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Contents

Viewpoint

Designing Better Exposure Notification Apps: The Role of Persuasive Design

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Abstract

Background: Digital contact tracing apps have been deployed worldwide to limit the spread of COVID-19 during this pandemic and to facilitate the lifting of public health restrictions. However, due to privacy-, trust-, and design-related issues, the apps are yet to be widely adopted. This calls for an intervention to enable a critical mass of users to adopt them.

Objective: The aim of this paper is to provide guidelines to design contact tracing apps as persuasive technologies to make them more appealing and effective.

Methods: We identified the limitations of the current contact tracing apps on the market using the Government of Canada's official exposure notification app (COVID Alert) as a case study. Particularly, we identified three interfaces in the COVID Alert app where the design can be improved. The interfaces include the no exposure status interface, exposure interface, and diagnosis report interface. We propose persuasive technology design guidelines to make them more motivational and effective in eliciting the desired behavior change.

Results: Apart from trust and privacy concerns, we identified the minimalist and nonmotivational design of exposure notification apps as the key design-related factors that contribute to the current low uptake. We proposed persuasive strategies such as self-monitoring of daily contacts and exposure time to make the no exposure and exposure interfaces visually appealing and motivational. Moreover, we proposed social learning, praise, and reward to increase the diagnosis report interface's effectiveness.

Conclusions: We demonstrated that exposure notification apps can be designed as persuasive technologies by incorporating key persuasive features, which have the potential to improve uptake, use, COVID-19 diagnosis reporting, and compliance with social distancing guidelines.

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KEYWORDS

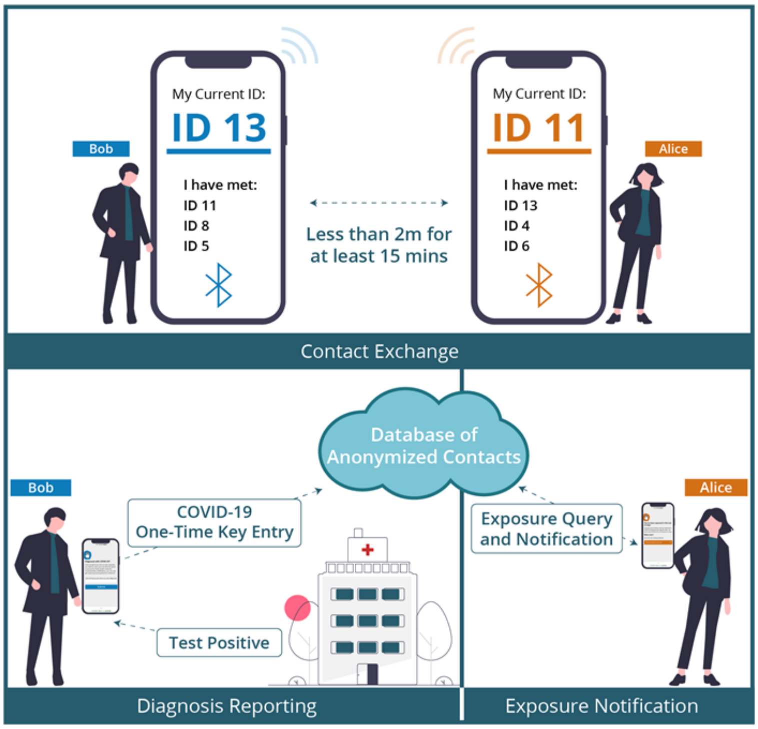
contact tracing app; exposure notification app; COVID Alert; COVID-19; persuasive technology; behavior change

Introduction

The COVID-19 pandemic, beginning in the early part of 2020, has led to the development and deployment of several digital health technologies to slow the spread of COVID-19. COVID-19 is a human-to-human transmittable respiratory disease caused by the coronavirus known as SARS-CoV-2, which emerged in December 2019. Its symptoms include cough, sore throat, and high fever, which have the potential to cause pneumonia and respiratory failure [1]. Most prevalent among the technologies aimed at curbing COVID-19 are digital contact tracing apps, which help public health authorities to track or notify individuals who may have come into close contact with a person who is infected. Traditionally, contact tracing has been a manual process whereby people, potentially exposed to a human-to-human transmittable disease, are identified by interviewing persons who are infected with whom the former may have had close contact [2]. However, with the advancement in mobile technology and privacy-preserving cryptography (eg, the Google/Apple Exposure Notification system), the practice of contact tracing has gone predominantly digital worldwide [3]. Digital contact tracing does not replace manual tracing techniques but augments it to fast-track the containment of COVID-19 [4,5]. The main advantage of digital over manual contact tracing is that it automates the labor-intensive process, especially in situations where there are a limited number of human contact tracers [2,6]. Digital contact tracing, if adopted by a critical mass of people, is more likely to be faster, more effective, and accurate in comparison to the fallible nature of human memories, especially given that COVID-19 infection may be asymptomatic for up to 14 days [7].

Figure 1 shows how the exposure notification app works in the real world. If Bob and Alice come in close contact (ie, within a 2-meter distance) for 15 minutes or more, both contacts exchange a dynamic randomly generated identification number. In the future, if Bob tests positive and uploads his one-time key given to him by the public health authority to the cloud-based database of anonymized contacts, Alice will be contacted via the app and advised on what to do next.

Figure 1. COVID-19 contact tracing and exposure notification process (adapted from Fairbank et al [8]).



Several countries worldwide, such as Australia, Canada, France, South Africa, and Singapore [9-11], have launched nationwide exposure notification apps in their respective official languages. The apps alert people who may have come in close contact with persons infected with COVID-19 for 15 minutes or more in the last 14 days. The Government of Canada's exposure notification app is called "COVID Alert" [12]. It is available in two languages (English and French) and can be downloaded from the Apple and Android stores by Canadian residents in the Northwest Territories, Prince Edward Island, Nova Scotia, Quebec, Manitoba, Saskatchewan, New Brunswick, Ontario, and Newfoundland and Labrador [13]. Given the current poor uptake of contact tracing apps in general [14], in this paper, we used the COVID Alert app as a case study to uncover some of the weaknesses in the current design of most exposure notification apps on the market and demonstrate how persuasive features can be incorporated in their design to improve their persuasiveness, uptake, and effectiveness.

The rest of the paper is organized as follows. We begin by covering the poor uptake and design of contact tracing apps on the market and the need to make them more motivationally appealing. We then focus on persuasive design, key persuasive strategies relevant to contact tracing apps, and incorporating persuasive design in exposure notification apps using the COVID Alert app as a case study. Finally, we discuss the potential benefits of the proposed persuasive design of exposure notification apps and the ethics of persuasive technology.

Poor Uptake of Current Exposure Notification Apps

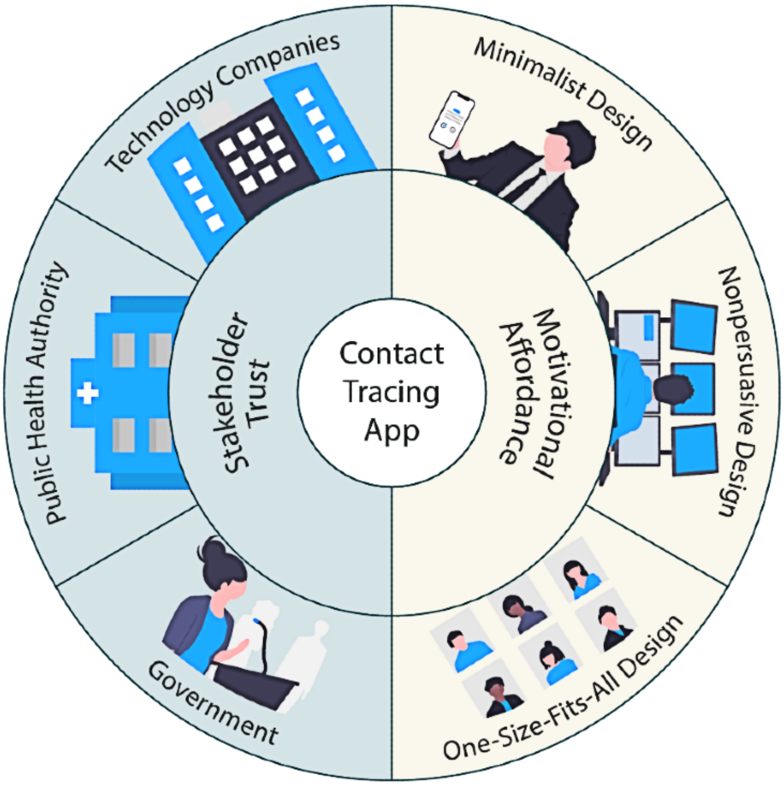
The Canadian Government has widely publicized the COVID Alert app, but acquiring a critical mass of users has been hampered due to privacy concerns, trust, and human factor design issues. Part of the adoption campaign involved Prime Minister Justin Trudeau urging Canadian residents, especially young people, to download and use the COVID Alert app to improve contact tracing and diminish disease trajectories [13]. In 2020, it was estimated that there were 31.38 million smartphone users in Canada [15]. Yet, as of November 26, 2020, the COVID alert app has only been downloaded about 5.5 million times from both Apple and Google stores [16]. This means (assuming each download can be associated with a unique smartphone user) approximately 17.5 percent of the smartphone users in Canada in 2020 downloaded the app as of November 26. The low adoption rate of the COVID Alert app among the Canadian population limits its effectiveness, as research shows that 56% of the population would have to use the app to considerably slow down the spread of the virus [17].

Problems With Current Contact Tracing and Exposure Notification Apps

There are several problems associated with the low uptake of contact tracing and exposure notification apps worldwide. Concerns hindering their adoption are privacy, data use, public surveillance, poor persuasive design, and lack of customization to mention but a few [7,18].

Broadly, these problems can be grouped into two categories, as shown in Figure 2. The first category is lack of trust in stakeholders (eg, government, tech companies, or public health authority) pertaining to data privacy and protection [19-21]. The second category is the lack of motivational affordances in the user interface (UI) design of exposure notification apps. In other words, these apps are minimalist, nonpersuasive, and use a one-size-fits-all approach, which can negatively impact adoption [20,22].

Figure 2. Stakeholder and design-related issues surrounding the low uptake of contact tracing and exposure notification apps.



Lack of Trust in Contact Tracing Stakeholders

Privacy and trust-related concerns have been raised by the public concerning how COVID-19 health and tech stakeholders will handle users' privacy and data [7]. For example, most Americans may trust COVID-19 stakeholders such as public health agencies and universities, but they do not trust tech companies such as Apple and Google, which developed the privacy-preserving Google/Apple Exposure Notification system, which most of the contact tracing apps on the market require and support to function properly [12]. A cross-section of US smartphone users was asked the question, "How much, if at all, do you trust _____ to ensure that people who report being diagnosed with coronavirus using their smartphone app remain anonymous — a great deal, a good amount, not too much or not at all?" A total of 56% of those polled (ie, nearly 3 in 5) did not trust tech companies such as Apple and Google, but 57% and 56% trusted public health agencies and universities a great deal or a good amount, respectively [23]. The limited trust in tech companies such as Apple and Google (<45%) may not come as a surprise given the widely reported Facebook-Cambridge Analytica Scandal about the 2016 United States elections [24].

