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Editorial

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

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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.

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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 marshaling 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.

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**

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**Editorial Notice**

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

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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.

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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

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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).

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

<table>
<thead>
<tr>
<th>Data</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk</td>
<td>357 (96.5)</td>
</tr>
<tr>
<td>Demographics</td>
<td>352 (95.1)</td>
</tr>
<tr>
<td>Other</td>
<td>107 (28.9)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Comparisons</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local to regional</td>
<td>283 (76.5)</td>
</tr>
<tr>
<td>To smaller subdivisions</td>
<td>283 (76.5)</td>
</tr>
<tr>
<td>To larger regions</td>
<td>255 (68.9)</td>
</tr>
<tr>
<td>Other</td>
<td>26 (7)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Risk factors</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevalence</td>
<td>351 (94.9)</td>
</tr>
<tr>
<td>Incidence</td>
<td>347 (95.1)</td>
</tr>
<tr>
<td>Other</td>
<td>41 (11.1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>363 (98.4)</td>
</tr>
<tr>
<td>Sex</td>
<td>352 (95.1)</td>
</tr>
<tr>
<td>Income</td>
<td>351 (94.6)</td>
</tr>
<tr>
<td>Education</td>
<td>336 (90.8)</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>326 (88.1)</td>
</tr>
<tr>
<td>Other</td>
<td>98 (26.5)</td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Types of research evidence</td>
</tr>
<tr>
<td>Best practice guidelines</td>
</tr>
<tr>
<td>Systematic reviews or meta-analyses</td>
</tr>
<tr>
<td>Practice-based evidence</td>
</tr>
<tr>
<td>Single studies</td>
</tr>
<tr>
<td>Qualitative</td>
</tr>
<tr>
<td>Quantitative</td>
</tr>
<tr>
<td>Other</td>
</tr>
<tr>
<td>Information about interventions</td>
</tr>
<tr>
<td>Magnitude of effect</td>
</tr>
<tr>
<td>Quality of study</td>
</tr>
<tr>
<td>Required human resources</td>
</tr>
<tr>
<td>Required financial resources</td>
</tr>
<tr>
<td>Heterogeneity in effect</td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human resources information</td>
</tr>
<tr>
<td>Type and intensity of training</td>
</tr>
<tr>
<td>Type of training to sustain program</td>
</tr>
<tr>
<td>Number of staff required</td>
</tr>
<tr>
<td>Discipline of staff</td>
</tr>
<tr>
<td>Financial resources information</td>
</tr>
<tr>
<td>Cost-effectiveness</td>
</tr>
<tr>
<td>Cost</td>
</tr>
<tr>
<td>Cost-utility</td>
</tr>
<tr>
<td>Economic modelling data</td>
</tr>
<tr>
<td>Other</td>
</tr>
</tbody>
</table>

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.

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

<table>
<thead>
<tr>
<th>Economic modeling data</th>
<th>Frontline public health or community providers, n/n (%)</th>
<th>Program or project management, n/n (%)</th>
<th>Senior management or administration, n/n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>23/67 (34)</td>
<td>20/53 (38)</td>
<td>10/24 (42)</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\)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).
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 study 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
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Conflicts of Interest
None declared.

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

AI: artificial intelligence

NCCMT: National Collaborating Centre for Methods and Tools
US Physicians’ and Nurses’ Motivations, Barriers, and Recommendations for Correcting Health Misinformation on Social Media: Qualitative Interview Study

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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 (e.g., personal choice) and professionally (e.g., to fulfill the responsibility of a health care professional) motivated to correct health misinformation on social media. However, they also faced intrapersonal (e.g., a lack of positive outcomes and time), interpersonal (e.g., harassment and bullying), and institutional (e.g., 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.

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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.** Participant characteristics (N=30).

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

Some participants had multiple specializations.

**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).

<table>
<thead>
<tr>
<th>Themes and subthemes</th>
<th>Codes (participants per profession), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Themes and subthemes</td>
<td>Physician (n=15)</td>
</tr>
</tbody>
</table>

#### Motivations to correct health misinformation on social media

**Personal motivations**
- Personal choice: 1 (7)
- Urge to correct people: 3 (20)

**Professional motivations**
- Stand up for what is right as a health care professional: 6 (40)
- Keep people safe: 1 (7)
- Opportunity to educate more people: 4 (27)

#### Barriers in correcting health misinformation on social media

**Intrapersonal barriers**
- Lack of positive outcome: 10 (67)
- Lack of time: 9 (60)
- Lack of self-efficacy: 3 (20)
- Avoidant behavior: 1 (7)
- Lack of voice to influence others: 2 (13)
- Difficulty in producing social media content: 3 (20)

**Interpersonal barriers**
- Harassment and bullying: 14 (93)
- Difficulty to have a meaningful conversation on the web: 13 (87)

**Institutional barriers**
- Lack of organizational support: 6 (40)
- Lack of social media training: 3 (20)

#### 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)
- Learn to use social media professionally: 2 (13)
- Connect with role models or mentors: 2 (13)
- Learn how to correct misinformation: 1 (7)

**Build a social media presence**
- Be on social media: 11 (73)
- Disseminate facts: 6 (40)
- Build an audience: 5 (33)
- Be part of a community: 3 (20)
- Maintain professionalism: 2 (13)

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 $\alpha=.82$). 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].
Personal Motivations

There were two personal motivations associated with correcting health misinformation on social media. 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: 6/15, 40%; 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 based his opinions on sheer numbers and didn’t do any research. [physician 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 intend 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 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
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 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.

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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.

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

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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.

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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.
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 $\chi^2$ 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.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Men</th>
<th>Women</th>
<th>All</th>
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<tbody>
<tr>
<td></td>
<td>No MetS (n=838)</td>
<td>MetS (n=311)</td>
<td>No MetS (n=1509)</td>
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<td>Age (years), mean (SD)</td>
<td>45.8 (13.6)</td>
<td>47.1 (12.9)</td>
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<td>BMI (kg/m²), mean (SD)</td>
<td>25.7 (3.9)</td>
<td>28.3 (3.8)</td>
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<td>Marital status, n (%)</td>
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<td>Married</td>
<td>673 (80.4)</td>
<td>271 (87.1)</td>
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<td>Single/divorced/widowed</td>
<td>164 (19.6)</td>
<td>40 (12.9)</td>
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<td>Smoking, n (%)</td>
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<tr>
<td>Never</td>
<td>662 (79.0)</td>
<td>243 (78.4)</td>
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<td>Current/past</td>
<td>176 (21.0)</td>
<td>67 (21.6)</td>
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<td>Education level, n (%)</td>
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<tr>
<td>Higher than diploma</td>
<td>406 (48.6)</td>
<td>121 (39.0)</td>
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<td>Diploma/below diploma</td>
<td>372 (44.6)</td>
<td>173 (55.8)</td>
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<tr>
<td>Illiterate/primary School</td>
<td>57 (6.8)</td>
<td>16 (5.2)</td>
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<tr>
<td>Cancer history, n (%)</td>
<td>3 (0.4)</td>
<td>1 (0.3)</td>
<td>.93</td>
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<tr>
<td>Hospitalization, n (%)</td>
<td>15 (1.8)</td>
<td>5 (1.6)</td>
<td>.84</td>
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<tr>
<td>Diabetes, n (%)</td>
<td>21 (2.7)</td>
<td>26 (9.1)</td>
<td>&lt;.001</td>
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<tr>
<td>Systolic blood pressure (mmHg), mean (SD)</td>
<td>112.9 (12.6)</td>
<td>120.6 (14.1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Waist circumference (cm), mean (SD)</td>
<td>91.3 (10.5)</td>
<td>98.1 (96.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High triglyceride, n (%)</td>
<td>141 (16.8)</td>
<td>246 (80.0)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Physical activity (km/week), mean (SD)</td>
<td>2.8 (0.4)</td>
<td>2.5 (0.4)</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

