 28.7% (160/557) and 26.4% (147/557) of patients, respectively. Urea and creatinine were elevated in 3.4% (19/557) and 4.8% (27/557) respectively. Aspartate transaminase (AST), alanine transaminase (ALT), and lactate dehydrogenase (LDH) were elevated in 10.2% (57/557), 8.8% (49/557), and 5.0% (28/557), respectively. Bilirubin total and direct were elevated in 9.2% (51/557) and 4.1% (23/557), respectively. Hyponatremia and hypokalemia were found in 5.0% (28/557) and 4.1% (23/557), respectively (Table 3).

Table 2. Mean laboratory values from COVID-19 patients admitted to Prince Hamzah Hospital (PHH; n=557).

Investigations	Value, mean (SD)
HB[a] (g⁄dL)	13.92 (1.73)
HCT[b] (%)	41.12 (5.18)
WBC[c] (⁄µL)	7190 (4.19)
Neutrophil (%)	52.82 (25.92)
Lymphocyte (%)	32.97 (15.99)
Basophil (%)	0.51 (0.35)
Monocyte (%)	9.17 (4.10)
Eosinophil (%)	1.59 (1.82)
Platelets (count⁄µL)	251,900 (107,320)
CRP[d] (mg/L)	14 (38)
ESR[e] (mm/h)	28.27 (28.96)
PT[f] (s)	13.54 (2.80)
INR[g]	1.05 (0.18)
Urea (mmol/L)	4.74 (2.13)
Creatinine (mmol/L)	74.08 (70.52)
Sodium (mmol/L)	125.77 (40.04)
Potassium (mmol/L)	4.68 (8.29)
AST[h] (U/L)	27.64 (23.15)
ALT[i] (U/L)	24.21 (22.18)
LDH[j] (U/L)	248.62 (301.74)
ALP[k] (U/L)	89.74 (66.82)
D-dimer (µg/mL)	0.524 (0.865)
Ferritin (ng/mL)	161.32 (262.51)
Bilirubin (total; µmol/L)	11.52 (5.49)
Bilirubin (direct; µmol/L)	2.73 (4.81)

[a]HB: hemoglobin.
[b]HCT: hematocrit.
[c]WBC: white blood cell.
[d]CRP: C-reactive protein.
[e]ESR: erythrocyte sedimentation rate.
[f]PT: prothrombin time.
[g]INR: international normalized ratio.
[h]AST: aspartate transaminase.
[i]ALT: alanine transaminase.
[j]LDH: lactate dehydrogenase.
[k]ALP: alkaline phosphatase.

Table 3. Laboratory data from COVID-19 patients admitted to Prince Hamzah Hospital (PHH; n=557).

Investigations	Number of patients	Relative percentage	Absolute percentage
HB[a] (g⁄dL) categories			
Low <12	55	10.3	9.9
Normal 12-16	418	78.3	75.0
High >16	61	11.4	11.0
ND[b]	23	N/A[c]	4.1
HCT[d] (%) categories			
Low <35	43	8.1	7.7
Normal 35-47	435	81.5	78.1
High >47	56	10.5	10.1
ND	23	N/A	4.1
WBC[e] (⁄µL) categories			
Low <4000	40	7.5	7.2
Normal 4000-11,000	466	87.4	83.7
High >11,000	27	5.1	4.8
ND	24	N/A	4.3
Neutrophil (%) categories			
Low <40	79	14.8	14.2
Normal 40-80	430	80.5	77.2
High >80	25	4.7	4.5
ND	23	N/A	4.1
Lymphocyte (%) categories			
Low <20	70	13.1	12.6
Normal 20-40	304	56.9	54.6
High >40	160	30.0	28.7
ND	23	N/A	4.1
Basophil (%) categories			
Low <0.5	250	46.6	44.9
Normal 0.5-1	258	48.1	46.3
High >1	28	5.2	5.0
ND	21	N/A	3.8
Monocyte (%) categories			
Low <2	4	0.8	0.7
Normal 2-10	383	71.9	68.8
High >10	146	27.4	26.2
ND	24	N/A	4.3
Eosinophil (%) categories			
Low <1	242	45.3	43.4
Normal 1-6	276	51.7	49.6
High >6	17	3.0	3.1
ND	22	N/A	3.9
Platelets (count⁄µL) categories			

Investigations	Number of patients	Relative percentage	Absolute percentage
Low <150,000	37	6.9	6.6
Normal 150,000-450,000	488	91.6	87.6
High >450,000	8	1.5	1.4
ND	24	N/A	4.3
CRP[f] (mg/L) categories			
Normal 0-5.0	322	66.3	57.8
High >5.0	160	33.2	28.7
ND	75	N/A	13.5
ESR[g] (mm/h) categories			
Normal 0-15	142	49.1	25.5
High >20	147	50.9	26.4
ND	268	N/A	48.1
PT[h] (s) categories			
Low <12	16	5.5	2.9
Normal 12-16	262	90.0	47.0
High >16	13	4.5	2.3
ND	266	N/A	47.8
INR[i] categories			
Low <0.85	1	0.4	0.2
Normal 0.85-1.15	255	92.4	45.8
High >1.15	20	7.2	3.6
ND	281	N/A	50.4
Urea (mmol/L) categories			
Low <2.86	39	7.8	7.0
Normal 2.86-8.2	444	88.4	79.7
High >8.2	19	3.8	3.4
ND	55	N/A	9.9
Creatinine (mmol/L) categories			
Low <59	161	31.1	28.9
Normal 59-104	329	63.3	59.1
High >104	27	5.2	4.8
ND	40	N/A	7.2
Sodium (mmol/L) categories			
Low <135	28	5.5	5.0
Normal 135-152	479	94.5	86.0
High >152	0	0.0	0.0
ND	50	N/A	9.0
Potassium (mmol/L) categories			
Low <3.5	23	4.5	4.1
Normal 3.5-5.3	476	93.9	85.5
High >5.3	8	1.6	1.4
ND	50	N/A	9.0

Investigations	Number of patients	Relative percentage	Absolute percentage
AST[j] (U/L) categories			
Normal ≤38	414	87.9	74.3
High >38	57	12.1	10.2
ND	86	N/A	15.4
ALT[k] (U/L) categories			
Normal ≤41	443	90.0	79.6
High >41	49	10.0	8.8
ND	65	N/A	11.7
LDH[l] (U/L) categories			
Low <125	13	3.6	2.3
Normal 125-378	321	88.7	57.6
High >378	28	7.7	5.0
ND	195	N/A	35.0
ALP[m] (U/L) categories			
Low <40	15	5.7	2.7
Normal 40-150	226	85.3	40.6
High >150	24	9.1	4.3
ND	292	N/A	52.4
D-dimer (µg/mL) categories			
Normal <0.5	265	78.4	47.6
High >0.5	73	21.6	13.1
ND	219	N/A	39.3
Ferritin (ng/mL) categories			
Low <12	11	3.7	2.0
Normal 12-300	255	86.7	45.8
High >300	28	9.5	5.0
ND	263	N/A	47.2
Bilirubin (total; µmol/L) categories			
Low <3	9	2.7	1.6
Normal 3-16	269	81.8	48.3
High >16	51	15.5	9.2
ND	228	N/A	40.9
Bilirubin (direct; µmol/L) categories			
Normal <5.1	282	92.5	50.6
High >5.1	23	7.5	4.1

Investigations	Number of patients	Relative percentage	Absolute percentage
ND	252	N/A	45.2

[a]HB: hemoglobin.
[b]ND: not determined.
[c]N/A: not applicable.
[d]HCT: hematocrit.
[e]WBC: white blood cell.
[f]CRP: C-reactive protein.
[g]ESR: erythrocyte sedimentation rate.
[h]PT: prothrombin time.
[i]INR: international normalized ratio.
[j]AST: aspartate transaminase.
[k]ALT: alanine transaminase.
[l]LDH: lactate dehydrogenase.
[m]ALP: alkaline phosphatase.

Radiological Features of COVID-19

The following radiological data were obtained for 135 COVID-19 patients. CT scan studies of the chest showed that the most common appearance of infiltrates was ground glass opacity (44/135, 32.6%), followed by broncho-alveolar consolidation (14/135, 10.4%). Central involvement was noticed in 7.4% (10/135) of the patients, while peripheral involvement was observed in 26.0% (35/135) of the patients. Also, 25.2% (34/135) of the patients had lesions that were located posteriorly, in comparison to 8.1% (11/135) who had anterior lesions and 25.2% (34/135) who had mediastinal lymphadenopathy. The most affected lobe was the right lower lobe (38/135, 28.1%), followed by the left lower lobe (33/135, 24.4%), left upper lobe (23/135, 17.0%), right upper lobe (22/135, 16.3%), and right middle lobe (20/135, 14.8%; Table 4).

Table 4. Clinical imaging data from a chest computed tomography scan for COVID-19 patients admitted to Prince Hamzah Hospital (PHH; n=135).

Variable	Number of patients	Relative percentage	Absolute percentage
Patterns of infiltrates			
Ground glass opacity	44	32.6	7.8
Broncho-alveolar consolidation	14	10.4	2.5
Crazy paving	4	3.0	0.7
Subpleural retraction	3	2.2	0.5
Bronchiectasis	2	1.5	0.4
Vascular dilatation	0	0.0	0.0
Central vs peripheral			
Central	10	7.4	1.8
Peripheral	35	26.0	6.3
Anterior vs posterior			
Anterior	11	8.1	2.0
Posterior	34	25.2	6.1
Pleural effusion	0	0.0	0.0
Mediastinal lymphadenopathy	34	25.2	6.1
Affected lobe			
Right upper lobe	22	16.3	4.0
Right middle lobe	20	14.8	3.6
Right lower lobe	38	28.1	6.8
Left upper lobe	23	17.0	4.1
Left lower lobe	33	24.4	5.9

X-ray scans showed that 3 patients (3/135, 2.2%) had solitary infiltrates, while 20 patients (20/135, 14.8%) had multiple infiltrates. Also, it showed that 4 patients (4/135, 3.0%) had peripheral lesions, 3 patients (3/135, 2.2%) had central lesions, and 1 patient (1/135, 0.7%) had both peripheral and central lesions. Regarding the most affected lung lobes, the data showed the following: left lower lobe (17/135, 12.6%), right lower lobe (21/135, 15.6%), right middle lobe (17/135, 12.6%), right upper lobe (12/135, 8.9%), and left upper lobe (12/135, 8.9%). Only 1 patient (1/135, 0.7%) had affected lung apices, and only 2 patients (2/135, 1.5%) had a pleural effusion. No patient had hilar involvement or a widened mediastinum (Table 5).

Table 5. Clinical imaging data from a chest x-ray for COVID-19 patients admitted to Prince Hamzah Hospital (PHH; n=135).

Variable	Number of patients	Relative percentage	Absolute percentage
Hilum affected	0	0.0	0.0
Infiltration			
Solitary	3	2.2	0.5
Multiple	20	14.8	3.5
ND[a]	112	83.0	20.1
Central vs peripheral			
Central	3	2.2	0.5
Peripheral	4	3.0	0.7
Both	1	0.7	0.2
ND	127	94.1	22.8
Affected lung lobes			
Right upper lobe	12	8.9	2.2
Right middle lobe	17	12.6	3.1
Right lower lobe	21	15.6	3.8
Left upper lobe	12	8.9	2.2
Left middle lobe	16	11.9	2.9
Left lower lobe	17	12.6	3.1
Affected lung apices	1	0.7	0.2
Pleural effusion	2	1.5	0.4
Widened mediastinum	0	0.0	0.0

[a]ND: not determined.

Associations Between Age, Gender, BMI, Hospitalization Duration and COVID-19 Clinical, Laboratory, Imaging Data

Men had a significantly higher frequency of having symptoms (symptom score) than women (244/479, 51.0% vs 19/78, 24.4%, *P*=.004). Furthermore, generalized malaise, diarrhea, chills/rigors, dry cough, rhinorrhea, and fever were significantly more frequent in men than in women (*P*≤.05). Mean heart rate and frequency of elevated heart rate were significantly higher in men than in women (*P*=.02). Past medical, past surgical, allergy, and smoking history were significantly higher in men than in women (*P*≤.001). Hemoglobin, hematocrit, monocyte %, basophile %, and creatinine levels were significantly higher in men than in women (*P*<.05), while ESR, alkaline phosphatase (ALP), and D-dimer levels were significantly higher in women than in men (*P*≤.05). Hospitalization duration and intensive care unit (ICU) admissions were significantly higher in men than in women (*P*=.000); 7 men and 1 woman were admitted to the ICU, and 2 men died. Table 6 shows the associations between age, gender, BMI, and hospitalization duration in relation to symptoms and signs, laboratory data, and imaging findings.

Table 6. Associations between age, gender, BMI, hospitalization duration and COVID-19 clinical, laboratory, imaging data.

Variable	*P* value for the associations			
	Age	Gender	BMI	Hospitalization duration
Symptoms				
Dry cough	.03	.02	.84	.000
Fever	.07	.03	.06	.000
Wet cough	.27	.13	.53	.001
Chills/rigors	.99	.003	.31	.000
Sweating	.99	.27	.61	.004
Generalized malaise	.01	.000	.23	.000
Myalgia	.40	.054	.19	.000
Shortness of breath	.001	.46	.23	.000
Headache	.02	.08	.22	.000
Hemoptysis	.72	.64	.23	.25
Diarrhea	.013	.04	.17	.000
Chest pain	.001	.27	.97	.002
Abdominal pain	.10	.34	.57	.003
Palpitations	.001	.53	.66	.01
Loss of taste	.000	.26	.48	.000
Loss of smell	.000	.23	.77	.006
Rhinorrhea	.003	.03	.02	.000
Nasal congestion	.14	.20	.16	.000
Symptom severity score	.03	.004	.047	.000
History				
Past medical history	.000	.001	.50	.000
Past surgical history	.000	.001	.42	.001
Allergy	.24	.000	.41	.000
Smoking	.000	.000	.19	.000
Signs				
Heart rate	.13	.02	.60	.000
Systolic blood pressure	.000	.42	.02	.001
Diastolic blood pressure	.008	.28	.04	.000
Respiratory rate	.08	.13	.87	.001
O_2 saturation	.000	.89	.74	.000
Laboratory				
Hemoglobin	.000	.000	.57	.34
Hematocrit	.000	.000	.72	.61
WBC[a]	.07	.31	.70	.000
Neutrophils	.000	.25	.26	.12
Basophils	.32	.046	.50	.72
Monocytes	.31	.02	.62	.000
Eosinophils	.000	.33	.61	.002
Lymphocytes	.000	.70	.23	.09
Platelets	.002	.47	.62	.35

Variable	*P* value for the associations			
	Age	Gender	BMI	Hospitalization duration
CRP[b]	.000	.51	.000	.006
ESR[c]	.000	.000	.03	.04
PT[d]	.04	.86	.97	.46
INR[e]	.35	.91	.30	.000
Urea	.000	.08	.16	.39
Creatinine	.000	.000	.000	.01
Sodium	.000	.77	.41	.79
Potassium	.04	.49	.30	.25
AST[f]	.005	.61	.41	.05
ALT[g]	.02	.14	.02	.06
LDH[h]	.045	.91	.11	.12
ALP[i]	.000	.04	.000	.07
D-dimer	.000	.01	.10	.24
Ferritin	.000	.26	.44	.51
Total bilirubin	.70	.31	.11	.67
Direct bilirubin	.33	.06	.93	.005
Imaging				
Chest x-ray	.000	.52	.02	.25
CT[j] scan conclusion	.001	.89	.003	.72
Other				
Hospitalization duration	.000	.001	.91	N/A[k]
Age	N/A	.23	.000	.000
Patient gender	.23	N/A	.16	.001
BMI	.000	.16	N/A	.91

[a]WBC: white blood cells.

[b]CRP: C-reactive protein.

[c]ESR: erythrocyte sedimentation rate.

[d]PT: prothrombin time.

[e]INR: international normalized ratio.

[f]AST: aspartate transaminase.

[g]ALT: alanine transaminase.

[h]LDH: lactate dehydrogenase.

[i]ALP: alkaline phosphatase.

[j]CT: computed tomography.

[k]N/A: not applicable.

Increased age was significantly associated with a higher frequency of symptoms (symptom score; *P*=.03); increased frequency of generalized malaise, headache, loss of smell, diarrhea, loss of taste, rhinorrhea, wet and dry cough, shortness of breath, chest pain, and palpitations; higher frequency of significant past medical, past surgical, and smoking history; and increased blood pressure, lower oxygen saturation, and higher BMI (*P*≤.05). Furthermore, increased age was significantly associated with elevated CRP, ESR, urea, creatinine, ALT, and ALP levels and positive imaging findings (*P*≤.05; Table 6). Higher BMI was associated with increased age; higher symptom score; elevated blood pressure, CRP, ESR, creatinine, ALT, and ALP levels; and positive imaging findings (*P*≤.05; Table 6). Hospitalization duration was positively associated with increased age, male gender, higher symptom score, history of smoking, significant past medical and surgical histories, elevated systolic blood pressure, elevated respiratory rate, lower oxygen saturation, elevated monocyte %, elevated

CRP and ESR, increased creatinine, and elevated D-dimer (P<0.05; Table 6).

Discussion

Principal Findings

Jordan has successfully managed to contain the first wave of the SARS-CoV2 virus by implementing early lockdowns. The lockdown began on March 18, 2020, when the number of known cases of the virus was less than 20. Jordan closed its borders on March 16, 2020 and kept arriving passengers in quarantine. Extensive contact tracing was carried out, and every person who tested positive for the virus was admitted to the hospital to control the spread of the virus [17]. These measures resulted in Jordan having fewer COVID-19 cases per capita compared with other countries in the region and around the world. By May 15, 2020, Jordan had 58 cases per 1 million population (1 M pop) and 0.9 deaths/1 M pop, compared with Portugal, which has about the same population and had 2776 cases/1 M pop and 116/1 M pop death, and with Greece, with 266 cases/1 M pop and 15 deaths/1 M pop. Neighboring Saudi Arabia had 1349 cases/1 M pop and 8 deaths/1 M pop [3,16-18].

Having all COVID-19–positive patients admitted to the hospital for isolation provided an opportunity to study the clinical and laboratory characteristics in patients with SARS-CoV2 viral infection in Jordan. PHH in Jordan was the main hospital designated to admit patients positive for the SARS-CoV2 virus. The patients were admitted regardless of their symptoms. In Jordan, most cases were in the age range of 21-40 years (34.1%), which is comparable to other studies [2,19]. Furthermore, a meta-analysis later in the pandemic by Pormohammad et al [4] had a mean age of 48 years for patients from studies around the world.

In this study, the younger age group (0-20 years old) represented about 29% of the cases, which was higher than the percentiles of young people infected in Saudi Arabia and China, where the percentages were about 15% [2,19]. More recently, in the United States, children under 18 years old represented 12% of all COVID-19 cases [20]. In South Korea, where all patients with positive tests were also admitted, only 9% of the patients were under 20 years of age, with the population under 24 years old representing about 24% of the nation's population [21]. The age group under 20 years old represents about 44% of the Jordanian population [18], and this is the most likely reason for this higher percentage of COVID-19 cases among the young. Also likely contributing to this is the fact that all patients with positive tests were admitted, and extensive contact tracing was carried out.

There were more men than women in this study (86% men), which is different from other studies that either showed a slightly increased percentage of male patients [4,19] or, in a more recent meta-analysis of 3 million patients, showed equal infection rates between the 2 sexes [22]. This difference is difficult to explain but could be caused by the fact that SARS-CoV2 infection was mainly contracted by travelers and men working in the trucking business who then spread the disease to their family members [16]. Regarding the symptoms of COVID-19 in this study, most patients were asymptomatic (52.6%), and among symptomatic patients, dry cough (21.7%) and generalized malaise (21.5%), followed by fever (19.4%), were the most prevalent symptoms. This is quite similar to other studies, including 2 meta-analyses that showed that fever and cough were the most common symptoms [10,23]. Less common symptoms such as headache (13.5%), rhinorrhea (10.2%), and diarrhea (10.2%) were reported at much higher percentages in this study [24]. This is most likely explained by the fact that all patients with SARS-CoV2 viral infection were admitted regardless of symptoms, whereas other studies mainly included patients hospitalized due to their symptoms.

In this study, only 13.1% of COVID-19 patients had lymphopenia, while 30% had lymphocytosis and 56.9% of patients had a normal lymphocyte count. This contrasts with most other studies that tended to show an association between lymphopenia and COVID-19 [4,10]. Some studies hypothesized that lymphopenia may correlate with disease severity, such that lymphocyte count could possibly be used as a prognostic factor for COVID-19 patients [25,26]. Since more than half of the patients in our study were asymptomatic, this may explain the low percentage of COVID-19 patients found to have lymphopenia.

Inflammatory markers in COVID-19 patients in our study, including CRP, ESR, and LDH, were inconsistent with the findings of 2 meta-analyses [4,10]. This is most likely due to the high percentage of asymptomatic (52.6%) patients in this study. This finding increases the possibility of a positive association between high inflammatory markers and the severity of COVID-19, as proposed by yet another meta-analysis [27]. Abnormal liver enzymes, including AST and ALT, were present at lower rates compared with the results found elsewhere [28].

The radiological data from CT and x-ray scans of 135 patients were collected and analyzed. The most common lesion detected by CT scan was ground glass appearance, and this is consistent with what was found in the meta-analysis done by Bao et al [9], but at a much lower rate than those authors found (32.6% vs 90.35%, respectively). Peripheral involvement was more common than central involvement, and posterior involvement was more common than anterior involvement. These findings are similar to what was found by another study [29]. Multilobar distribution was more common than unilobar distribution, and the lower lobes were more affected than the upper lobes. Other studies found similar results [30,31]. The majority of patients who underwent chest x-ray had normal results, while Wong et al [31] found that 69% of the patients had abnormal findings on their chest radiography. This may be related to the fact that the majority of the patients in our study were asymptomatic.

When comparing male patients to female patients admitted with SARS-CoV2 infection, it was noted that male patients were more symptomatic than female patients (51.0% vs 24.4%, P<.05). Men were also more likely to be admitted to ICUs. In a meta-analysis that compared around 3 million patients from around the world [22], men had higher rates of ICU admission and mortality as well. The reason for this difference in morbidity and mortality between the sexes may be due to differences in the adaptive and innate immune systems, as the adaptive

immune system in women has a higher number of CD 4 T cells [32,33] and stronger CD 8 cytotoxic activity [34]. Women also have more B cells and antibody production [32,35]. The reason for these differences is due to X-linked genes that affect the immune response to viruses [15,35].

Age was associated with increased symptoms (P<.05) and abnormal lab results. This has been documented in many other studies [36,37]. Age is also related to increased comorbidities, and in 1 meta-analysis in which there was an attempt to control for comorbidities, age itself remained a weak risk factor [38]. In our study, having an increased BMI was associated with having more symptoms, and this finding is similar to other studies and meta-analyses [39,40].

This study is the first to address the clinical, laboratory, and radiological features of COVID-19 patients in Jordan, and it was conducted with 557 patients, a considerable number of participants. A downside of this study is that all of the participants were from 1 center (PHH). Also, the data regarding laboratory testing and imaging were incompletely collected.

Conclusions

This is the first study to describe in detail all the clinical, laboratory, and imaging findings of the first 557 confirmed COVID-19 patients admitted to PHH in Jordan. Most cases were asymptomatic, male, and overweight or obese. Generalized malaise and dry cough were the most common symptoms. Only 2.5% had a respiratory rate over 25 breaths/minute, and 2% had an oxygen saturation below 85%. Lymphocytosis and elevated CRP, ESR, and D-dimer were the most common laboratory abnormalities, while ground glass opacity was the most common imaging finding. Men had a significantly higher frequency of symptoms, smoking, abnormal laboratory findings, and ICU admissions compared to women. Hospitalization duration was positively correlated with increased age, male gender, symptom score, history of smoking, elevated systolic blood pressure, elevated respiratory rate, elevated monocyte %, and elevated CRP, ESR, creatinine, and D-dimer.

Acknowledgments

We would like to thank the Hashemite University, the Ministry of Health, the Ministry of Higher Education and Research, and PHH in Jordan for their support. We would like to thank all participants who agreed to be part of this study. The authors would like to acknowledge the Global Health (GHD) for their technical support. We thank Dr Joel Fuller Voughan for editing the manuscript.