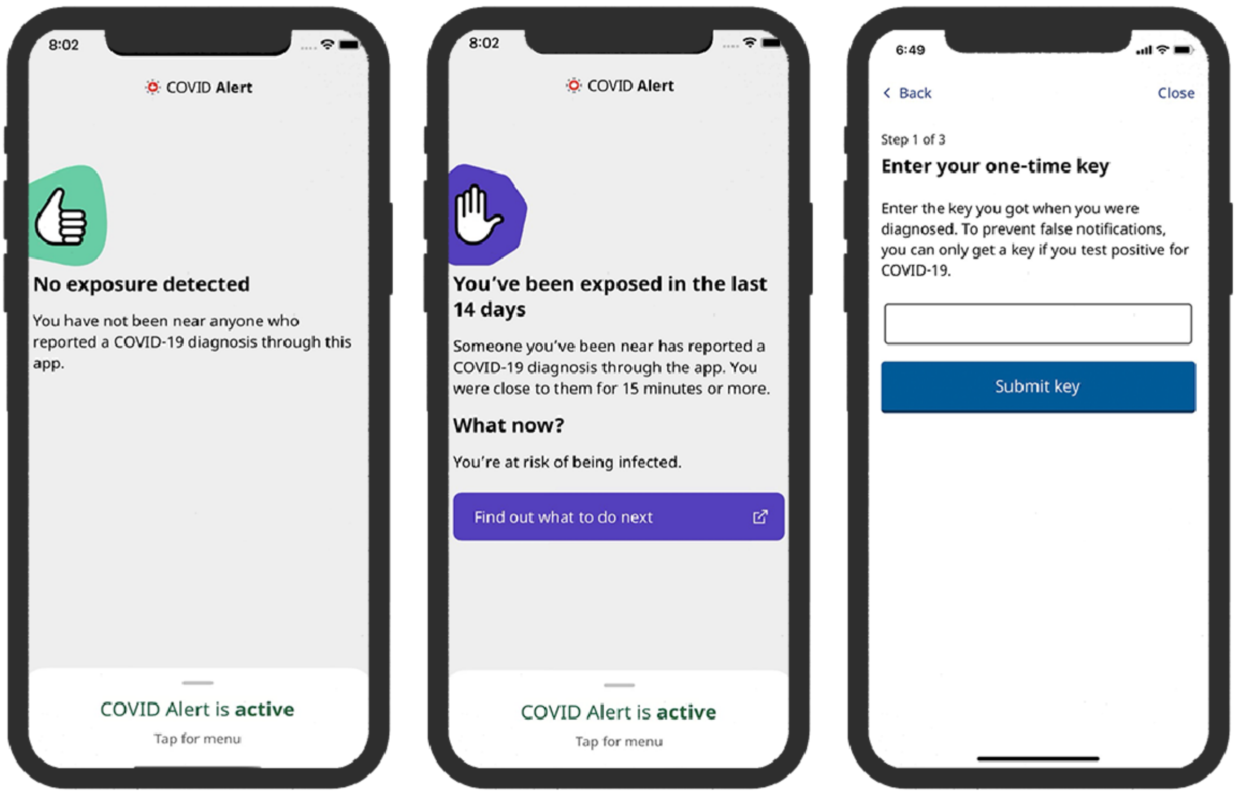
Lack of Motivational Affordances in Exposure Notification Apps

High uptake is crucial for exposure notification apps to be effective in mitigating the spread of COVID-19. However, according to Walrave et al [25], "*it* remains unclear how we can motivate citizens to use these apps." Although the government and tech companies have taken some measures to increase public trust by way of decentralization of collected data [12], Bluetooth contact tracing, and nontracking/storage of users' location data via global positioning technology, much is yet to be done in the area of persuasive design to increase the adoption rate. For example, the current version of the COVID Alert app is minimalist [26] and lacks motivational affordances and incentives [27]. Motivational affordances are the persuasive elements that satisfy users' needs. According to Zhang [28], when an information and communication technology (ICT) satisfies users' motivational needs, they feel enjoyment and want it more. Hence, "the ultimate goal of designing an ICT for human use is to achieve high motivational affordance so that users would be attracted to it, really want to use it, and cannot live without it" [28]. However, "[a]part from providing receiving notifications about possible infections, current contract tracing apps appear to not provide a clear benefit to the user" [29]. Specifically, most of them lack vital persuasive features that motivate people to use digital health technologies to monitor and manage their health behaviors. Hence, the lack of persuasive features may contribute to low adoption rates of many contact tracing and exposure notification apps on the market [30].

Digital health researchers have stated that incorporating persuasive features into contact tracing apps could increase their adoption and use by the wider population [27]. In other words, contact tracing apps are more likely to be effective as persuasive technologies than as traditional information systems focused on functionality.

Persuasive technology is an interactive system intentionally designed to change attitudes or behaviors positively through persuasion and social influence but not through coercion or deception [31]. However, the current version of the COVID Alert app lacks basic persuasive and social influence principles that can motivate more users to download and use the app more frequently. Figure 3 shows the three main functional UIs of the COVID Alert app: "No Exposure," "Exposure," and "Diagnosis Report." Apart from being minimalistic, all three UIs do not support essential persuasive features such as monitoring of the users' daily contacts and exposure time. This may help them regulate themselves concerning observing social (physical) distancing guidelines in public settings.

Figure 3. Key user interfaces in the COVID Alert app (Government of Ontario [32]).



Persuasive Design

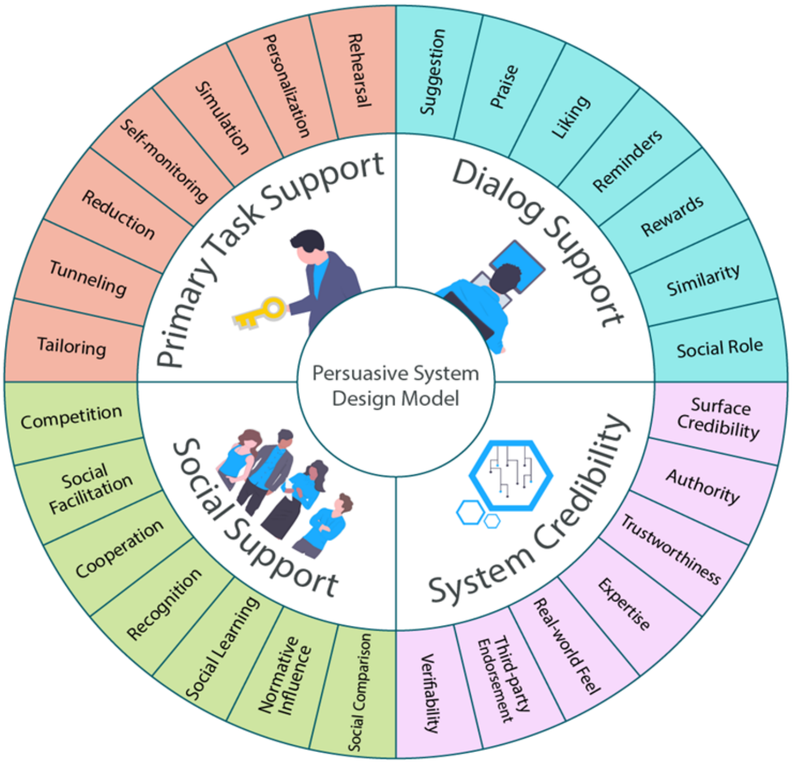
Persuasive design involves applied social psychology theories in the design of technologies to change behaviors and attitudes. Hence, persuasive technology, also called "Captology" by Fogg [31], is regarded as the intersection of computer systems (from the field of human-computer interaction) and the art of persuasion (from the field of psychology). A typical example of a persuasive technology is a mobile fitness app aimed at motivating people to exercise more to improve their mental well-being and physical fitness. Persuasive design focuses on influencing human behavior, attitude, motivation, and compliance through the systematic design of a system's features and affordances to promote behavior change.

Persuasive Techniques

There are two main design frameworks commonly used in designing and evaluating persuasive technologies. The first framework is called Cialdini's [33] principles of persuasion, which comprise six persuasive techniques: authority, commitment, reciprocity, liking, consensus, and scarcity [34,35]. The second framework is called the persuasive system design model [36], which comprises 28 persuasive techniques and extends Fogg's [31] seven persuasive techniques. The persuasive system design model includes four broad categories (primary task support, dialogue support, system credibility support, and social support) as shown in Figure 4 [36,37].

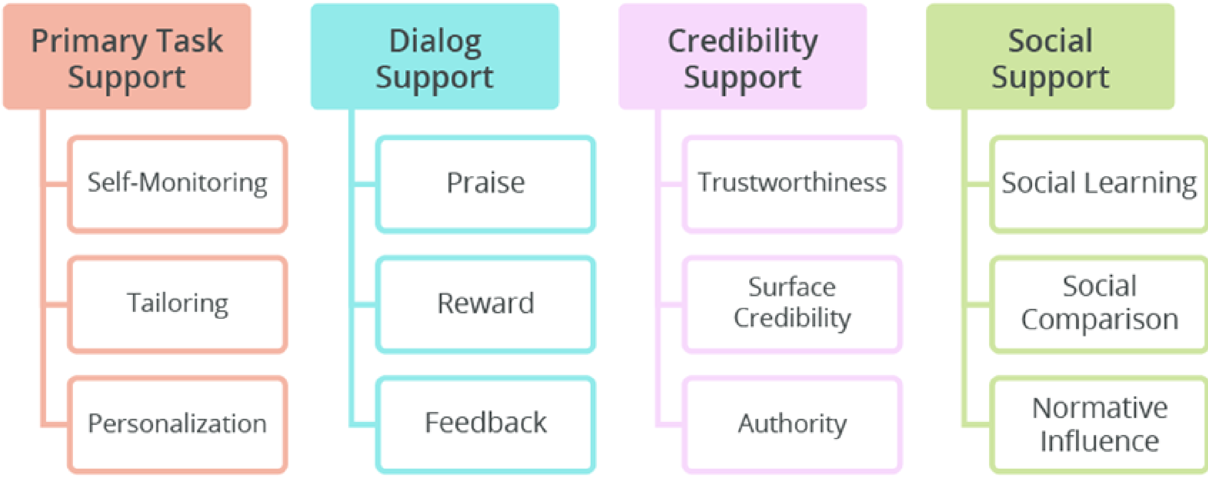
First, primary task support includes persuasive techniques that help the user to carry out the target behavior easily and effectively. Second, dialogue support includes persuasive techniques that motivate the user to perform the target behavior through feedback and interaction with the persuasive application. Third, social support includes persuasive techniques that motivate the user to carry out the target behavior through social influence. Finally, system credibility support includes persuasive techniques that make the persuasive application look credible to the user [38].

Figure 4. Persuasive system design model [36,37].



Each of the four categories in the persuasive system design model comprises seven persuasive techniques. Figure 5 shows three persuasive techniques in each of the four categories relevant to contact tracing apps. For example, primary task support comprises self-monitoring, tailoring, and personalization, and social support includes social learning, social comparison, and normative influence. These techniques, widely studied in persuasive technology research, have proven effective in changing health behaviors such as physical activity [39,40]. Moreover, dialogue support comprises praise, reward, and feedback. In particular, reward, be it virtual, tangible, or monetary, holds potential in motivating behavior change, as people from both high-income and low-income countries are receptive to it [41]. Finally, credibility support comprises trustworthiness, surface credibility, and authority. Research [36] shows that persuasive apps perceived as trustworthy and credible are more likely to motivate behavior change. Prior studies found a direct or indirect relationship between source trustworthiness [42] or perceived credibility [43] and behavioral intentions. Moreover, Oyibo et al [44] found that people from both high-income and low-income countries are receptive to the authority strategy. Interestingly, current exposure notification apps on the market are already equipped with the authority and credibility strategies by default given that they were sponsored by national governments that symbolize authority. However, the issue of trust in the area of data protection and privacy remains a roadblock to adoption [23].

Figure 5. Twelve contact tracing app persuasive techniques from the persuasive system design model.



Example Implementation of Key Persuasive Design Techniques

Persuasive techniques are implemented in most mobile health apps on the market to motivate behavior change and help users achieve their goals. Figure 6 shows a fitness app called "BEN'FIT," in which reward/self-monitoring and social learning/social comparison are, respectively, implemented in the personal and social versions (Oyibo et al [45]). Self-monitoring enables the user to track their physical activity, including calories burned and step count over time. Regarded as the cornerstone of persuasive apps, self-monitoring fosters self-awareness and commitment, among other advantages shown in Figure 7 [46]. In the context of contact tracing apps, Cruz et al [47] found that over 50% of their surveyed participants wanted to know how many infected people they have come in contact with and how many infected people have passed through a given location. Reward provides users with something to strive for and reinforces behaviors [48]. Feedback allows the user to get important information about their behavior at specific points in time, for example, after achieving a 10,000 steps milestone. Feedback is not listed as a dialogue support feature in the persuasive system design model, yet it is used as a persuasive feature in motivating behavioral change. Social learning and social comparison, which are correlated [49], use social pressure to motivate the target behavior [48].