*P values are based on the unpaired t test and by the χ² test for qualitative variables.*
Table 2. Comparison of baseline characteristics in the training and test datasets (N=2259).

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

<sup>a</sup><sup>P</sup> values are based on the t test for quantitative variables and on the χ<sup>2</sup> 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 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 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.

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

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

<table>
<thead>
<tr>
<th>Predicted status</th>
<th>Actual status</th>
<th>Correct classification rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>MetS</td>
<td>MetS</td>
<td>96.6</td>
</tr>
<tr>
<td></td>
<td>No MetS</td>
<td>99.3</td>
</tr>
<tr>
<td>No MetS</td>
<td>140</td>
<td>96.6</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>99.3</td>
</tr>
</tbody>
</table>

\(^{a}\)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


Abbreviations

FFQ: Food Frequency Questionnaire
HDL-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

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Designing a Clinical Decision Support Tool That Leverages Machine Learning for Suicide Risk Prediction: Development Study in Partnership With Native American Care Providers

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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 (oneIDI 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.

<table>
<thead>
<tr>
<th>Factors Indicating Higher Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Multiple risky behaviors (eg, high-risk substance use and suicidal ideation)</td>
</tr>
<tr>
<td>• Share openly and agree to wellness checks</td>
</tr>
<tr>
<td>• Crying or tearful</td>
</tr>
<tr>
<td>• Have problems with substance use</td>
</tr>
<tr>
<td>• Lack a family support system</td>
</tr>
<tr>
<td>• Report recent suicidal ideation</td>
</tr>
<tr>
<td>• Have been referred multiple times</td>
</tr>
<tr>
<td>• Have a history of suicide attempt or attempts</td>
</tr>
<tr>
<td>• Report feeling unsafe</td>
</tr>
<tr>
<td>• Live in an unhealthy home environment</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Factors Indicating Lower Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Acknowledging that an act occurred and attributing it to a spur of the moment mistake</td>
</tr>
<tr>
<td>• Indicating a lack of current suicidal ideation when asked</td>
</tr>
</tbody>
</table>

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-risk, 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.

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Conflicts of Interest
None declared.

Multimedia Appendix 1
In-depth interview guide.

[DOCX File, 16 KB - publichealth_v7i9e24377_app1.docx]

References


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


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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

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

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ORIGINAL PAPER

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

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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.

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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 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.

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

*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).
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 (CDC).
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

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(page number not for citation purposes)
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.

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**Conflicts of Interest**

None declared.

**References**


Abbreviations

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

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

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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 collect information on finding casual sex partners, perceived HIV infection, and HIV risk behaviors.

Results: Among 767 participants, 310 (40.4%) reported finding casual 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.

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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 in a bar, park, or other?” and “Have you ever have sexual intercourse with men you met on the Internet, such as with Blued, WeChat, a chat room, or other?” 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, relying 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. (Table 1).

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

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

a1 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).

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

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).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Met partners on the internet, % (n/n)</th>
<th>Odds ratio (95% CI)</th>
<th>P value</th>
<th>Adjusted odds ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16-24</td>
<td>43.3 (105/248)</td>
<td>1</td>
<td>.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25-34</td>
<td>41.8 (141/337)</td>
<td>0.980 (0.703-1.366)</td>
<td>.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥35</td>
<td>35.2 (64/182)</td>
<td>0.739 (0.498-1.096)</td>
<td>.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Education level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school or below</td>
<td>39.5 (115/291)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>College or above</td>
<td>41.0 (195/476)</td>
<td>1.062 (0.789-1.430)</td>
<td>.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Registry area</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Native</td>
<td>43.4 (183/422)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>36.8 (127/345)</td>
<td>0.761 (0.568-1.018)</td>
<td>.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sex role</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Receives</td>
<td>38.5 (77/200)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inserts/both</td>
<td>41.1 (233/567)</td>
<td>1.780 (0.645-1.249)</td>
<td>.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Knowledge of HIV infection</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct</td>
<td>41.8 (264/631)</td>
<td>1</td>
<td>&lt;.001</td>
<td>1.565 (0.979-2.503)</td>
<td>.06</td>
</tr>
<tr>
<td>Incorrect/no knowledge</td>
<td>33.8 (46/136)</td>
<td>0.711 (0.482-1.048)</td>
<td>.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Watched a pornographic video on the internet in the past 6 months</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>25.0 (40/160)</td>
<td>1</td>
<td>.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;1/week</td>
<td>42.0 (111/264)</td>
<td>2.176 (1.411-3.357)</td>
<td>&lt;.001</td>
<td>1.565 (0.979-2.503)</td>
<td>.06</td>
</tr>
<tr>
<td>≥1/week</td>
<td>46.4 (159/343)</td>
<td>2.592 (1.710-3.930)</td>
<td>&lt;.001</td>
<td>1.881 (1.201-2.948)</td>
<td>.006</td>
</tr>
<tr>
<td><strong>Discussed the topic of finding partners on the internet with friends in the past 6 months</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>24.2 (103/425)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>60.5 (207/342)</td>
<td>4.794 (3.515-6.537)</td>
<td>&lt;.001</td>
<td>4.018 (2.910-5.548)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Perceived risk of HIV infection from casual sex partners sought on the internet</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>28.8 (102/354)</td>
<td>1</td>
<td>&lt;.001</td>
<td>2.034 (1.441-2.873)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Medium</td>
<td>49.3 (149/302)</td>
<td>2.406 (1.743-3.321)</td>
<td>&lt;.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>53.3 (49/92)</td>
<td>2.815 (1.760-4.503)</td>
<td>&lt;.001</td>
<td>2.528 (1.530-4.176)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

a—; not determined.
bMissing 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).