This work was supported by the Scientific Research and Innovation Support Fund, Ministry of Higher Education and Research, Jordan.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Data collection sheet.
[XLSX File (Microsoft Excel File), 62 KB - publichealth_v7i9e28005_app1.xlsx]

Multimedia Appendix 2
Demographic, clinical, laboratory, and imaging data of COVID-19 patients.
[XLSX File (Microsoft Excel File), 3369 KB - publichealth_v7i9e28005_app2.xlsx]

References

1. Lu H, Stratton CW, Tang Y. Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. J Med Virol 2020 Apr;92(4):401-402 [FREE Full text] [doi: 10.1002/jmv.25678] [Medline: 31950516]
2. Wang L, Wang Y, Ye D, Liu Q. Review of the 2019 novel coronavirus (SARS-CoV-2) based on current evidence. Int J Antimicrob Agents 2020 Jun;55(6):105948 [FREE Full text] [doi: 10.1016/j.ijantimicag.2020.105948] [Medline: 32201353]
3. WHO Coronavirus (COVID-19) Dashboard. World Health Organization. URL: https://covid19.who.int/ [accessed 2021-09-07]
4. Pormohammad A, Ghorbani S, Baradaran B, Khatami A, J Turner R, Mansournia MA, et al. Clinical characteristics, laboratory findings, radiographic signs and outcomes of 61,742 patients with confirmed COVID-19 infection: A systematic review and meta-analysis. Microb Pathog 2020 Oct;147:104390 [FREE Full text] [doi: 10.1016/j.micpath.2020.104390] [Medline: 32681968]
5. Grant MC, Geoghegan L, Arbyn M, Mohammed Z, McGuinness L, Clarke EL, et al. The prevalence of symptoms in 24,410 adults infected by the novel coronavirus (SARS-CoV-2; COVID-19): A systematic review and meta-analysis of 148 studies from 9 countries. PLoS One 2020 Jun 23;15(6):e0234765 [FREE Full text] [doi: 10.1371/journal.pone.0234765] [Medline: 32574165]
6. Jordan RE, Adab P, Cheng KK. Covid-19: risk factors for severe disease and death. BMJ 2020 Mar 26;368:m1198. [doi: 10.1136/bmj.m1198] [Medline: 32217618]

7. Jiang F, Deng L, Zhang L, Cai Y, Cheung CW, Xia Z. Review of the Clinical Characteristics of Coronavirus Disease 2019 (COVID-19). J Gen Intern Med 2020 May 4;35(5):1545-1549 [FREE Full text] [doi: 10.1007/s11606-020-05762-w] [Medline: 32133578]
8. Terpos E, Ntanasis-Stathopoulos I, Elalamy I, Kastritis E, Sergentanis TN, Politou M, et al. Hematological findings and complications of COVID-19. Am J Hematol 2020 Jul;95(7):834-847 [FREE Full text] [doi: 10.1002/ajh.25829] [Medline: 32282949]
9. Bao C, Liu X, Zhang H, Li Y, Liu J. Coronavirus Disease 2019 (COVID-19) CT Findings: A Systematic Review and Meta-analysis. J Am Coll Radiol 2020 Jun;17(6):701-709 [FREE Full text] [doi: 10.1016/j.jacr.2020.03.006] [Medline: 32283052]
10. Rodriguez-Morales AJ, Cardona-Ospina JA, Gutiérrez-Ocampo E, Villamizar-Peña R, Holguin-Rivera Y, Escalera-Antezana JP, Latin American Network of Coronavirus Disease 2019-COVID-19 Research (LANCOVID-19). Clinical, laboratory and imaging features of COVID-19: A systematic review and meta-analysis. Travel Med Infect Dis 2020 Mar;34:101623 [FREE Full text] [doi: 10.1016/j.tmaid.2020.101623] [Medline: 32179124]
11. Jin J, Bai P, He W, Wu F, Liu X, Han D, et al. Gender Differences in Patients With COVID-19: Focus on Severity and Mortality. Front Public Health 2020 Apr 29;8:152 [FREE Full text] [doi: 10.3389/fpubh.2020.00152] [Medline: 32411652]
12. Gebhard C, Regitz-Zagrosek V, Neuhauser HK, Morgan R, Klein SL. Impact of sex and gender on COVID-19 outcomes in Europe. Biol Sex Differ 2020 May 25;11(1):29 [FREE Full text] [doi: 10.1186/s13293-020-00304-9] [Medline: 32450906]
13. Cai H. Sex difference and smoking predisposition in patients with COVID-19. The Lancet Respiratory Medicine 2020 Apr;8(4):e20. [doi: 10.1016/s2213-2600(20)30117-x]
14. Saheb Sharif-Askari N, Saheb Sharif-Askari F, Alabed M, Temsah M, Al Heialy S, Hamid Q, et al. Airways Expression of SARS-CoV-2 Receptor, ACE2, and TMPRSS2 Is Lower in Children Than Adults and Increases with Smoking and COPD. Mol Ther Methods Clin Dev 2020 Sep 11;18:1-6 [FREE Full text] [doi: 10.1016/j.omtm.2020.05.013] [Medline: 32537478]
15. Ambrosino I, Barbagelata E, Ortona E, Ruggieri A, Massiah G, Giannico OV, et al. Gender differences in patients with COVID-19: a narrative review. Monaldi Arch Chest Dis 2020 May 25;90(2):1 [FREE Full text] [doi: 10.4081/monaldi.2020.1389] [Medline: 32449614]
16. COVID-19 Statistical Report - Jordan. Ministry of Health. URL: https://corona.moh.gov.jo/en [accessed 2021-09-07]
17. Jordan. WorldoMeter. URL: https://www.worldometers.info/coronavirus/country/jordan/ [accessed 2021-09-07]
18. Population estimates. Department of Statistics Jordan. URL: http://dosweb.dos.gov.jo/DataBank/Population_Estimares/PopulationEstimates.pdf [accessed 2021-09-07]
19. Alsofayan YM, Althunayyan SM, Khan AA, Hakawi AM, Assiri AM. Clinical characteristics of COVID-19 in Saudi Arabia: A national retrospective study. J Infect Public Health 2020 Jul;13(7):920-925 [FREE Full text] [doi: 10.1016/j.jiph.2020.05.026] [Medline: 32534945]
20. Children and COVID-19: State-Level Data Report. American Academy of Pediatrics. URL: https://services.aap.org/en/pages/2019-novel-coronavirus-covid-19-infections/children-and-covid-19-state-level-data-report [accessed 2021-09-07]
21. Coronavirus Disease-19, Republic of Korea. Ministry of Health. URL: http://ncov.mohw.go.kr/en [accessed 2021-09-07]
22. Peckham H, de Gruijter NM, Raine C, Radziszewska A, Ciurtin C, Wedderburn LR, et al. Male sex identified by global COVID-19 meta-analysis as a risk factor for death and ITU admission. Nat Commun 2020 Dec 09;11(1):6317 [FREE Full text] [doi: 10.1038/s41467-020-19741-6] [Medline: 33298944]
23. Li L, Huang T, Wang Y, Wang Z, Liang Y, Huang T, et al. COVID-19 patients' clinical characteristics, discharge rate, and fatality rate of meta-analysis. J Med Virol 2020 Jun 23;92(6):577-583 [FREE Full text] [doi: 10.1002/jmv.25757] [Medline: 32162702]
24. Chen J, Qi T, Liu L, Ling Y, Qian Z, Li T, et al. Clinical progression of patients with COVID-19 in Shanghai, China. J Infect 2020 May;80(5):e1-e6 [FREE Full text] [doi: 10.1016/j.jinf.2020.03.004] [Medline: 32171869]
25. Wagner J, DuPont A, Larson S, Cash B, Farooq A. Absolute lymphocyte count is a prognostic marker in Covid-19: A retrospective cohort review. Int J Lab Hematol 2020 Dec 10;42(6):761-765 [FREE Full text] [doi: 10.1111/ijlh.13288] [Medline: 32779838]
26. Zhao Q, Meng M, Kumar R, Wu Y, Huang J, Deng Y, et al. Lymphopenia is associated with severe coronavirus disease 2019 (COVID-19) infections: A systemic review and meta-analysis. Int J Infect Dis 2020 Jul;96:131-135 [FREE Full text] [doi: 10.1016/j.ijid.2020.04.086] [Medline: 32376308]
27. Zeng F, Huang Y, Guo Y, Yin M, Chen X, Xiao L, et al. Association of inflammatory markers with the severity of COVID-19: A meta-analysis. Int J Infect Dis 2020 Jul;96:467-474 [FREE Full text] [doi: 10.1016/j.ijid.2020.05.055] [Medline: 32425643]
28. Garrido I, Liberal R, Macedo G. Review article: COVID-19 and liver disease-what we know on 1st May 2020. Aliment Pharmacol Ther 2020 Jul 02;52(2):267-275 [FREE Full text] [doi: 10.1111/apt.15813] [Medline: 32402090]
29. Salehi S, Abedi A, Balakrishnan S, Gholamrezanezhad A. Coronavirus Disease 2019 (COVID-19): A Systematic Review of Imaging Findings in 919 Patients. American Journal of Roentgenology 2020 Jul;215(1):87-93. [doi: 10.2214/ajr.20.23034]
30. Han R, Huang L, Jiang H, Dong J, Peng H, Zhang D. Early Clinical and CT Manifestations of Coronavirus Disease 2019 (COVID-19) Pneumonia. American Journal of Roentgenology 2020 Aug;215(2):338-343. [doi: 10.2214/ajr.20.22961]

31. Wong HYF, Lam HYS, Fong AH, Leung ST, Chin TW, Lo CSY, et al. Frequency and Distribution of Chest Radiographic Findings in Patients Positive for COVID-19. Radiology 2020 Aug;296(2):E72-E78 [FREE Full text] [doi: 10.1148/radiol.2020201160] [Medline: 32216717]
32. Abdullah M, Chai P, Chong M, Tohit ERM, Ramasamy R, Pei CP, et al. Gender effect on in vitro lymphocyte subset levels of healthy individuals. Cell Immunol 2012 Jan;272(2):214-219. [doi: 10.1016/j.cellimm.2011.10.009] [Medline: 22078320]
33. Lee B, Yap H, Chew F, Quah T, Prabhakaran K, Chan GS, et al. Age- and sex-related changes in lymphocyte subpopulations of healthy Asian subjects: From birth to adulthood. Cytometry 1996 Mar 15;26(1):8-15. [doi: 10.1002/(sici)1097-0320(19960315)26:1<8::aid-cyto2>3.0.co;2-e]
34. Hewagama A, Patel D, Yarlagadda S, Strickland FM, Richardson BC. Stronger inflammatory/cytotoxic T-cell response in women identified by microarray analysis. Genes Immun 2009 Jul 12;10(5):509-516 [FREE Full text] [doi: 10.1038/gene.2009.12] [Medline: 19279650]
35. Conti P, Younes A. Coronavirus COV-19/SARS-CoV-2 affects women less than men: clinical response to viral infection. J Biol Regul Homeost Agents 2020;34(2):339-343. [doi: 10.23812/Editorial-Conti-3] [Medline: 32253888]
36. O'Driscoll M, Ribeiro Dos Santos G, Wang L, Cummings DAT, Azman AS, Paireau J, et al. Age-specific mortality and immunity patterns of SARS-CoV-2. Nature 2021 Feb 02;590(7844):140-145. [doi: 10.1038/s41586-020-2918-0] [Medline: 33137809]
37. Liu Y, Mao B, Liang S, Yang J, Lu H, Chai Y, Shanghai Clinical Treatment Experts Group for COVID-19. Association between age and clinical characteristics and outcomes of COVID-19. Eur Respir J 2020 May;55(5):2001112 [FREE Full text] [doi: 10.1183/13993003.01112-2020] [Medline: 32312864]
38. Romero Starke K, Petereit-Haack G, Schubert M, Kämpf D, Schliebner A, Hegewald J, et al. The Age-Related Risk of Severe Outcomes Due to COVID-19 Infection: A Rapid Review, Meta-Analysis, and Meta-Regression. Int J Environ Res Public Health 2020 Aug 17;17(16):5974 [FREE Full text] [doi: 10.3390/ijerph17165974] [Medline: 32824596]
39. Hamer M, Gale CR, Kivimäki M, Batty GD. Overweight, obesity, and risk of hospitalization for COVID-19: A community-based cohort study of adults in the United Kingdom. Proc Natl Acad Sci U S A 2020 Sep 01;117(35):21011-21013 [FREE Full text] [doi: 10.1073/pnas.2011086117] [Medline: 32788355]
40. Chang T, Chou C, Chang L. Effect of obesity and body mass index on coronavirus disease 2019 severity: A systematic review and meta-analysis. Obes Rev 2020 Nov;21(11):e13089. [doi: 10.1111/obr.13089] [Medline: 32929833]

Abbreviations

ACE2: angiotensin-converting enzyme 2
ALP: alkaline phosphatase
ALT: alanine transaminase
AST: aspartate transaminase
COPD: chronic obstructive pulmonary disease
CRP: C-reactive protein
CT: computed tomography
ESR: erythrocyte sedimentation rate
ICU: intensive care unit
IRB: institutional review board
LDH: lactate dehydrogenase
PCR: polymerase chain reaction
PHH: Prince Hamzah Hospital
RT-PCR: reverse transcription polymerase chain reaction

Edited by DR Saadeh, T Sanchez, Y Khader; submitted 16.02.21; peer-reviewed by M Popovic, R Menhas; comments to author 14.04.21; revised version received 05.05.21; accepted 12.05.21; published 21.09.21.

Please cite as:
Qaisieh R, Al-Tamimi M, El-Hammuri N, Shalabi M, Kilani MM, Taha H, Al-Muhtaseb A, Alfarrajin I, Abu Shaqra M, Hamdan A
Clinical, Laboratory, and Imaging Features of COVID-19 in a Cohort of Patients: Cross-Sectional Comparative Study
JMIR Public Health Surveill 2021;7(9):e28005
URL: https://publichealth.jmir.org/2021/9/e28005
doi:10.2196/28005
PMID:34081600

Original Paper

COVID-19 Vaccine Perception in South Korea: Web Crawling Approach

Hocheol Lee[1], PhD; Eun Bi Noh[1,2], MPH; Sung Jong Park[3], MPH; Hae Kweun Nam[4], MS; Tae Ho Lee[1], PhD; Ga Ram Lee[3], BA; Eun Woo Nam[1,2], PhD

[1]Yonsei Global Health Center, Yonsei University, Wonju, Republic of Korea

[2]Department of Health Administration, Yonsei University Graduate School, Wonju, Republic of Korea

[3]Department of Information Statistics, Yonsei University Graduate School, Wonju, Republic of Korea

[4]Department of Preventive Medicine, Wonju College of Medicine, Yonsei University, Wonju, Republic of Korea

Corresponding Author:
Eun Woo Nam, PhD
Department of Health Administration, Yonsei University Graduate School
Unit 412, Chang-jo gwan
1 Yonseidae-gil
Wonju, 26493
Republic of Korea
Phone: 82 33 760 2413
Fax: 82 33 760 2519
Email: ewnam@yonsei.ac.kr

Abstract

Background: The US Centers for Disease Control and Prevention and the World Health Organization emphasized vaccination against COVID-19 because physical distancing proved inadequate to mitigate death, illness, and massive economic loss.

Objective: This study aimed to investigate Korean citizens' perceptions of vaccines by examining their views on COVID-19 vaccines, their positive and negative perceptions of each vaccine, and ways to enhance policies to increase vaccine acceptance.

Methods: This cross-sectional study analyzed posts on NAVER and Instagram to examine Korean citizens' perception of COVID-19 vaccines. The keywords searched were "vaccine," "AstraZeneca," and "Pfizer." In total 8100 posts in NAVER and 5291 posts in Instagram were sampled through web crawling. Morphology analysis was performed, overlapping or meaningless words were removed, sentiment analysis was implemented, and 3 public health professionals reviewed the results.

Results: The findings revealed a negative perception of COVID-19 vaccines; of the words crawled, the proportion of negative words for AstraZeneca was 71.0% (476/670) and for Pfizer was 56.3% (498/885). Among words crawled with "vaccine," "good" ranked first, with a frequency of 13.43% (312/2323). Meanwhile, "side effect" ranked highest, with a frequency of 29.2% (163/559) for "AstraZeneca," but 0.6% (4/673) for "Pfizer." With "vaccine," positive words were more frequently used, whereas with "AstraZeneca" and "Pfizer" negative words were prevalent.

Conclusions: There is a negative perception of AstraZeneca and Pfizer vaccines in Korea, with 1 in 4 people refusing vaccination. To address this, accurate information needs to be shared about vaccines including AstraZeneca, and the experiences of those vaccinated. Furthermore, government communication about risk management is required to increase the AstraZeneca vaccination rate for herd immunity before the vaccine expires.

(JMIR Public Health Surveill 2021;7(9):e31409) doi:10.2196/31409

KEYWORDS

COVID-19 vaccine; COVID-19; instagram; social media; infodemiology; sentiment analysis; vaccine perception; South Korea; web crawling; AstraZeneca; Pfizer

Introduction

COVID-19 was first reported in Wuhan in December 2019, and on March 11, 2020, the World Health Organization (WHO) declared it a pandemic. As of May 10, 2021, COVID-19 has spread to 221 countries and 159,145,765 confirmed cases and 3,310,621 deaths have been reported internationally [1]. Furthermore, the global economic loss due to COVID-19 in

2020 was estimated at US $9trillion [2]. Accordingly, the US Centers for Disease Control and Prevention (CDC) and the WHO determined that physical (social) distancing alone was insufficient to prevent and eliminate COVID-19 and stressed the need for vaccination while simultaneously initiating the development of COVID-19 vaccines [3,4].

As of May 17, 2021, 7% of the world's population have been vaccinated [5]. However, because clinical trials for vaccines advanced quickly, and vaccines were approved in accelerated processes over a short period, negative information regarding COVID-19 vaccines has proliferated [6], due to which the number of people refusing to be vaccinated has increased. Previous studies have examined people's hesitancy toward vaccines [7-9]. One study [10] reported a variety of significant reasons for vaccine refusal, including lack of trust in the vaccines, deaths due to vaccination, negative rumors about the vaccines, religious beliefs, antigovernment sentiment, public health messaging failure, and a lack of understanding regarding the need for vaccination.

The COVID-19 vaccination rate is rising slowly relative to the initial plans due to incorrect information and negative perception. Thus, there is an opinion that it may have a negative impact on herd immunity in communities [11]. To increase vaccine acceptance, it is necessary to identify the positive and negative aspects of perception regarding COVID-19 vaccination and for governments to respond expeditiously, based on empirical findings. Furthermore, the WHO strongly encourages governments to deliver the accurate information about COVID-19 vaccines to citizens [12]. It is well-known that risk communication using social media, such as Facebook, Twitter, and YouTube, was the most effective way to disseminate information during the SARS epidemic in 2013 [13,14]. That is, governments' risk communication during the COVID-19 pandemic is critical for increasing the acceptance of nonpharmaceutical approaches and COVID-19 vaccines. Korea is 1 of 5 representative countries that responded successfully to the COVID-19 infection [15]. However, the vaccination rate here is lower, compared with that in other more developed countries, as there was a delay in securing vaccine supplies. Moreover, the vaccine refusal rate is 33%, ranking 64th worldwide. Furthermore, with the extensive coverage of vaccine side effects by the media, negative information has become widespread among citizens [16]. This negative information regarding COVID-19 vaccines is spreading on popular Korean social media platforms—with YouTube being the most common, followed by NAVER and Instagram [17].

In Korea, COVID-19 vaccination commenced on February 26, 2021, initially administered to adults aged over 65 years in long-term care hospitals and nursing homes, and to health care professionals. The country developed the following plan and is currently proceeding as planned: adults aged over 60, pharmacy employees, disabled persons, and homeless persons were vaccinated in Q2; all adults were vaccinated in Q3; and all citizens who were unvaccinated are targeted in Q4 [18].

Since early 2021, 2 types of COVID-19 vaccines, AstraZeneca (AZ) and Pfizer, have been produced in Korea. As of May 10, 2021, 4,181,003 people have been vaccinated—2,014,788 with AZ and 2,166,215 with Pfizer. The vaccine refusal rate in Korea was 33%, and these individuals refused to be vaccinated despite being eligible for COVID-19 vaccination. Hence, Korean vaccine experts predict that it would not be feasible to reach herd immunity against COVID-19 by December 2021, because the proportion of vaccinated persons will not reach 70% [19]. Citizens' refusal to be vaccinated poses a major problem to the government's plan.

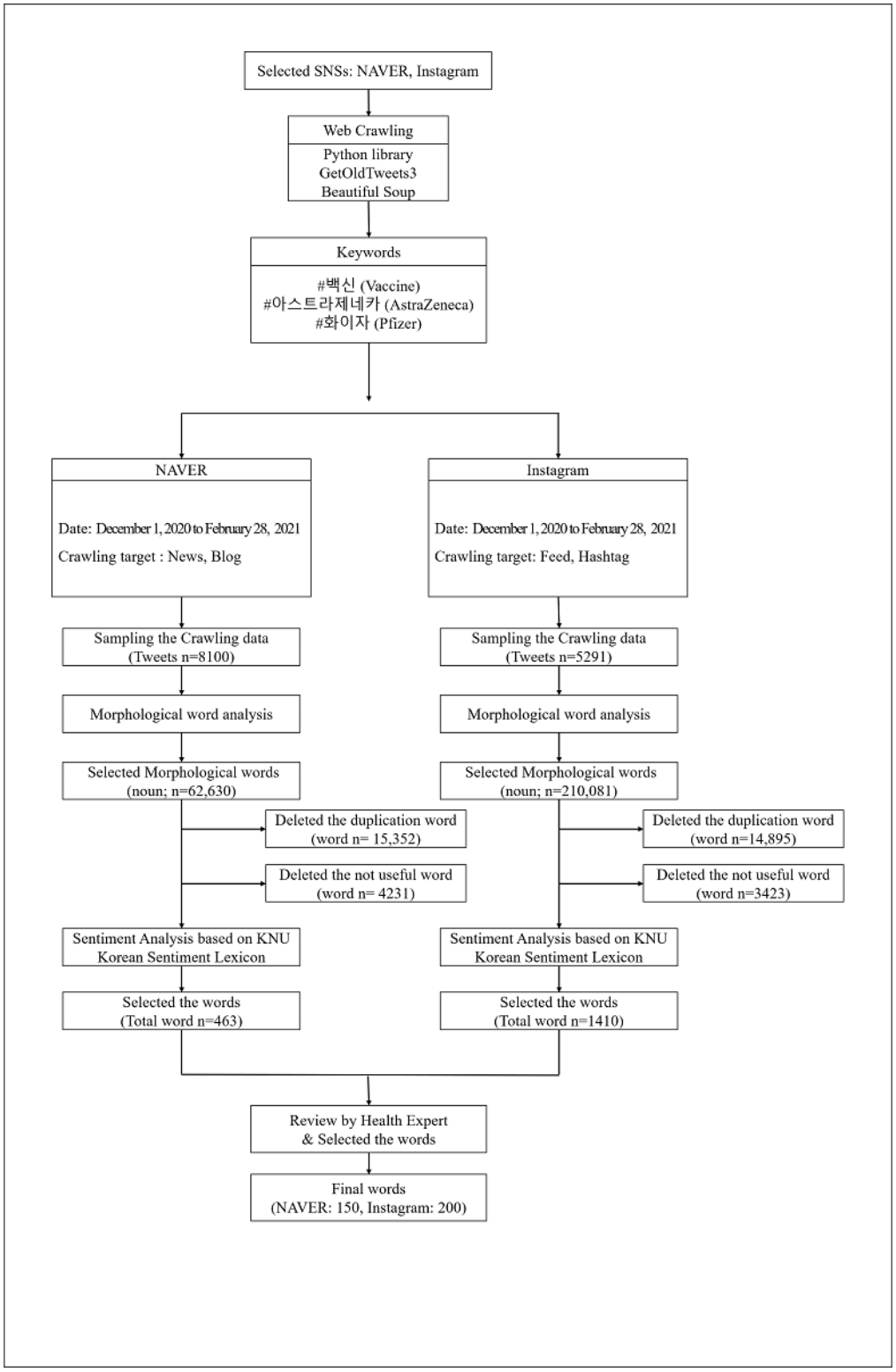
Accordingly, the purpose of this study was to investigate Korean citizens' perceptions of COVID-19 vaccines. The specific objectives were to (1) investigate their perception of COVID-19, (2) examine the positive and negative aspects of the perception of each type of vaccine, and finally, (3) provide evidence needed to develop policies to increase vaccine acceptance by examining the current perception of COVID-19 vaccines.

Methods

Study Design

This cross-sectional study analyzed posts uploaded to NAVER and Instagram (2 social network sites [SNSs] available in Korea) between December 1, 2020, and February 28, 2021, to examine Korean citizens' perception of COVID-19 vaccines. A flowchart of the study is presented in Figure 1.

Figure 1. Research flowchart. SNSs: social network sites, KNU: Kunsan National University.



Data Collection

To examine the COVID-10 vaccine perception of the participants, who were Korean citizens, their SNS posts were analyzed. Data were collected from the 2 most popular SNSs in Korea: NAVER and Instagram. Posts uploaded to NAVER blogs and news and Instagram feeds between December 1, 2020, and February 28, 2021, were collected. To compile the data, web crawling was performed using Requests in Python 3.8.3 Library, Beautiful Soup, and Webdriver. The keywords utilized were “vaccine,” “AstraZeneca,” and “Pfizer.” The search was performed using the search bar in NAVER and the hashtag search in Instagram.

A total of 8100 posts in NAVER and 5291 in Instagram were sampled through web crawling. Morphology analysis was performed, and the NAVER posts were classified into 62,630 words and Instagram posts into 210,081 words. Overlapping or meaningless words were removed, resulting in 463 words from

NAVER and 1410 words from Instagram. Then, sentiment analysis was performed, and 3 public health professionals reviewed the results. Finally, 150 words from NAVER and 200 words from Instagram were included in the analysis.

Statistical Analysis

The words were collected from 2 representative SNSs in Korea, NAVER and Instagram, and were categorized as positive or negative for the purpose of analysis. To classify the words as positive or negative, text mining was performed based on the KNU Korean Sentiment Lexicon [20].

The KNU Korean Sentiment Lexicon, created by the Kunsan University in Korea, is an emotional dictionary consisting of positive and negative words that are used to express people's basic emotions. Each word in the emotional dictionary was determined through the consensus of evaluators using a Likert 5-point scale—"very negative," "negative," "neutral," "positive," and "very positive"—ranging from 2 (very positive) to –2 (very negative). Based on the score, each emotional expression is classified as either positive or negative.

Next, the rankings of the words classified as positive or negative were visualized separately for "vaccine," "AstraZeneca," and "Pfizer," using the word cloud technique. Positive and negative words that were used with the keywords were ranked based on their frequency.

Lastly, the words that were common to "AstraZeneca" and "Pfizer" were visualized by presenting the words associated with AZ on the x-axis and those associated with Pfizer on the y-axis to show word frequency according to the type of vaccine.

Results

Crawling Data Characteristics

In this study, to investigate vaccine acceptance, web crawling was performed using the keywords "vaccine," "AstraZeneca," and "Pfizer" on posts in 2 SNSs available in Korea (Instagram and NAVER) between December 1, 2020, and February 28, 2021. A total of 5291 Instagram posts and 8100 NAVER posts were sampled (Table 1).