Figure 6. Implementation of SM, RW, SC, and SL in a fitness app aimed at promoting physical activity [46]. RW: reward; SC: social comparison; SL: social learning; SM: self-monitoring.

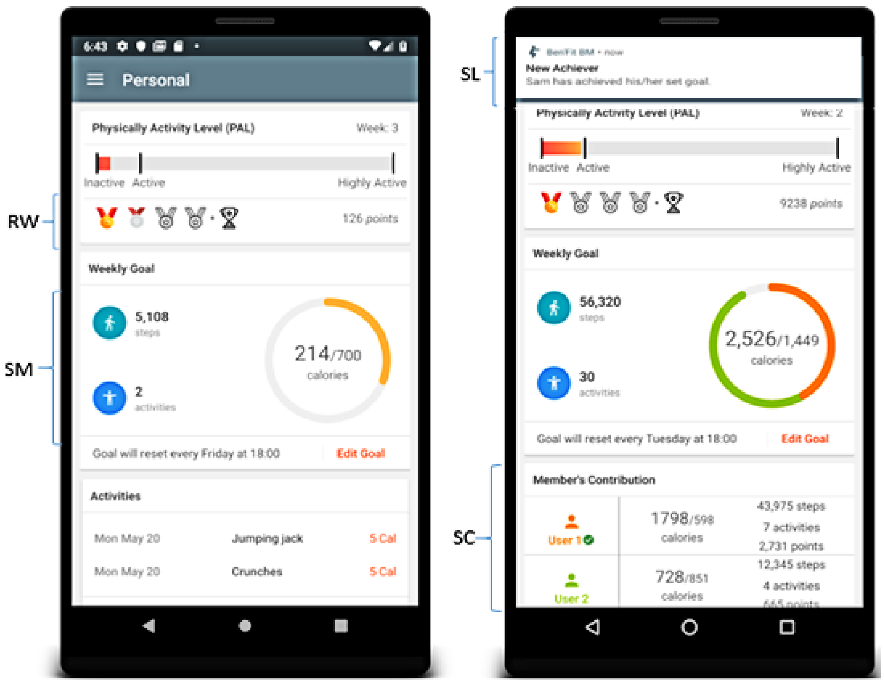
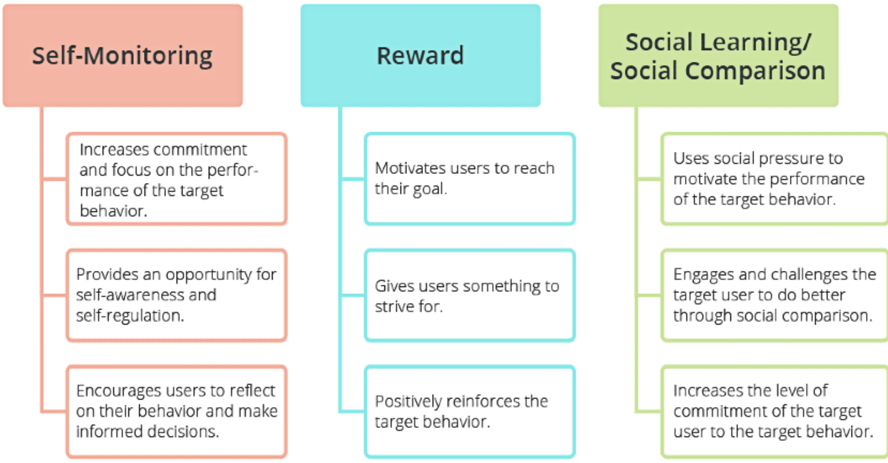


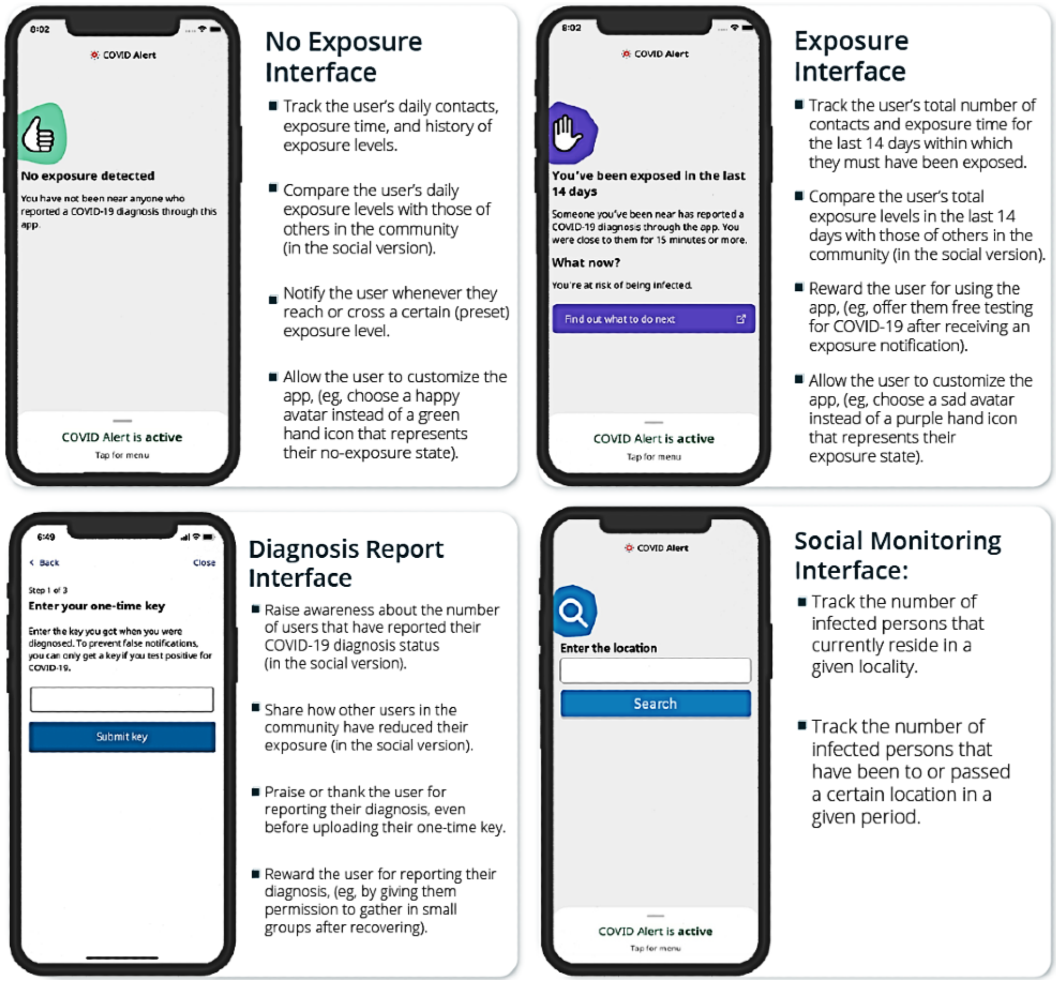
Figure 7. Advantages of self-monitoring, reward, social learning, and social comparison [47].



Incorporating Persuasive Design in Exposure Notification Apps

The COVID Alert app can be redesigned to be more appealing and motivating to the target users by incorporating essential persuasive features to increase its effectiveness. Figure 8 provides guidelines for integrating persuasive features such as self-monitoring, praise, reward, social comparison, and social learning. However, prior research in the physical activity domain shows that Canadians are more likely to be receptive to personal than social strategies [50]. For this reason, there should be a personal and a social version of the app to enable the target users to make a choice based on their preferences.

Figure 8. Guidelines for incorporating persuasive features into key user interfaces of exposure notification apps using COVID Alert as a case study.



No Exposure Interface

In the no exposure UI, a self-monitoring feature, which tracks daily contacts and exposure time, and showcases historical behavior, can be incorporated in the second half of the screen, which is currently blank. The implementation of the self-monitoring feature is presented in Oyibo et al [51]. In the social version, a social comparison feature, which compares the user's exposure levels (daily contacts and exposure time) with those of others in the community, can be incorporated as well. In addition, users can be allowed to customize the app (eg, choose a happy face avatar instead of a green hand icon that represents their no exposure state). Research shows that well-designed avatars can improve the user experience by drawing a closer connection between the user's lived and digital identities as, for example, avatars possess some human signifiers like facial expressions that convey emotion [52]. This is in line with the liking principle in the persuasive system design model (Figure 4), which states that people are more likely to be persuaded by people similar to them or that are attractive [33,36].

Exposure Interface

In the exposure UI, a self-monitoring feature, which tracks the total number of contacts and approximately when the user was exposed, can be incorporated in the middle of the screen, as shown in Figure 8. The implementation of the self-monitoring feature is presented in Oyibo et al [51]. As in the no exposure UI, users should be able to customize the app (eg, choose a sad face avatar instead of a purple hand icon to represent their exposed state). In addition, in the social version, they should be given the choice to compare their exposure levels with those of others in the community as an additional means of motivation and insight.

Diagnosis Report Interface

In the diagnosis report UI, a social learning feature, which informs the user about the number of persons that have reported their COVID-19 diagnosis for a given period (eg, day or week), can be incorporated in the middle of the screen as shown in Figure 8. This additional statistical information can encourage users, when infected, to report their diagnosis to ensure the safety of the community. The implementation of the social learning feature is presented in Oyibo et al [51]. Moreover, users can be praised or rewarded for reporting their diagnosis. In a recent study, Jonker et al [53] found that respondents preferred apps that offer them incentives such as a token monetary reward (€5 [US $6] or €10 [US $12] a month), permission to gather in small groups (eg, after recovering), or free testing for COVID-19 after receiving an exposure alert.

Social Location Monitoring Interface

In addition to the 12 persuasive features drawn from the persuasive system design model (Figure 4), hot spot monitoring, which we call "Social Location Monitoring," can be used as a persuasive strategy to promote adoption and use. Social location monitoring is the tracking and gathering of information about a location that includes the number of persons who are infected that currently reside in, have been to, or passed the location in a given period to help users make informed decisions. Figure 8 shows a hypothetical interface for incorporating social location monitoring to motivate beneficial behaviors (eg, avoiding hot spots, social distancing, and wearing a mask). In a recent study, Li et al [54] found that respondents were more willing to install contact tracing apps that collect users' location data than those that do not, due to the additional benefits they provide about hot spot information and analysis. Social location monitoring can help local authorities allocate resources in a better way and enact better health care policies during the COVID-19 pandemic [55].

Potential Impact of the Proposed Persuasive Design

The projected impact of the persuasive design of exposure notification apps includes improved uptake, frequent use, increased report of diagnosis, and compliance with social distancing guidelines. In future research efforts, we hope to implement these persuasive design guidelines and conduct a study to investigate the effectiveness of the persuasive design of exposure notification apps using the COVID Alert app as a case study. Although research has shown that persuasive design can promote behavior change (eg, in the physical domain or health eating), it is still not certain whether the proposed persuasive design guidelines for exposure notification apps can promote the target behaviors. Hence, there is a need for empirical research in the future to investigate the effectiveness of the proposed persuasive system design guidelines.