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

a—: not determined.
bMissing number of casual sex partners sought on the internet=17.
cMissing data: perceived risk of HIV infection from casual sex partners sought on the internet=9.
dMissing 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


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]


**Abbreviations**

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

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

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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.

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https://publichealth.jmir.org/2021/9/e30406
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).

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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 ($\alpha$) of .05, and a frequency of exposure of 1% in controls and 8% in cases, the test power ($1-\beta$) 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 (2000g 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 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.

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 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**

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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).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Town 1, n (%)</th>
<th>Town 2, n (%)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>156 (39.0)</td>
<td>196 (49.0)</td>
<td>.01</td>
</tr>
<tr>
<td>Female</td>
<td>244 (61.0)</td>
<td>204 (51.0)</td>
<td></td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
<td>.04</td>
</tr>
<tr>
<td>White</td>
<td>211 (52.8)</td>
<td>235 (58.7)</td>
<td></td>
</tr>
<tr>
<td>Brown-skinned</td>
<td>112 (28.0)</td>
<td>117 (29.2)</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>70 (17.5)</td>
<td>40 (10.0)</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>7 (1.7)</td>
<td>8 (2.1)</td>
<td></td>
</tr>
<tr>
<td><strong>Age group (years)</strong></td>
<td></td>
<td></td>
<td>.29</td>
</tr>
<tr>
<td>0-12</td>
<td>23 (5.8)</td>
<td>33 (8.2)</td>
<td></td>
</tr>
<tr>
<td>13-18</td>
<td>17 (4.2)</td>
<td>22 (5.5)</td>
<td></td>
</tr>
<tr>
<td>19-30</td>
<td>53 (13.2)</td>
<td>66 (16.5)</td>
<td></td>
</tr>
<tr>
<td>31-45</td>
<td>81 (20.2)</td>
<td>78 (19.5)</td>
<td></td>
</tr>
<tr>
<td>46-59</td>
<td>113 (28.3)</td>
<td>109 (27.2)</td>
<td></td>
</tr>
<tr>
<td>≥60</td>
<td>113 (28.3)</td>
<td>92 (23.0)</td>
<td></td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
<td>.01</td>
</tr>
<tr>
<td>Homemaker/unemployed</td>
<td>69 (17.2)</td>
<td>49 (12.2)</td>
<td></td>
</tr>
<tr>
<td>Retiree</td>
<td>84 (21.0)</td>
<td>54 (13.5)</td>
<td></td>
</tr>
<tr>
<td>Student/teacher/professor</td>
<td>58 (14.5)</td>
<td>66 (16.5)</td>
<td></td>
</tr>
<tr>
<td>Rural worker</td>
<td>28 (7.0)</td>
<td>23 (5.8)</td>
<td></td>
</tr>
<tr>
<td>Storekeeper/clerk/local employee/independent worker</td>
<td>130 (32.5)</td>
<td>155 (38.7)</td>
<td></td>
</tr>
<tr>
<td>Health care professional</td>
<td>15 (3.8)</td>
<td>13 (3.3)</td>
<td></td>
</tr>
<tr>
<td>Logistics worker</td>
<td>16 (4.0)</td>
<td>40 (10.0)</td>
<td></td>
</tr>
<tr>
<td><strong>Smoking status</strong></td>
<td></td>
<td></td>
<td>.36</td>
</tr>
<tr>
<td>Nonsmoker</td>
<td>252 (63.0)</td>
<td>271 (67.7)</td>
<td></td>
</tr>
<tr>
<td>Former smoker</td>
<td>79 (19.7)</td>
<td>68 (17.0)</td>
<td></td>
</tr>
<tr>
<td>Current smoker</td>
<td>69 (17.3)</td>
<td>61 (15.3)</td>
<td></td>
</tr>
<tr>
<td><strong>BCG³ vaccinated?</strong></td>
<td></td>
<td></td>
<td>.41</td>
</tr>
<tr>
<td>Yes</td>
<td>355 (88.7)</td>
<td>362 (90.5)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>45 (11.3)</td>
<td>38 (9.5)</td>
<td></td>
</tr>
<tr>
<td><strong>COVID-19 high-risk group?</strong></td>
<td></td>
<td></td>
<td>.04</td>
</tr>
<tr>
<td>Yes</td>
<td>220 (55.0)</td>
<td>191 (47.8)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>180 (45.0)</td>
<td>209 (52.2)</td>
<td></td>
</tr>
<tr>
<td><strong>Did you meet someone exclusively for leisure/socializing purposes during the past 10 days?</strong></td>
<td></td>
<td></td>
<td>.01</td>
</tr>
<tr>
<td>Yes</td>
<td>156 (39.0)</td>
<td>202 (50.5)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>244 (61.0)</td>
<td>198 (49.5)</td>
<td></td>
</tr>
<tr>
<td><strong>Do you wear mask at work?</strong></td>
<td></td>
<td></td>
<td>.07</td>
</tr>
<tr>
<td>Yes, all the time</td>
<td>138 (34.6)</td>
<td>131 (32.7)</td>
<td></td>
</tr>
<tr>
<td>Yes, most of the time</td>
<td>49 (12.2)</td>
<td>33 (8.2)</td>
<td></td>
</tr>
<tr>
<td>Yes, only sometimes</td>
<td>25 (6.2)</td>
<td>15 (3.8)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>29 (7.2)</td>
<td>34 (8.5)</td>
<td></td>
</tr>
<tr>
<td>Not applicable (do not work or home office)</td>
<td>159 (39.8)</td>
<td>187 (46.8)</td>
<td></td>
</tr>
<tr>
<td>Variable</td>
<td>Town 1, n (%)</td>
<td>Town 2, n (%)</td>
<td>P value</td>
</tr>
<tr>
<td>---------------------------------------------------------</td>
<td>---------------</td>
<td>---------------</td>
<td>---------</td>
</tr>
<tr>
<td><strong>Do you wear mask while walking on the streets?</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes, all the time</td>
<td>260 (65.0)</td>
<td>278 (69.5)</td>
<td>.24</td>
</tr>
<tr>
<td>Yes, most of the time</td>
<td>60 (15.0)</td>
<td>41 (10.3)</td>
<td></td>
</tr>
<tr>
<td>Yes, only sometimes</td>
<td>34 (8.5)</td>
<td>37 (9.2)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>25 (6.3)</td>
<td>19 (4.7)</td>
<td></td>
</tr>
<tr>
<td>Not applicable (do not leave the house)</td>
<td>21 (5.2)</td>
<td>25 (6.3)</td>
<td></td>
</tr>
<tr>
<td><strong>Do you pull the mask down to talk to someone?</strong></td>
<td></td>
<td></td>
<td>.38</td>
</tr>
<tr>
<td>Yes, always</td>
<td>32 (8.0)</td>
<td>26 (6.5)</td>
<td></td>
</tr>
<tr>
<td>Yes, sometimes</td>
<td>42 (10.5)</td>
<td>53 (13.3)</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>326 (81.5)</td>
<td>321 (80.2)</td>
<td></td>
</tr>
<tr>
<td><strong>Are you regularly taking exclusively for COVID-19 prevention?</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vitamin or mineral</td>
<td>23 (5.8)</td>
<td>30 (7.5)</td>
<td>.32</td>
</tr>
<tr>
<td>Hydroxychloroquine</td>
<td>0 (0)</td>
<td>1 (0.2)</td>
<td>.32</td>
</tr>
<tr>
<td>Herbal medicine</td>
<td>7 (1.8)</td>
<td>2 (0.5)</td>
<td>.09</td>
</tr>
<tr>
<td>Ivermectin</td>
<td>_b</td>
<td>23 (5.8)</td>
<td>N/A²</td>
</tr>
</tbody>
</table>