The 7-day period during which the largest volume of data was collected from Instagram, 998/5291 posts (18.86%), was between February 22, 2021 and February 28, 2021. From NAVER, the data were collected uniformly for approximately 630/8100 (7.78%) posts per period.

Table 1. The frequency of crawling data.

Date	Instagram (n=5291)	NAVER (n=8100)
	Crawling data, n (%)	Crawling data, n (%)
December 1-7, 2020	239 (4.52)	630 (7.78)
December 8-15, 2020	496 (9.37)	630 (7.78)
December 16-21, 2020	447 (8.45)	630 (7.78)
December 22-28, 2020	379 (7.16)	630 (7.78)
December 29-31, 2020	216 (4.08)	270 (3.33)
January 1-7, 2021	300 (5.67)	630 (7.78)
January 8-15, 2021	355 (6.71)	630 (7.78)
January 16-21, 2021	429 (8.11)	630 (7.78)
January 22-28, 2021	282 (5.33)	630 (7.78)
January 29-31, 2021	187 (3.53)	270 (3.33)
February 1-7, 2021	287 (5.42)	630 (7.78)
February 8-15, 2021	253 (4.78)	630 (7.78)
February 16-21, 2021	423 (7.99)	630 (7.78)
February 22-28, 2021	998 (18.86)	630 (7.78)

Crawling Data Ranking

Of the words collected separately by using the keywords "vaccine," "AstraZeneca," and "Pfizer," the 20 most frequent words are summarized in Table 2. The 20 most frequent words that were crawled with "vaccine" appeared 2323 times. The frequency of the top 20 words crawled with "AstraZeneca" and "Pfizer" were 559 and 486, respectively.

Table 2. Ranking of the crawled data according to word frequency for each vaccine type.

Rank	Type				Vaccine (n=2323)	
	AstraZeneca (n=559)		Pfizer (n=486)			
	Word	n (%)	Word	n (%)	Word	n (%)
1	Safe effect	163 (29.2)	Escape	179 (36.8)	Good	312 (13.4)
2	Possibility	47 (8.4)	Difficult	39 (8.0)	Treatment	231 (9.9)
3	Safety	45 (8.1)	Achieved	39 (8.0)	Health	217 (9.3)
4	Prevention	42 (7.5)	Good	35 (7.2)	Safety	215 (9.3)
5	Treatment	26 (4.7)	Abnormal	26 (5.3)	Death	145 (6.2)
6	Trust	23 (4.1)	Pain	19 (3.9)	Prevention	139 (5.9)
7	Anxiety	22 (3.9)	Peace	18 (3.7)	Possibility	137 (5.9)
8	Difficult	22 (3.9)	No	16 (3.3)	Safe effect	123 (5.2)
9	Refusal	20 (3.6)	Giving up	15 (3.1)	Tough	103 (4.4)
10	Distrust	20 (3.6)	Having a cold	11 (2.3)	Risk	90 (3.9)
11	Ill	19 (3.4)	Value	11 (2.3)	Infected	90 (3.9)
12	Health	17 (3.0)	Fainting	10 (2.1)	Recovery	80 (3.4)
13	Increase	15(2.7)	Need	10 (2.1)	Rise	73 (3.1)
14	Concerned	13 (2.3)	Risk	9 (1.9)	Happy	62 (2.7)
15	Stability	12 (2.1)	Limit	9 (1.9)	Hope	56 (2.4)
16	Shortage	11 (2.0)	Convulsion	8 (1.6)	Overcoming	55 (2.4)
17	Okay	11 (2.0)	Righteous Person	8 (1.6)	Late	55 (2.4)
18	Experts	11 (2.0)	Cautious	8 (1.6)	Anxiety	49 (2.1)
19	Overcoming	10 (1.8)	Improvement	8 (1.6)	Illness	46 (2.0)
20	Recovery	10 (1.8)	Understanding	8 (1.6)	Banned	45 (1.9)

Among the words crawled with “vaccine,” “good” ranked first, with a frequency of 312/2323 (13.43%). The words that ranked second to fifth were “treatment” (231/2323, 9.94%), “health” (217/2323, 9.34%), “safety” (215/2323, 9.26%), and “death” (145/2323, 6.24%), respectively.

Of the words crawled with “AstraZeneca,” “side effect” ranked first, with a frequency of 163/559 (29.2%), followed by “possibility” (47/559, 8.4%), “safety” (45/559, 8.4%), “prevention” (42/559, 7.5%), and “treatment” (26/559, 4.7%).

Of the words crawled with “Pfizer,” “escape” was the most frequent (179/486, 36.8%). The words ranked second to fifth were “difficult” (39/486, 8.0%), “achieved” (39/486, 8.0%), “good” (35/486, 7.2%), and “abnormal” (26/486, 5.3%), respectively.

Classification of Crawled Data Into Positive and Negative Words

The crawled data were classified as positive or negative using a positive/negative classification system and by consulting with 3 public health experts (Table 3).

Table 3. Counts and frequencies of positive and negative words in the crawled data.

	Type				Vaccine	
	Pfizer		AstraZeneca			
	Word count (n=122)	Frequency (n=885)	Word count (n=89)	Frequency (n=670)	Word count (n=146)	Frequency (n=3698)
Positive	47 (38.5)	387 (43.7)	37 (41.6)	194 (29.0)	43 (29.5)	1981 (53.6)
Negative	75 (61.5)	498 (56.3)	52 (58.4)	476 (71.0)	103 (70.5)	1717 (46.4)

Of the words crawled with “vaccine,” 103/146 (70.5%) were classified as negative and 43/146 (29.5%) as positive. Thus, there were more negative words. However, positive words were used more frequently (1981/3698, 53.57%).

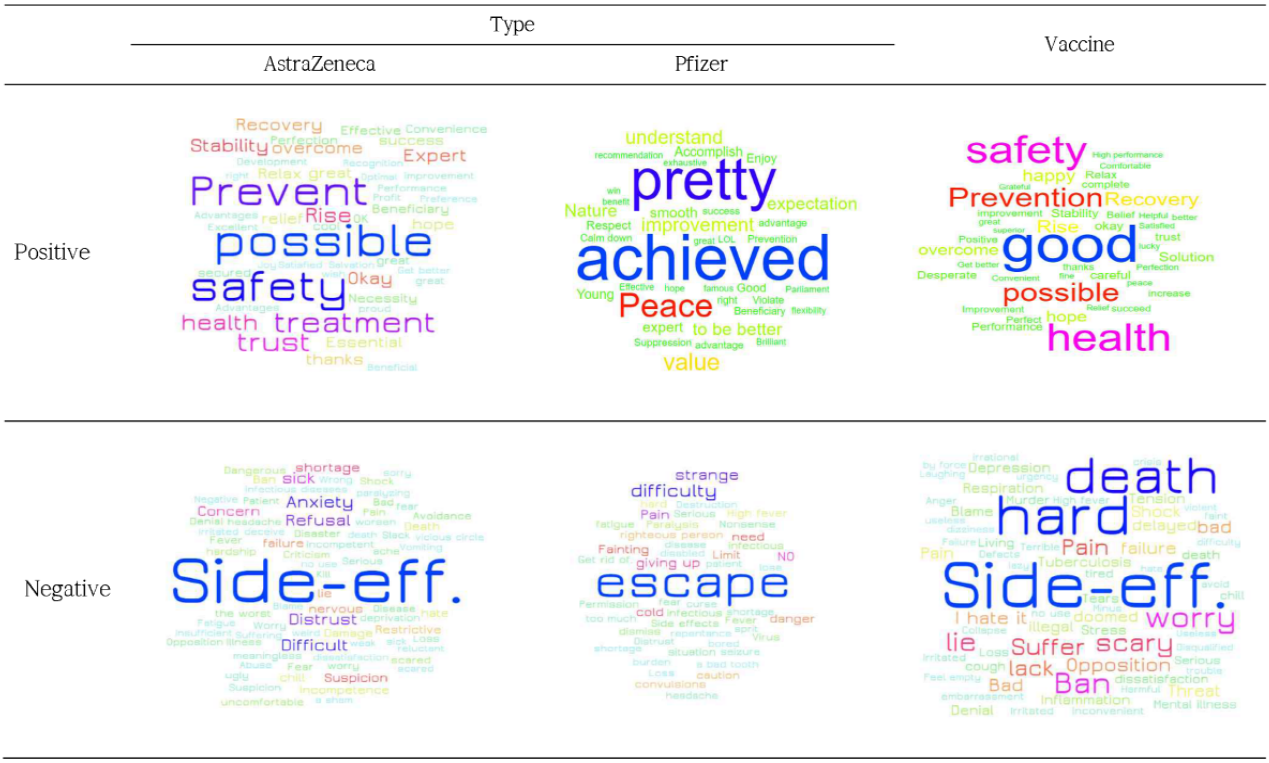
Of the words crawled with “Pfizer,” 75/122 (61.5%) were classified as negative and 47/122 (38.5%) as positive; thus, there were more negative words in the data. Negative words were used more frequently (498/885, 56.3%).

Of the words crawled with "AstraZeneca," 52/89 (58%) were classified as negative and 37/89 (42%) as positive; thus, there were more negative words. Again, negative words were more frequently used (476/670, 71.0%) than positive words (194/670, 29.0%).

With respect to "vaccine," positive words were more frequently used than negative words; however, regarding "AstraZeneca" and "Pfizer" negative words were more frequently used than positive ones.

Word cloud visualizations (Figure 2) were created separately for positive and negative words classified based on the crawled data with the keywords of "vaccine," "AstraZeneca," and "Pfizer." Regarding "vaccine," positive words were "good," "safety," "hope," "recovery," and "overcoming," and negative words were "side effect," "tough," "death," "concerned," and "lies."

Figure 2. Word cloud visualizations of crawled data. Side-eff: side-effects.

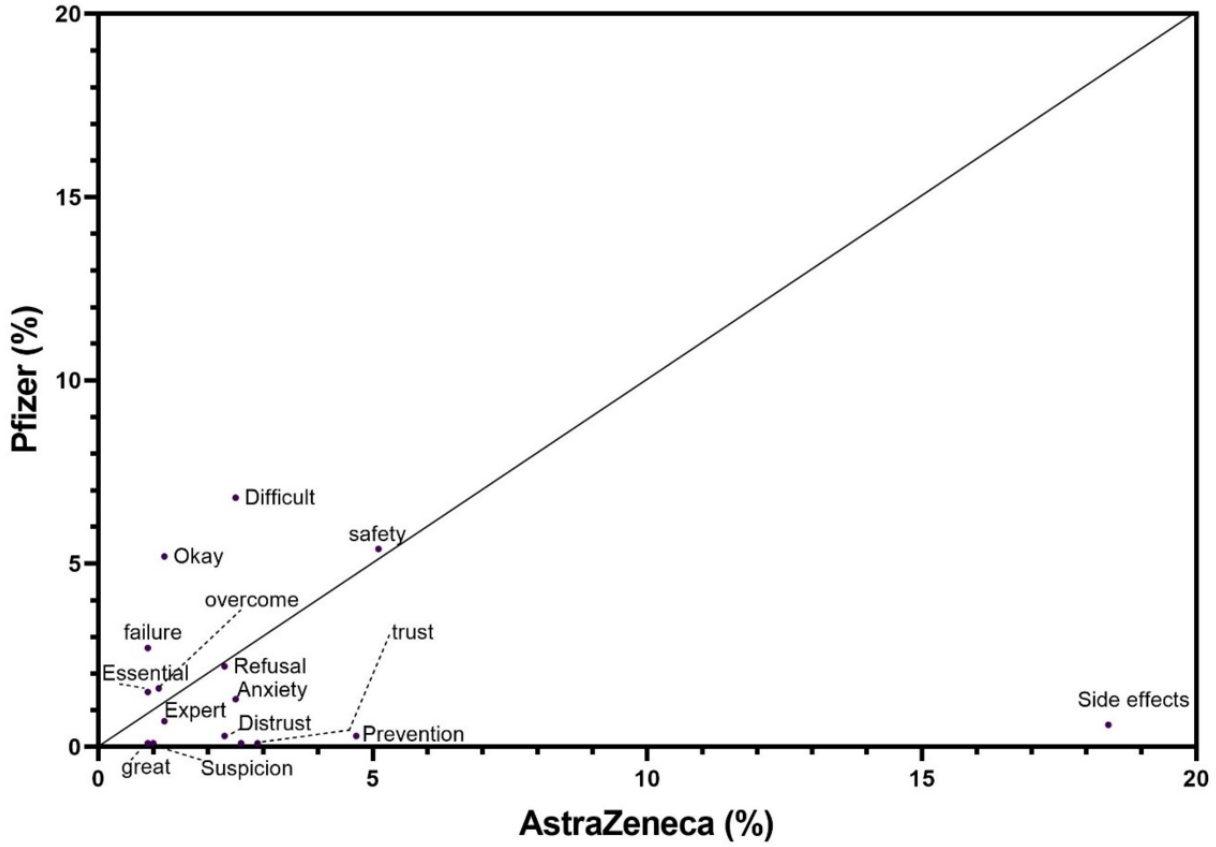


For AZ, positive words included "possibility," "safety," "prevention," "treatment," and "trust," and negative words were "side effect," "anxiety," "difficult," and "refusal." With respect to Pfizer, positive words were "achieved," "good," and "value," and negative words were "escape," "difficult," "pain," and "giving up."

Of the positive and negative words crawled with the vaccine types, "AstraZeneca" and "Pfizer," as keywords, those found for both types of vaccine were examined for their frequencies (Figure 3). A total of 16 words were commonly associated with AZ and Pfizer. Of those, "side effect" showed the highest frequency (163/559, 29.2%) for AZ. By contrast, the frequency of "side effect" for Pfizer was 0.6% (4/673). Additionally, "prevention," "treatment," "trust," "anxiety," and "distrust" demonstrated higher frequencies for AZ compared with Pfizer.

However, "difficult," "okay," "failure," "safety," "overcoming," and "essential" were more frequently used with Pfizer compared with AZ.

Figure 3. Comparison of the crawled words for the AstraZeneca and Pfizer vaccines.



Discussion

Principal Findings

The purpose of this study was to (1) examine Korean citizens' perceptions of COVID-19 vaccines, (2) identify their overall views of the vaccines including the positive and negative aspects of their perceptions, and (3) provide evidence for policy development to increase COVID-19 vaccine acceptance.

To do so, a web crawling approach was used to collect data from NAVER and Instagram using "vaccine," "AstraZeneca," and "Pfizer" as the keywords. In a previous study using the existing web crawling technique to analyze citizens' perceptions, data were collected from a variety of SNSs, including Google Trends, Twitter, and Facebook [21]. However, our study crawled data from the most popular SNSs in Korea: NAVER and Instagram.

For the data crawled with "vaccine," the proportion of positive words (1981/3698, 53.57%) was higher than that of negative words (1717/3698, 46.43%), which revealed that citizens' perceptions of vaccination is somewhat positive. According to a study that examined public perception in Bangladesh based on over 10,000 Facebook posts using "vaccine" as the keyword [22], the proportion of citizens who regarded vaccination positively (74.61%) was similar to this study's findings. Of the positive words used in the posts, "nice" was most regularly used (13.4%), followed by "treatment" (9.9%), "health" (9.3%), "safety" (9.3%), "prevention" (6.0%), "recovery" (3.4%), and "hope" (2.4%). The findings showed positive expectations regarding prevention, elimination, and treatment through vaccination against COVID-19.

By contrast, the results of the analysis conducted in this study with the 2 vaccine types available in Korea, AZ and Pfizer, showed that negative perception was stronger, as shown by the frequency of negative words associated with AZ and Pfizer: 71.0% (476/670) and 56.3% (498/885), respectively. This finding is consistent with that of a previous study—that is, negative viewpoints were more prevalent in Korean citizens and that there was a stronger negative perception regarding the AZ vaccine [23]. The public's perception became negative due to reports of people developing thrombocytopenia after receiving the AZ vaccination. In particular, the perception changed negatively in people who were still deciding whether to be vaccinated [24]. Additionally, this study found that Korean citizens were concerned about the side effects of AZ, and therefore tended to refuse it, as revealed by the finding that words widely associated with AZ included "side effects," "anxiety," and "refusal."

As of May 2021, Korea secured AZ and Pfizer vaccine supplies and initiated vaccinating health care professionals and people aged 60 years or older. By May 20, 2021, 2% of the general population were vaccinated [25]. The Korean government is planning to vaccinate at least 70% of the population by December 2021 to achieve herd immunity.

Several studies have emphasized the need for mass acceptance of vaccination to achieve the goal of herd immunity [26]. However, as shown in this study, there is an intense negative

perception about AZ and Pfizer vaccines in Korea. Research indicates that the main cause of such a negative viewpoint is the failure of the government to communicate risk [27].

Risk communication is a component of a country's preparedness, proposed by the WHO, for infection prevention, control, and management [28]. The Middle East respiratory syndrome coronavirus (MERS-CoV) outbreak in Korea is a representative of the impact of national capacity for risk communication during an outbreak. During the MERS-CoV outbreak, the Korean government promptly shared information with citizens, and citizens' trust in the information played a crucial role in preventing the spread of the infection [29]. Since MERS-CoV, in 2017, Korea received a score of 3.6 out of 5 points by the Joint External Evaluation, a WHO evaluation system for risk communication [30]. During the current COVID-19 pandemic, Korea demonstrated excellent risk communication capacity based on the experience with MERS-CoV and was named, along with New Zealand, Australia, and Taiwan, as a country that successfully responded to the COVID-19 pandemic [31]. However, regarding the COVID-19 vaccination policy, the psychology of refusal is widespread, with 1 of 4 people refusing to be vaccinated. According to an online survey conducted with 1093 Korean adults [32], 62.6% of the respondents trusted the government's effort for vaccination. This level was similar to our study's finding regarding trust (1981/3698, 53.57%) based on data crawling with the keyword "vaccine." Furthermore, 70.5% of respondents in the study indicated that the Pfizer vaccine was safe, while 30.4% responded that the AZ vaccine was safe [32]. This finding is consistent with the findings of this study regarding a negative perception of AZ (476/670, 71.0%). Moreover, in the online survey, side effects were the primary reason for the negative perception of AZ, which concurs with the findings of this study. According to the studies conducted by the manufacturers/developers of AZ, only 28 out of 17 million people vaccinated with AZ experienced side effects; therefore, side effects are not a serious concern. The WHO, US CDC, and Korea Disease Control and Prevention Agency (formerly Korea Centers for Disease Control and Prevention [KCDC]) strongly recommend AZ [33,34]. However, trust in the government's risk communication decreased, and the vaccination program slowed down. In the United States, the "lack of trust in information delivered by the government" was the second most common (12.5%) reason for citizens' reluctance toward getting vaccinated against COVID-19 [35].

Thus, this study makes the following 3 suggestions to increase COVID-19 vaccine acceptance and to achieve herd immunity. The first is to share the cases vaccinated with the AZ in anticipation of a bandwagon effect. The stakeholders who make decisions regarding COVID-19 vaccination policy (including the president, high-ranking officials) can promote safety after being vaccinated with AZ. It has been reported that celebrities and entertainers sharing their experiences in infomercials are also effective [36].

Second, risk communication is a valuable tool to promote policies and increase trust in the government. The government should not only accurately and rapidly provide information regarding COVID-19 vaccines, but should also share evidence-based, reliable information to increase citizens' trust. Additionally, when promoting the COVID-19 vaccination policy, the gap between experts and non-experts in terms of risk information should be considered, and messaging should be strategically presented to aid in understanding the risks.

Finally, it is suggested that incentives be provided to persons who are vaccinated. Korea signed a priority contract with AZ to secure vaccine supplies. Because AZ has a short shelf life, vaccines that have passed the expiry date should be discarded if vaccination does not progress as planned. Fortunately, smartphone penetration is high in Korea, and if the person to be vaccinated misses their appointment, the next person in the vaccine registration list is notified through a smartphone notification. In Korea, this is termed "No Show." Providing incentives for people who are vaccinated ought to be considered to increase AZ acceptance within a specified time, and to change people's perceptions.

This study has a few limitations. First, the data were obtained from NAVER and Instagram; thus, there is a limitation in representativeness. Because internet users tend to be young, the opinions of older people were not fully reflected in the study's findings. Second, only the texts posted on the internet were analyzed, and the study's findings do not reflect various demographic characteristics, educational levels, and access to health information of the people who posted the texts. In future research, nationwide survey studies should be performed by considering these limitations and factoring in characteristics of the study's participants. Third, because the "KNU Korean Sentiment Lexicon" is a latest word classification tool in Korea, the number of studies pertaining to COVID-19 that have used this tool is limited. Hence, more studies are needed on the words that are classified as either positive or negative in this tool.

Conclusion

This study examined COVID-19 vaccine acceptance in Korea using a web crawling approach with 3 keywords: "vaccine," "AstraZeneca," and "Pfizer." It was found that 71.0% (476/670) of the words crawled with "AstraZeneca" were classified as negative, and the proportion of negative words associated with Pfizer was 56.3% (498/885). Side effects were found to be the greatest concern regarding AZ. To address this problem, accurate information sharing about COVID-19 vaccines, including AZ, is suggested. Additionally, it is suggested that the experiences of people who are vaccinated should be shared in anticipation of a bandwagon effect. Finally, the government ought to increase the AZ vaccination rate by managing communication about risks so that vaccination occurs before the vaccine expires.

Acknowledgments

We express our gratitude to everyone working to overcome COVID-19 in South Korea and throughout the world. This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2021R1C1C2005464).

Authors' Contributions

HL and EWN conceptualized the study. SJP, GL, and HL were responsible for data curation. SJP, GRL, and HL performed formal analysis. HL took care of funding acquisition. HL and EBN performed the methodologies mentioned. SJP, GRL, and HL performed software analysis. EBN was responsible for validation and HL for visualization. HL, THL, and HKN contributed to writing (original draft). All authors contributed to writing (review and editing).

Conflicts of Interest

None declared.