Ethics of Persuasive Design

Ethical concerns about the app and impact of persuasive design have been raised in the gray and academic literature. Admittedly, in the wrong hands, persuasive design can be exploited or used to manipulate unsuspecting users for financial and other gains [56]. We regard this as "persuasive design for unethical gains." One area that experts believe that persuasive technologies have been unethically used is digital apps for children. Research shows that the amount of kids' screen time in 2018 was 10 times the amount in 2011, with kids spending an average of 6 hours and 40 minutes using persuasive technologies such as game apps and social media. Hence, some health professionals believed "children's behaviors are being exploited in the name of the tech world's profit" [56]. This led 50 psychologists in 2018 to send a letter to the American Psychological Association (APA) "accusing psychologists working at tech companies of using 'hidden manipulation techniques' [and prevailing on] the APA to take an ethical stand on behalf of kids" [56]. However, leveraging persuasive design for financial gains or unethical benefits is not what "persuasive design for behavior change" is about. Rather, the sole purpose for persuasive design for behavior change is to support the user in adopting and performing behaviors beneficial to themselves or society. An example of behavior change beneficial to the individual is eating healthy or exercising regularly. A persuasive app can be used to promote these behaviors. An example of such an app is "List It" [57]. The app motivates users to select healthy options from a shopping list. Moreover, a behavior change beneficial to the society is commuting by public transportation (eg, bus or train) instead of driving one's personal car [58]. Broadly speaking, eco-friendly behaviors aimed at reducing carbon footprints will help, on a large scale, reduce global warming and climate change [59]. An example of a persuasive app aimed at reducing carbon footprints is "EcoIsland" [60]. The app, which supports the feedback strategy, encourages users to perform eco-friendly activities (turning down the room heater by 1 °C, commuting by train instead of driving a car, etc) to reduce carbon dioxide emission. Overall, the guiding moral principle (also known as the golden rule) of persuasive technology is that "designers of persuasive technology should not create any artifact that persuades someone to do or think something that they (the designers) would not want to be persuaded of themselves" [61].

Conclusions

In this paper, we identified some of the issues surrounding the low uptake of contact tracing and exposure notification apps deployed by national governments worldwide to curb the spread of COVID-19 and speed up the lifting of public health restrictions. Specifically, we pinpointed lack of trust, concerns about privacy and data use by COVID-19 stakeholders, and the nonmotivational design of contact tracing and exposure notification apps as potential reasons for the low adoption rates worldwide. Using the Government of Canada's COVID Alert app as a case study, we provided persuasive technology design guidelines that can help incorporate persuasive features in contact tracing and exposure notification apps to increase their uptake, frequent use, and compliance with social distancing guidelines. For example, we identified three use cases (no exposure status, exposure status, and diagnosis report interfaces) that can support persuasive features such as self-monitoring of the number of daily contacts and COVID-19 exposure time, and social learning about other users that have reported their diagnosis over a given period. In future work, we hope to conduct a user study to investigate the effectiveness of the implemented guidelines among Canadian residents using the COVID Alert app as a case study [51].

Acknowledgments

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Conflicts of Interest

None declared.

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Abbreviations

APA: American Psychological Association
ICT: information and communication technology
UI: user interface

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Review

Defining Digital Public Health and the Role of Digitization, Digitalization, and Digital Transformation: Scoping Review

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Abstract

Background: The recent proliferation and application of digital technologies in public health has spurred interest in *digital public health*. However, as yet, there appears to be a lack of conceptual clarity and consensus on its definition.

Objective: In this scoping review, we seek to assess formal and informal definitions of digital public health in the literature and to understand how these definitions have been conceptualized in relation to digitization, digitalization, and digital transformation.

Methods: We conducted a scoping literature search in Ovid MEDLINE, Embase, Google Scholar, and 14 government and intergovernmental agency websites encompassing 6 geographic regions. Among a total of 409 full articles identified, we reviewed 11 publications that either formally defined digital public health or informally described the integration of digital technologies into public health in relation to digitization, digitalization, and digital transformation, and we conducted a thematic analysis of the identified definitions.

Results: Two explicit definitions of digital public health were identified, each with divergent meanings. The first definition suggested digital public health was a reimagination of public health using new ways of working, blending established public health wisdom with new digital concepts and tools. The second definition highlighted digital public health as an asset to achieve existing public health goals. In relation to public health, *digitization* was used to refer to the technical process of converting analog records to digital data, *digitalization* referred to the integration of digital technologies into public health operations, and *digital transformation* was used to describe a cultural shift that pervasively integrates digital technologies and reorganizes services on the basis of the health needs of the public.

Conclusions: The definition of digital public health remains contested in the literature. Public health researchers and practitioners need to clarify these conceptual definitions to harness opportunities to integrate digital technologies into public health in a way that maximizes their potential to improve public health outcomes.

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KEYWORDS

digital public health; digital transformation; digitalization; scoping review; digitization; definition; mobile phone

Introduction

Background

The past two decades have been characterized by rapid proliferation and application of digital technologies in various domains of public health [1,2]. A wide range of these digital technologies, including mobile apps, social media, wearables, artificial intelligence, and big data, have been deployed with promises of increased speed, efficiency, and cost-effectiveness of public health services [3]. The increasing importance of digital technologies in public health is underscored by the creation of strategic frameworks by international and regional public health agencies to harness the potential benefits of digital technologies to improve public health outcomes [4].

Recognition of the importance of digital technologies in public health services is further emphasized by the increasingly common use of the term *digital public health* within public health discourse [5]. The use of this term was popularized following the publication of the digital-first strategy of Public Health England in 2017 [6]. It has now been used to describe a wide range of public health activities that consider and use digital technologies [6]. For example, universities around the world have begun to offer graduate programs in digital public health [7,8], some public health journals have made calls for special editions on digital public health [9], and others have established topical sections with a specific focus on digital public health [10]. Digital public health conferences and high-level intergovernmental forums on digital public health are also now commonplace [11].

Although the integration of digital technologies into clinical medicine has been broadly characterized within the eHealth and digital health literature, the unique considerations of integrating digital technologies into public health, including services focused on disease prevention and population health needs, have been less well defined [12,13]. The intended meaning of digital public health appears to be implicitly understood as the integration of digital technologies in delivering public health services [7,9]. However, there appears to be a lack of clarity and consensus on a formal definition of digital public health. As interest in the use of digital technologies in public health grows exponentially, especially with recent developments in response to the COVID-19 pandemic [14], the need to clearly define digital public health has become more pressing. Achieving such conceptual clarity and consensus can help inform and align ongoing development, advocacy, policy, research, and implementation in the field to maximize its impact on achieving public health goals, as well as facilitate the evaluation of these efforts across jurisdictions.

Objective

To the best of our knowledge, there are presently no published reviews aimed at defining digital public health in the literature. Therefore, we aim to understand how public health researchers and practitioners conceptualize and define digital public health through a scoping review of the literature. Given the nascent nature of the field of digital public health, we framed our review to include both formal and informal definitions and descriptions of digital public health found in the existing literature.

Methods

Overview

The findings presented in this study are part of a larger scoping review aimed at conceptualizing the breadth of digital public health, the methods for which are described elsewhere [15]. For this study, we used the framework by Arksey and O'Malley [16] with adaptations as suggested by Levac et al [17]. This framework is useful in clarifying complex concepts and has been widely used in emergent fields of health research where available evidence is heterogeneous. Our reporting adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for scoping reviews [18].

Data Sources

We searched the MEDLINE (Ovid) and Embase (Ovid) bibliographic and citation databases for relevant literature on digital and public health. Gray literature searches were conducted using Google Scholar and manual searches of 14 agency and country-specific websites (Multimedia Appendix 1). Manual reference list searches were also conducted for included articles to identify additional publications of relevance. This expansive literature search was pragmatic given the emergent nature of the field of digital public health.

We explored the intersection between digital health and closely related domains (eg, virtual health, mobile health or mHealth, eHealth, digit* or different suffixes of *digit*, such as digitization) with public health domains as described by the Canadian Public Health Association [19] to determine our final search terms to be applied to the bibliographic databases. This approach balanced our aim to comprehensively assess the literature while ensuring precision by including general search terms such as *digital health* and *public health*. Considering that our focus was on broad conceptual articles, we included search terms (Textbox 1) that excluded primary studies such as cross-sectional studies and clinical trials using the *NOT* Boolean operator. We limited our searches to publications in English and a time frame between January 2000 and June 2020, the time when we conducted the literature search.

Textbox 1. Search terms.

Digital health

"mHealth" or "m-health," "eHealth" or "e-health," "virtual health," "mobile health," "online health," "internet-based health," "computer-based health," "health informatics," "social media," "predictive algorithms," "artificial intelligence," "machine learning," "big data," "web-based health," "digital public health," "digital health," "digitalization," "digital tools," "digital technologies," "telehealth"

Public health (combined using AND)

"public health," "health promotion," "health prevention," "health protection," "health policy," "health determinants," "health evaluation," "health economics," "public health ethics," "risk assessment," "epidemiology," "community health," "emergency preparedness," "emergency response," "health equity," "social justice," "social determinants," "public health surveillance"

Excluded (using NOT)

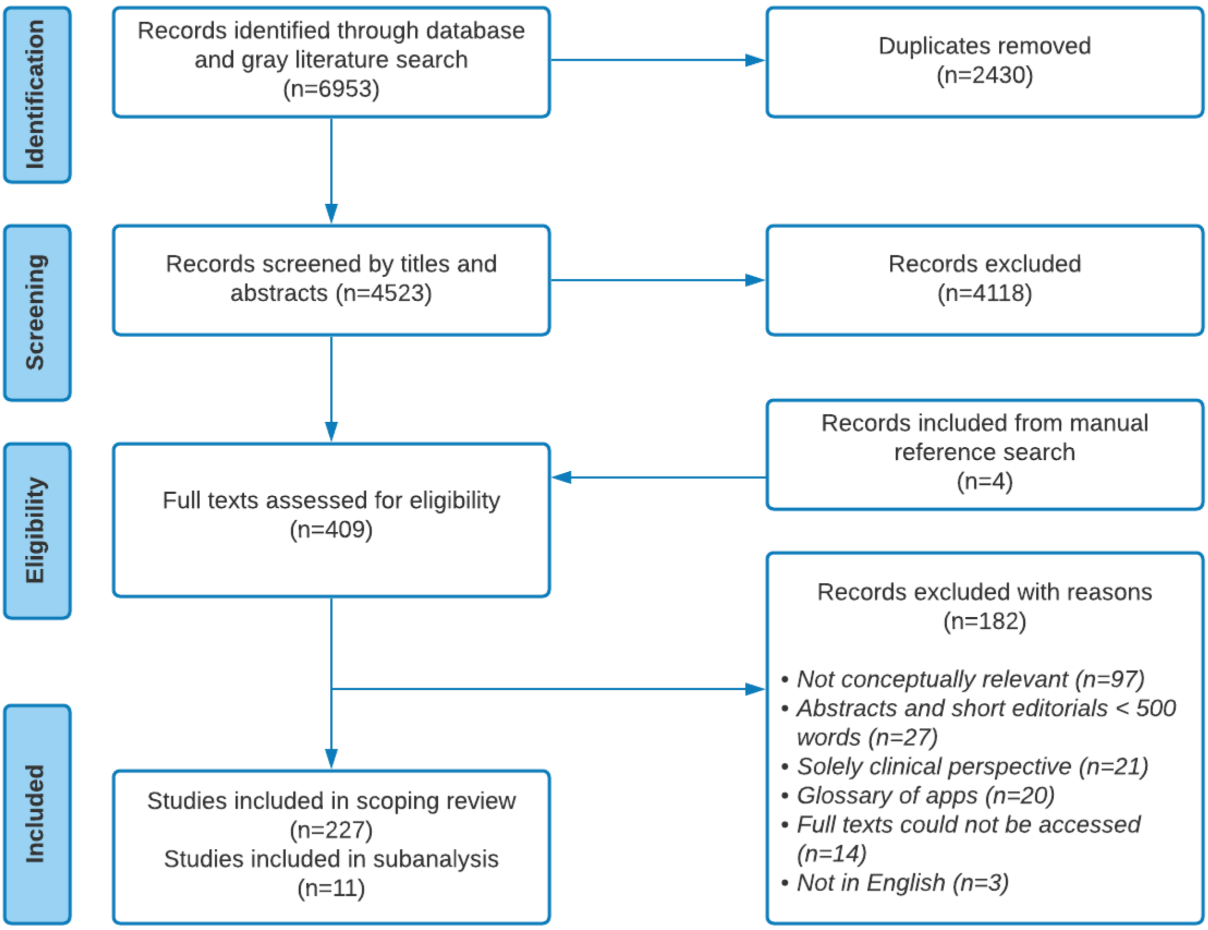
"trial," "cross-sectional"

In addition, we used a simpler search strategy for the gray literature, using only the search terms *digital* AND *public health* on Google Scholar given that traditional advanced search terms as described above yielded imprecise results. The same terms were applied in the Google search engine to inspect 14 preidentified government and intergovernmental agency websites (Multimedia Appendix 1). For example, to search the Government of Canada website [20], we used the search terms *digital* and *public health* with *site:canada.ca* on Google to identify relevant publications. This was done to ensure consistency of our searches across included websites. The first 100 returns from Google Scholar and each website were reviewed. Relevant publications from all searches were exported to Covidence (Veritas Health Innovation) [21] for citation management and review.