²BCG: Bacillus Calmette Guérin.

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).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Households, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Did this household receive visitors in the 14-day period before the household index date?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>14 (35)</td>
</tr>
<tr>
<td>No</td>
<td>26 (65)</td>
</tr>
<tr>
<td>Was any celebration (eg, barbecue or dinner party) held in this household in the 14-day period before the household index date?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>4 (10)</td>
</tr>
<tr>
<td>No</td>
<td>36 (90)</td>
</tr>
<tr>
<td>Did the index case of this household attend any celebration in the 14-day period before the household index date?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>9 (22.5)</td>
</tr>
<tr>
<td>No</td>
<td>31 (77.5)</td>
</tr>
<tr>
<td>Is the index case a logistics worker?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>28 (70)</td>
</tr>
<tr>
<td>No</td>
<td>12 (30)</td>
</tr>
<tr>
<td>Is any member of this household a logistics worker?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>31 (78)</td>
</tr>
<tr>
<td>No</td>
<td>9 (23)</td>
</tr>
<tr>
<td>Measures taken to reduce viral transmission</td>
<td></td>
</tr>
<tr>
<td>Sharing the same bed with the infected person was avoided</td>
<td>19 (48)</td>
</tr>
<tr>
<td>Sharing the same couch with the infected person was avoided</td>
<td>17 (42.5)</td>
</tr>
<tr>
<td>Sharing eating utensils with the infected person was avoided</td>
<td>16 (40)</td>
</tr>
<tr>
<td>The infected person washed his own sheets and other bedding</td>
<td>10 (25)</td>
</tr>
<tr>
<td>The infected person stayed in a separate room, walking out only when absolutely necessary</td>
<td>8 (20)</td>
</tr>
<tr>
<td>The infected person used a separate bathroom</td>
<td>6 (15)</td>
</tr>
<tr>
<td>How often did the household members perform hand hygiene while there was one active COVID-19 case in the house?</td>
<td></td>
</tr>
<tr>
<td>Frequently</td>
<td>31 (78)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>6 (15)</td>
</tr>
<tr>
<td>Rarely</td>
<td>3 (8)</td>
</tr>
<tr>
<td>Did the active COVID-19 case use to wear mask while near other people in shared areas of the house?</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>27 (68)</td>
</tr>
<tr>
<td>Yes, always or almost always</td>
<td>12 (30)</td>
</tr>
<tr>
<td>Yes, only sometimes</td>
<td>1 (3)</td>
</tr>
</tbody>
</table>

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).
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).

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.
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.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Case, n (%)</th>
<th>Control, n (%)</th>
<th>Odds ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homemaker/unemployed</td>
<td>7 (7.4)</td>
<td>49 (12.0)</td>
<td>1.0 (reference)</td>
<td>N/A*</td>
</tr>
<tr>
<td>Retiree</td>
<td>7 (7.4)</td>
<td>55 (14.0)</td>
<td>0.9 (0.3-2.6)</td>
<td>.78</td>
</tr>
<tr>
<td>Student/teacher/professor</td>
<td>24 (25.3)</td>
<td>64 (16.3)</td>
<td>2.5 (1.0-6.3)</td>
<td>.05</td>
</tr>
<tr>
<td>Rural worker</td>
<td>0 (0)</td>
<td>23 (5.8)</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Storekeeper/clerk/local employee/independent worker</td>
<td>19 (20.0)</td>
<td>153 (38.9)</td>
<td>0.8 (0.3-2.1)</td>
<td>.70</td>
</tr>
<tr>
<td>Health care professional</td>
<td>5 (5.3)</td>
<td>13 (3.3)</td>
<td>2.6 (0.7-9.5)</td>
<td>.15</td>
</tr>
<tr>
<td>Logistics worker</td>
<td>33 (34.7)</td>
<td>38 (9.7)</td>
<td>5.8 (2.3-14.6)</td>
<td>.01</td>
</tr>
<tr>
<td><strong>How many people do you live with?</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alone or with 1 person</td>
<td>11 (11.6)</td>
<td>122 (31.0)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>With 2 or 3 people</td>
<td>54 (56.8)</td>
<td>220 (56.0)</td>
<td>2.7 (1.4-5.4)</td>
<td>.01</td>
</tr>
<tr>
<td>With 4 or more people</td>
<td>30 (31.6)</td>
<td>51 (13.0)</td>
<td>6.5 (3.0-14.0)</td>
<td>.01</td>
</tr>
<tr>
<td><strong>Number of rooms per person in the house</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;2</td>
<td>38 (40.0)</td>
<td>225 (57.3)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>≤2</td>
<td>57 (60.0)</td>
<td>168 (42.7)</td>
<td>2.0 (1.3-3.2)</td>
<td>.01</td>
</tr>
<tr>
<td><strong>Do you live with or are you a logistics worker?</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>17 (17.9)</td>
<td>305 (77.6)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Yes, I live with a logistics worker</td>
<td>45 (47.4)</td>
<td>50 (12.7)</td>
<td>16.1 (8.6-30.4)</td>
<td>.01</td>
</tr>
<tr>
<td>Yes, I am a logistics worker</td>
<td>33 (34.7)</td>
<td>38 (9.7)</td>
<td>15.6 (7.9-30.6)</td>
<td>.01</td>
</tr>
<tr>
<td>Smoking status</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonsmoker</td>
<td>73 (76.8)</td>
<td>266 (67.7)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Former smoker</td>
<td>16 (16.8)</td>
<td>66 (16.8)</td>
<td>0.9 (0.5-1.6)</td>
<td>.67</td>
</tr>
<tr>
<td>Current smoker</td>
<td>6 (6.3)</td>
<td>61 (15.5)</td>
<td>0.4 (0.1-0.9)</td>
<td>.02</td>
</tr>
<tr>
<td><strong>Did you have close contact</strong> with a COVID-19 case?</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>46 (48.4)</td>
<td>369 (93.9)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Yes</td>
<td>49 (51.6)</td>
<td>24 (6.1)</td>
<td>16.4 (9.2-29.1)</td>
<td>.01</td>
</tr>
<tr>
<td><strong>Do you have frequent contact</strong> with a logistics worker?</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>33 (34.7)</td>
<td>285 (66.7)</td>
<td>1.0 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Yes</td>
<td>62 (65.3)</td>
<td>108 (33.3)</td>
<td>5.0 (3.1-8.0)</td>
<td>.01</td>
</tr>
</tbody>
</table>

*aN/A: not applicable.