References

1. Countries where COVID-19 has spread. Worldometer. 2020. URL: https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/ [accessed 2021-08-16]
2. International Monetary Fund. The Great Lockdown: Worst Economic Downturn Since the Great Depression. 2020. URL: https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/ [accessed 2021-08-16]
3. Hogan A, Winskill P, Watson O, Walker PGT, Whittaker C, Baguelin M, Imperial College COVID-19 Response Team, et al. Report 33: Modelling the Allocation and Impact of a COVID-19 Vaccine Imperial College London. 2020. URL: https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-33-vaccine/ [accessed 2021-08-16]
4. Saad-Roy CM, Wagner CE, Baker RE, Morris SE, Farrar J, Graham AL, et al. Immune life history, vaccination, and the dynamics of SARS-CoV-2 over the next 5 years. Science 2020 Nov 13;370(6518):811-818 [FREE Full text] [doi: 10.1126/science.abd7343] [Medline: 32958581]
5. Coronavirus (COVID-19) Vaccinations. URL: https://ourworldindata.org/covid-vaccinations [accessed 2021-08-16]
6. Burki T. Vaccine misinformation and social media. The Lancet Digital Health 2019 Oct;1(6):e258-e259. [doi: 10.1016/S2589-7500(19)30136-0]
7. Larson HJ, Jarrett C, Eckersberger E, Smith DM, Paterson P. Understanding vaccine hesitancy around vaccines and vaccination from a global perspective: a systematic review of published literature, 2007-2012. Vaccine 2014 Apr 17;32(19):2150-2159 [FREE Full text] [doi: 10.1016/j.vaccine.2014.01.081] [Medline: 24598724]
8. Schmid P, Rauber D, Betsch C, Lidolt G, Denker M. Barriers of Influenza Vaccination Intention and Behavior - A Systematic Review of Influenza Vaccine Hesitancy, 2005 - 2016. PLoS One 2017 Jan 26;12(1):e0170550 [FREE Full text] [doi: 10.1371/journal.pone.0170550] [Medline: 28125629]
9. Siddiqui M, Salmon DA, Omer SB. Epidemiology of vaccine hesitancy in the United States. Hum Vaccin Immunother 2013 Dec;9(12):2643-2648 [FREE Full text] [doi: 10.4161/hv.27243] [Medline: 24247148]
10. Schwarzinger M, Watson V, Arwidson P, Alla F, Luchini S. COVID-19 vaccine hesitancy in a representative working-age population in France: a survey experiment based on vaccine characteristics. The Lancet Public Health 2021 Apr;6(4):e210-e221. [doi: 10.1016/s2468-2667(21)00012-8]
11. Stratégie de vaccination contre le Sars-Cov-2 - Recommandations préliminaires sur la stratégie de priorisation des populations à vacciner. 2020. URL: https://www.has-sante.fr/jcms/p_3221338/fr/strategie-de-vaccination-contre-le-sars-cov-2-recommandations-preliminaires-sur-la-strategie-de-priorisation-des-populations-a-vacciner [accessed 2021-08-16]
12. Abrams EM, Greenhawt M. Risk Communication During COVID-19. J Allergy Clin Immunol Pract 2020 Jun;8(6):1791-1794 [FREE Full text] [doi: 10.1016/j.jaip.2020.04.012] [Medline: 32304834]
13. Houston JB, Hawthorne J, Perreault MF, Park EH, Goldstein Hode M, Halliwell MR, et al. Social media and disasters: a functional framework for social media use in disaster planning, response, and research. Disasters 2015 Jan 22;39(1):1-22. [doi: 10.1111/disa.12092] [Medline: 25243593]
14. Chan JL, Purohit H. Challenges to Transforming Unconventional Social Media Data into Actionable Knowledge for Public Health Systems During Disasters. Disaster Med Public Health Prep 2020 Jun 15;14(3):352-359. [doi: 10.1017/dmp.2019.92] [Medline: 31610817]
15. Lee H, Kim JE, Moon SJ, Lee JH, Nam EW. Government Response to COVID-19 Using Stringency Index Among 151 Countries and Six Regions. SSRN. 2020. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3631304 [accessed 2021-08-16]
16. Ray J. Over 1 Billion Worldwide Unwilling to Take COVID-19 Vaccine. URL: https://news.gallup.com/poll/348719/billion-unwilling-covid-vaccine.aspx [accessed 2021-08-16]

17. DMC. 2021 Social Media Market and Status Analysis Report. URL: https://www.trendmonitor.co.kr/tmweb/trend/etcTrend/detail.do?bIdx=766&code=&trendType=dmc&prevMonth=&currentPage=1 [accessed 2021-08-16]
18. Korea Disease Control Prevention Agency. COVID-19 Vaccine and Vaccination. 2021. URL: http://ncv.kdca.go.kr/ [accessed 2021-08-16]
19. Jung J. Preparing for the Coronavirus Disease (COVID-19) Vaccination: Evidence, Plans, and Implications. J Korean Med Sci 2021 Feb 22;36(7):e59 [FREE Full text] [doi: 10.3346/jkms.2021.36.e59] [Medline: 33619920]
20. DILAB: The KNU Korean Sentiment Lexicon. URL: http://dilab.kunsan.ac.kr/ [accessed 2021-08-16]
21. Ginsberg J, Mohebbi MH, Patel RS, Brammer L, Smolinski MS, Brilliant L. Detecting influenza epidemics using search engine query data. Nature 2009 Feb 19;457(7232):1012-1014. [doi: 10.1038/nature07634] [Medline: 19020500]
22. Al-Zaman MS. An exploratory study of social media users' engagement with COVID-19 vaccine-related content. F1000Res 2021 Jun 23;10:236. [doi: 10.12688/f1000research.51210.3]
23. Voysey M, Clemens SAC, Madhi SA, Weckx LY, Folegatti PM, Aley PK, Oxford COVID Vaccine Trial Group. Safety and efficacy of the ChAdOx1 nCoV-19 vaccine (AZD1222) against SARS-CoV-2: an interim analysis of four randomised controlled trials in Brazil, South Africa, and the UK. Lancet 2021 Jan 09;397(10269):99-111 [FREE Full text] [doi: 10.1016/S0140-6736(20)32661-1] [Medline: 33306989]
24. Sønderskov KM, Dinesen PT, Østergaard SD. Sustained COVID-19 vaccine willingness after safety concerns over the Oxford-AstraZeneca vaccine. Dan Med J 2021 Mar 31;68(5):A03210292 [FREE Full text] [Medline: 33870886]
25. COVID-19 vaccination tracker Internet. 2021. URL: https://graphics.reuters.com/world-coronavirus-tracker-and-maps/vaccination-rollout-and-access/ [accessed 2021-05-05]
26. Lazarus JV, Ratzan SC, Palayew A, Gostin LO, Larson HJ, Rabin K, et al. A global survey of potential acceptance of a COVID-19 vaccine. Nat Med 2021 Feb 20;27(2):225-228 [FREE Full text] [doi: 10.1038/s41591-020-1124-9] [Medline: 33082575]
27. Lane S, MacDonald NE, Marti M, Dumolard L. Vaccine hesitancy around the globe: Analysis of three years of WHO/UNICEF Joint Reporting Form data-2015-2017. Vaccine 2018 Jun 18;36(26):3861-3867 [FREE Full text] [doi: 10.1016/j.vaccine.2018.03.063] [Medline: 29605516]
28. World Health Organization. International Health Regulations (2005) Core Capacity Workbook: A Series of Exercises to Assist the Validation of Core Capacity Implementation Levels (No. WHO/HSE/GCR/2015.13). 2015. URL: https://apps.who.int/iris/handle/10665/190819 [accessed 2021-08-22]
29. Noh J, Yoo K, Kwon Y, Hong J, Lee Y, Park K. Effect of Information Disclosure Policy on Control of Infectious Disease: MERS-CoV Outbreak in South Korea. Int J Environ Res Public Health 2020 Jan 01;17(1):305 [FREE Full text] [doi: 10.3390/ijerph17010305] [Medline: 31906369]
30. World Health Organization. Joint External Evaluation of IHR Cope Capacities of the Republic of Korea. 2017. URL: https://www.who.int/ihr/publications/jee-mission-report-rok/en/ [accessed 2017-08-28]
31. Lim B, Kyoungseo HE. COVID-19 in Korea: Success based on past failure. Asian Econ Pap 2021 May 15;20(2):62 [FREE Full text] [doi: 10.1162/asep_a_00803]
32. KBS. A Report on the Trend of Change in the Perception of COVID 19 in General Public in Korea. URL: https://news.kbs.co.kr/datafile/2021/04/16/3042616185615059 83.pdf [accessed 2021-05-05]
33. Lopez Bernal J, Andrews N, Gower C, Robertson C, Stowe J, Tessier E, et al. Effectiveness of the Pfizer-BioNTech and Oxford-AstraZeneca vaccines on covid-19 related symptoms, hospital admissions, and mortality in older adults in England: test negative case-control study. BMJ 2021 May 13;373:n1088 [FREE Full text] [doi: 10.1136/bmj.n1088] [Medline: 33985964]
34. Tobaiqy M, Elkout H, MacLure K. Analysis of Thrombotic Adverse Reactions of COVID-19 AstraZeneca Vaccine Reported to EudraVigilance Database. Vaccines (Basel) 2021 Apr 16;9(4):393 [FREE Full text] [doi: 10.3390/vaccines9040393] [Medline: 33923530]
35. Nguyen KH, Srivastav A, Razzaghi H, Williams W, Lindley MC, Jorgensen C, et al. COVID-19 vaccination intent, perceptions, and reasons for not vaccinating among groups prioritized for early vaccination - United States, September and December 2020. Am J Transplant 2021 Apr 31;21(4):1650-1656 [FREE Full text] [doi: 10.1111/ajt.16560] [Medline: 33788992]
36. Volpp KG, Loewenstein G, Buttenheim AM. Behaviorally Informed Strategies for a National COVID-19 Vaccine Promotion Program. JAMA 2021 Jan 12;325(2):125-126. [doi: 10.1001/jama.2020.24036] [Medline: 33315079]

Abbreviations

AZ: AstraZeneca
CDC: US Centers for Disease Control and Prevention
KCDC: Korea Centers for Disease Control and Prevention
MERS-CoV: The Middle East respiratory syndrome coronavirus
SNSs: social network sites
WHO: World Health Organization

Edited by G Eysenbach; submitted 22.06.21; peer-reviewed by F Saleem, M Park, M Salimi; comments to author 14.07.21; revised version received 18.07.21; accepted 04.08.21; published 08.09.21.

Please cite as:
Lee H, Noh EB, Park SJ, Nam HK, Lee TH, Lee GR, Nam EW
COVID-19 Vaccine Perception in South Korea: Web Crawling Approach
JMIR Public Health Surveill 2021;7(9):e31409
URL: https://publichealth.jmir.org/2021/9/e31409
doi:10.2196/31409
PMID:34348890

Original Paper

Assessing COVID-19 Vaccine Uptake and Effectiveness Through the North West London Vaccination Program: Retrospective Cohort Study

Ben Glampson[1*], BSc, MSc; James Brittain[2], BSc, MBBS, MRCS; Amit Kaura[2], MBChB; Abdulrahim Mulla[2], BTech; Luca Mercuri[2], PhD; Stephen J Brett[2], MD, FRCA, FFICM; Paul Aylin[3], MBChB, FFPH, FRCPE; Tessa Sandall[4], BA; Ian Goodman[4], MBBChir, MA, FRCGP; Julian Redhead[1], MBBS, FCEM, FRCP, MFSEM, DipSEM; Kavitha Saravanakumar[4], BSc, MSc; Erik K Mayer[1,2,5*], BSc (Hons), MBBS (Hons), PhD, FRCS, FFCI

[1]National Institute for Health Research Imperial Biomedical Research Centre, Imperial College Healthcare National Health Service Trust, London, United Kingdom

[2]Department of Surgery and Cancer, Imperial College London, London, United Kingdom

[3]School of Public Health, Imperial College London, London, United Kingdom

[4]North West London Collaboration of Clinical Commissioning Groups, London, United Kingdom

[5]National Institute for Health Research Imperial Patient Safety Translational Research Centre, Imperial College Healthcare National Health Service Trust, London, United Kingdom

[*]these authors contributed equally

Corresponding Author:
Erik K Mayer, BSc (Hons), MBBS (Hons), PhD, FRCS, FFCI
Department of Surgery and Cancer
Imperial College London
10th Floor QEQM building, St Mary's Hospital Campus
Praed Street
London, W2 1NY
United Kingdom
Phone: 44 2078082076
Email: e.mayer@imperial.ac.uk

Abstract

Background: On March 11, 2020, the World Health Organization declared SARS-CoV-2, causing COVID-19, as a pandemic. The UK mass vaccination program commenced on December 8, 2020, vaccinating groups of the population deemed to be most vulnerable to severe COVID-19 infection.

Objective: This study aims to assess the early vaccine administration coverage and outcome data across an integrated care system in North West London, leveraging a unique population-level care data set. Vaccine effectiveness of a single dose of the Oxford/AstraZeneca and Pfizer/BioNTech vaccines were compared.

Methods: A retrospective cohort study identified 2,183,939 individuals eligible for COVID-19 vaccination between December 8, 2020, and February 24, 2021, within a primary, secondary, and community care integrated care data set. These data were used to assess vaccination hesitancy across ethnicity, gender, and socioeconomic deprivation measures (Pearson product-moment correlations); investigate COVID-19 transmission related to vaccination hubs; and assess the early effectiveness of COVID-19 vaccination (after a single dose) using time-to-event analyses with multivariable Cox regression analysis to investigate if vaccination independently predicted positive SARS-CoV-2 in those vaccinated compared to those unvaccinated.

Results: In this study, 5.88% (24,332/413,919) of individuals declined and did not receive a vaccination. Black or Black British individuals had the highest rate of declining a vaccine at 16.14% (4337/26,870). There was a strong negative association between socioeconomic deprivation and rate of declining vaccination (r=–0.94; P=.002) with 13.5% (1980/14,571) of individuals declining vaccination in the most deprived areas compared to 0.98% (869/9609) in the least. In the first 6 days after vaccination, 344 of 389,587 (0.09%) individuals tested positive for SARS-CoV-2. The rate increased to 0.13% (525/389,243) between days 7 and 13, before then gradually falling week on week. At 28 days post vaccination, there was a 74% (hazard ratio 0.26, 95% CI 0.19-0.35) and 78% (hazard ratio 0.22, 95% CI 0.18-0.27) reduction in risk of testing positive for SARS-CoV-2 for individuals that received

the Oxford/AstraZeneca and Pfizer/BioNTech vaccines, respectively, when compared with unvaccinated individuals. A very low proportion of hospital admissions were seen in vaccinated individuals who tested positive for SARS-CoV-2 (288/389,587, 0.07% of all patients vaccinated) providing evidence for vaccination effectiveness after a single dose.

Conclusions: There was no definitive evidence to suggest COVID-19 was transmitted as a result of vaccination hubs during the vaccine administration rollout in North West London, and the risk of contracting COVID-19 or becoming hospitalized after vaccination has been demonstrated to be low in the vaccinated population. This study provides further evidence that a single dose of either the Pfizer/BioNTech vaccine or the Oxford/AstraZeneca vaccine is effective at reducing the risk of testing positive for COVID-19 up to 60 days across all age groups, ethnic groups, and risk categories in an urban UK population.

(JMIR Public Health Surveill 2021;7(9):e30010) doi:10.2196/30010

KEYWORDS

health informatics; real-word evidence; COVID-19; medical informatics; vaccine; vaccination

Introduction

Background

On March 11, 2020, the World Health Organization declared the novel coronavirus, SARS-CoV-2 that causes COVID-19, as a pandemic with governments worldwide implementing restrictive measures to slow the spread of the virus and prompting an international effort to develop an effective vaccine [1]. Development of a COVID-19 vaccine by a partnership of BioNTech and Pfizer had commenced on January 10, 2020, following the publication of the SARS-CoV-2 genetic sequencing data, and on December 2, 2020, the United Kingdom became the first country to approve a COVID-19 vaccine after regulators granted emergency use authorization to BNT162b2 mRNA produced by Pfizer and BioNTech following the publication of results of the phase 3 trials [2,3]. The UK mass vaccination program commenced on December 8, 2020 [2]. By December 30, 2020, the ChAdOx1 nCoV-19 adenoviral vaccine, developed by Oxford University/AstraZeneca, was granted regulatory approval by the Medicines and Healthcare Products Regulatory Agency (MHRA), and its use was included in the UK vaccination program [2,4]. The Moderna vaccine was the third COVID-19 vaccine to be approved for use by the MHRA on January 8, 2021, and further vaccines are in development and awaiting approval for use [1]. The Joint Committee on Vaccination and Immunisation established the strategy, on behalf of the Government, for the rapid distribution of a first dose of a vaccine to groups of the population deemed to be most vulnerable to severe COVID-19 infection [5]. By February 26, 2021, 29% of the UK population had received at least one dose of an approved COVID-19 vaccine [6]. The Joint Committee on Vaccination and Immunisation–stated target was to have offered a first vaccine dose to everyone in priority groups one, two, three, and four by February 15, 2021 [7].

Anticipated vaccination coverage of priority groups has been reduced by vaccine hesitancy, which is present in the United Kingdom and Continental European populations alike [8,9]. To ensure the sufficient and rapid uptake of the offered vaccination program, identifying and addressing vaccination hesitancy and resistance (ie, the positions where one is unsure about taking a vaccine or where one is absolutely against taking a vaccine) is essential [10]. The use of vaccination centers has been reported to increase vaccine hesitancy, possibly due to fear of transmission, but is the only feasible way of administering large numbers of vaccinations rapidly given logistical and cold storage constraints [9]. Identifying and understanding COVID-19 vaccine hesitancy within distinct populations may aid future public health messaging.

Real-world data supporting the effectiveness of the vaccination strategy in the UK population is needed to guide health policy. This real-word data-driven evidence study of the UK COVID-19 vaccination program in the North West London (NWL) population used a unique data set established as part of the Gold Command COVID-19 response in NWL [11], which included the pre-established Whole System Integrated Care (WSIC) data collated for the purposes of population health in the sector.

WSIC is an innovative data sharing initiative by the NWL Collaboration of Clinical Commissioning Groups (CCGs) and has been designed to improve data sharing and interoperability [12,13]. WSIC dashboards link provider data from four acute, two mental health, and two community Trusts across eight CCGs; social care data from eight boroughs; and 360 general practitioner (GP) practices to generate an integrated care record for direct patient benefit. The COVID-19 dashboard allows access to data on vaccination and SARS-CoV-2 testing within minutes or hours of the data being recorded in source data systems. The vaccination dashboard uses GP clinical systems (SystemOne, eMIS), pathology laboratories (NWL Pathology and The Doctor's Laboratory), national COVID-19 test results, and daily COVID-19 situation reports from the Northwest London secondary care organizations.

Aims and Objectives

The aim of this study is to assess the early vaccine administration coverage and vaccine effectiveness and outcome data across an integrated care system of eight CCGs leveraging a unique population-level care data set.

The study objectives were:

- To describe vaccination coverage across NWL CCGs and identify subgroups according to sociodemographic factors and including where vaccination offer was declined
- To investigate the impact of vaccine administration on possible virus transmission by assessing rates of positive testing after vaccination and to examine the potential importance of continued isolation following the delivery of a single dose of a COVID-19 vaccine

- To assess the early effectiveness of COVID-19 vaccination over a 10-week follow-up period stratified across population subgroups and by vaccine type, and compared with rates of SARS-CoV-2 positive testing rates in the nonvaccinated population

Methods

Study Design

The study was a retrospective cohort design. Data were captured to support the NWL response to the COVID-19 pandemic on behalf of NWL Gold Command as part of Whole Systems Integrated Care. Anonymized data covering vaccinated and unvaccinated individuals from NWL were accessed in the iCARE (Imperial Clinical Analytics Research and Evaluation) system [11] for analysis.

Participants and Setting

All adults older than 16 years, eligible to be offered a COVID-19 vaccine and registered with a GP or with a resident postcode in the NWL catchment area were included in the analysis. The eligible population was considered as a static group over the study period based on data available on February 24, 2021.

Vaccinated individuals were defined as persons receiving a vaccine within the NWL vaccine program time period, considered December 8, 2020, to February 15, 2021, inclusive. Vaccination status was provided either directly via acute hubs or via GP electronic patient record systems via primary care hubs. The unvaccinated group were considered those that had not received a vaccine during the same NWL vaccine program time period.

Individuals were counted as declining a vaccine if they indicated that they did not want a vaccine to their GP and did not then receive a vaccine. Rates of declining vaccination were calculated using the denominator of those who received a vaccine or those that declined a vaccine. Individuals who initially declined vaccination but then were vaccinated after February 15, 2021, and before February 24, 2021, were not included as vaccinated.

Follow-up analysis included data until February 24, 2021 (inclusive), for both groups, allowing over a week of follow up for all individuals.

Variables

The analysis data set was created through the combination of data from GP primary care systems, including SARS-CoV-2 test results (pillar 2), vaccination status and type, contraindications to COVID-19 vaccination, vaccination decline, age, gender, ethnic group, clinically extremely vulnerable status, and decile of deprivation; social care data sets, including care home and housebound status; pathology laboratory data, including SARS-CoV-2 test results obtained from NWL Pathology, The Doctors Laboratory (pillar 1), and national SARS-CoV-2 test results; and NWL acute Trust patient-level situation reports, including admission and discharge dates.

Risk groups were defined in WSIC (based on the Joint Committee on Vaccination and Immunisation priority cohorts); these were based primarily on individuals in care homes, then those classed as clinically extremely vulnerable, and then on age groups of individuals. Therefore, in the analysis where risk groups were used, it should be assumed that the care home and clinical extremely vulnerable can be of any age. Those in care homes were predominantly, although not exclusively, older individuals. Frontline key worker status could not be identified from the data available and therefore could not be analyzed separately.

Outcomes measured were the date of result for the first positive swab for all individuals (lateral flow test results were excluded), and results included tests from pillar one and two [2]. All nonpositive (negative, inconclusive, and error) were grouped as nonpositive results, with the assumption that all nonnegative tests would be followed with a second test, and these positive results would be included if returned. The denominator for the week-on-week population groups was calculated based on the number of individuals with follow-up data available up to the start of each weekly time period and who had not previously tested positive. Testing rates pre- and postvaccination were examined to identify if changes in individual's likelihood of being tested could impact changes in levels of positive SARS-CoV-2 testing.

Secondary outcomes of hospitalization due to COVID-19 were measured as vaccinated patients admitted to the hospital who had tested positive for SARS-CoV-2 prior to admission or recorded a positive result in the first 7 days of inpatient stay [14]. All secondary care data were recorded from situation reports data submitted by NWL acute Trusts. This does not include diagnosis data or reason for admission to hospital.

Individuals that received Moderna vaccines (n=3) were excluded from analysis comparing vaccination types due to insufficient numbers. Patients who died (all cause) between December 8, 2020, and February 24, 2021, were excluded from the main analysis and included in a subanalysis, as date of death in the upstream systems is updated variably and therefore likely to be an underestimate.

Identification of Bias

Variations in prevalence of COVID-19 in the population across the timescale of this longitudinal study may alter the rate of positive testing in both the vaccinated and unvaccinated groups. To address these potential confounding factors, prevalence of positivity in the background population and the rate of vaccination delivery were compared.

Unequal use of vaccine type across risk cohorts could make a direct comparison of vaccine outcome data unreliable. We have stated the delivery rates of vaccination types and adjusted denominators appropriately for return to follow up.

Individuals with COVID-19 that did not test positive (untested or asymptomatic) would be included in the COVID-19 negative population. It was assumed that individuals not testing positive were negative. The data set does not include lateral flow positive tests, which may be more represented in key frontline workers, although frontline workers make up a minority number of the overall NWL population.

The cause of hospital admission of patients was not provided in the NWL acute Trust situation reports and therefore was not available. It was assumed that a COVID-19–related admission would include any patient testing positive in the period prior to an admission or within 7 days of an admission, as per the Public Health England definition [14]. It was not appropriate to compare hospital admissions between vaccinated and unvaccinated groups, as the vaccination program has targeted the most high-risk individuals, with therefore a presumed higher risk of admission, due to comorbidities.

Statistical Analysis Methods

Known missing data included vaccination type for <1% of vaccinated individuals; these data were included in analysis of overall vaccinations but excluded from vaccination type breakdowns (unless indicated).

Pearson product-moment correlations were used to measure the correlation between individuals declining a vaccination and socioeconomic deprivation status. Index of multiple deprivation (IMD) deciles are the official measure of deprivation in the United Kingdom [15] and are assigned to individuals based on home postcode.

Vaccine effect estimation was calculated using time-to-event analysis. Cumulative SARS-CoV-2 positive results were graphically displayed using Kaplan-Meier curves stratified by vaccination status. Follow-up time commenced on December 8, 2020, which was the start of the vaccination program, for those unvaccinated and commenced on the day of vaccination for those vaccinated. All patients were followed up until a positive SARS-CoV-2 test result or censoring on February 24, 2021. As a positive SARS-CoV-2 test result is a nonfatal event, we used mortality as a competing risk (ie, the individual died before having the outcome event).

Multivariable Cox regression analysis was used to investigate whether vaccination independently predicted having a SARS-CoV-2–positive swab during follow-up compared to unvaccinated individuals, after adjusting for age, gender, ethnicity, IMD, and vaccine manufacturer. We performed a time-dependent Cox regression analysis of vaccination effectiveness on SARS-CoV-2 positivity during follow-up in all individuals up to 28 days post vaccination in the following time intervals: 0-7, 8-14, 15-21, and 22-28 days. Analyses were performed with the use of R software, version 4.0.1 (R Foundation for Statistical Computing).

Ethics

This study was undertaken within a research database that was given favorable ethics approval by the West Midlands Solihull Research Ethics Committee (reference 18/WM/0323; IRAS project ID 252449). All data used in this paper were fully anonymized before analysis.

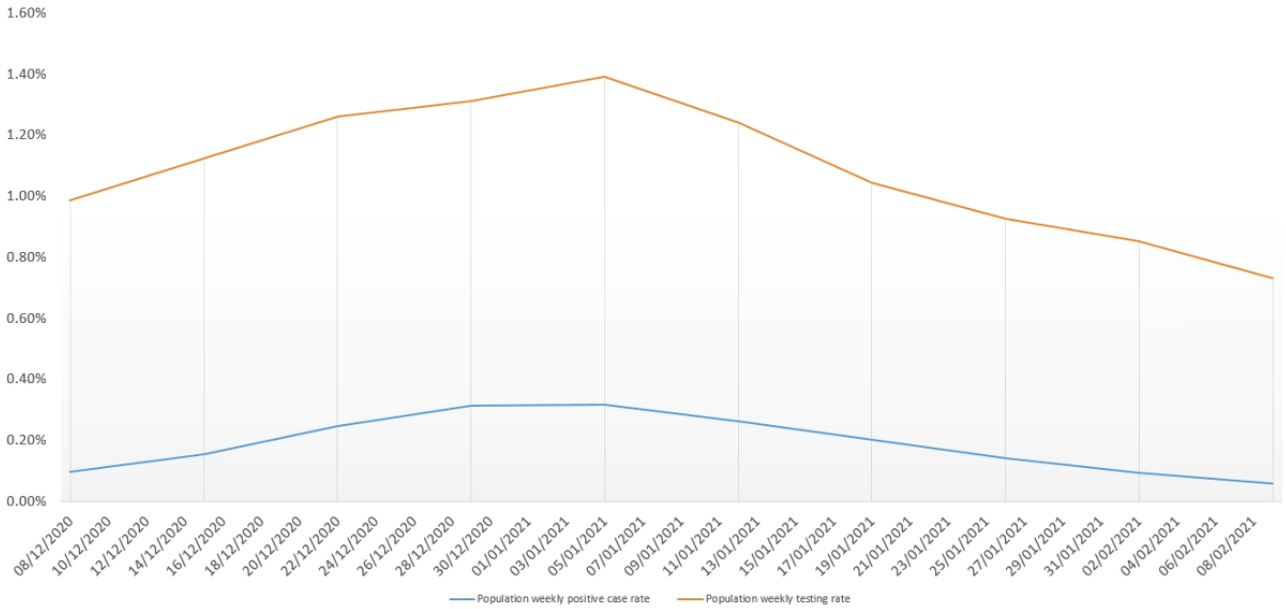
Results

Vaccination Coverage

In NWL, 2,183,939 individuals were eligible to receive a COVID-19 vaccine. A total of 1,059,280 (48.5%) were female; 930,877 (42.6%) were White; 529,492 (24.2%) were Asian or Asian British; 166,011 (7.6%) were Black or Black British; 60,483 (2.8%) were mixed race; and 189,877 (8.7%) were other ethnic groups. There was no ethnicity recorded for 307,099 (14.1%) individuals.