Screening Procedure

Titles and abstracts were screened on the basis of pre-established inclusion and exclusion criteria. We included articles that broadly conceptualized digital health from a population and public health perspective and were published in English between January 2000 and June 2020. We drew on the definition of public health by the Canadian Association of Public Health: an organized effort of society to keep persons healthy and prevent injury, illness, and premature death, including a combination of programs, services, and policies that protect and promote the health of all [19]. We excluded publications evaluating specific health programs or interventions and those focused solely on clinical perspectives or short summaries of less than 500 words. Two reviewers (II and AXTX) screened 25% (1131/4523) of the titles and abstracts independently and discussed them to resolve screening discrepancies. The remaining titles and abstracts were screened by at least one reviewer. All full texts and gray literature included in the initial screening were then independently assessed by both reviewers using a structured framework (Multimedia Appendix 2), with discussions to resolve discrepancies and achieve consensus for inclusion. For this analysis of full texts included in the review, we identified articles that formally or informally defined the notion of digital public health. During our review, we found that a significant number of articles made references to the terms *digitization*, *digitalization*, and *digital transformation* in public health. Therefore, we expanded our review to include articles that clarified the roles of digitization, digitalization, and digital transformation in relation to public health. A summary of the selection process is described in Figure 1.

Figure 1. Flow diagram of the search and study selection process following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for scoping reviews.



Data Extraction and Analysis

Selected full texts were imported into QSR NVivo version 12. The bibliographic characteristics of the selected articles, including article type, publication year, country where the research was conducted, and continent of institutional affiliation of the first author, were extracted. The extraction and analysis were conducted by one reviewer, who discussed emergent perspectives and findings with the research team to refine the analysis. Considering that the analysis aimed to derive meanings for digital public health, including both formal and informal definitions of digital public health and related terms, we applied a thematic analysis to the selected papers following the recommendations of Braun and Clarke for thematic analysis [22]. Beginning with initial data familiarization and coding using inductive techniques, we noted references to the integration of digital technologies in relation to public health using the terms *digitization*, *digitalization*, and *digital transformation*. We searched through initial codes to identify substantive definitions and implicit definitions relative to these terms. Finally, we reviewed the themes and summarized the perspectives identified in the form of a narrative report.

Results

Overview

The characteristics of the 11 articles included in our review are presented in Table 1. All selected articles were published between 2009 and 2020, with 91% (10/11) published between 2016 and 2020, reflecting the nascent nature of the subject. Furthermore, 82% (9/11) were led by authors with institutional affiliations in Europe, with only 1 article published by an author in North America. All 11 articles, to varying extents, clarified the roles of digitization, digitalization, and digital transformation in relation to public health.

Table 1. Characteristics of included articles defining digital public health and clarifying digitization, digitalization, and digital transformation in relation to public health (January 2000 to June 2020; N=11).

Study	Article type	Country or agency of first author	Continent	Definition of digital public health	Description of digitization	Description of digitalization	Description of digital transformation
Azzopardi-Muscat and Sørensen [5] and Azzopardi-Muscat et al [23]	Commentary	Malta	Europe	Not stated	Not stated	Not stated directly; it supposes that digitalization extends beyond platforms and mechanisms, through which patients interact with health services, to include health-related smartphone apps, quantified self-measurements of physiological variables, and use of big data drawing on lifestyle data to profoundly alter health outcomes.	An important and influential process that has substantial impact on health systems and will fundamentally alter the future of health.
Expert Panel on Effective Ways of Investing in Health [24]	Report	European Commission	Europe	Not stated	The process of changing information or data into a digital format. It involves creating a digital version (using bits and bytes) of analog or physical sources such as documents, images, sounds, and more. This creates a code, which can subsequently be used in the context of a process, product, or service. In this case, in a health service.	The use of digital technologies in the context of the production and delivery of a product or service. Such digital technologies allow health services to be organized, produced, and delivered in new ways. It could range from the use of computers and electronic health records to home monitoring of patients, electronic medical devices, and computer-aided visualization.	An important and influential process that has substantial impact. It is a complex and multifaceted issue. It indicates that health care services and systems are in a transition in which more health services and processes will be digitalized. It encompasses the instrumented effort to meaningfully introduce new digital information and communication technologies and the corresponding new processes into the health care sector.
Fitzpatrick et al [25]	Review	Ireland	Europe	Not stated	Not stated	Not stated	Implies cultural process of change that appreciates that one size does not fit all settings.
Lu [26]	Commentary	United States	North America	Not stated	Changing reports so that their contained information may be available electronically.	Not stated	Not stated
Mählmann et al [27]	Commentary	Netherlands	Europe	Not stated	Not stated	Not stated	A driver of change in all industries, through which the collection, storage, processing, and analysis of large amounts of heterogeneous data may occur at high speed.

Study	Article type	Country or agency of first author	Continent	Definition of digital public health	Description of digitization	Description of digitalization	Description of digital transformation
Odone et al [28]	Commentary	European Public Health Association	Europe	Digital public health is not a discipline per se but an asset the public health community has to fulfill its aims and mission. The health system goals of quality, accessibility, efficiency, and equity of health care embraced by public health professionals are unaltered by the process of digitalization.[a]	Not stated	Digitalization is a set of tools or a means to achieve public health aims and not an aim in itself. It should support and enable the implementation of public health principles but not modify them.	Not stated
Public Health England [6]	Report	England	Europe	A reimagining of public health using new ways of working, blending established public health wisdom with new digital concepts and tools. It recognizes the rapidly changing context of technology, exploring new models of public health using technology and introducing flexibility and resilience that will allow us to adapt our public health practice and improve outcomes.[b]	Not stated	Not stated	End-to-end transformation of public health services founded strongly on user needs. It requires the harnessing and creation of novel, nontraditional partnerships across governments, academia, the technology industry, and scientific bodies. Such transformation can leverage multiple skills and resources to help drive efficiency and deliver value for money across public health.
Rachadell et al [29]	Report	European Public Health Association	Europe	Not stated	A technical process	The use of digital technologies in the context of production and delivery of a product or service. Such digital technologies allow health services to be organized, produced, and delivered in new ways.	A complex but important and influential process that has a substantial impact on health care.
Ricciardi et al [30]	Commentary	Italy	Europe	Not stated	Digitization is a technical process.	The use of digital technologies in the context of the production and delivery of a product or service. Such digital technologies allow health care services to be organized, produced, and delivered in new ways. Digitalization is therefore less of a *technical* process (like digitization), it is also an organizational and cultural process.	Digital transformation encompasses the instrumented effort to meaningfully introduce new digital information and communication technologies and the corresponding new processes into the health care sector. This process may be influenced by ongoing developments outside the health sector.

Study	Article type	Country or agency of first author	Continent	Definition of digital public health	Description of digitization	Description of digitalization	Description of digital transformation
World Health Organization [4]	Report	World Health Organization	N/A[c]	Not stated	Not stated	Not stated	A disruptive process that allows for the integration of technologies such as the internet of things, artificial intelligence, big data analytics, and blockchain, along with interoperability of patient data through health data standards to potentially enhance health outcomes by advancing disease detection and response, health outcomes by improving medical diagnosis, data-based treatment decisions, and self-management of care.
World Health Organization Regional Office for Europe [31]	Report	World Health Organization	Europe	Not stated; however, the authors note that there is a need to advocate for stronger links between digital health and public and population health objectives and to align the work of digital partners inside and outside the health sector.	Not stated	Digitalization of health systems encompasses the establishment and ongoing maintenance of certain basic elements of infrastructure, including but not limited to hospital information systems, electronic health records and associated clinical support systems, electronic prescription and dispensing systems, telehealth and telemedicine (the provision of health care from a distance), registers and registries, mobile health, public health surveillance, and information portals for patients and health professionals.	Not stated

[a]Predicated on the digital transformation of public health services that is founded on user needs.

[b]Definition predicated on the digitalization of public health practices. Digital tools therefore serve to facilitate the already established public health goals and functions in a way that allows the practice to reap the potential benefits of digitalization.

[c]N/A: not applicable.

Defining Digital Public Health

Regarding the main objective of our analysis to understand the definition of digital public health, we only found 3 articles that formally offered 2 definitions of digital public health within our sample (Table 1). One of the articles was by Public Health England and defined digital public health as a reimagination of public health, blending established public health wisdom with new digital concepts and tools [6,32]. This article further described digital public health as the exploration of new models of public health using technology while introducing flexibility and resilience to allow the adaptation of public health practice to improve health outcomes [6,32]. However, a second clear description offered by Odone et al [28] referred to digital public health not as a discipline per se but as an asset that the public health community can use to fulfill its aims and mission to ensure quality, accessibility, efficiency, and equity of health care—aims that remain unaltered by the process of digitalization.

Digitization of Public Health

Textbox 2 summarizes the perspectives identified in the selected articles relating to digitization, digitalization, and digital transformation in public health. In relation to public health, 3 articles described digitization as a *technical process* of converting analog (including paper-based) health records to digital formats that may then be available for use electronically [24,26,30].

Textbox 2. Emergent perspectives on digitization, digitalization, and digital transformation from thematic analysis (January 2000 to June 2020).

Digitization

- Technical process [24,26,30]

Digitalization

- Inclusion of technology in producing and delivering services [24,29,30]
- Facilitates new ways of delivering health services [24,29,30]
- An organizational and cultural process [29,30]
- Supports but does not change public health goals [28]
- Ongoing establishment and maintenance of technology for health services [31]

Digital transformation

- Complex and multifaceted process [6,24,29,30]
- Fundamental change in the culture and model of service delivery [24,25,30]
- Ongoing change process [24,29,30]
- A disruptive process requiring concerted effort at a meaningful integration of technology into health [30,31]
- Extends beyond the health sector [24,27,30]
- Person-centered [6,32]
- A transition process [24]

Digitalization of Public Health

We identified 5 perspectives related to digitalization in the literature (Textbox 2). Overall, 3 articles referred to digitalization in terms of the *integration of technology in the production of services* [24,29,30]. Of note is that 2 articles used the third as a main reference to this claim. Furthermore, these articles suggested that the integration of technology "allows health services to be organized and delivered in new ways" [24,29,30]. Two of the articles further described digitalization as less of a technical process as in digitization and more of an "organizational and cultural process" [29,30]. Another article referred to digitalization as a process that "supports public health" principles and enables their implementation but does not alter the goals of public health [28]. Yet another article described digitalization in terms of the "establishment and ongoing maintenance of basic infrastructure," including but not limited to hospital information systems, electronic medical records, mobile health, and public health surveillance [31].

Digital Transformation of Public Health

Regarding digital transformation in relation to public health, we identified 7 perspectives. First, 4 articles described digital transformation in terms of its "complexity and multifaceted dimensions," requiring interdisciplinary collaborations to ensure the influential process of transformation [6,24,29,30]. Three of the articles described digital transformation as a "fundamental change in the culture and model of delivery" of health services [24,25,30]. Furthermore, 3 articles suggested that digital transformation "extends beyond health care" to other industries [24,27,30]. These 3 articles described digital transformation as being both health-specific and driven by the broader changes in society, including the widespread availability of smartphones and the increased awareness and tracking of health and lifestyle data, as well as storage and processing of large amounts of heterogeneous data that may not be directly related to health but are relevant in understanding health and health outcomes in populations. Digital transformation was also described in 4 articles as a "disruptive process involving concerted effort to meaningfully integrate technologies" and their related new processes in public health services [4,24,27,30]. This involves the formation of nontraditional partnerships across governments, academia, the technology industry, and scientific bodies. In addition, 2 articles asserted that digital transformation of public health services is founded strongly on user needs (ie, it is person-centered) [6,32]. However, 1 article used digitalization and digital transformation interchangeably and described digital transformation as the process of *transition* in which more public health services and processes will be digitalized [24]. Of note, many articles described these processes in relation to health services, health systems, and the health sector, with public health services subsumed within all 3 terms [24,31].