*bClose 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.

*cFrequent contact was defined as having close contact at least once a week.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Crude odds ratio (95% CI)</th>
<th>Adjusted odds ratio (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do you live with or are you a logistics worker?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>1 (reference)</td>
<td>1 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Yes, I live with a logistics worker</td>
<td>16.1 (8.6-30.4)</td>
<td>6.9 (3.3-14.5)</td>
<td>.01</td>
</tr>
<tr>
<td>Yes, I am a logistics worker</td>
<td>15.6 (7.9-30.6)</td>
<td>18.0 (8.4-38.7)</td>
<td>.01</td>
</tr>
<tr>
<td>Did you have close contact(^b) with a COVID-19 case?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>1 (reference)</td>
<td>1 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Yes</td>
<td>16.4 (9.2-29.1)</td>
<td>13.4 (6.6-27.3)</td>
<td>.01</td>
</tr>
<tr>
<td>How many people do you live with?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alone or with 1 person</td>
<td>1 (reference)</td>
<td>1 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>With 4 or more people</td>
<td>6.5 (3.0-14.0)</td>
<td>2.7 (1.1-7.1)</td>
<td>.04</td>
</tr>
<tr>
<td>Smoking status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonsmoker</td>
<td>1 (reference)</td>
<td>1 (reference)</td>
<td>N/A</td>
</tr>
<tr>
<td>Current smoker</td>
<td>0.4 (0.1-0.9)</td>
<td>0.2 (0.1-0.7)</td>
<td>.01</td>
</tr>
</tbody>
</table>

\(^a\)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


Abbreviations

- GDP: gross domestic product
- OR: odds ratio
- RT-PCR: reverse transcriptase–polymerase chain reaction
Estimation of COVID-19 Period Prevalence and the Undiagnosed Population in Canadian Provinces: Model-Based Analysis

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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.

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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.
**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.

<table>
<thead>
<tr>
<th>Province and age cohort (years)</th>
<th>Population</th>
<th>Cumulative diagnoses as of November 30, 2020</th>
<th>Cumulative deaths as of November 30, 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quebec</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;30</td>
<td>2,829,745</td>
<td>45,778</td>
<td>4</td>
</tr>
<tr>
<td>30-69</td>
<td>4,534,110</td>
<td>71,658</td>
<td>584</td>
</tr>
<tr>
<td>≥70</td>
<td>1,121,110</td>
<td>26,476</td>
<td>6467</td>
</tr>
<tr>
<td>Ontario</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;30</td>
<td>5,227,392</td>
<td>38,464</td>
<td>0</td>
</tr>
<tr>
<td>30-69</td>
<td>7,607,840</td>
<td>62,331</td>
<td>471</td>
</tr>
<tr>
<td>≥70</td>
<td>1,731,315</td>
<td>15,692</td>
<td>3084</td>
</tr>
<tr>
<td>Alberta</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;30</td>
<td>1,674,906</td>
<td>23,207</td>
<td>3</td>
</tr>
<tr>
<td>30-69</td>
<td>2,314,614</td>
<td>32,223</td>
<td>67</td>
</tr>
<tr>
<td>≥70</td>
<td>381,796</td>
<td>4013</td>
<td>491</td>
</tr>
<tr>
<td>British Columbia</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;30</td>
<td>1,681,252</td>
<td>12,054</td>
<td>0</td>
</tr>
<tr>
<td>30-69</td>
<td>2,747,468</td>
<td>18,624</td>
<td>67</td>
</tr>
<tr>
<td>≥70</td>
<td>642,616</td>
<td>3108</td>
<td>374</td>
</tr>
</tbody>
</table>

Table 2. Canadian provincial COVID-19 seroprevalence surveys conducted between March 2020 and July 2020 used for model fitting.

<table>
<thead>
<tr>
<th>Province and survey date</th>
<th>Seroprevalence</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age adjusted % (95% CI)</td>
<td>Total assays, n</td>
</tr>
</tbody>
</table>
| 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. Seroprevalence in Ontario for the months of July and August 2020.

<table>
<thead>
<tr>
<th>Month</th>
<th>Age group</th>
<th>Seroprevalence % (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 2020</td>
<td>&lt;30</td>
<td>0.28 (0.15-0.40)</td>
</tr>
<tr>
<td></td>
<td>30-69</td>
<td>1.13 (0.95-1.31)</td>
</tr>
<tr>
<td></td>
<td>≥70</td>
<td>1.20 (1.05-1.35)</td>
</tr>
<tr>
<td>August 2020</td>
<td>&lt;30</td>
<td>0.29 (0.16-0.42)</td>
</tr>
<tr>
<td></td>
<td>30-69</td>
<td>1.20 (1.05-1.35)</td>
</tr>
<tr>
<td></td>
<td>≥70</td>
<td>1.25 (1.09-1.40)</td>
</tr>
</tbody>
</table>
Table 3. Provincial COVID-19 seroprevalence surveys between July 2020 and August 2020 used for model validation in Ontario, Canada.

<table>
<thead>
<tr>
<th>Date</th>
<th>Seroprevalence</th>
<th>Total assays, n</th>
<th>Positive assays, n (%)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 31, 2020</td>
<td>1.1 (0.8-1.3)</td>
<td>7001</td>
<td>70 (0.99)</td>
<td>[20]</td>
</tr>
<tr>
<td>August 31, 2020</td>
<td>1.1 (0.8-1.3)</td>
<td>6789</td>
<td>72 (1.06)</td>
<td>[19]</td>
</tr>
</tbody>
</table>

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

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Conflicts of Interest

None declared.

Multimedia Appendix 1
References


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

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Associations Between the Perceived Severity of the COVID-19 Pandemic, Cyberchondria, Depression, Anxiety, Stress, and Lockdown Experience: Cross-sectional Survey Study

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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.

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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 [25,26,27]. 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.