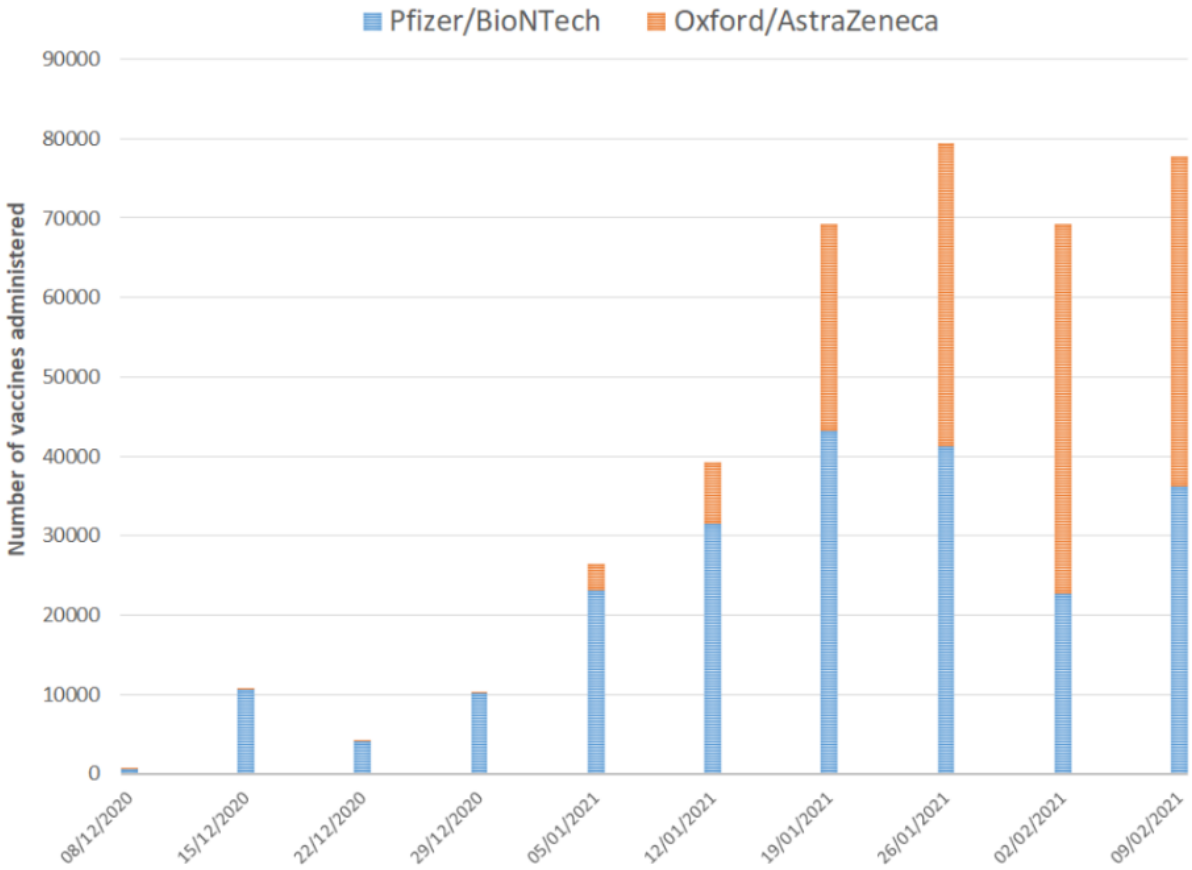
The week-on-week testing rate as a proportion of the overall NWL eligible population reached a peak of 1.39% (n=30,396 tested persons) of the population by the week commencing January 5, 2021 (Figure 1). After this, it fell to 0.73% (n=15,946) of the population in the week commencing February 9, 2021. Eligible population prevalence of positive cases in a week peaked in early January at 0.32% (n=6805 cases) and then fell steadily each week to 0.06% (n=1017 cases) of the population in the week commencing February 9, 2021, with the average across all weeks in the study being 0.19%.

Figure 1. Weekly person SARS-CoV-2 testing rate compared to weekly positive case rate in population eligible for vaccination over duration of study.



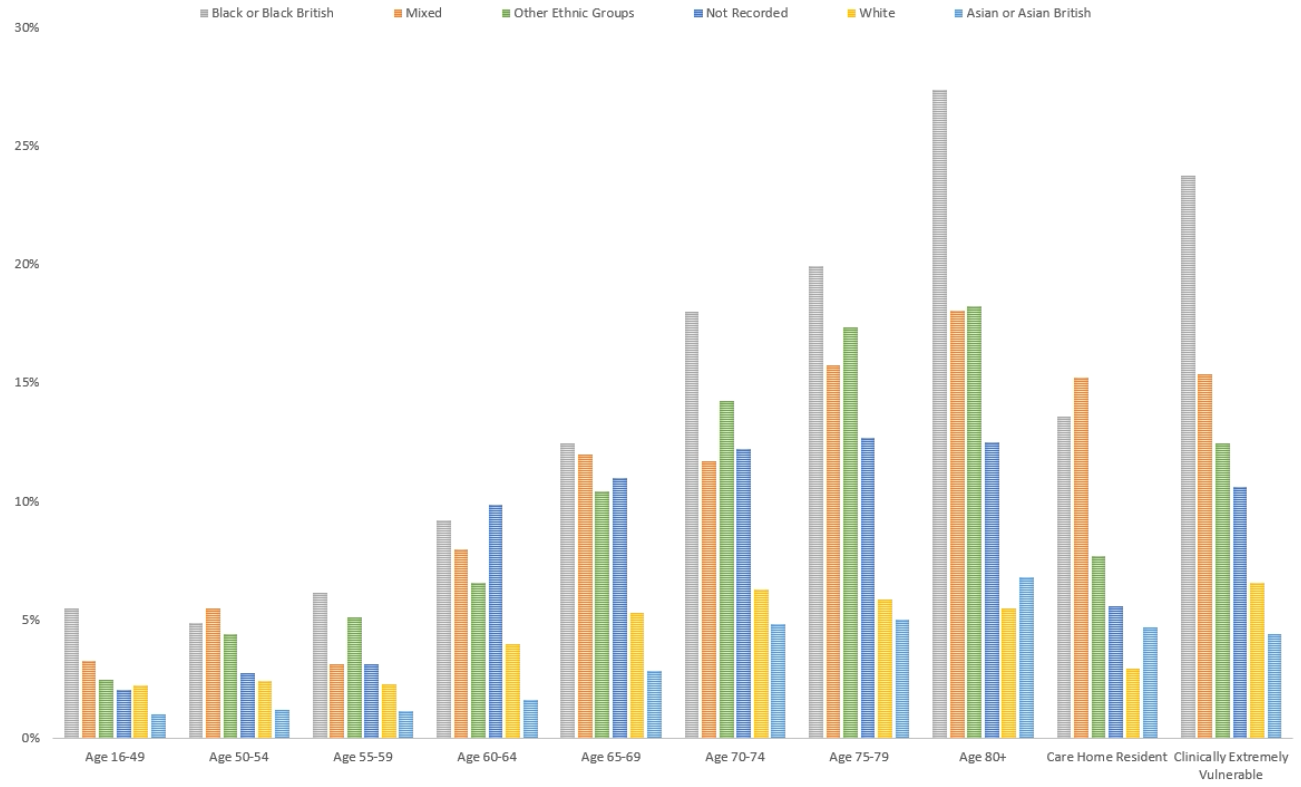
By February 15, 2021, 389,587 (17.84%) individuals had received at least one dose of a COVID-19 vaccine. Vaccination administration notably increased from early January 2021 with the period between January 5 and February 15, 2021, accounting for 363,304 (93.25%) of the total 389,587 vaccines administered (Figure 2). The number of Oxford/AstraZeneca vaccines administered started to reach parity with Pfizer/BioNTech by mid-January. In the NWL vaccination program time period overall, 223,201 (57.29%) Pfizer/BioNTech and 163,452 (41.96%) Oxford/AstraZeneca vaccines were administered. Pfizer was administered to the majority of individuals aged 16-49 years (n=47,817/71,585, 66.80%), 75-79 years (n=25,348/41,057, 61.74%), and 80 years or older (n=42,090/58,116, 72.42%). In those aged 50-74 years, Pfizer and AstraZeneca were administered with similar proportions (Pfizer: n=89,419/174,115, 51.3%); AstraZeneca was administered to the majority of care home residents (n=3822/5186, 73.7%) and in the clinically extremely vulnerable (n=21,014/38,532, 54.5%).

Figure 2. Number of first dose vaccinations given per week in the eligible population from December 8, 2020, during the 10-week study period (numbers of vaccines administered defined as all first dose vaccines delivered within the 7-day period from the weekly start date indicated).



During the NWL vaccine program time period, 413,919 individuals were offered a vaccine and 24,332 (5.88%) people declined and did not receive a vaccination. In the vaccinated group, 2957 patients had initially declined but subsequently went on to receive a vaccination, indicating a hesitancy rate of 0.71% (where an individual is initially unsure about taking a vaccine) over the study period. Over the study time period, the rate of declining a vaccination across all Black, Asian, and minority ethnic groups was 6.39% (11,528/180,210) compared with the White group at 4.92% (9788/187,090). Black or Black British individuals had the highest rate of declining a vaccine at 16.14% (4337/26,870). Mixed ethnicity groups' vaccine declining rate was 10.39% (895/8613). In the Asian and Asian British groups, the rate of declining vaccines was the lowest at 3.21% (3867/120,291). Other ethnic groups' declination rate was 9.95% (2429/24,409), and the ethnicity unrecorded group declination rate was 8.52% (3016/35,419). Within the Black or Black British individuals, the highest rates of declining vaccination during the study period were seen in those 80 years or older or those clinically extremely vulnerable at 27.58% (1384/5018) and 23.97% (940/3911), respectively (Figure 3).

Figure 3. The percentage of population declining vaccination across Whole System Integrated Care risk categories according to ethnicity during the study period.



Overall during the study period, there were similar rates of declining vaccination between gender (female: 13,595/229,732, 5.92%; male: 10,736/184,180, 5.83%). Younger males had a higher rate of declining vaccination than younger females (younger than 65 years, female: 1817/83,872, 2.17%; younger than 65 years, male: 1903/60,221, 3.16%). Conversely, older females had a higher rate of declining vaccination than older males (65 years or older, female: 9594/120,8327, 0.94%; 65 years or older, male: 7186/101,438, 7.08%). There was a strong negative association between deprivation and rate of declining vaccination (r=–0.94; P=.002) with 13.5% (1980/14,571) of individuals declining vaccination in the most deprived postcodes compared to 0.98% (869/9609) in the least deprived postcodes. For individuals living in the most deprived areas (bottom decile), those with the highest rates of vaccine decline were older than 70 years (70-74 years: 344/1963, 17.52%; 75-80 years: 275/1448, 18.99%; 80 years or older: 524/2022, 25.91%), clinically extremely vulnerable (377/1967, 19.17%), and from Black and Black British (337/1967, 25.79%) communities.

Impact of Vaccine Administration on Possible Virus Transmission

In the first 6 days after vaccination, 344 of 389,587 (0.09%) individuals tested positive for SARS-CoV-2. The rate increased to 0.13% (525/389,243) between days 7 and 13, before then gradually falling week by week (Table 1). By week 7, fewer than 20 persons were testing positive each week (weekly rate≤0.05% week 5 onward). Over the same time period, no appreciable decrease in the amount of testing of the vaccinated population was observed, indicating that this was not an effect linked to a reduction in levels of testing in individuals after vaccination.

Care home residents and housebound individuals had a higher rate of positivity in the second week post vaccination at 0.35% (55/15,742) compared with the non–care home or housebound group at 0.13% (525/389,249; Table 1). After the second week, the rate of positivity decreased, although it took until week 5 to reach less than 0.1%. There was a trend to suggest the rate of positivity decrease week on week was slower when compared with the non–care home and housebound group, but absolute numbers of positive cases in care homes and housebound individuals were very low. Overall, the mean age of care home and housebound residents was 80.6 years.

Table 1. Absolute numbers of first positive SARS-CoV-2 tests per week after day of vaccination and weekly rates of testing based on individuals available for follow-up (excluding previously positive cases).[a]

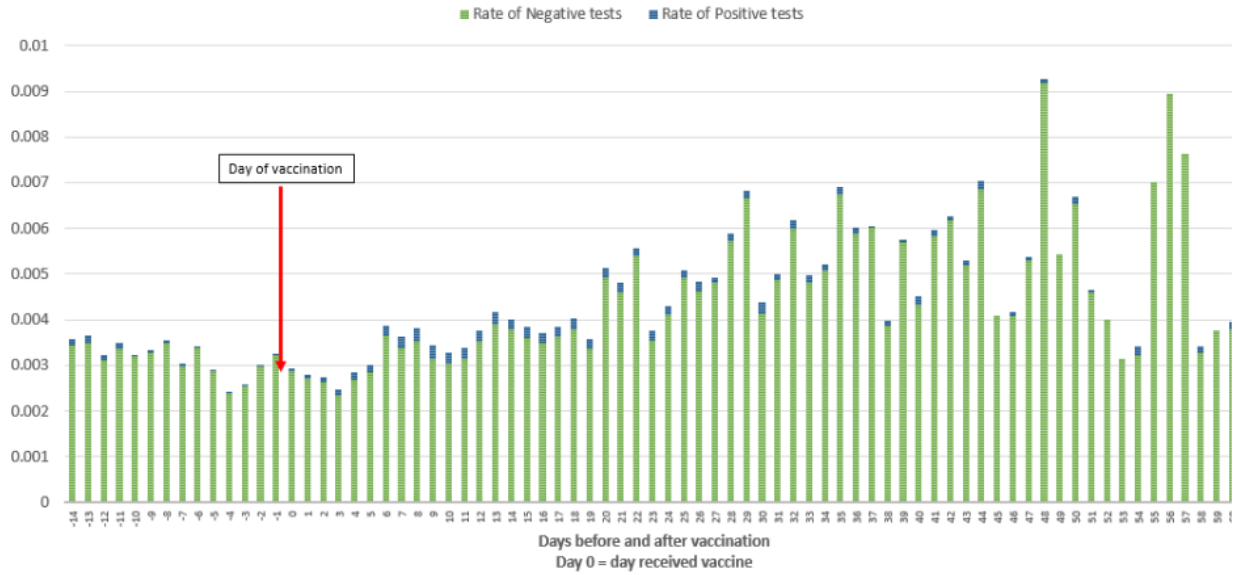
Vaccinations	Days after vaccination										
	<7 (week 1)	7-13 (week 2)	14-20 (week 3)	21-27 (week 4)	28-34 (week 5)	35-41 (week 6)	42-48 (week 7)	49-55 (week 8)	56-62 (week 9)	63-69 (week 10)	≥70 (≥week 11)
Vaccinated individuals time to first positive test after vaccination, n	344	525	332	147	87	48	16	13	11	<5[b]	0
Total vaccinated population completed to period of follow-up (excluding previously positive patients), n	389,587	389,243	330,523	261,447	184,847	111,555	62,283	31,757	20,097	14,200	2519
First positive individuals by population completed to follow-up time to first positive (not previously positive), %	0.09	0.13	0.10	0.06	0.05	0.04	0.03	0.04	0.05	0.01	0.00
Vaccinated individuals (excluding care home or housebound residents) time to first positive test after vaccination, n	319	470	284	129	71	46	13	10	9	<5	0
Total vaccinated population (excluding care home and housebound residents) completed to period of follow-up (excluding previously positive patients), n	373,820	373,501	315,666	248,136	173,336	105,834	59,574	30,674	19,338	13,763	2431
First positive individuals by population completed to follow-up time to first positive (not previously positive; excluding care home and housebound), %	0.09	0.13	0.09	0.05	0.04	0.04	0.02	0.03	0.05	0.01	0.00
Vaccinated care home or housebound individuals time to first positive test after vaccination, n	25	55	48	18	16	<5	<5	<5	<5	0	0
Total vaccinated care home or housebound population completed to period of follow-up (excluding previously positive patients), n	15,767	15,742	14,860	13,317	11,556	5770	2749	1090	771	443	92
First positive care home or housebound individuals by population completed to follow-up time to first positive (not previously positive), %	0.16	0.35	0.32	0.14	0.14	0.03	0.11	0.28	0.26	0.00	0.00

[a]Rates are stratified by individuals in care homes or housebound and those in the rest of the vaccinated population.

[b]Low numbers (1-4) have been replaced with <5.

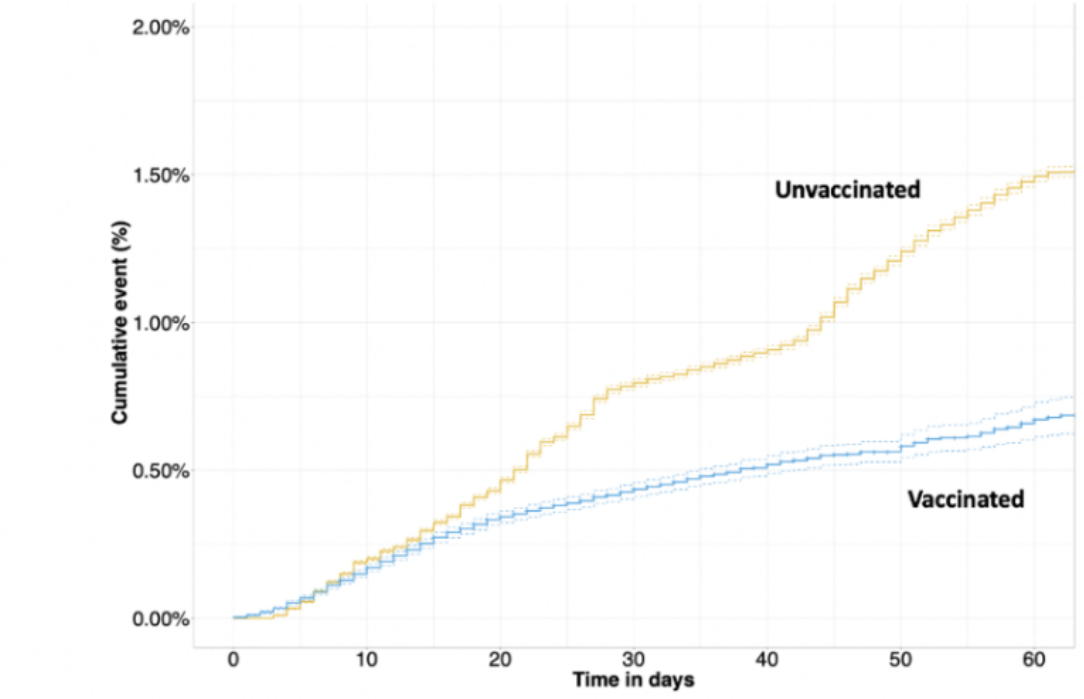
The testing rate was lowest in the 3- to 4-day period either side of the day of vaccination (Figure 4). After vaccination, the testing rate increased and remained, on average, higher until day 60. Data after day 60 was not included at the daily level due to low numbers. The reduction in positive test results after vaccination could not be attributed to overall reduction in testing over time.

Figure 4. The proportion of all SARS-CoV-2 tests in the vaccinated population (not limited to the first positive) each day following administration of their first vaccine dose, based on the number of individuals available for follow-up to the end of the study period, split by positive and nonpositive results.



In summary, Table 1 shows that infections decrease from day 14 post vaccination to rates that are lower than, or equivalent to, the population weekly levels (Figure 1), and these decreases are not a result of a reduction in testing post vaccination (Figure 4). The risk of COVID-19 infection rate was lower in the vaccinated population than the unvaccinated population (Figure 5). The time to testing positive in the vaccinated group compared with the unvaccinated group was similar until day 15 post vaccination when the groups appear to diverge (Figure 5).

Figure 5. Cumulative event rate with a positive SARS-CoV-2 test result in the vaccinated and unvaccinated groups available for follow-up. Numbers at risk are calculated at 10-day intervals. Dotted lines depict 95% CIs.



COVID-19 Vaccination Effectiveness

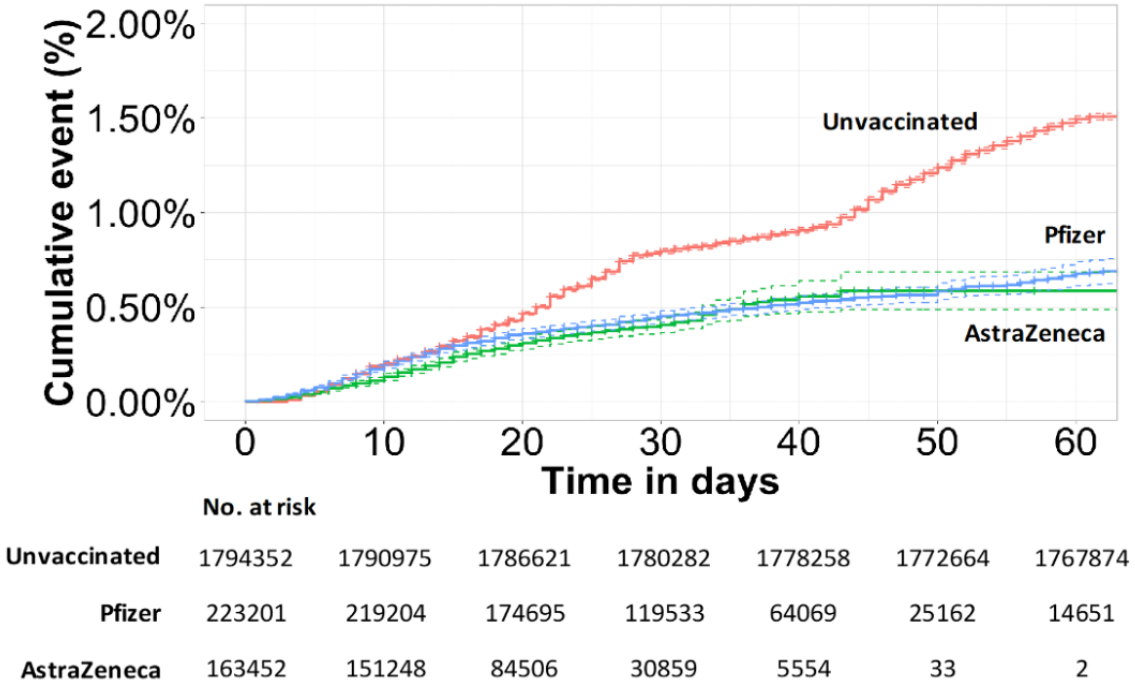
Vaccination effectiveness was measured according to the rates and hazard ratios (HRs) of testing positive post vaccination compared to the unvaccinated population. In individuals that tested positive post vaccination, levels of hospital admissions due to COVID-19 were measured. Of the eligible vaccination cohort, the average length of follow-up post vaccination was 29 days, with a range of follow-up being 10 to 79 days. The time to testing positive in the vaccinated group compared with the unvaccinated groups was similar until day 15 post vaccination when the groups appear to diverge, with a smaller cumulative risk in the vaccinated population of testing positive over time (Figure 5).

At 28 days post vaccination, there was a 74% (HR 0.26, 95% CI 0.19-0.35) and 78% (HR 0.22, 95% CI 0.18-0.27) reduction in risk of testing positive for COVID-19 for individuals that received the Oxford/ AstraZeneca and Pfizer/BioNTech vaccines, respectively, when compared with unvaccinated individuals (Table 2). There was a lack of significant follow-up data in the Oxford/AstraZeneca group to make a meaningful comparison past 28 days; therefore, these results are not displayed with HRs in Table 2. As a reflection of differences in availability of each of the vaccines, patients who were administered the Pfizer vaccination had longer follow-up to those who were administered the AstraZeneca vaccine (Figure 6). There were no differences in SARS-CoV-2–positive event rates comparing people who had the Pfizer and Oxford/AstraZeneca vaccinations (Figure 6).

Table 2. Time-dependent Cox regression analysis of vaccination effect each week following delivery on SARS-CoV-2 positivity during follow-up in all individuals up to 28 days post vaccination.

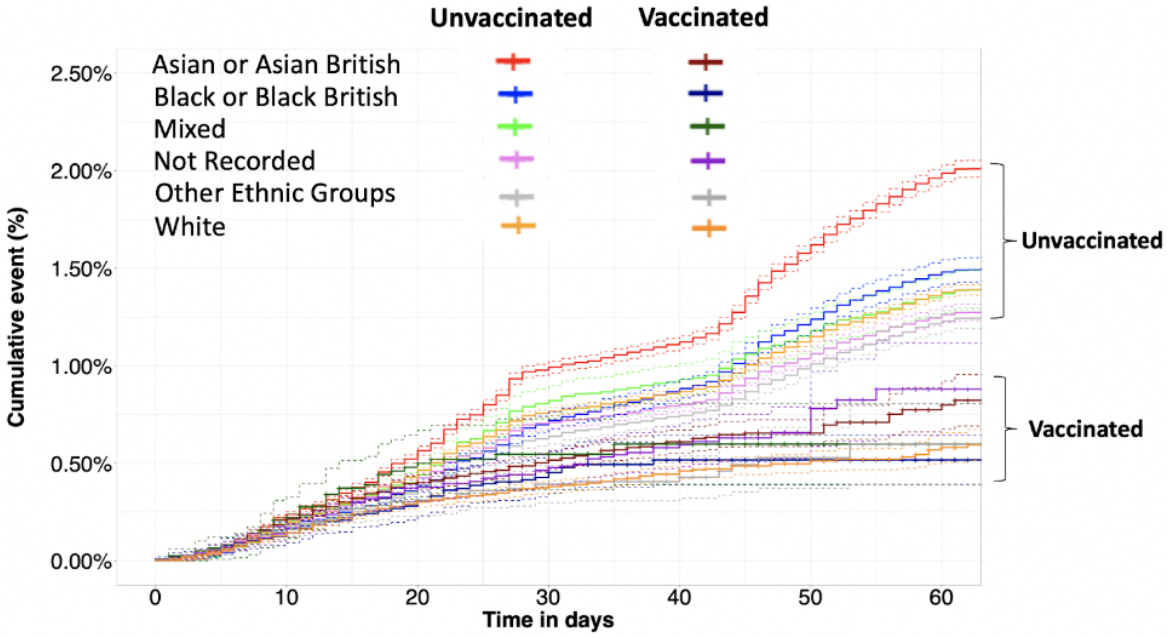
Week period (days)	No vaccination	Oxford/AstraZeneca		Pfizer/BioNTech	
		Hazard ratio (95% CI)	*P* value	Hazard ratio (95% CI)	*P* value
0-7	1.0 (Reference)	0.71 (0.60-0.84)	<.001	1.03 (0.91-1.17)	.65
8-14	1.0 (Reference)	0.68 (0.59-0.80)	<.001	0.90 (0.80-1.00)	.06
15-21	1.0 (Reference)	0.59 (0.49-0.71)	<.001	0.42 (0.36-0.50)	<.001
22-28	1.0 (Reference)	0.26 (0.19-0.35)	<.001	0.22 (0.18-0.27)	<.001

Figure 6. Cumulative event rate of testing positive comparing Pfizer and AstraZeneca vaccination groups to the unvaccinated group available for follow-up. Numbers at risk are calculated at 10-day intervals. Vaccination type was not available for 2934 patients. Dotted lines depict 95% CIs.