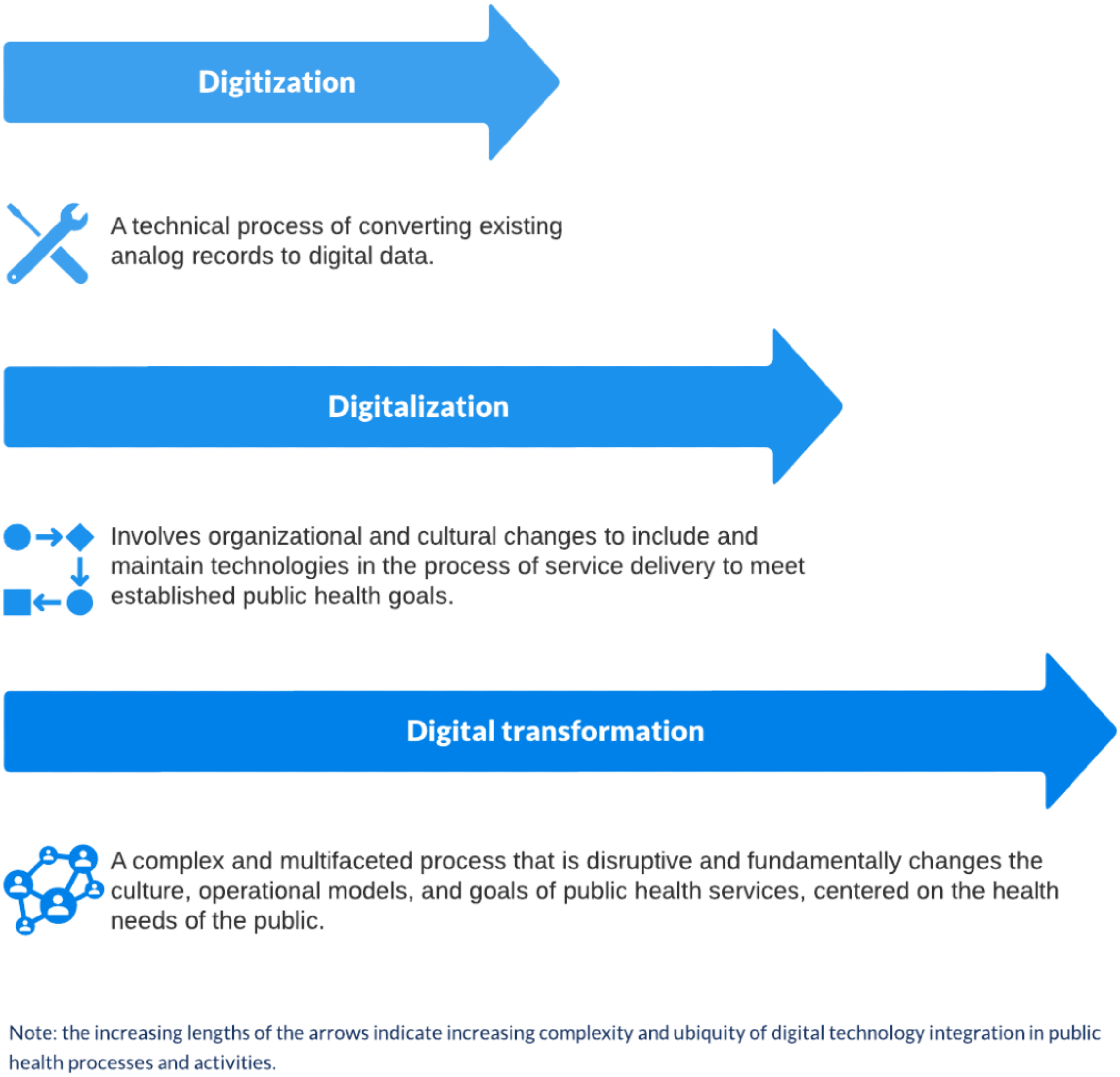
Discussion

Principal Findings

In this review, we sought to understand how public health researchers and practitioners conceptualize and define digital public health. Overall, we found that, as this emerging field draws growing attention, the term *digital public health* has been diversely defined. First, we found 2 formal definitions of digital public health. Although the Public Health England definition is predicated on digital transformation and embraces a transformational role for digital technologies in public health [6], the definition by Odone et al [28] suggests that digitalization is essential in a supporting role that helps facilitate existing public health goals. Despite different visions of the role of digital technology in public health, both definitions agree that digital public health involves the integration of digital technologies into public health to achieve public health goals, suggesting that this integration can potentially improve outcomes and efficiency of services.

Informal descriptions of the roles played by digitization, digitalization, and digital transformation in relation to public health were identified. Although there were some divergent views, the general perception in the reviewed literature was that all 3 concepts represent increasing levels of complexity, comprehensiveness, and thoughtfulness in the integration of digital technologies into public health practices (Figure 2), where digital transformation encompasses the most complex and fundamental integration of digital technology across the sector [30]. Nevertheless, some authors conceptualized digital transformation as being a transitional phase on the way to the digitalization of public health [24].

Figure 2. Emergent perspectives on digitization, digitalization, and digital transformation in relation to public health from thematic analysis.



Digitization in Public Health

Our finding of digitization as a technical process involving the conversion of analog information into digital formats (signals) agrees with descriptions of the term in the literature [33-35]. This process is considered the most basic attempt at using digital technologies that allows converted digital information to be used in multiple ways, even beyond the initial use case the data were generated to address [34,36]. For example, digitization of existing paper-based immunization records may allow the data to be linked to other databases to evaluate health prevention programs [34].

Digitalization in Public Health

In contrast, digitalization has been described in the literature as a sociotechnical process that involves the integration of digital technologies into existing operations and tasks with the goal of improving efficiency and *adding value* to users [34,35]. Such integration of digital technologies into existing operations may allow for data to be automatically generated in a way that enables automation and improved efficiency. An example of digitalization is the use of computer systems and electronic health records at a sexually transmitted infection clinic that allows for the generation of health data during the process of service delivery, ensuring that such data may be used to inform disease prevention, surveillance, and health care quality improvement [37-39]. Nevertheless, it must be acknowledged that digitization and digitalization have been used interchangeably in the literature, with digitization used in this context to refer to processes that are more consistent with digitalization [40]. We make the distinction between digitization and digitalization to draw attention to the higher level of complexity involved in the process of digitalizing public health services [28,30].

Digital Transformation in Public Health

The descriptions of digital transformation appear to be more consistent in the literature and are congruent with our findings [40]. The general perception is that digital transformation represents the most comprehensive, complex, and pervasive form of technology integration [30,34,35]. More specifically, it is said to involve the development of new *business models* that are more aligned with service user needs (ie, the public) in a way that offers more *value* to the public and the implementing organizations [30,34,35]. For example, in sexually transmitted infection testing services, digital transformation may be envisioned as the creation of web-based testing portals, self-testing models, health education, and promotion of services through mobile apps and clinic-based referral systems that are all interconnected in a technological ecosystem built around the needs of the public to ensure that health is equitable and of high quality. Such pervasive transformation in technologies, management processes, and relationships is said to require development of new competencies among workers within organizations and agencies, with a focus on cross-functional collaborations as opposed to siloed operations within specific health agencies and aspects of the health systems [35,41]. Digital transformation is considered as typically involving a series of distinct digitalization initiatives with an overarching aim to facilitate far-reaching, person-centered organizational change [40]. Furthermore, the depth of digital integration implies that organizations and agencies must fine-tune their key performance indicators [34]. Practitioners suggest that these indicators should extend beyond user access numbers or similar indicators associated with digitalization (eg, the number of people accessing health services on the web or the number of downloads) to more user-centric measures such as web-based sentiment, engagement, and value sharing [34]. The collective assessment of these intermediate measures may describe how well the complex systems of change are operating and how well long-term public health goals are achieved [34].

Clarifying Digitization, Digitalization, and Digital Transformation in Relation to Public Health

Despite the increasing popularity of the term *digital public health*, our study showed that researchers and practitioners have not yet attempted to achieve conceptual consensus on how it is defined. We also found that, despite general agreements about the implications of digitization, digitalization, and digital transformation of public health, the health-related literature still conflates these terms. For example, a recent call to use the COVID-19 pandemic as a catalyst for digitization in Africa went on to describe processes that might be best described as digitalization [42]. Similarly, a more recent definition of digital public health (the only additional definition we found after the completion of our literature search) suggested that digital public health referred to the use of technology, new types of data, and new ways of working that come with the digitization of public health and associated data [43]. However, the description of these processes might at the minimum be referred to as digitalization. The varied perceptions and conflation of the terms *digitization*, *digitalization*, and *digital transformation* is not new, as these terms have sparked long-standing debates among practitioners and researchers in other industries such as business, finance, and commerce that have also sought to integrate digital technologies [34-36]. Despite this, descriptions of digitization, digitalization, and digital transformation in other fields of research and industry are mostly congruent with our findings, albeit with a few divergent views [34].

Clarifying the definition of digital public health and making the distinction between digitization, digitalization, and digital transformation as applied in this emergent field has significant implications for ongoing research and development. Conceptual clarity can help define goals and operational strategies for integrating digital technologies into public health to ensure their successful implementation and evaluation. Such conceptual clarity may also be helpful in ensuring comparability of outcomes involving digital technologies across jurisdictions. Furthermore, determining the extent to which digital technologies may be integrated into public health services is helpful for advocacy and planning purposes. By this, we mean a careful consideration of the role of digital technologies in facilitating organizational goals, either as a supporter (which does not alter public health goals) or as an enabler (which fundamentally alters the operational models to achieve public health goals) [44].

The Role of Digitalization in Public Health and Its Implication for Practice

Conceptualizing digital public health in relation to digitalization supposes that digital technologies play a supportive role or serve as *tools* available to public health practitioners to achieve existing public health goals [23,28]. This conceptualization aims to integrate digital technologies to meet public health needs more efficiently while firmly maintaining focus on public health goals rather than on technologies and how they alter public health functions [28]. Health system goals to ensure the quality, accessibility, efficiency, and equity of health services remain unaltered despite acknowledgment that digital technologies must be thoughtfully leveraged in public health efforts [28]. Perhaps envisioning digital public health in this manner resists the technological determinism that has been characteristic of a more pervasive integration of digital technologies [45,46]. Technological determinism is the assertion that the use of digital technologies inevitably leads to improved processes, services, and outcomes [45]. This assertion is as yet unproven. However, conceptualizing digital public health as a supporting tool to improve existing public health functions may result in siloed, heterogeneous digitalization initiatives with potentially limited interoperability and impact on the public and health systems. This limitation has already been seen in the existence of multiple pilot digital initiatives with data systems that are not interoperable within mainstream public health systems [47].

The Role of Digital Transformation in Public Health and its Implication for Practice

Conversely, conceptualizing digital public health as a product of digital transformation may offer a few advantages. In addition to potentially being more person-centered and cost-efficient [6], a comprehensive and structured integration of digital technologies into public health functions would possibly allow public health practitioners and decision-makers to consider ways to ensure a cohesive approach to digital public health that transcends current public health silos. This approach embraces the cross-functional, nontraditional relationships between professionals within and outside traditional public health practice, which allows for the exchange of information across public health systems and other health-related systems to gain a better understanding of the determinants of health and identify strategies to improve health and achieve public health goals and functions. This contrasts with siloed approaches to integrate digital technologies within organizations, health agencies, and health systems that have often resulted in interoperability issues, inhibiting the development of digital public health for years [48]. Nevertheless, public health practitioners, managers, and decision-makers would also face significant challenges. The major issue would be maintaining fundamental public health goals like health equity if public health systems are to be fundamentally changed despite the existing digital divide [49]. This is important given that access to digital health technologies is often structured by peoples' socioeconomic status and social positions [1,49-51]. This differential access to technology is also often reflected as over- and underrepresentation of various sociodemographic groups in the digital data informing public health practice [52]. If cross-functional collaborations are to be fostered, further challenges exist regarding data ownership, privacy, and security, as well as clarifying the roles of public and private partners in digital public health [48].