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### 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 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: $\chi^2/df=3.57$, 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 $\alpha=.88$, 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. Two psychometrics professors were invited to evaluate the questionnaire items and to modify any unclear or ambiguous questions, forming 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 0.83, 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: $\chi^2/df=3.57$, 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 $\alpha=.88$, which indicated that the reliability of the questionnaire was good.
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: $\chi^2/df=2.96$, 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 $\alpha=.77$, 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 $\alpha=0.86, 0.85$, 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 $\alpha=.93$, 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.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean (SD)</th>
<th>Variables</th>
<th>Perceived severity</th>
<th>Depression</th>
<th>Anxiety</th>
<th>Stress</th>
<th>Cyberchondria</th>
<th>Lockdown experience</th>
</tr>
</thead>
<tbody>
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<td>Perceived severity</td>
<td>53.66 (8.90)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>1</td>
<td>0.36</td>
<td>0.41</td>
<td>0.46</td>
<td>0.36</td>
<td>0.51</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P value</td>
<td>—</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression</td>
<td>6.68 (7.55)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>0.36</td>
<td>1</td>
<td>0.84</td>
<td>0.84</td>
<td>0.38</td>
<td>0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P value</td>
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<td>—</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anxiety</td>
<td>6.20 (7.57)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>0.41</td>
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<td>1</td>
<td>0.85</td>
<td>0.38</td>
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<td>P value</td>
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<td>&lt;.001</td>
<td>&lt;.001</td>
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</tr>
<tr>
<td>Stress</td>
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<tr>
<td>r</td>
<td>0.46</td>
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<td>1</td>
<td>0.39</td>
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<td>&lt;.001</td>
<td></td>
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<td>Cyberchondria</td>
<td>31.64 (8.20)</td>
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<tr>
<td>r</td>
<td>0.36</td>
<td>0.38</td>
<td>0.38</td>
<td>0.39</td>
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<td>0.33</td>
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<tr>
<td>P value</td>
<td>&lt;.001</td>
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<td>&lt;.001</td>
<td>—</td>
<td>&lt;.001</td>
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<tr>
<td>Lockdown experience</td>
<td>33.30 (7.06)</td>
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<tr>
<td>r</td>
<td>0.51</td>
<td>0.52</td>
<td>0.50</td>
<td>0.54</td>
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<tr>
<td>P value</td>
<td>&lt;.001</td>
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*Not applicable.*

Mediating Effects

In the absence of cyberchondria, the positive predictive effects of perceived severity of the COVID-19 pandemic on depression ($\beta=0.36$, $t=8.51$, $P<.001$), anxiety ($\beta=0.41$, $t=9.84$, $P<.001$), and stress ($\beta=0.46$, $t=11.45$, $P<.001$) 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 ($\beta=0.26$, $t=5.85$, $P<.001$), anxiety ($\beta=0.31$, $t=7.24$, $P<.001$), and stress ($\beta=0.37$, $t=8.83$, $P<.001$) were also significant. Perceived severity of the COVID-19 pandemic had a positive predictive effect on cyberchondria ($\beta=0.36$, $t=8.59$, $P<.001$). The positive predictive effects of cyberchondria on depression ($\beta=0.29$, $t=6.66$, $P<.001$), anxiety ($\beta=0.27$, $t=6.24$, $P<.001$), and stress ($\beta=0.26$, $t=6.14$, $P<.001$) 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 stress (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 ($\beta=0.10$, $t=2.59$, $P=.009$), but the product of perceived severity of the COVID-19 pandemic and lockdown experience had no significant predictive effect on depression ($\beta=0.05$, $t=1.38$, $P=.17$). 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: $\beta=0.31$, $t=5.74$, $P<.001$) than that for individuals with low negative lockdown experience (1 SD below the mean: $\beta=0.11$, $t=2.02$, $P=.04$).
The product of perceived severity of the COVID-19 pandemic and lockdown experience ($\beta=0.07$, $t=2.01$, $P=.045$) and the product of cyberchondria and lockdown experience ($\beta=0.10$, $t=2.50$, $P=.01$) 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: $\beta=0.26$, $t=4.15$, $P<.001$) than that for individuals with low negative lockdown experience (1 SD below the mean: $\beta=0.12$, $t=2.33$, $P=.02$).

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: $\beta=0.30$, $t=5.43$, $P<.001$) than that for individuals with low negative lockdown experience (1 SD below the mean: $\beta=0.10$, $t=1.84$, $P=.07$).
The product of perceived severity of the COVID-19 pandemic and lockdown experience had a significant predictive effect on stress ($\beta=0.09$, $t=2.75$, $P=.006$), but the product of cyberchondria and lockdown experience had no significant predictive effect on stress ($\beta=0.05$, $t=1.44$, $P=.15$). 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: $\beta=0.33$, $t=5.46$, $P<.001$) than that for individuals with low negative lockdown experience (1 SD below the mean: $\beta=0.14$, $t=2.91$, $P=.004$).

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.
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.

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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.

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Morocco's National Response to the COVID-19 Pandemic: Public Health Challenges and Lessons Learned

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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.

(Introduction)

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 were 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 began 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 Ed Dahab 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].
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 lopinavir/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 was 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

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## Conflicts of Interest

None declared.

## References


## Abbreviations

- **AZM**: azithromycin
- **CNOUSP**: Centre National des Opérations d’Urgence de Santé Publique
- **CQ**: chloroquine
- **CSO**: civil society organization
COVID-19 Vaccine Perception in South Korea: Web Crawling Approach

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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.

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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.
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 the analysis.
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.**

<table>
<thead>
<tr>
<th>Date</th>
<th>Instagram (n=5291)</th>
<th>NAVER (n=8100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crawling data, n (%)</td>
<td>Crawling data, n (%)</td>
<td></td>
</tr>
<tr>
<td>December 1-7, 2020</td>
<td>239 (4.52)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>December 8-15, 2020</td>
<td>496 (9.37)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>December 16-21, 2020</td>
<td>447 (8.45)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>December 22-28, 2020</td>
<td>379 (7.16)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>December 29-31, 2020</td>
<td>216 (4.08)</td>
<td>270 (3.33)</td>
</tr>
<tr>
<td>January 1-7, 2021</td>
<td>300 (5.67)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>January 8-15, 2021</td>
<td>355 (6.71)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>January 16-21, 2021</td>
<td>429 (8.11)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>January 22-28, 2021</td>
<td>282 (5.33)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>January 29-31, 2021</td>
<td>187 (3.53)</td>
<td>270 (3.33)</td>
</tr>
<tr>
<td>February 1-7, 2021</td>
<td>287 (5.42)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>February 8-15, 2021</td>
<td>253 (4.78)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>February 16-21, 2021</td>
<td>423 (7.99)</td>
<td>630 (7.78)</td>
</tr>
<tr>
<td>February 22-28, 2021</td>
<td>998 (18.86)</td>
<td>630 (7.78)</td>
</tr>
</tbody>
</table>