Unvaccinated care home residents were four times as likely compared with individuals aged 16-49 to test positive (HR 4.05, 95% CI 3.48-4.71). Unvaccinated Asian or British Asian individuals had a multivariable adjusted HR of 1.45 (95% CI 1.41-1.49) of testing positive by 60 days compared to the White group (Multimedia Appendix 1). All ethnic groups benefited from vaccination, with the greatest reduction in risk due to vaccination seen in Asian or Asian British individuals (Figure 7).

Figure 7. Cumulative event rate of testing for SARS-CoV-2 positive in the vaccinated and unvaccinated groups available for follow-up, stratified by ethnicity. Dotted lines depict 95% CIs.



Unvaccinated men were less likely to test positive within 60 days than women (HR 0.89, 95% CI 0.86-0.91; Multimedia Appendix 1); however, there was no significant difference between the genders in the vaccinated population (Table 3). There were no significant differences in HRs associated with a positive result with vaccination across ethnicities, IMD decile groups, or gender. Significant differences in HRs show that infections in older age groups (65-69 years, 70-74 years, 75-80 years, and 80 years or older) and in clinically extremely vulnerable were present, showing these groups are significantly less likely to be infected post vaccination, indicating vaccine effectiveness in the oldest population groups (Table 3).

In total, 288 vaccinated individuals were admitted to hospital post vaccination who tested positive for SARS-CoV-2 after vaccination and before (or up to 7 days into) their inpatient stay; this accounted for only 0.07% (288/389,587) of vaccinated individuals. Of these patients, 54% (n=155) were admitted before day 14 after vaccination. Admission rates of vaccinated individuals available to follow up peaked at 0.03% (n=102) in days 7 to 13 after vaccination and reduced to 0.01% (n≤5) or lower from days 28 to 34 after vaccination.

Between December 8, 2020, and February 24, 2021, there were a total of 441 all-cause deaths, which comprised 161 (36.5%) and 280 (64.5%) in the vaccinated and unvaccinated groups, respectively. Of the 161 deaths in the vaccinated group, 18 (11.2%) had a positive SARS-CoV-2 test in the 28 days preceding death (1 in 21,739 of all vaccinated patients). Of the 280 deaths in the unvaccinated group, 68 (24.3%) had a positive SARS-CoV-2 test in the 28 days preceding death (1 in 556 of all unvaccinated patients).

Table 3. Multivariable Cox regression analysis showing hazard ratio of a positive SARS-CoV-2 result during follow-up with vaccination in all patients and across different age, ethnic, gender, and IMD decile groups up to day 60 post vaccination.[a]

Variables	Hazard ratio (95% CI)	*P* value
Vaccination		
No vaccination (reference)	1	N/A[b]
Vaccination	0.64 (0.43-0.95)	.03
Age (years)		
16-49 (reference)	1	N/A
50-54	0.75 (0.58-0.98)	.03
55-59	0.82 (0.64-1.06)	.13
60-64	0.79 (0.61-1.02)	.07
65-69	0.41 (0.32-0.54)	<.001
70-74	0.26 (0.20-0.33)	<.001
75-79	0.29 (0.23-0.38)	<.001
≥80	0.29 (0.24-0.36)	<.001
Care home resident	0.76 (0.56-1.05)	.13
Clinically extremely vulnerable	0.30 (0.24-0.38)	<.001
Ethnicity		
White (reference)	1	N/A
Asian or British Asian	0.91 (0.80-1.02)	.11
Black or Black British	0.98 (0.77-1.25)	.89
Mixed	1.29 (0.91-1.82)	.15
Other ethnic groups	1.06 (0.83-1.35)	.65
Gender		
Female (reference)	1	N/A
Male	1.02 (0.91-1.15)	.69
IMD[c] decile		
1 (reference)	1	N/A
2	1.03 (0.74-1.43)	.87
3	1.11 (0.82-1.51)	.49
4	0.97 (0.71-1.32)	.83
5	1.08 (0.79-1.48)	.62
6	1.04 (0.76-1.42)	.79
7	0.80 (0.58-1.12)	.24
8	0.84 (0.59-1.20)	.33
9	0.93 (0.65-1.34)	.72
10	0.83 (0.56-1.21)	.33

[a]Cox regression model included an interaction term between having the vaccination and individual patient groups (age, ethnicity, gender, IMD decile).
[b]N/A: not applicable.
[c]IMD: index of multiple deprivation.

Discussion

Principal Results

By February 15, 2021, the NWL vaccination program had vaccinated 17.84% (389,587/2,183,939) of the eligible population, according to priority, with at least one dose of a COVID-19 vaccine over a 10-week period, commencing December 8, 2020. Understanding and addressing vaccine hesitancy, across the population offered a vaccine, represents an important improvement opportunity to maximize widespread population vaccination coverage; in this study, 5.88% (24,332/413919) of the NWL eligible population declined a vaccine. Rates of vaccine decline within Black and Black British groups were three times greater (16.14%, 4337/26,870) than the White population. A quarter of Black and Black British individuals who were 80 years or older, or were clinically extremely vulnerable (27.58% and 23.97%, respectively) declined the vaccine. This finding is supported by similar reports examining vaccine hesitancy [16]. There was a strong negative correlation between deprivation score and vaccine hesitancy; individuals in the most deprived areas declined vaccinations at a rate 13 times higher than those in the most affluent areas. Overall across NWL, the highest rates of vaccine decline were seen in older adults and Black British people living in the most deprived areas. The causes for this were not assessed by this study but highlights an important area of focus for quality improvement, public and societal engagement, and outreach initiatives to improve vaccination coverage across all population groups, especially in relation to findings that indicate vaccine effectiveness.

As previous studies have shown, this data supports the strategy of prioritizing the older adult and care home residents, as unvaccinated care home residents were four times as likely to test positive (HR 4.05, 95% CI 3.48-4.71) compared with individuals aged 16-49 years. There is further evidence of differing susceptibility to COVID-19 across sociodemographic groups, which could support further vaccine prioritization to those who would benefit most; unvaccinated Asian and Asian British individuals were at increased risk of testing positive for SARS-CoV-2 compared to the White population (HR 1.45, 95% CI 1.41-1.49), and unvaccinated women more likely to test positive in 60 days than men (male HR 0.89, 95% CI 0.86-0.91).

The incubation period to develop symptoms indicative of COVID-19 is on average 5 to 6 days but can be as long as 14 days [5,7]. This means that the majority of transmission at the point of vaccination should be detected and confirmed by positive test results within 14 days of vaccination. The rate of positive COVID-19 cases in the second week (days 7-13) after receiving a vaccine at a vaccination hub or via a roving team for care home and housebound individuals, peaked at 0.13% (525/389,243). Although this was higher than 0.09% (344/389,587) recorded in days 1 to 6, it was lower than the average weekly person testing positive rate recorded in the total population at 0.19% (average weekly 4112/2,183,503) This supports the conclusion that the act of vaccine delivery in NWL did not increase SARS-CoV-2 transmission above that already seen in the background population. Despite overall low levels of positive testing in the vaccinated group, however, the increase in positive tests recorded in days 7 to 13 after vaccination do suggest some potential for increased SARS-CoV-2 transmission at or after the time of vaccination. It is impossible to identify and separate out several possible contributors to this, including in the days postvaccination individuals were more liberal with isolation and social distancing measures before immunity resulting from vaccination had become effective, some transmission of SARS-CoV-2 occurring at time of vaccine administration, or individuals were asymptomatic but infected when attending for vaccination. Certainly, regarding the latter, there is some evidence to support this, as a number of individuals tested positive within 5 days of attending for vaccination (Figure 4).

In the care home residents or housebound individuals, the rise in positive case rate in the second week post vaccination was greater than that of the rest of the vaccinated population (55/15,742, 0.35% compared to 525/389,243, 0.13%) in non–care home and housebound individuals. This higher rate needs to be interpreted within the context of physically frail groups having innate vulnerability to SARS-CoV-2 transmission [17]. Equally, it is not possible to determine the contribution of postvaccination easing of social distancing and isolation measures prior to the vaccination generating an immune response that provides effective protection. There is also some evidence that the time for older adults to develop effective immunity takes longer than the younger population [18]. This is supported by a trend suggesting the rate of positivity decreases week on week more slowly when compared with the non–care home and housebound group, but absolute numbers of positive cases in care homes and housebound individuals were very low. These results highlight the importance of maintaining physical COVID-19 restriction procedures post vaccination, particularly in the first fortnight. Care home residents and housebound individuals may be particularly vulnerable in the immediate period post vaccination, thus, emphasizing the need to maintain social distancing and restricting visitors to care homes to prevent exposure until population prevalence of COVID-19 has fallen to sufficient levels to make transmission unlikely and time has elapsed to allow postvaccination immunity to develop in this higher risk population. The rise in positive case rates seen in the care home population after the seventh week post vaccination (n≤5 of 1090, 0.28%) raises concerns that the immunological effects of the single vaccine dose may be waning in the frail older adult population over time, which could be due to immunosenescence. The significance of this, however, needs to be interpreted within the small numbers completing follow-up in this group (n=1090). Further studies to examine this are required, as it will have implications for timing of second vaccine administration, which may well vary across priority groups.

Overall, in the NWL population, the rate of positive testing in the vaccinated group compared with the unvaccinated group was similar until day 15, whereafter vaccination reduced an individual's chance of testing positive for COVID-19 beyond 10 weeks of follow-up. The cumulative risk reduction of testing positive for SARS-CoV-2 at 60 days was 36% (HR 0.64, 95% CI 0.43-0.95; *P*=.03) when receiving a single dose of any

vaccine. By the fourth week of follow up (days 22-28), there was similar efficacy for vaccination, with a 74% (HR 0.26, 95% CI 0.19-0.35) and 78% (HR 0.22, 95% CI 0.18-0.27) reduction in risk of testing positive for SARS-CoV-2 in the Oxford/AstraZeneca group and Pfizer/BioNTech group, respectively, compared with the unvaccinated population. There were insufficient numbers of individuals with enough follow-up data in the Oxford/AstraZeneca group to power a statistical comparison between vaccine types beyond 28 days.

The reduction in severity of cases is also evident as demonstrated by the low numbers of admissions to hospitals for vaccinated individuals, with admission rates dropping 14 days post vaccination. Further work is required to compare admissions in the vaccinated population and comparable control populations, including for non–COVID-19 reasons. The vaccinated and unvaccinated populations are inherently different, as vaccination was rolled out according to the priority groups first.

Limitations

This study uses a unique linked data set that provides real-time data for clinical and operational care delivery, especially relevant during the COVID-19 pandemic. This study highlights the use of these data for generating real-world evidence in accordance with translational data analytics, in addition to data collected through prospective clinical trials. The large sample size of over 2 million people receiving 389,587 doses of a vaccine is a strength of the study with a comparatively long follow-up time compared to other studies that have been reported to date. The cost of running an randomized controlled trial of this size would be significant, but equally, outcome measurements from real-world evidence are less robust, and the results must be interpreted accordingly. The lack of robust control groups to compare with the vaccinated population is problematic, but further analysis similar to methods used by Kaura et al [19] on emulating clinical trials using observational data may be able to address these issues. Follow-up time commenced on December 8, 2020, which was the start of the vaccination program, for those unvaccinated and commenced on the day of vaccination for those vaccinated. Further studies are required that match individuals in the vaccinated and unvaccinated groups on a daily or weekly basis to avoid bias due to differential follow-up start times between the vaccinated and unvaccinated groups, with the potential for exposure to different SARS-CoV-2 strains during follow-up. Soon after the vaccination program started, the national decision was made to schedule the administration of the second vaccination doses, for both Oxford/AstraZeneca and Pfizer/BioNTech, for 10 to 12 weeks after the first dose. As the majority of the first dose vaccinations in NWL were completed in the last 10 weeks of the study period, too small a number of the population had received a second dose at time of data extraction, such that no meaningful analysis could be done addressing completion of the two dose vaccine schedule. Hospitalization due to COVID-19 in the vaccinated population was examined but not compared to the unvaccinated population. This was due to the inherent differences in the groups based on the rollout of vaccinations to those at the highest risk first, meaning unvaccinated individuals would not serve as a suitable control.

The low specificity and sensitivity of some testing mechanisms may provide a degree of error, as rates of positive SARS-CoV-2 tests are used to estimate COVID-19 prevalence in the population. Test results available included pillar one and two but not lateral flow test results. No data were collected on COVID-19 symptoms, and so no assessment on the effects of vaccination on COVID-19 symptoms could be made. By capturing only pillars one and two testing data, this study likely misses asymptomatic cases of COVID-19 in the population, underestimating its true rate. Variation in the prevalence of COVID-19 in the population during the study period could impact the results of the study. Declining rates of COVID-19 in the population during the time of maximal vaccine delivery could have amplified the observed effects of the vaccine.

Only SARS-CoV-2–positive results in the vaccinated group were included in this analysis; therefore, we were not able to assess the impact of antibodies developed from previous COVID-19 infection compared with antibodies developed because of vaccination. However, there remain multiple confounders that cannot be determined from the data, namely, unconfirmed infections, asymptomatic positive individuals, and the uncertain length of time that postvaccination immunity persists. The likely dominant SARS-CoV-2 variant in the examined population at time of study was B1.1.7 [20]. Data on SARS-CoV-2 variants were not collected during the study. The study findings therefore may not be comparable in populations with differing dominant SARS-CoV-2 strains.

Comparison With Prior Work

A reduction in the risk of testing positive became apparent from day 15 after the administration of a single dose of vaccine in our study. This finding is similar to phase three trial [3] data showing a benefit from day 10 to 13 after a first dose in the Pfizer vaccine and from day 18 in a real-world data study [21]. Interim analysis of four randomized controlled trials in Brazil, South Africa, and the United Kingdom examining the safety and the efficacy of the Oxford/AstraZeneca vaccine did not report efficacy data of a first dose before day 21 post vaccination, showing an efficacy of 64.1% (95% CI 50.5-73.9) after 21 days [4]. Our study demonstrated an observable reduction in risk of testing positive before 21 days, with a 29% (95% CI 16%-40%; $P<.001$) and 32% (95% CI 20%-41%; $P<.001$) reduction in the first (days 0-6) and second (days 7-13) week, respectively, after receiving a first dose of Oxford/AstraZeneca (Multimedia Appendix 2).

Our findings show at 22 to 28 days post vaccination there is a 78% (HR 0.22, 95% CI 0.18-0.27) reduction in risk of testing positive for SARS-CoV-2 after a single dose of the Pfizer/BioNTech vaccine in a cohort representative of a UK urban population. This is comparable to real-world evidence in an Israeli population administered the Pfizer/BioNTech vaccine, showing the early effectiveness of a single dose was estimated to be 52% during the first 24 days after vaccination [21], although a reanalysis of the same data by Hunter and Brainard [22] estimated that, by day 24, vaccine effectiveness had reached 90%. The variation in study design may explain differences seen in efficacy, as the Israeli study used the vaccinated population in days 1 to 12 of vaccination as the control group

compared to an unvaccinated control group in our study. Hall et al [23] studied the outcomes of the Pfizer/BioNTech vaccine on a cohort of National Health Service (NHS) health care workers as part of the SIREN study with a similar length of follow-up. This prospective cohort study found reduced levels of vaccine coverage in minority groups, especially Black or Black British groups, similar to our findings, even within a health care worker population. A single dose of Pfizer/BioNTech vaccine demonstrated vaccine effectiveness of 72% (95% CI 58-86) 21 days after the first dose, comparable to our findings, although in a purely working age population [23].

Bernal et al [24] are awaiting peer review of their test negative case-control study estimating the effect of vaccination with the BNT162b2 and ChAdOx1 COVID-19 vaccines in an older population 70 years or older in England. Individuals 80 years or older immunized with BNT162b2 vaccine demonstrated an effectiveness of 70% (95% CI 59%-78%) from 28 to 34 days. ChAdOx1 vaccine effects were seen from 14 to 20 days after vaccination, reaching an effectiveness of 60% (95% CI 41%-73%) from 28 to 34 days and further increasing to 73% (95% CI 27%-90%) from day 35 onward. Similar to our findings Bernal et al [24] demonstrated an increased risk of testing positive in the first 14 days after receiving a vaccine, and those 80 years or older were at particular risk in the first 9 days after vaccination (odds ratio up to 1.48, 95% CI 1.23-1.77).

The causes of vaccine decline were not assessed in this study, but predictors of negative attitudes to vaccines both before and during the COVID-19 pandemic have been described previously in the literature, with most common reasons for hesitancy reported as fear of side effects and long-term health effects and lack of trust in vaccines, particularly among Black respondents [25,26]. Groups with higher rates of vaccine decline are also the same groups seen to be at an increased risk of serious complications from COVID-19, highlighting an important area of focus for outreach initiatives [27].

Conclusions

This study provides further evidence that a single dose of either the Pfizer/BioNTech vaccine or the Oxford/AstraZeneca vaccine is effective at reducing the risk of testing positive for SARS-CoV-2 up to 60 days across all adult age groups, ethnic groups, and risk categories in an urban UK population. There was no difference in effectiveness up to 28 days between the Oxford/AstraZeneca and Pfizer/BioNTech vaccines. In those declining vaccination, higher rates were seen in those living in the most deprived areas and in Black and Black British groups.

There was no definitive evidence to suggest COVID-19 was transmitted as a result of vaccination hubs during the vaccine administration rollout in NWL, and the risk of contracting COVID-19 or becoming hospitalized after vaccination has been demonstrated to be very low in the vaccinated population. Individuals appear to be less susceptible to COVID-19 transmission in the first weeks after receiving a vaccine as compared with the unvaccinated population; however, a clear message reinforcing the need to continue social distancing restrictions post vaccination should be delivered at the time of vaccination and potentially for up to 21 days. There is also evidence to suggest that in the care home and housebound population, the period of social distancing measures should be more carefully adhered to post vaccination, as initial evidence suggests the time to potentially acquire immunity in this group could take longer than in the general population.

Acknowledgments

The authors would like to acknowledge members of the North West London Data & Analytics Gold Command for contribution to interpretation of the findings: Roger Chinn, Martin Kuper, Jacques Naude, Merav Dover, James Biggin-Lamming, Sanjay Gautama, and Kevin Jarrold. The authors would also like to acknowledge Owain Griffiths from Whole Systems Integrated Care for helping with data access and data quality checks.

This study uses data provided by patients and collected by the National Health Service (NHS) as part of their care and support. Using patient data is vital to improve health and care for everyone. There is potential to make better use of information from people's patient records, to understand more about disease, develop new treatments, monitor safety, and plan NHS services. Patient data should be kept safe and secure to protect everyone's privacy, and it's important that there are safeguards to make sure that it is stored and used responsibly. Everyone should be able to find out about how patient data is used (#datasaveslives).

This research was enabled by the Imperial Clinical Analytics Research and Evaluation (iCARE) environment and Whole System Integrated Care (WSIC), and used the iCARE and WSIC team and data resources [11]. The research was supported by the National Institute for Health Research (NIHR) Imperial Biomedical Research Centre, the NIHR Imperial Patient Safety Translational Research Centre, and the North West London NIHR Applied Research Collaboration. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR, or the Department of Health and Social Care. AK is funded by a British Heart Foundation clinical research training fellowship (FS/20/18/34972).

We are unable to extract or publish patient-level data from the iCARE and WSIC due to data protection restrictions. Any request to access data can be made to Nwlccgs.covid19IG@nhs.net referring to the title of this paper.

Authors' Contributions

BG, JB, JR, AK, IG, and EKM conceived the study aims and objectives. AM and LM carried out the programming to extract and curate the data from the source data tables. BG, AK, and EKM undertook all data analyses. JB, BG, AK, and EKM drafted the

manuscript. BG, JB, AK, AM, LM, SJB, PA, TS, IG, JR, KS, and EKM provided a critical review of the manuscript. All authors read and approved the final version of the manuscript. EKM is guarantor for this paper. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.
The guarantor (EKM) affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as originally planned (and, if relevant, registered) have been explained.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplementary Table. Multivariable Cox regression analysis showing hazard ratio of a positive SARS-CoV-2 result in the unvaccinated group across different age, ethnic, gender, and index of multiple deprivation decile groups to day 60 post vaccination.
[DOCX File , 24 KB - publichealth_v7i9e30010_app1.docx]

Multimedia Appendix 2
Supplementary Figure. Cumulative event rate of testing SARS-CoV-2–positive over the first 2 weeks from day of vaccination comparing Pfizer and AstraZeneca vaccination groups to the unvaccinated group. Dotted lines depict 95% CIs.
[PNG File , 280 KB - publichealth_v7i9e30010_app2.png]

References

1. Sharma O, Sultan AA, Ding H, Triggle CR. A review of the progress and challenges of developing a vaccine for COVID-19. Front Immunol 2020;11:585354. [doi: 10.3389/fimmu.2020.585354] [Medline: 33163000]
2. UK COVID-19 vaccine uptake plan. GOV.UK. 2021 Feb 13. URL: https://www.gov.uk/government/publications/covid-19-vaccination-uptake-plan/uk-covid-19-vaccine-uptake-plan [accessed 2021-02-28]
3. Polack FP, Thomas SJ, Kitchin N, Absalon J, Gurtman A, Lockhart S, C4591001 Clinical Trial Group. Safety and efficacy of the BNT162b2 mRNA Covid-19 vaccine. N Engl J Med 2020 Dec 31;383(27):2603-2615 [FREE Full text] [doi: 10.1056/NEJMoa2034577] [Medline: 33301246]
4. Voysey M, Clemens S, Madhi S, Weckx LY, Folegatti PM, Aley PK, Oxford COVID Vaccine Trial Group. Safety and efficacy of the ChAdOx1 nCoV-19 vaccine (AZD1222) against SARS-CoV-2: an interim analysis of four randomised controlled trials in Brazil, South Africa, and the UK. Lancet 2021 Jan 09;397(10269):99-111 [FREE Full text] [doi: 10.1016/S0140-6736(20)32661-1] [Medline: 33306989]
5. Optimising the COVID-19 vaccination programme for maximum short-term impact. GOV.UK. 2021. URL: https://www.gov.uk/government/publications/prioritising-the-first-covid-19-vaccine-dose-jcvi-statement/optimising-the-covid-19-vaccination-programme-for-maximum-short-term-impact [accessed 2021-04-28]
6. Coronavirus (COVID-19) vaccinations. Our World in Data. 2021. URL: https://ourworldindata.org/covid-vaccinations [accessed 2021-04-28]
7. UK COVID-19 vaccines delivery plan. GOV.UK. URL: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/951928/uk-covid-19-vaccines-delivery-plan-final.pdf [accessed 2021-04-28]
8. Murphy J, Vallières F, Bentall RP, Shevlin M, McBride O, Hartman TK, et al. Psychological characteristics associated with COVID-19 vaccine hesitancy and resistance in Ireland and the United Kingdom. Nat Commun 2021 Jan 04;12(1):29. [doi: 10.1038/s41467-020-20226-9] [Medline: 33397962]
9. Schwarzinger M, Watson V, Arwidson P, Alla F, Luchini S. COVID-19 vaccine hesitancy in a representative working-age population in France: a survey experiment based on vaccine characteristics. Lancet Public Health 2021 Apr;6(4):e210-e221 [FREE Full text] [doi: 10.1016/S2468-2667(21)00012-8] [Medline: 33556325]
10. MacDonald NE, SAGE Working Group on Vaccine Hesitancy. Vaccine hesitancy: definition, scope and determinants. Vaccine 2015 Aug 14;33(34):4161-4164 [FREE Full text] [doi: 10.1016/j.vaccine.2015.04.036] [Medline: 25896383]
11. Imperial Clinical Analytics, Research and Evaluation (iCARE). NIHR Imperial Biomedical Research Centre. URL: https://imperialbrc.nihr.ac.uk/facilities/icare/ [accessed 2021-04-28]
12. Whole Systems Integrated Care (WSIC). North West London Clinical Commissioning Group. URL: https://www.nwlondonccgs.nhs.uk/professionals/whole-systems-integrated-care-wsic-dashboards-and-information-sharing [accessed 2021-04-28]
13. Bottle A, Cohen C, Lucas A, Saravanakumar K, Ul-Haq Z, Smith W, et al. How an electronic health record became a real-world research resource: comparison between London's Whole Systems Integrated Care database and the Clinical Practice Research Datalink. BMC Med Inform Decis Mak 2020 Apr 20;20(1):71 [FREE Full text] [doi: 10.1186/s12911-020-1082-7] [Medline: 32312259]