There are internal and external pressures to envision digital public health as a product of digital transformation [47,53]. As digital change occurs outside of health care, public sentiments now suggest that people must be considered as informed health users who demand involvement in decisions and actions concerning their health [47,54]. Increases in health care costs associated with aging populations provides further incentives to empower users of public health services through in-depth integration of digital technologies [47]. Finally, the growing omnipresence of user-generated data from activities outside the public health systems further creates pressure to conceptualize digital public health as a digital transformation that ensures integration into a well-coordinated health system [34].

Future Directions

We do not intend to make assertions as to which conceptualization of digital public health, as related to digitalization and digital transformation, is better suited for the complex challenges facing public health practitioners. Rather, we present the implications of each definition of digital public health as identified in the literature. Further qualitative research is required to delineate meanings that researchers and practitioners ascribe to digital public health on the basis of geopolitical jurisdictions [28,30]. Our study suggests that Europe-based scholars are leading in the conceptualizations of digital public health, at least within the academic and health systems literature, compared with discussions taking place in English in other continents. As part of our work, we intend to consult with health agencies, public health practitioners, and other relevant experts to adopt a working definition and conceptual framework for digital public health within our context. Research is also required to evaluate which conceptualization better promotes public health goals and facilitates integration of digital technologies that improve the health and health-related outcomes of the public. As interest in digital public health continues to grow during the COVID-19 pandemic, it is imperative to generate robust and meaningful evidence to clearly guide the development of the field. Given the diverse definitions that digital health has attained, consensus building around the envisioning, definition, and operationalization of digital public health is critical.

Limitations

The findings of this study should be considered in view of its limitations. First, our literature search was conducted in June 2020. We are aware of the sharp increase in publications on digital health and digital public health as a result of the COVID-19 pandemic. Given that more recent literature has been skewed by attention to the COVID-19 pandemic, we considered it more expedient to assess articles published by the date of our initial search in 2020. To ensure that we did not miss any significant additions, we conducted a cursory search of *digital public health* on PubMed in March 2021 and found only one additional definition published in English by Murray et al [43] that was referenced in the discussion above. Furthermore, our restriction to articles published in English may have inadvertently excluded other potential definitions of digital public health.

Conclusions

Digital public health continues to be diversely defined and conceptualized in the literature as attention to the subject increases among researchers and practitioners. Available definitions are divergent in relation to their conceptualization of the roles of digitalization and digital transformation in digital public health. It is still unclear which definition would better help improve public health practices and outcomes. Public health researchers and practitioners can better develop the field with more clarity and consensus on the definition of digital public health, and the role of digitalization and digital transformation in this definition, by encapsulating the intent of their practice and providing a clear road map for ongoing development.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Agency and country websites searched for gray literature.
[DOCX File , 13 KB - publichealth_v7i11e30399_app1.docx]

Multimedia Appendix 2
Framework for full-text review.
[DOCX File , 19 KB - publichealth_v7i11e30399_app2.docx]

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Original Paper

Long-Term Survival Among Histological Subtypes in Advanced Epithelial Ovarian Cancer: Population-Based Study Using the Surveillance, Epidemiology, and End Results Database

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Abstract

Background: Actual long-term survival rates for advanced epithelial ovarian cancer (EOC) are rarely reported.

Objective: This study aimed to assess the role of histological subtypes in predicting the prognosis among long-term survivors (≥5 years) of advanced EOC.

Methods: We performed a retrospective analysis of data among patients with stage III-IV EOC diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States. We used the chi-square test, Kaplan–Meier analysis, and multivariate Cox proportional hazards model for the analyses.

Results: We included 8050 patients in this study, including 6929 (86.1%), 743 (9.2%), 237 (2.9%), and 141 (1.8%) patients with serous, endometrioid, clear cell, and mucinous tumors, respectively. With a median follow-up of 91 months, the most common cause of death was primary ovarian cancer (80.3%), followed by other cancers (8.1%), other causes of death (7.3%), cardiac-related death (3.2%), and nonmalignant pulmonary disease (3.2%). Patients with the serous subtype were more likely to die from primary ovarian cancer, and patients with the mucinous subtype were more likely to die from other cancers and cardiac-related disease. Multivariate Cox analysis showed that patients with endometrioid (hazard ratio [HR] 0.534, *P*<.001), mucinous (HR 0.454, *P*<.001), and clear cell (HR 0.563, *P*<.001) subtypes showed better ovarian cancer-specific survival than those with the serous subtype. Similar results were found regarding overall survival. However, ovarian cancer–specific survival and overall survival were comparable among those with endometrioid, clear cell, and mucinous tumors.

Conclusions: Ovarian cancer remains the primary cause of death in long-term ovarian cancer survivors. Moreover, the probability of death was significantly different among those with different histological subtypes. It is important for clinicians to individualize the surveillance program for long-term ovarian cancer survivors.

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KEYWORDS

ovarian epithelial carcinoma; survivors; histology; survival rate; survival; ovarian; cancer; surveillance; epidemiology; women's health; reproductive health; Surveillance, Epidemiology, and End Results; ovary; oncology; survivorship; long-term outcome; epithelial

Introduction

Background

Advanced stage (stage III-IV) epithelial ovarian cancer (EOC) is usually incurable. However, approximately 25% and 15% of patients with EOC survive for >5 years and >10 years, respectively [1-4]. Although it largely remains unknown why long-term survivors have a better outcome, investigating the underlying mechanisms or factors is key for developing individualized follow-up strategies for patients with EOC. Several epidemiological, clinical, and genetic factors have been associated with the long-term survival of patients with EOC [5,6].

Based on the World Health Organization classification of tumors of female reproductive organs, which was published in 2014, EOC can be classified into five histological subtypes: high-grade serous, low-grade serous, endometrioid, clear cell, and mucinous [7]. A previous study using the California Cancer Registry reported that the nonserous subtype is an independent predictor of long-term survival in EOC; favorable prognoses were observed among patients with the endometrioid, mucinous, and clear cell subtypes than in those with the serous subtype [3]. However, the same study also included patients with early-stage EOC, and it may thus not reflect the true long-term survival characteristics of patients with advanced-stage EOC.

The endometrioid and mucinous subtypes are typically low-grade and early-stage, and patients with these subtypes show a better outcome than those with the high-grade serous subtype [8-10]. Moreover, although the clear cell subtype exhibits high-grade features, it is more likely to present with early-stage disease and is associated with a better outcome than high-grade serous cancers [11]. However, several studies, including ours, have confirmed that advanced mucinous and clear cell cancers display aggressive behavior, and patients with these have lower survival than those with high-grade serous tumors, which can perhaps be attributed to chemoresistance characteristics [12-18]. Accordingly, this study aimed to assess the role of histological subtypes in predicting the prognosis of long-term survivors (≥5 years) of advanced EOC.

Methods

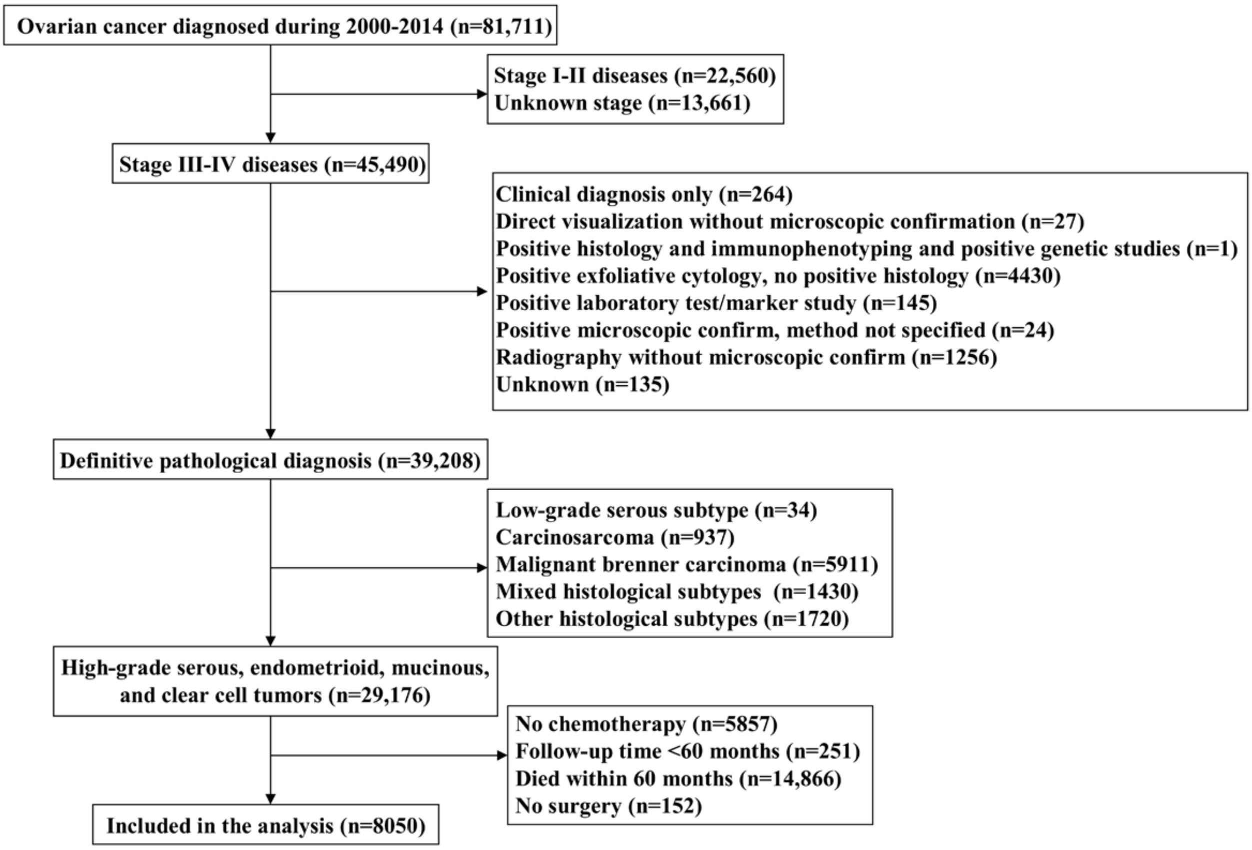
We extracted EOC data from the Surveillance, Epidemiology, and End Results (SEER) database of the United States, which is a publicly available database and contains deidentified information on cancer incidence, demographic and clinicopathological variables, patterns of the first course of treatment, and survival data [19]. We selected patients of all ages who were diagnosed with stage III-IV EOC from 2000 to 2014. We included long-term ovarian cancer survivors (≥5 years) in this study. The patient selection flowchart is shown in Figure 1. We included those with high-grade serous, endometrioid, clear cell, and mucinous subtypes. Patients who did not undergo any surgery or did not receive chemotherapy were excluded. In addition, patients who died within 60 months after the diagnosis of ovarian cancer or who had follow-up times of <60 months were also excluded. The analysis of the SEER database was exempt from the approval process of the institutional review board considering the presence of deidentified patient information.

A total of 29,176 patients with stage III-IV EOC were identified. Of these patients, 5857 did not receive chemotherapy, 251 patients had a follow-up time of <60 months, 14,866 patients died within 60 months, and 152 patients did not receive surgery. A total of 8050 EOC patients with ≥5 years' survival were included in this study.