**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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Type</th>
<th>Vaccine (n=2323)</th>
<th>AstraZeneca (n=559)</th>
<th>Pfizer (n=486)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Word n (%)</td>
<td>Word n (%)</td>
<td>Word n (%)</td>
</tr>
<tr>
<td>1</td>
<td>Safe effect</td>
<td>163 (29.2)</td>
<td>Escape 179 (36.8)</td>
<td>Good 312 (13.4)</td>
</tr>
<tr>
<td>2</td>
<td>Possibility</td>
<td>47 (8.4)</td>
<td>Difficult 39 (8.0)</td>
<td>Treatment 231 (9.9)</td>
</tr>
<tr>
<td>3</td>
<td>Safety</td>
<td>45 (8.1)</td>
<td>Achieved 39 (8.0)</td>
<td>Health 217 (9.3)</td>
</tr>
<tr>
<td>4</td>
<td>Prevention</td>
<td>42 (7.5)</td>
<td>Good 35 (7.2)</td>
<td>Safety 215 (9.3)</td>
</tr>
<tr>
<td>5</td>
<td>Treatment</td>
<td>26 (4.7)</td>
<td>Abnormal 26 (5.3)</td>
<td>Death 145 (6.2)</td>
</tr>
<tr>
<td>6</td>
<td>Trust</td>
<td>23 (4.1)</td>
<td>Pain 19 (3.9)</td>
<td>Prevention 139 (5.9)</td>
</tr>
<tr>
<td>7</td>
<td>Anxiety</td>
<td>22 (3.9)</td>
<td>Peace 18 (3.7)</td>
<td>Possibility 137 (5.9)</td>
</tr>
<tr>
<td>8</td>
<td>Difficult</td>
<td>22 (3.9)</td>
<td>No 16 (3.3)</td>
<td>Safe effect 123 (5.2)</td>
</tr>
<tr>
<td>9</td>
<td>Refusal</td>
<td>20 (3.6)</td>
<td>Giving up 15 (3.1)</td>
<td>Tough 103 (4.4)</td>
</tr>
<tr>
<td>10</td>
<td>Distrust</td>
<td>20 (3.6)</td>
<td>Having a cold 11 (2.3)</td>
<td>Risk 90 (3.9)</td>
</tr>
<tr>
<td>11</td>
<td>Ill</td>
<td>19 (3.4)</td>
<td>Value 11 (2.3)</td>
<td>Infected 90 (3.9)</td>
</tr>
<tr>
<td>12</td>
<td>Health</td>
<td>17 (3.0)</td>
<td>Fainting 10 (2.1)</td>
<td>Recovery 80 (3.4)</td>
</tr>
<tr>
<td>13</td>
<td>Increase</td>
<td>15 (2.7)</td>
<td>Need 10 (2.1)</td>
<td>Rise 73 (3.1)</td>
</tr>
<tr>
<td>14</td>
<td>Concerned</td>
<td>13 (2.3)</td>
<td>Risk 9 (1.9)</td>
<td>Happy 62 (2.7)</td>
</tr>
<tr>
<td>15</td>
<td>Stability</td>
<td>12 (2.1)</td>
<td>Limit 9 (1.9)</td>
<td>Hope 56 (2.4)</td>
</tr>
<tr>
<td>16</td>
<td>Shortage</td>
<td>11 (2.0)</td>
<td>Convulsion 8 (1.6)</td>
<td>Overcoming 55 (2.4)</td>
</tr>
<tr>
<td>17</td>
<td>Okay</td>
<td>11 (2.0)</td>
<td>Righteous Person 8 (1.6)</td>
<td>Late 55 (2.4)</td>
</tr>
<tr>
<td>18</td>
<td>Experts</td>
<td>11 (2.0)</td>
<td>Cautious 8 (1.6)</td>
<td>Anxiety 49 (2.1)</td>
</tr>
<tr>
<td>19</td>
<td>Overcoming</td>
<td>10 (1.8)</td>
<td>Improvement 8 (1.6)</td>
<td>Illness 46 (2.0)</td>
</tr>
<tr>
<td>20</td>
<td>Recovery</td>
<td>10 (1.8)</td>
<td>Understanding 8 (1.6)</td>
<td>Banned 45 (1.9)</td>
</tr>
</tbody>
</table>

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 198/3698 (53.57%). 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.

<table>
<thead>
<tr>
<th>Type</th>
<th>Pfizer (n=122)</th>
<th>Frequency (n=885)</th>
<th>AstraZeneca (n=89)</th>
<th>Frequency (n=670)</th>
<th>Vaccine (n=146)</th>
<th>Frequency (n=3698)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Word count</td>
<td>47 (38.5)</td>
<td>387 (43.7)</td>
<td>37 (41.6)</td>
<td>194 (29.0)</td>
<td>43 (29.5)</td>
</tr>
<tr>
<td>Positive</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>43 (29.5)</td>
<td>1981 (53.6)</td>
</tr>
<tr>
<td></td>
<td>Word count</td>
<td>75 (61.5)</td>
<td>498 (56.3)</td>
<td>52 (58.4)</td>
<td>476 (71.0)</td>
<td>103 (70.5)</td>
</tr>
<tr>
<td>Negative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>103 (70.5)</td>
<td>1717 (46.4)</td>
</tr>
</tbody>
</table>

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,” “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.
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.

**Figure 2.** Word cloud visualizations of crawled data. Side-eff: side-effects.

<table>
<thead>
<tr>
<th>Type</th>
<th>Vaccine</th>
</tr>
</thead>
<tbody>
<tr>
<td>AstraZeneca</td>
<td>Positive: “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.”</td>
</tr>
<tr>
<td>Pfizer</td>
<td>Positive: “achieved,” “good,” and “value,” and negative words were “escape,” “difficult,” “pain,” and “giving up.”</td>
</tr>
</tbody>
</table>

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.”

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.
**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
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

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Assessing COVID-19 Vaccine Uptake and Effectiveness Through the North West London Vaccination Program: Retrospective Cohort Study

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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.

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**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%).