14. PHE and LSHTM: the contribution of nosocomial infections to the first wave, 28 January 2021. GOV.UK. 2021 Jan 28. URL: https://www.gov.uk/government/publications/phe-and-lshtm-the-contribution-of-nosocomial-infections-to-the-first-wave-28-january-2021 [accessed 2021-04-28]
15. English indices of deprivation 2019. GOV.UK. URL: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019 [accessed 2021-04-28]
16. Factors influencing COVID-19 vaccine uptake among minority ethnic groups, 17 December 2020. GOV.UK. URL: https://www.gov.uk/government/publications/factors-influencing-covid-19-vaccine-uptake-among-minority-ethnic-groups-17-december-2020 [accessed 2021-04-28]
17. Perrotta F, Corbi G, Mazzeo G, Boccia M, Aronne L, D'Agnano V, et al. COVID-19 and the elderly: insights into pathogenesis and clinical decision-making. Aging Clin Exp Res 2020 Aug;32(8):1599-1608 [FREE Full text] [doi: 10.1007/s40520-020-01631-y] [Medline: 32557332]
18. Ramasamy M, Minassian A, Ewer K, Flaxman A, Folegatti P, Owens D, Oxford COVID Vaccine Trial Group. Safety and immunogenicity of ChAdOx1 nCoV-19 vaccine administered in a prime-boost regimen in young and old adults (COV002): a single-blind, randomised, controlled, phase 2/3 trial. Lancet 2021 Dec 19;396(10267):1979-1993 [FREE Full text] [doi: 10.1016/S0140-6736(20)32466-1] [Medline: 33220855]
19. Kaura A, Sterne JAC, Trickey A, Abbott S, Mulla A, Glampson B, et al. Invasive versus non-invasive management of older patients with non-ST elevation myocardial infarction (SENIOR-NSTEMI): a cohort study based on routine clinical data. Lancet 2020 Aug 29;396(10251):623-634 [FREE Full text] [doi: 10.1016/S0140-6736(20)30930-2] [Medline: 32861307]
20. Investigation of SARS-CoV-2 variants of concern in England. Technical briefing 6. Public Health England. URL: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/961299/Variants_of_Concern_VOC_Technical_Briefing_6_England-1.pdf [accessed 2021-04-28]
21. Chodick G, Tene L, Patalon T, Gazit S, Tov AB, Cohen D, et al. The effectiveness of the first dose of BNT162b2 vaccine in reducing SARS-CoV-2 infection 13-24 days after immunization: real-world evidence. medRxiv Preprint posted online on January 29, 2021. [doi: 10.1101/2021.01.27.21250612]
22. Hunter PR, Brainard J. Estimating the effectiveness of the Pfizer COVID-19 BNT162b2 vaccine after a single dose. A reanalysis of a study of 'real-world' vaccination outcomes from Israel. medRxiv Preprint posted online on February 3, 2021. [doi: 10.1101/2021.02.01.21250957]
23. Hall VJ, Foulkes S, Saei A, Andrews N, Oguti B, Charlett A, The SIREN Study Group, et al. Effectiveness of BNT162b2 mRNA vaccine against infection and COVID-19 vaccine coverage in healthcare workers in England, multicentre prospective cohort study (the SIREN Study). SSRN J Preprint posted online on February 22, 2021. [FREE Full text] [doi: 10.2139/ssrn.3790399]
24. Bernal JL, Andrews N, Gower C, Stowe J, Robertson C, Tessier E, et al. Early effectiveness of COVID-19 vaccination with BNT162b2 mRNA vaccine and ChAdOx1 adenovirus vector vaccine on symptomatic disease, hospitalisations and mortality in older adults in the UK: a test negative case control study. medRxiv Preprint posted online on March 2, 2021. [FREE Full text] [doi: 10.1101/2021.03.01.21252652]
25. Razai MS, Osama T, McKechnie DGJ, Majeed A. Covid-19 vaccine hesitancy among ethnic minority groups. BMJ 2021 Feb 26;372:n513. [doi: 10.1136/bmj.n513] [Medline: 33637577]
26. Robertson E, Reeve KS, Niedzwiedz CL, Moore J, Blake M, Green M, et al. Predictors of COVID-19 vaccine hesitancy in the UK household longitudinal study. medRxiv Preprint posted online on January 2, 2021. [doi: 10.1101/2020.12.27.20248899]
27. Paul E, Steptoe A, Fancourt D. Attitudes towards vaccines and intention to vaccinate against COVID-19: implications for public health communications. Lancet Reg Health Eur 2021 Feb;1:100012 [FREE Full text] [doi: 10.1016/j.lanepe.2020.100012] [Medline: 33954296]

Abbreviations

CCG: Collaboration of Clinical Commissioning Group
GP: general practitioner
HR: hazard ratio
iCARE: Imperial Clinical Analytics Research and Evaluation
IMD: index of multiple deprivation
MHRA: Medicines and Healthcare Products Regulatory Agency
NHS: National Health Service
NIHR: National Institute for Health Research
NWL: North West London
WSIC: Whole System Integrated Care

Edited by T Sanchez; submitted 05.05.21; peer-reviewed by M Lamba, A Mavragani; comments to author 07.06.21; revised version received 01.07.21; accepted 08.07.21; published 17.09.21.

Please cite as:
Glampson B, Brittain J, Kaura A, Mulla A, Mercuri L, Brett SJ, Aylin P, Sandall T, Goodman I, Redhead J, Saravanakumar K, Mayer EK
Assessing COVID-19 Vaccine Uptake and Effectiveness Through the North West London Vaccination Program: Retrospective Cohort Study
JMIR Public Health Surveill 2021;7(9):e30010
URL: https://publichealth.jmir.org/2021/9/e30010
doi:10.2196/30010
PMID:34265740

Original Paper

Designing a Clinical Decision Support Tool That Leverages Machine Learning for Suicide Risk Prediction: Development Study in Partnership With Native American Care Providers

Emily E Haroz[1], MA, PhD; Fiona Grubin[1], BS, MSPH; Novalene Goklish[1], BS, MS; Shardai Pioche[1], BA, MSW; Mary Cwik[1], BA, MA, PhD; Allison Barlow[1], BA, MA, MPH, PhD; Emma Waugh[1], BS, MPH; Jason Usher[1], BA, MPH; Matthew C Lenert[2], MS, PhD; Colin G Walsh[2,3,4], MA, MD

[1]Center for American Indian Health, Department of International Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, United States

[2]Department of Biomedical Informatics, Vanderbilt University Medical Center, Nashville, TN, United States

[3]Department of Medicine, Vanderbilt University Medical Center, Nashville, TN, United States

[4]Department of Psychiatry, Vanderbilt University Medical Center, Nashville, TN, United States

Corresponding Author:
Emily E Haroz, MA, PhD
Center for American Indian Health
Department of International Health
Johns Hopkins Bloomberg School of Public Health
415 N Washington St
Baltimore, MD, 21231
United States
Phone: 1 410 449 0051
Email: eharoz1@jhu.edu

Abstract

Background: Machine learning algorithms for suicide risk prediction have been developed with notable improvements in accuracy. Implementing these algorithms to enhance clinical care and reduce suicide has not been well studied.

Objective: This study aims to design a clinical decision support tool and appropriate care pathways for community-based suicide surveillance and case management systems operating on Native American reservations.

Methods: Participants included Native American case managers and supervisors (N=9) who worked on suicide surveillance and case management programs on 2 Native American reservations. We used in-depth interviews to understand how case managers think about and respond to suicide risk. The results from interviews informed a draft clinical decision support tool, which was then reviewed with supervisors and combined with appropriate care pathways.

Results: Case managers reported acceptance of risk flags based on a predictive algorithm in their surveillance system tools, particularly if the information was available in a timely manner and used in conjunction with their clinical judgment. Implementation of risk flags needed to be programmed on a dichotomous basis, so the algorithm could produce output indicating high versus low risk. To dichotomize the continuous predicted probabilities, we developed a cutoff point that favored specificity, with the understanding that case managers' clinical judgment would help increase sensitivity.

Conclusions: Suicide risk prediction algorithms show promise, but implementation to guide clinical care remains relatively elusive. Our study demonstrates the utility of working with partners to develop and guide the operationalization of risk prediction algorithms to enhance clinical care in a community setting.

(JMIR Public Health Surveill 2021;7(9):e24377) doi:10.2196/24377

KEYWORDS

suicide prevention; machine learning; Native American health; implementation

Introduction

Background

Some of the biggest successes in suicide prevention have come from populations with the greatest needs, including Native American communities. The White Mountain Apache Tribe in Arizona has been a leader in this field with their award-winning program surveillance and case management program, called Celebrating Life (CL). After a spike in youth suicides in 2001, tribal leaders leveraged sovereignty and mandated a community-wide suicide surveillance system [1]. Since then, all people working or living on the reservation are required by law to report incidents of suicidal ideation, attempts, deaths, nonsuicidal self-injury, and high-risk substance use, as defined by high-risk patterns of alcohol and drug use, particularly for youth and adolescents in a central registry. Each of these reports is then followed up on in person by trained Apache case managers.

The registry, brief contact, and case management system comprise the backbone of the CL program. International evidence supports this model as a promising approach to reduce the number of people who die by suicide [2]. CL also incorporates more upstream suicide prevention efforts, such as brief culturally informed interventions delivered to children and families at their homes or in schools [3,4], gatekeeper training programs, and door-to-door campaigns. CL has contributed to reducing suicide rates by 38% and suicide attempts by 57% on the Fort Apache Indian Reservation [5]. Given its success, several tribes are in the process of adapting and replicating CL to their own settings.

As awareness of the surveillance and case management programs has grown, so has the volume of referrals. Reaching all those reported to be at risk of suicide and associated behavior is challenging in settings with high demand and large geographies covering hundreds of square miles. Therefore, prioritization is necessary. Currently, the prioritization of cases for in-person follow-ups is based on the severity of the incident behavior reported and the age of the individual. Case managers first try to see clients with a reported suicide attempt, followed by nonsuicidal self-injury, then ideation, and finally, high-risk substance use. If the client has more than 1 referral for an attempt, then case managers use the date of the reported event as another layer of prioritization [1]. This prioritization model attends to those with the most severe reported behaviors, but it does not consider the long-term risk of being suicidal.

Case managers generally rely on in-person interviews or questionnaires to assess the suicide risk of individuals already identified as at risk in the community and who are reported to the surveillance system. Administering assessments requires time, training, and mastery of the case manager role. The reliance on face-to-face approaches to identify someone at heightened risk of suicide is generally the standard practice, yet recent evidence suggests that such assessments may not be insufficient to identify who is at risk and when [1,6]. What drives someone to attempt to die by suicide is complex, yet current methods for risk detection are relatively simple, combining limited factors (eg, 5 questions) in simplistic ways (eg, sum scores) [7]. Despite decades of research, psychiatrists' ability to identify those at risk is only slightly better than chance [8]. There is growing recognition that methods and models that account for greater complexity are needed to advance suicide prevention efforts [9].

Machine learning applied to suicide risk identification is a promising approach to address this complexity. Machine learning is the application of algorithms to data to gain insight into meaningful patterns that are often difficult for humans to recognize [7]. Recent work applying these methods to suicide prevention shows both promising and potential challenges. The results from several individual studies have reported an increase in predictive accuracy using artificial intelligence [9,10]. However, a recent meta-analysis indicated that machine learning models also have limitations, including low positive predictive values [11]. This is likely a result of the low prevalence of suicide in the general population. However, others have argued that despite low positive predictive value, machine learning algorithms still hold significant promise because of their low cost and overall net benefit [12]. These methods are also thought to be more easily scaled because they rely on electronic data and computing power, both of which are increasingly available. Instead of relying on specialists to conduct assessments, data can be passed through an algorithm and digitally convey a level of risk for future suicidal behaviors.

This Study

Despite the promise of improved accuracy and potential for scalability, implementing risk algorithm implementation as a clinical tool remains rare. Risk algorithms may be useful, but they are certainly not sufficient to prevent suicide alone. It is critical for any algorithm to be optimized in the setting in which it will be used [7]. In 2017, the White Mountain Apache Tribe and Johns Hopkins Center for American Indian Health (JHCAIH) collaborated to develop and validate a machine learning algorithm to help identify people reported to CL who were most at risk for suicide death or attempts [13]. In this study, we aim to understand how to implement this algorithm to inform care. To answer this question, we used qualitative input from case managers and supervisors to explore (1) how they consider and evaluate risk, (2) how they prioritize cases, (3) what could be done for different levels of risk in their communities, and (4) how the algorithm should be implemented in their workflow? The results of this project informed the implementation of the said risk algorithm into practice, helping case managers to identify and attend to those most at risk of dying by or attempting suicide.

Methods

Overview

This project is nested in two larger projects, one of which is the Southwest Hub for Youth Suicide Prevention, focused on youth suicide prevention in Native American communities (National Institute of Mental Health [NIMH] U19MH113136-02S3). The Southwest Hub includes a research study and a public health practice approach that supports 5 other tribes in the southwest and in Montana to implement CL in their settings. The second study, Sustainability of Suicide Prevention Programs in Native

communities, focuses on understanding the implementation and sustainability of these surveillance and case management programs, as they are scaled to other tribal partners (NIMH K01MH116335). The focus of this manuscript is to implement the machine learning algorithm within these suicide surveillance and case management programs to help case managers identify and respond to risk. For this study, qualitative in-depth interviews (IDIs) were conducted with case managers from 3 communities implementing CL. The institutional review board at Johns Hopkins School of Public Health and Navajo Nation both determined this project as exempt from oversight because it did not qualify as human subjects research. The White Mountain Apache Tribal Health Board approved this project at the time of grant submission.

Existing CL Workflow

The existing structure of the CL workflow has been described in detail elsewhere [1]. Briefly, when a referral occurs, the CL staff fill out an intake form (called the *yellow form*). This form includes demographics and basic information on the reportable behavior. Following the intake form, CL case managers attempt to locate each individual. Prioritization of who to find first has been described earlier. If contact is made, during the follow-up visit, case managers gather more information on a follow-up form (called the *pink form*), confirm the behavior, and provide referrals and additional resources. The follow-up form assesses the circumstances around the event and the relevant risk and protective factors. This information is stored in a secure web-based portal.

Study Participants

Given the aim of the study to obtain insight and input from case managers, a purposeful sampling strategy [14] was used to recruit participants. Participants were eligible to be interviewed if they were current case managers from 3 communities (the White Mountain Apache Tribe and 2 sites in Navajo Nation that serve rural populations) where the CL system was implemented. All staff members were notified of the opportunity to participate and were free to decline. A total of 9 case managers and supervisors participated in 8 IDIs (one IDI was conducted with 2 staff members simultaneously as a joint interview). All participants were employees of the JHCAIH and represented all possible case managers and supervisors in each community.

Data Collection and Management

IDIs were conducted by a female JHCAIH research associate with a master's degree in public health and with experience in qualitative data collection and analysis. The interviewer works across a number of suicide prevention projects and is familiar with participants through collaboration with CL and other projects. The interviewer was asked to conduct these interviews by the lead author, so they did not have any particular interest in this topic. Participants were approached for the study through face-to-face meetings. IDIs took place in quiet, private office settings and lasted approximately 30 minutes on average. None of the participants refused to participate or dropped out. We developed an interview guide for IDIs to elicit information that could inform the primary research aim of understanding CL staff perceptions and evaluation and response to risk as well as ideas for how to incorporate a risk algorithm into their work and caseload management (Multimedia Appendix 1). IDI questions covered CL staff's daily work experience, how they evaluate various levels of risk and what resources and responses are used for individuals at risk, what factors inform their assessments of suicidality, and ideas for when and how a risk algorithm could be most useful to them. Although the development of our guide was not directly informed by an implementation science framework, our approach overlaps with an exploration of the intervention characteristics, inner setting, and characteristics of the individual domains of the Consolidated Framework for Implementation Research (CFIR) [15]. Other domains in the CFIR were not explored directly in the interview guide questions. IDIs were audio recorded, transcribed, and deidentified. Once transcripts had been checked for accuracy by the interviewer, audio recordings were deleted. All files were stored on a secure electronic server, and access was password protected.

Qualitative Data Analysis

Consistent with methodological approaches to establish the trustworthiness of thematic analysis, data analysis of the transcripts was an iterative process [16]. A preliminary codebook of a priori codes was developed based on the interview guide. A priori codes included codes designed to capture concepts, such as surveillance system experiences, definitions of suicide risk, and risk flag utility. Furthermore, 2 researchers reviewed all transcripts and independently performed in-depth vertical analysis [17] of 2 transcripts to elicit emergent codes from the transcripts. The 2 coders reviewed each code from the 2 transcripts and discussed their disagreements. This review process led to enhanced definitions of each a priori code, a set of emergent codes, and improved consistency between coders. Emergent codes captured important relevant concepts such as program implementation challenges, resource use, and local causes of suicidal behaviors. Iterative discussion among the coders and the lead author supported the revision and development of a final codebook that included a set of 27 a priori and emergent codes. Additional emergent codes were added during the final coding process by each coder and discussed as a team. Dedoose (version 8.3.10, SocioCultural Research Consultants, LLC) [18] was used to apply the finalized codebook to all 8 transcripts (each coder coded 4 transcripts). A coding report was developed by the 2 coders by compiling all pieces of coded text under their respective codes. The analysis team (ie, 2 coders) then examined the consistency of the coded text and discussed any discrepancies that arose. Discrepancies were resolved through consensus agreement. The final coding report included general summaries for each code and the selection of the most representative quotes. As a final step, the coding team organized codes, their summaries, and their representative quotes into broad thematic categories. Qualitative results were then synthesized to inform the implementation of algorithms and associated care pathways.

Results

Participants

A total of 9 case managers completed the IDIs. All (9/9, 100%) participants were women. The case managers from White Mountain Apache Tribe all had over 2 years of experience, whereas the case managers from Navajo Nation had less than a year of case management experience. A total of 33% (3/9) of participants had master's degrees, whereas the other case managers (6/9, 67%) had bachelor's degrees.

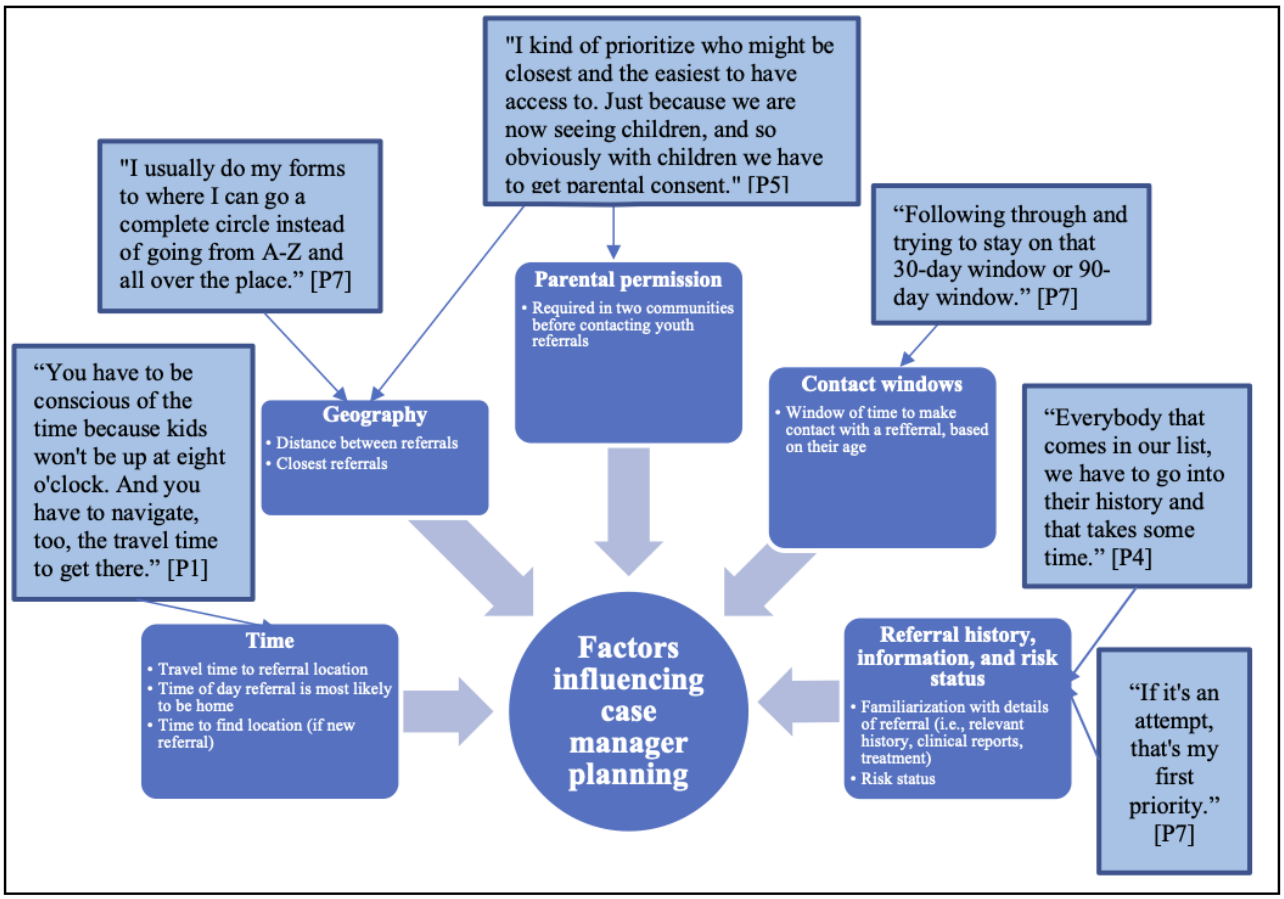
Qualitative Data Results

The results are organized into four thematic categories: (1) planning and prioritization of follow-up visits; (2) suicide risk, definition, and causes; (3) interventions and responses; and (4) considerations for risk flags and algorithms. We report detailed findings under these 4 thematic categories and how this information was used to inform the algorithm implementation and care pathways.

Planning for Follow-ups and Prioritization of Cases

Participants described how they plan their workdays, keep track of referrals and follow-ups, and schedule subsequent visits. The factors that case managers consider when planning their days are illustrated in Figure 1. After risk status, geography and time were important considerations. For example, case managers considered how long it takes to reach a person's location, including how much time is needed to physically find an individual. Home addresses on reservations are often unreliable and, in some cases, do not exist. Finally, case managers also considered the date the referral was made, as there are reportable time windows in which a follow-up visit should be completed.

Figure 1. Factors influencing case manager planning and representative quotes.



Case managers primarily use current behavior and a person's known history to make decisions about the order of follow-up visits. According to existing protocols, reported suicide attempts are the top priority, followed by intentional self-harm, suicidal ideations, and high-risk substance use. Some participants noted that high-risk substance use on its own could often be youth experimentation, but that high-risk use in conjunction with suicidal ideation would raise their level of concern. A history of previous suicidal risk behavior is also a factor for consideration, although more experientially, where case managers might be familiar with an individual, rather than having documentation of an individual's behaviors over time. One case manager (P7) noted the amount of time it takes to look into a person's history, "Everybody that comes in our list, we have to go into their history and that takes some time."

Prioritization of cases based on risk status also interacted with factors such as time and geography. High-priority cases are seen first, but other less risky cases that are nearby may be checked on: "If you're going into one area, you're going to do the priority, there's more people that are within that little radius, you're going to try and hit those then go to the next priority area" [P1].

Other staff (P5) indicated that sometimes geography and time are more of a priority than risk status: "I kind of prioritize who closest and the easiest to have access to." Staff in all communities discussed encountering unexpected challenges that disrupt their plans each day, such as being unable to locate a residence or attempting a follow-up, but finding their intended client is not home. To overcome some of these challenges, the participants outlined how they collaborated with community partners. For example, in one community, community-based chapter houses that are similar to local town halls represent a valuable local resource that supports case managers in locating and learning about referrals: "If there's no house description, of course, there's a physical description or location or address on the referral system, so a lot of times I go to the Chapter houses because they're a great resource for me" [P3].

Suicide Risk: Causes and Definitions

Participants outlined some of the factors that contribute to suicide in their communities, including sexual abuse, substance use problems, stress, and lack of family support. Some described how limited access to education compounds family problems and difficult home environments to make life more difficult, which can lead to substance use as a way to cope with feelings of despair and suicidal thoughts. Participants characterized the connection between substance use and suicidal behavior as an indication of someone who might be at long-term risk of suicide:

> *It comes back to drugs and alcohol. Kids feel neglected; that's why they feel suicidal. Under the influence of pressure of drugs and alcohol, they get involved, they get hooked.* [P8]

When asked about how they assess a person's risk status, participants generally agreed that each case and situation varied and must be evaluated in context. Case managers described the ability to observe a person's level of risk when talking to them, including their attitude, body language, and reactions. Although we asked about signs and indicators of high, low, or medium risk, case managers only described the risk in terms of high or low risk, and not on a continuum. Textbox 1 outlines the factors that participants described as signaling higher or lower risk for suicidal behaviors. Factors included participant behaviors in the moment (ie, crying), reported risk factors such as feeling currently unsafe or lacking a support system, and past history of risky behavior. For example, one participant (P5) said, "Especially if you start to notice, maybe their environment is not safe or it's unhealthy, then that definitely puts them at more risk."

Textbox 1. Factors indicating higher or lower risk of engaging in suicidal behaviors.

Factors Indicating Higher Risk

- Multiple risky behaviors (eg, high-risk substance use and suicidal ideation)
- Share openly and agree to wellness checks
- Crying or tearful
- Have problems with substance use
- Lack a family support system
- Report recent suicidal ideation
- Have been referred multiple times
- Have a history of suicide attempt or attempts
- Report feeling unsafe
- Live in an unhealthy home environment

Factors Indicating Lower Risk

- Acknowledging that an act occurred and attributing it to a spur of the moment mistake
- Indicating a lack of current suicidal ideation when asked

Some disagreement arose in relation to referrals who were very open about their experiences compared with those who denied the occurrence of the event. For example, one case manager stated as follows:

> *The ones that are more high-risk are the ones where I notice...they're the ones that are pretty open about it. They're the ones that want to talk and they're the ones that will tell me what's going on...The ones that I know are high-risk usually agree to those wellness checks.* [P3]

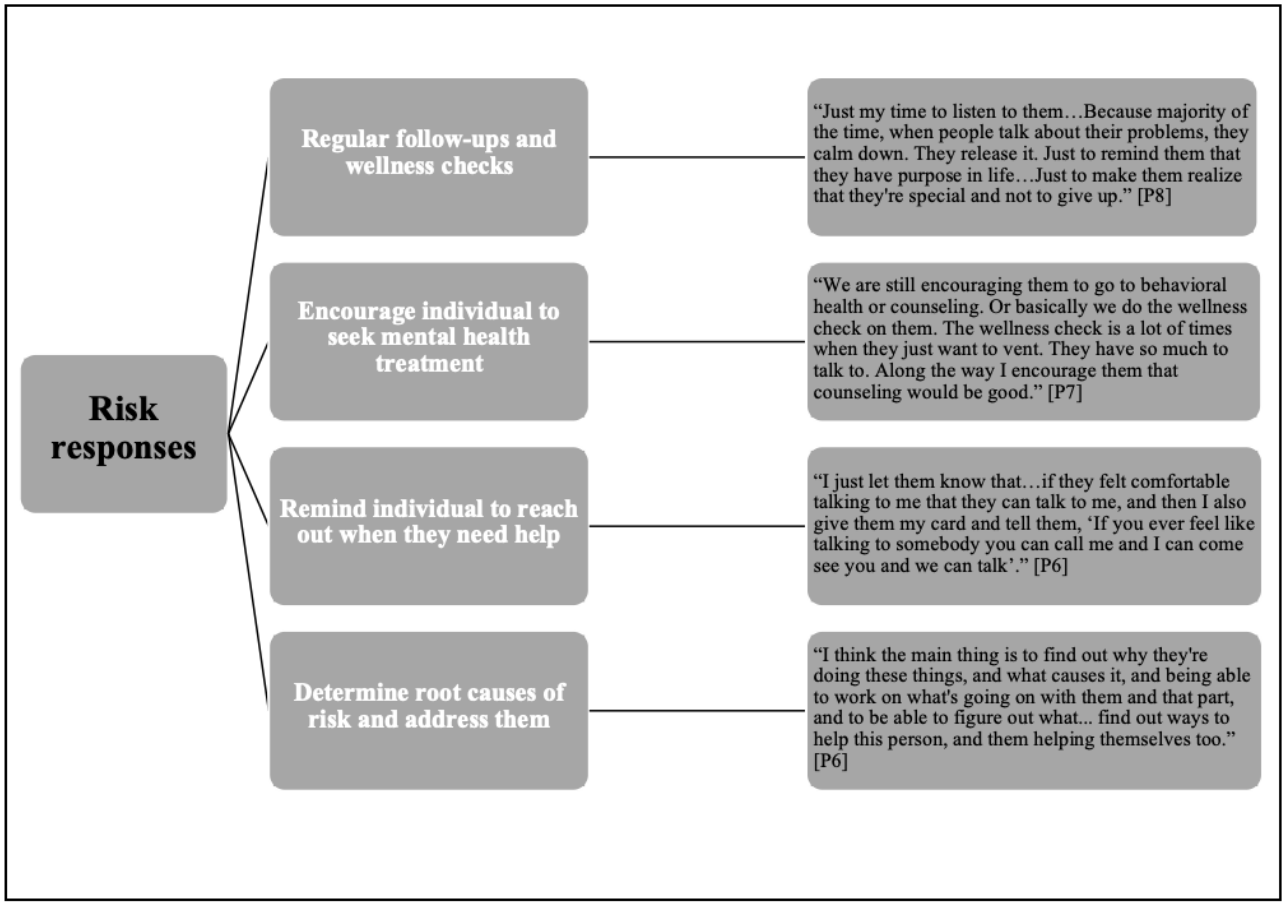
Other participants felt that denial of an act was an indication of increased risk. Receiving repeat, multiple referrals was also viewed as an indicator of higher risk, but participants also noted that some suicide deaths have occurred in people who were never referred to the system and had no obvious indicators of being at high risk.

Interventions and Responses

Participants described responses for those at long-term risk (ie, they are at risk, but behavior is not imminent) and those at more urgent risk (ie, suicidal behavior is imminent). The main response for those at more long-term risk was facilitating connections for individuals to local resources and services to support their mental health and well-being. Within existing CL resources, case managers can offer brief contact interventions

in the form of regular wellness checks, short psychosocial interventions related to suicide prevention and substance use, support access to counseling when they encounter someone who is at risk, and provide support services to families who have lost a member because of suicide. The responses specific to suicide risk are shown in Figure 2.

Figure 2. Responses to long-term suicide risk.



When responding specifically to an urgent risk, participants described offering immediate support such as transport to counseling services or the emergency department:

> *I'll tell them right then and there, 'do you feel like you want to speak to a counselor, because I'm here and I can give you a ride, I can sit there and help you fill out forms, I can sit there, and I can support you.*' [P7]

If necessary, case managers described protocols to call the police for support by transporting people at urgent risk to the local emergency department. For less severe urgent risk, the response involves safety planning, attending to acute risk factors through referrals to local services, making sure individuals are aware of what resources they can reach out to, and scheduling wellness checks.

Risk Flags and Algorithms

Many participants agreed that generated risk flags indicating individuals with high priority or risk would be useful in planning and case prioritization:

> *That would be great...would be very helpful, especially in our prioritizing so that, we know that we're accurate, we're not missing people or anything.* [P2]

Participants also felt it would be ideal to learn about a risk flag as soon as possible to initiate immediate follow-up, particularly if a person is flagged for being at long-term risk. When following up with individuals who have been flagged by the algorithm, some participants suggested that additional, separate follow-up should be carried out with flagged individuals based on current follow-up protocols and geared toward obtaining more information to facilitate better care and monitoring. The existing protocols allowed for wellness checks as desired by the individual, but some case managers felt that these should be mandated as a way to provide more ongoing support. This was considered a way to use resources effectively and efficiently if provided to those at the highest risk and would provide a more uniform approach to follow-up care.

Some participants were less sure about the potential utility of risk flags but suggested risk flag reports should include as much information as possible to help build case managers' trust in the algorithm because they could compare it with the factors and flag using their own judgment to assess the algorithm's accuracy. Knowing more about why the algorithm generated a flag would also support case managers in explaining the surveillance system and risk flags to community partners, building trust across collaborations. Participants suggested that risk flag reports should try to convey an individual's history

and the statistical chance that they might exhibit dangerous behaviors in addition to the reasons they were flagged:

> *I think it would be great to have an algorithm that does flag high risk individuals, if alcohol, drug use, higher risk factors, domestic violence, sexual violence...what are the risk factors of getting flagged, and that would be great to see and see if there is a correlation between the actual data that we're putting in and knowing those individuals whether or not are higher risk, and seeing how it actually pops up and the algorithm to see how it correlates.* [P2]

The need for information to accompany risk flag reports was underscored by participants noting that integrating knowledge of an individual's history is essential: "How can we help someone if we don't know their history?" [P9].

Qualitative Results Synthesis to Inform Implementation

Our findings related to the four broad thematic categories of (1) planning and prioritization of follow-up visits; (2) suicide risk, definition, and causes; (3) interventions and responses; and (4) considerations for risk flags or algorithms that help inform the implementation of algorithms and associated care pathways. First, findings from planning and prioritization of follow-up visits demonstrated the importance of understanding a person's history when prioritizing for follow-up care. Leveraging historical records on the individual to identify future risk status using the algorithm expedites this process. The algorithm itself was designed with implementation in mind using simple mathematical formulas based on responses to items on a data collection form that asks about the individual's history and current circumstances [14]. Our findings from thematic category 2, suicide risk, definition, and causes, clearly showed that all case managers thought of risk as dichotomous. This informed how we operationalize the continuous probability score to produce a dichotomous risk status. Case managers also brought up several considerations they use in determining the risks that are captured through clinical observation such as crying or observations of the living situation. On the basis of this information, implementation of the algorithm had to ensure a way for case manager clinical judgment to factor into the classification of risk status.

For the interventions and responses theme, our findings suggest that there were numerous approaches that the case managers could implement depending on risk status without the introduction of new intervention approaches. Given that brief contact intervention in the form of wellness checks is already part of the program, albeit an optional addition if the individual expresses interest, and evidence supporting the effectiveness of regular contact with individuals to reduce risk [19,20], program leaders decided to mandate regular wellness checks to ensure that those deemed to be at high risk would receive continued contact with staff. This brief contact approach could also be combined with other evidence-based interventions, such as safety planning and brief psychosocial interventions, that staff already have experience in providing.

Finally, the findings from the theme of broad considerations for the implementation of risk flags and algorithms corroborated the importance of considering an individual's behavioral history in the approach, while also emphasizing the importance of timeliness of the notification of risk status and the importance of trustworthiness of the risk status. On the basis of these findings and the need to get this information to the case manager as soon as possible, the algorithm is programmed into the follow-up data collection form. The case manager can use this on a mobile device, and a notification automatically informs them of risk status at the end of the visit. A report of all high-risk cases is also generated and reviewed on a biweekly basis to ensure timely follow-up. Regarding trust in the algorithm, a dichotomous score was selected to maximize the diagnostic specificity. This was done to ensure that the risk flag was not flagging individuals who were clearly not at risk. The favoring of diagnostic specificity with the algorithm was only done in the context of our theme 2 findings that showed how case managers could enhance diagnostic sensitivity through clinical evaluation of the person and circumstances.

Together, the information from our findings is depicted in the process flow chart in Figure 3. First, the CL system receives an intake form, and a case manager attempts to locate the individual to follow up with them. When the case manager makes contact, the follow-up form (or *pink form*) is completed. This pink form incorporates information about the individual's past as well as the current circumstances and circumstances around the reported event. The risk flag is generated at the end of the pink form, immediately notifying the case manager of the person's risk status. Biweekly meetings are held to review these cases, as well as any other cases determined to be at high risk by the case manager. Finally, all high-risk cases receive mandated longitudinal wellness checks in concordance with evidence-based brief contact interventions.

Figure 3. Clinical decision and appropriate care pathways tool. Pink form is the name for the follow-up form that is used at the follow-up visit.

Discussion

Principal Findings

This study sought to understand if and how a suicide risk prediction algorithm could be used to inform care provided by paraprofessional case managers to those at risk of suicide. We designed this study to inform the implementation of the risk prediction algorithm in CL suicide surveillance and case management programs. Case managers indicated that they consider several factors, including current behavior, past history, and geographic location, to help them prioritize the individual to be followed up first. Suicide risk was thought of in dichotomous terms with many interrelated factors indicating higher risk and fewer factors indicating lower risk. Acute or urgent risk was addressed through immediate support and transportation or consultation with emergency services. For individuals who were at a higher risk, but not in need of emergency services, case managers highlighted the importance of several responses that could be provided within the constraints of existing resources, including regular wellness checks, encouraging and supporting the individual to seek mental health treatment, and reminding the individual to reach out for help.

Most case managers agreed that an additional tool to help them identify and prioritize high-risk cases would be useful. They expressed an interest in the algorithm producing a dichotomous result that was timely and highly trustworthy. This indication would then guide them in providing an appropriate care pathway that was compatible with existing resources. Taken together, the results of this study informed the clinical decision support (CDS) and the corresponding care pathways. Each individual is flagged as high-risk or low-risk after the completion of an in-person follow-up. If the person is flagged as high-risk, the case manager provides regular wellness checks for that individual. If the person is flagged as low -isk, no additional procedures are performed, unless the case manager determines otherwise. These procedures are now being implemented in partnership with the White Mountain Apache Tribe.

Despite robust interest, machine learning models have rarely been translated into clinical care [21]. In recent years, there has been a proliferation of suicide risk prediction models [11,13,22-24], but the implementation of these models has been much more limited. The Veterans Health Administration's Recovery Engagement and Coordination for Health-Veterans Enhanced Treatment program has had some early success implementing predictive models and associated care into their suicide prevention efforts [25]. Veterans Health Administration's Recovery Engagement and Coordination for Health-Veterans Enhanced Treatment is focused on the initial identification of high-risk individuals from a population-based sample. In contrast, our model is aimed at prioritizing outreach and follow-up care to those already identified as at risk. This was an important distinction. More work is needed to further explore whether our model and associated care pathways are appropriate for initial risk identification and care. Although our model incorporates some past historical features, it draws primarily on structured information collected by the case manager. This is in contrast to many electronic health record–based models that have been developed that draw on existing variables in records that are not readily available or asked about by

clinicians. This difference in approaches was primarily driven by computational barriers and the feasibility of implementing the model given the existing information technology infrastructure. Notwithstanding, to the best of our knowledge, this study was among the first to adopt a qualitative approach to guide the implementation of a suicide risk prediction algorithm in a clinical- and community-based care setting. The use of qualitative methods, including user-centered design methods, has been used for other decision support tools, including those related to gun safety and suicide [26] and in-hospital clinical deterioration [27].

Several key challenges in suicide prevention emerged from these qualitative interviews. First, providing these services in rural and high-poverty areas is challenging. Case manager participants reported difficulty in finding clients, not having addresses, and driving long distances to ensure in-person follow-up. Tools that could help with streamlining driving routes and prioritizing cases within those routes may be helpful. There was also confusion about what indicates risk—clients are either open about their experiences or deny them, and these two reactions indicated different levels of risk to different case managers. Clinical judgment is valuable in determining the risk of suicide but is insufficient [28]. Explicitly valuing case managers' clinical judgment was critical, but given conflicting interpretations and differing levels of experience, the addition of an algorithm to aid these decisions was seen as valuable.

Case managers also raised some issues that we were unable to address in our CDS design. For example, case managers expressed a desire for complete transparency in what the algorithm used to calculate a risk score and how that score is computed. For example, a case manager stated, "...see if there is a correlation between the actual data that we're putting in and knowing those individuals whether or not are higher risk and seeing how it actually pops up and the algorithm to see how it correlate."

Although we were able to consider the broad importance of trustworthiness, we were not able to fully comply with the specifics of this need, given constraints on the underlying data collection platform and the amount of time it would take to process this information for each individual. Future work will continue to explore this issue with case managers as the CDS is implemented. Although stakeholder opinions are critical to designing tools that work in practice, other considerations, including the underlying computational infrastructure and organization and care context, are critical to consider in the design and implementation process of any such tool.

Although we did not use a specific implementation science framework to guide our study, the themes that arose in our study are consistent with several constructs in the CFIR [15]. For example, themes that emerged around the intervention characteristics included the relative advantage of the algorithm with the existing standard of care and the considerations of the complexity of the approach and the need for the algorithm to produce a dichotomous indicator to enhance interpretability. The domain characteristics of the individuals also emerged in our data, particularly around the knowledge and beliefs about the intervention being critical to successful implementation. Finally, themes related to the outer setting emerged as well. Cosmopolitanism, or the need to network with other organizations to help find individuals, was considered critical. The importance of external policies and incentives also increased. This was particularly related to the need for parental permission before contacting youth in two out of the three settings, which was discussed as a challenge confronted while implementing the program. Our methodological approach was focused more on the intervention and direct implementers of CL, given the narrow focus on how to operationalize the algorithms. However, other themes, particularly those related to the outer context, emerged as important factors to consider when broadly implementing CL-type programs and predictive analytics in practice.

Limitations

We interviewed all case managers employed at the time of the interviews for this study, as qualitative feedback from them would be highly relevant to inform local implementation. However, the sample size was small and limited the transferability of our findings to other contexts. We also may not have reached saturation through sampling. Further work could continue to explore these themes with other case managers as they become available to understand if more data collection and analyses are warranted. One interview was conducted with 2 participants simultaneously, which could have limited their ability to provide feedback in the same way as the other participants. We were unable to explore differences in interviews based on the experience of the case managers, as our sample size was small and many of the potential differences could be confounded with relative differences in the length of time that the programs had been implemented at each site. Finally, our participants did not have experience using the algorithm, which meant that their responses were based on a hypothetical situation. Their views on the algorithm, its utility, and its implementation may change over time—views that would be important to capture to ensure ongoing successful implementation.

Conclusions

Careful thought and planning should be put into implementation efforts to fully realize the potential of suicide risk prediction algorithms. To our knowledge, this study is among the first to use qualitative methods to study implementation considerations for a suicide risk prediction algorithm in a community context. Our findings guided the development of CDS and associated care pathways. These findings inform the implementation of the algorithm to enhance clinical care for individuals at risk of suicide. This body of work also reflects tribal communities' commitments to innovative, efficient, and effective solutions to reduce suicide in native communities with the potential to scale to other communities in need.

Acknowledgments

The authors acknowledge the study participants and all study team members and stakeholders who contributed their time and expertise in this project.

Funding for this project was provided by the NIMH grant U19MH113136-02S3. EH is also supported by NIMH grant K01MH116335. MCL's effort was supported by National Library of Medicine grant 4T15LM007450-15.

Conflicts of Interest

None declared.

Multimedia Appendix 1
In-depth interview guide.
[DOCX File , 16 KB - publichealth_v7i9e24377_app1.docx]

References

1. Cwik MF, Barlow A, Goklish N, Larzelere-Hinton F, Tingey L, Craig M, et al. Community-based surveillance and case management for suicide prevention: an American Indian tribally initiated system. Am J Public Health 2014 Jun;104(S3):18-23. [doi: 10.2105/ajph.2014.301872]
2. Riblet NB, Shiner B, Young-Xu Y, Watts BV. Strategies to prevent death by suicide: meta-analysis of randomised controlled trials. Br J Psychiatry 2017 Jun 02;210(6):396-402. [doi: 10.1192/bjp.bp.116.187799] [Medline: 28428338]
3. Cwik M, Goklish N, Masten K, Lee A, Suttle R, Alchesay M, et al. "Let our Apache Heritage and Culture Live on Forever and Teach the Young Ones": Development of the elders' resilience curriculum, an upstream suicide prevention approach for American Indian youth. Am J Community Psychol 2019 Sep 16;64(1-2):137-145. [doi: 10.1002/ajcp.12351] [Medline: 31313327]
4. Cwik M, Tingey L, Lee A, Suttle R, Lake K, Walkup JT, et al. Development and piloting of a brief intervention for suicidal American Indian adolescents. Am Indian Alsk Native Ment Health Res 2016;23(1):105-124. [doi: 10.5820/aian.2301.2016.105] [Medline: 28562844]
5. Cwik MF, Tingey L, Maschino A, Goklish N, Larzelere-Hinton F, Walkup J, et al. Decreases in suicide deaths and attempts linked to the white mountain apache suicide surveillance and prevention system, 2001–2012. Am J Public Health 2016 Dec;106(12):2183-2189. [doi: 10.2105/ajph.2016.303453]
6. Carter G, Milner A, McGill K, Pirkis J, Kapur N, Spittal MJ. Predicting suicidal behaviours using clinical instruments: systematic review and meta-analysis of positive predictive values for risk scales. Br J Psychiatry 2017 Jun 02;210(6):387-395. [doi: 10.1192/bjp.bp.116.182717] [Medline: 28302700]
7. Linthicum KP, Schafer KM, Ribeiro JD. Machine learning in suicide science: applications and ethics. Behav Sci Law 2019 May;37(3):214-222 [FREE Full text] [doi: 10.1002/bsl.2392] [Medline: 30609102]
8. Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, et al. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. Psychol Bull 2017 Feb;143(2):187-232. [doi: 10.1037/bul0000084] [Medline: 27841450]
9. Ribeiro JD, Franklin JC, Fox KR, Bentley KH, Kleiman EM, Chang BP, et al. Letter to the Editor: Suicide as a complex classification problem: machine learning and related techniques can advance suicide prediction - a reply to Roaldset (2016). Psychol Med 2016 Jul;46(9):2009-2010. [doi: 10.1017/S0033291716000611] [Medline: 27091309]
10. Kessler RC, Warner CH, Ivany C, Petukhova MV, Rose S, Bromet EJ, Army STARRS Collaborators. Predicting suicides after psychiatric hospitalization in US Army soldiers: the Army Study To Assess Risk and rEsilience in Servicemembers (Army STARRS). JAMA Psychiatry 2015;72(1):49-57 [FREE Full text] [doi: 10.1001/jamapsychiatry.2014.1754] [Medline: 25390793]
11. Belsher BE, Smolenski DJ, Pruitt LD, Bush NE, Beech EH, Workman DE, et al. Prediction models for suicide attempts and deaths: a systematic review and simulation. JAMA Psychiatry 2019 Jun 01;76(6):642-651. [doi: 10.1001/jamapsychiatry.2019.0174] [Medline: 30865249]
12. Kessler RC, Bossarte RM, Luedtke A, Zaslavsky AM, Zubizarreta JR. Suicide prediction models: a critical review of recent research with recommendations for the way forward. Mol Psychiatry 2020 Jan 30;25(1):168-179 [FREE Full text] [doi: 10.1038/s41380-019-0531-0] [Medline: 31570777]
13. Haroz EE, Walsh CG, Goklish N, Cwik MF, O'Keefe V, Barlow A. Reaching those at highest risk for suicide: development of a model using machine learning methods for use with native American communities. Suicide Life Threat Behav 2020 Apr;50(2):422-436 [FREE Full text] [doi: 10.1111/sltb.12598] [Medline: 31692064]
14. Palinkas LA, Horwitz SM, Green CA, Wisdom JP, Duan N, Hoagwood K. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Adm Policy Ment Health 2015 Sep;42(5):533-544 [FREE Full text] [doi: 10.1007/s10488-013-0528-y] [Medline: 24193818]

15. Damschroder LJ, Aron D, Keith R, Kirsh SR, Alexander JA, Lowery JC. Fostering implementation of health services research findings into practice: a consolidated framework for advancing implementation science. Implement Sci 2009 Aug 07;4:50 [FREE Full text] [doi: 10.1186/1748-5908-4-50] [Medline: 19664226]
16. Nowell LS, Norris JM, White DE, Moules NJ. Thematic analysis: striving to meet the trustworthiness criteria. Int J Qual Methods 2017 Oct 02;16(1):160940691773384. [doi: 10.1177/1609406917733847]
17. Gaudet S, Robert DA. A Journey Through Qualitative Research: From Design to Reporting. London: SAGE Publications Ltd; 2018.
18. Dedoose Computer Software Version 8.3.10. Sociocultural Research Consultants, Los Angeles, CA. 2011. URL: https://www.dedoose.com/ [accessed 2021-08-13]
19. Motto JA, Bostrom AG. A randomized controlled trial of postcrisis suicide prevention. Psychiatr Serv 2001 Jun;52(6):828-833. [doi: 10.1176/appi.ps.52.6.828] [Medline: 11376235]
20. Luxton DD, June JD, Comtois KA. Can postdischarge follow-up contacts prevent suicide and suicidal behavior? A review of the evidence. Crisis 2013 Jan 01;34(1):32-41. [doi: 10.1027/0227-5910/a000158] [Medline: 22846445]
21. Sendak MP, D'Arcy J, Kashyap S, Gao M, Nichols M, Corey K, et al. A path for translation of machine learning products into healthcare delivery. EMJ Innov 2020 Jan 27:1-14. [doi: 10.33590/emjinnov/19-00172]
22. Kessler RC, Hwang I, Hoffmire CA, McCarthy JF, Petukhova MV, Rosellini AJ, et al. Developing a practical suicide risk prediction model for targeting high-risk patients in the Veterans health Administration. Int J Methods Psychiatr Res 2017 Sep 04;26(3):e1575 [FREE Full text] [doi: 10.1002/mpr.1575] [Medline: 28675617]
23. Walsh CG, Ribeiro JD, Franklin JC. Predicting risk of suicide attempts over time through machine learning. Clin Psychol Sci 2017 Apr 11;5(3):457-469. [doi: 10.1177/2167702617691560]
24. Walsh CG, Ribeiro JD, Franklin JC. Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning. J Child Psychol Psychiatry 2018 Dec 30;59(12):1261-1270. [doi: 10.1111/jcpp.12916] [Medline: 29709069]
25. Matarazzo BB, Brenner LA, Reger MA. Positive predictive values and potential success of suicide prediction models. JAMA Psychiatry 2019 Aug 01;76(8):869-870. [doi: 10.1001/jamapsychiatry.2019.1519] [Medline: 31241754]
26. Betz ME, Knoepke CE, Siry B, Clement A, Azrael D, Ernestus S, et al. 'Lock to Live': development of a firearm storage decision aid to enhance lethal means counselling and prevent suicide. Inj Prev 2019 Sep 13;25(Suppl 1):i18-i24 [FREE Full text] [doi: 10.1136/injuryprev-2018-042944] [Medline: 30317220]
27. Jeffery AD, Novak L, Kennedy B, Dietrich M, Mion L. Participatory design of probability-based decision support tools for in-hospital nurses. J Am Med Inform Assoc 2017 Nov 01;24(6):1102-1110 [FREE Full text] [doi: 10.1093/jamia/ocx060] [Medline: 28637180]
28. Barzilay S, Yaseen ZS, Hawes M, Kopeykina I, Ardalan F, Rosenfield P, et al. Determinants and predictive value of clinician assessment of short-term suicide risk. Suicide Life Threat Behav 2019 Apr 17;49(2):614-626. [doi: 10.1111/sltb.12462] [Medline: 29665120]

Abbreviations

CDS: clinical decision support
CFIR: Consolidated Framework for Implementation Research
CL: Celebrating Life
IDI: in-depth interview
JHCAIH: Johns Hopkins Center for American Indian Health
NIMH: National Institute of Mental Health

Edited by P Sullivan, T Sanchez; submitted 20.10.20; peer-reviewed by BJ Yarborough, G Simon, I Shubina, J Richards, G Simon; comments to author 21.12.20; revised version received 10.03.21; accepted 15.06.21; published 02.09.21.

Please cite as:
Haroz EE, Grubin F, Goklish N, Pioche S, Cwik M, Barlow A, Waugh E, Usher J, Lenert MC, Walsh CG
Designing a Clinical Decision Support Tool That Leverages Machine Learning for Suicide Risk Prediction: Development Study in Partnership With Native American Care Providers
JMIR Public Health Surveill 2021;7(9):e24377
URL: https://publichealth.jmir.org/2021/9/e24377
doi:10.2196/24377
PMID:34473065

Publisher:
JMIR Publications
130 Queens Quay East.
Toronto, ON, M5A 3Y5
Phone: (+1) 416-583-2040
Email: support@jmir.org