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).
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 rates<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

<table>
<thead>
<tr>
<th>Vaccinations</th>
<th>Days after vaccination</th>
<th>&lt;7 (week 1)</th>
<th>7-13 (week 2)</th>
<th>14-20 (week 3)</th>
<th>21-27 (week 4)</th>
<th>28-34 (week 5)</th>
<th>35-41 (week 6)</th>
<th>42-48 (week 7)</th>
<th>49-55 (week 8)</th>
<th>56-62 (week 9)</th>
<th>63-69 (week 10)</th>
<th>≥70 (≥week 11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vaccinated individuals time to first positive test after vaccination, n</td>
<td></td>
<td>344</td>
<td>525</td>
<td>332</td>
<td>147</td>
<td>87</td>
<td>48</td>
<td>16</td>
<td>13</td>
<td>11</td>
<td>&lt;5^b</td>
<td>0</td>
</tr>
<tr>
<td>Total vaccinated population completed to period of follow-up (excluding previously positive patients), n</td>
<td></td>
<td>389,587</td>
<td>389,243</td>
<td>330,523</td>
<td>261,447</td>
<td>184,847</td>
<td>111,555</td>
<td>62,283</td>
<td>31,757</td>
<td>20,097</td>
<td>14,200</td>
<td>2519</td>
</tr>
<tr>
<td>First positive individuals by population completed to follow-up time to first positive (not previously positive), %</td>
<td></td>
<td>0.09</td>
<td>0.13</td>
<td>0.10</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Vaccinated individuals (excluding care home or housebound residents) time to first positive test after vaccination, n</td>
<td></td>
<td>319</td>
<td>470</td>
<td>284</td>
<td>129</td>
<td>71</td>
<td>46</td>
<td>13</td>
<td>10</td>
<td>9</td>
<td>&lt;5</td>
<td>0</td>
</tr>
<tr>
<td>Total vaccinated population (excluding care home and housebound residents) completed to period of follow-up (excluding previously positive patients), n</td>
<td></td>
<td>373,820</td>
<td>373,501</td>
<td>315,666</td>
<td>248,136</td>
<td>173,336</td>
<td>105,834</td>
<td>59,574</td>
<td>30,674</td>
<td>19,338</td>
<td>13,763</td>
<td>2431</td>
</tr>
<tr>
<td>First positive individuals by population completed to follow-up time to first positive (not previously positive; excluding care home and housebound), %</td>
<td></td>
<td>0.09</td>
<td>0.13</td>
<td>0.09</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Vaccinated care home or housebound individuals time to first positive test after vaccination, n</td>
<td></td>
<td>25</td>
<td>55</td>
<td>48</td>
<td>18</td>
<td>16</td>
<td>&lt;5</td>
<td>&lt;5</td>
<td>&lt;5</td>
<td>&lt;5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total vaccinated care home or housebound population completed to period of follow-up (excluding previously positive patients), n</td>
<td></td>
<td>15,767</td>
<td>15,742</td>
<td>14,860</td>
<td>13,317</td>
<td>11,556</td>
<td>5770</td>
<td>2749</td>
<td>1090</td>
<td>771</td>
<td>443</td>
<td>92</td>
</tr>
<tr>
<td>First positive care home or housebound individuals by population completed to follow-up time to first positive (not previously positive), %</td>
<td></td>
<td>0.16</td>
<td>0.35</td>
<td>0.32</td>
<td>0.14</td>
<td>0.14</td>
<td>0.03</td>
<td>0.11</td>
<td>0.28</td>
<td>0.26</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

^aRates are stratified by individuals in care homes or housebound and those in the rest of the vaccinated population.  
^bLow 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.
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).
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.

<table>
<thead>
<tr>
<th>Week period (days)</th>
<th>No vaccination</th>
<th>Oxford/AstraZeneca</th>
<th>Pfizer/BioNTech</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hazard ratio (95% CI)</td>
<td>P value</td>
<td>Hazard ratio (95% CI)</td>
</tr>
<tr>
<td>0-7</td>
<td>1.0 (Reference)</td>
<td>0.71 (0.60-0.84)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>8-14</td>
<td>1.0 (Reference)</td>
<td>0.68 (0.59-0.80)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>15-21</td>
<td>1.0 (Reference)</td>
<td>0.59 (0.49-0.71)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>22-28</td>
<td>1.0 (Reference)</td>
<td>0.26 (0.19-0.35)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

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).
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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hazard ratio (95% CI)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vaccination</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No vaccination (reference)</td>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>Vaccination</td>
<td>0.64 (0.43-0.95)</td>
<td>.03</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16-49 (reference)</td>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>50-54</td>
<td>0.75 (0.58-0.98)</td>
<td>.03</td>
</tr>
<tr>
<td>55-59</td>
<td>0.82 (0.64-1.06)</td>
<td>.13</td>
</tr>
<tr>
<td>60-64</td>
<td>0.79 (0.61-1.02)</td>
<td>.07</td>
</tr>
<tr>
<td>65-69</td>
<td>0.41 (0.32-0.54)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>70-74</td>
<td>0.26 (0.20-0.33)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>75-79</td>
<td>0.29 (0.23-0.38)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>80+</td>
<td>0.29 (0.24-0.36)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Care home resident</td>
<td>0.76 (0.56-1.05)</td>
<td>.13</td>
</tr>
<tr>
<td>Clinically extremely vulnerable</td>
<td>0.30 (0.24-0.38)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Ethnicity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White (reference)</td>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>Asian or British Asian</td>
<td>0.91 (0.80-1.02)</td>
<td>.11</td>
</tr>
<tr>
<td>Black or Black British</td>
<td>0.98 (0.77-1.25)</td>
<td>.89</td>
</tr>
<tr>
<td>Mixed</td>
<td>1.29 (0.91-1.82)</td>
<td>.15</td>
</tr>
<tr>
<td>Other ethnic groups</td>
<td>1.06 (0.83-1.35)</td>
<td>.65</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female (reference)</td>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>Male</td>
<td>1.02 (0.91-1.15)</td>
<td>.69</td>
</tr>
<tr>
<td><strong>IMD decile</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (reference)</td>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>2</td>
<td>1.03 (0.74-1.43)</td>
<td>.87</td>
</tr>
<tr>
<td>3</td>
<td>1.11 (0.82-1.51)</td>
<td>.49</td>
</tr>
<tr>
<td>4</td>
<td>0.97 (0.71-1.32)</td>
<td>.83</td>
</tr>
<tr>
<td>5</td>
<td>1.08 (0.79-1.48)</td>
<td>.62</td>
</tr>
<tr>
<td>6</td>
<td>1.04 (0.76-1.42)</td>
<td>.79</td>
</tr>
<tr>
<td>7</td>
<td>0.80 (0.58-1.12)</td>
<td>.24</td>
</tr>
<tr>
<td>8</td>
<td>0.84 (0.59-1.20)</td>
<td>.33</td>
</tr>
<tr>
<td>9</td>
<td>0.93 (0.65-1.34)</td>
<td>.72</td>
</tr>
<tr>
<td>10</td>
<td>0.83 (0.56-1.21)</td>
<td>.33</td>
</tr>
</tbody>
</table>

*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% (544/389,587) 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 average weekly person testing positive rate recorded in the total population by 0.1% (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...
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 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.

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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.

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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).

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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
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**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

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