This study could be used to assist physicians in prognostic assessment at the time of diagnosis of EOC and help physicians better understand EOC from the long-term survivors to prolong the survival time of short-term survivors. The SEER program collects long-term follow-up cancer data, thus allowing us to assess the long-term survivors of EOC. We included the following demographic, clinicopathological, and treatment variables: age at diagnosis, race, stage, histological subtype, and nodal status. The definition of the staging system was based on the American Joint Committee on Cancer (AJCC) sixth edition staging system. The primary endpoints of this study were ovarian cancer–specific survival (OCSS) and overall survival (OS). OCSS was defined as the time from diagnosis to death due to ovarian cancer, censoring at the date of last contact, or nonovarian cancer related–death. OS was defined as the time from diagnosis of ovarian cancer to the death from any cause.

The association among demographic, clinicopathological, and treatment variables for the histological subtypes was compared using the chi-square test and the Fisher exact test. Survival comparisons were made using Kaplan–Meier analysis and compared using the log-rank test. Multivariate Cox proportional hazards model was used to determine the prognostic factors associated with OCSS and OS. Prognostic factors with statistical significance on univariate analyses were entered into multivariate analyses. The proportional hazard assumption was tested both graphically and using the Schoenfield residual test to address whether our data met the proportional odds assumption, allowing for the use of the Cox proportional hazards model. Sensitivity analyses were performed on the basis of the age at diagnosis, race, AJCC staging, and nodal status to investigate the effect of the histological subtype on survival outcomes. SPSS (version 22.0, IBM Corp) and Stata/SE (version 14, StataCorp) were used for analyses, and $P<.05$ indicated statistical significance.

Figure 1. Flow diagram of the study cohort.



Results

Patient Characteristics

Patient characteristics and causes of death data are listed in Table 1. Of the entire cohort, 6929 (86.1%), 743 (9.2%), 237 (2.9%), and 141 (1.8%) showed the presence of serous, endometrioid, clear cell, and mucinous tumors, respectively. The majority of patients were aged ≥50 years (76.8%, n=6138), white race (86.6%, n=6975), stage III disease (75.6%, n=6164), and nodal negative disease (57.8%, n=4651). Patients with the serous subtype were more likely to be older (*P*<.001) and diagnosed with stage IV disease (*P*<.001) than those with the other 3 histological subtypes. In addition, patients with the serous subtype had a higher risk of regional lymph node metastasis than those with the endometrioid and mucinous subtypes (35.7% vs 26.2%-31.5%), while those with the clear cell subtype had a higher risk of regional lymph node metastasis than those with the other 3 histological subtypes (42.6% vs 26.2%-35.7%) (*P*<.001).

Table 1. Baseline patient characteristics and causes of death by histological subtype in patients with epithelial ovarian cancer diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

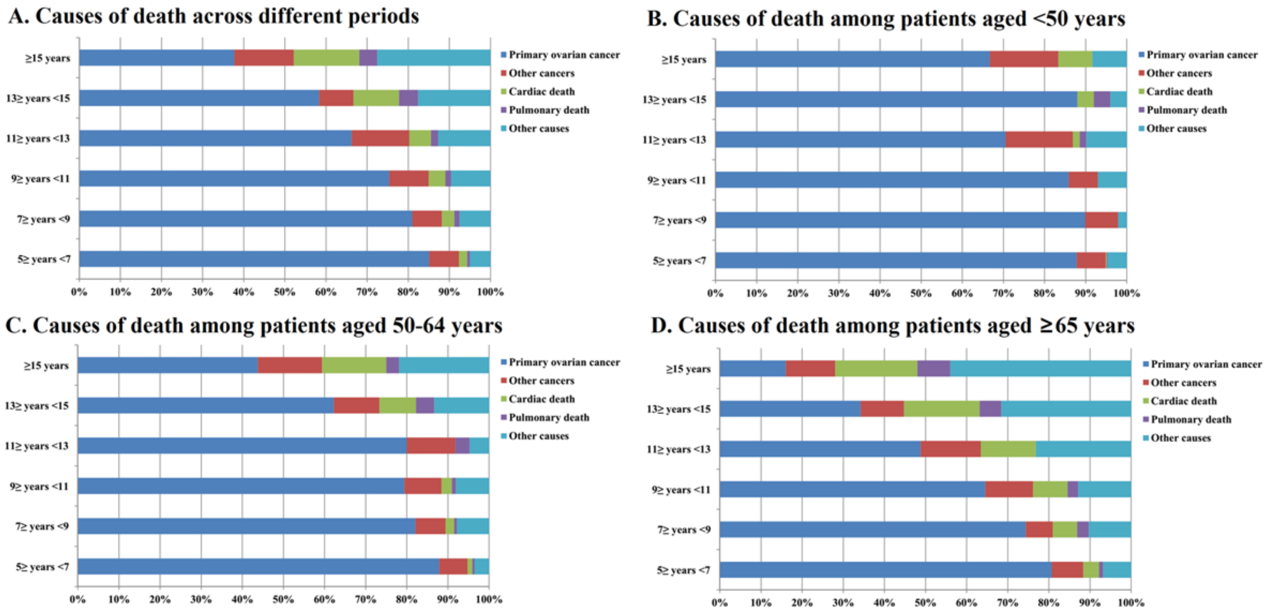
Variables	Patients, n	Serous subtype, n (%)	Endometrioid subtype, n (%)	Mucinous subtype, n (%)	Clear cell subtype, n (%)	*P* value
Age (years)						<.001
<50	1867	1528 (22.1)	231 (31.1)	51 (36.2)	57 (24.1)	
50-64	3662	3146 (45.4)	323 (43.5)	64 (45.4)	129 (54.4)	
≥65	2521	2255 (32.5)	189 (25.4)	26 (18.4)	51 (21.5)	
Race						<.001
White	6975	6037 (87.1)	616 (82.9)	124 (87.9)	198 (83.5)	
Black	420	371 (5.4)	41 (5.5)	3 (2.1)	5 (2.1)	
Other	655	521 (7.5)	86 (11.6)	14 (9.9)	34 (14.3)	
American Joint Committee on Cancer stage						<.001
III	6164	5235 (75.6)	629 (84.7)	113 (80.1)	187 (78.9)	
IV	1886	1694 (24.4)	114 (15.3)	28 (19.9)	50 (21.1)	
Nodal status						<.001
Negative	4651	3954 (57.1)	477 (64.2)	99 (70.2)	121 (51.1)	
Positive	2849	3477 (35.7)	234 (31.5)	37 (26.2)	101 (42.6)	
Unknown	550	498 (7.2)	32 (4.3)	5 (3.5)	15 (6.3)	
Death (n=3874)						<.001
Primary ovarian cancer	3111	2819 (81.8)	199 (68.4)	33 (61.1)	60 (73.2)	
Other cancers	312	266 (7.7)	37 (12.7)	7 (13.0)	2 (2.4)	
Cardiac death	123	96 (2.8)	12 (4.1)	9 (16.7)	6 (7.3)	
Pulmonary deaths	44	36 (1.0)	2 (0.7)	1 (1.9)	5 (6.1)	
Other causes	284	230 (6.7)	41 (14.1)	4 (7.4)	9 (11.0)	

Causes of Death in Long-Term Ovarian Cancer Survivors

This cohort included 5967 patients surviving for ≥5 years and <10 years (60-119 months) and 2353 patients surviving ≥10 years (≥120 months). With a median follow-up of 91 (range 60-227) months, a total of 3874 deaths were recorded. The most common cause of death was primary ovarian cancer (80.3%, n=3111), followed by other cancers (8.1%, n=312), other causes of death (7.3%, n=284), cardiac-related death (3.2%, n=123), and nonmalignant pulmonary disease (3.2%). Patients with the serous subtype were more likely to die from primary ovarian cancer, and those with the mucinous subtype were more likely to die from other cancers and cardiac-related disease (Table 1). Among those surviving ≥5 years and <10 years, 83.3% died owing to primary ovarian cancer, 7.4% died owing to other cancers, 6.0% died owing to other causes, 2.4% died owing to cardiac disease, and 0.9% died owing to nonmalignant pulmonary disease. For patients surviving ≥10 years, 63.0% died owing to primary ovarian cancer, 14.9% died owing to other causes, 12.1% died owing to other cancers, 7.7% died owing to cardiac disease, and 2.3% died owing to nonmalignant pulmonary disease.

The causes of death after stratification by years of survival after diagnosis of EOC for long-term survivors are detailed in Figure 2. Figure 2A shows that in the entire cohort, with an increase in the time from diagnosis, death because of ovarian cancer–related causes decreases, while death owing to cardiac disease and other causes increases. In patients aged <50 years and 50-64 years, death due to ovarian cancer–related disease remained the main cause of death with an increase in the time from diagnosis, and death from primary ovarian cancer was still significant among other causes of death even 15 years after diagnosis of ovarian cancer (Figure 2B and 2C). Among those aged ≥65 years, death because of ovarian cancer–related causes decreased and death due to cardiac disease and other causes increased (Figure 2D).

Figure 2. Causes of death after stratification by years of survival after diagnosis of epithelial ovarian cancer for long-term survivors: (A) the entire cohort; (B) patients aged <50 years; (C) patients aged 50-64 years; and (D) patients aged ≥65 years.



Survival Outcomes and Prognostic Analyses

Kaplan–Meier analysis was conducted to compare the survival curves among the 4 histological subtypes (Figure 3). The results showed that serous subtype had a significantly lower OCSS (*P*<.001) and OS (*P*<.001) compared to those with the other 3 histological subtypes, while comparable OCSS (*P*=.55) (Figure 3A) and OS (*P*=.91) (Figure 3B) were observed among those with endometrioid, mucinous, and clear cell cancers.

Univariate and multivariate analyses were used to determine the prognostic factors related to OCSS and OS. Univariate analyses showed that age at diagnosis, AJCC staging, nodal status, and histological subtype were the prognostic factors associated with OCSS and OS (Tables 2 and 3). The results showed that age at diagnosis, AJCC staging, nodal status, and histological subtype were also the independent prognostic factors associated with OCSS and OS. Patients with endometrioid (hazard ratio [HR] 0.534, 95% CI 0.462-0.617, *P*<.001), mucinous (HR 0.454, 95% CI 0.322-0.641, *P*<.001), and clear cell (HR 0.563, 95% CI 0.436-0.727, *P*<.001) subtypes showed better OCSS than those with the serous subtype. Similar results were obtained regarding OS. Using clear cell tumor as a reference, similar OCSS and OS were observed in endometrioid (OCSS: HR 0.949, 95% CI 0.711-1.267, *P*=.72; OS: HR 1.014, 95% CI 0.793-1.295, *P*=.91) and mucinous cancers (OCSS: HR 0.807, 95% CI 0.528-1.235, *P*=.32; OS: HR 0.969, 95% CI 0.687-1.366, *P*=.86) compared to those with clear cell tumor. The effect of the histological subtype on OCSS (Figure 4A) and OS (Figure 4B) met the proportional hazard assumption, which showed that the constant HRs from the Cox model were reliable.

Since we observed similar survival outcomes among patients with endometrioid, mucinous, and clear cell cancers, we combined these histological subtypes under the nonserous subtype to compare the survival outcomes with those of serous cancers. Kaplan–Meier analysis showed that patients with the serous subtype had a significantly lower OCSS (*P*<.001) (Figure 5A) and OS (*P*<.001) (Figure 5B) than those with nonserous tumors.

Sensitivity analyses were focused on age at diagnosis, race, AJCC staging, and nodal status to investigate the effect of histology on survival outcomes (Table 4). The obtained results indicated that patients with the serous subtype had lower OCSS and OS than those with the nonserous subtype, stratified by age at diagnosis, stage at diagnosis, and nodal stage. Among White patients and those of other races, the serous subtype was characterized with lower OCSS and OS than the nonserous subtype. Between the serous and nonserous subtypes, the OCSS and OS were comparable among Black patients. The effect of the histology on OCSS (Figure 4C) and OS (Figure 4D) met the proportional hazard assumption, which indicated that the constant HRs ratios from the Cox model were reliable.

Figure 3. Comparison of ovarian cancer–specific survival (A) and overall survival (B) among the 4 histological subtypes of the epithelial ovarian cancer diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

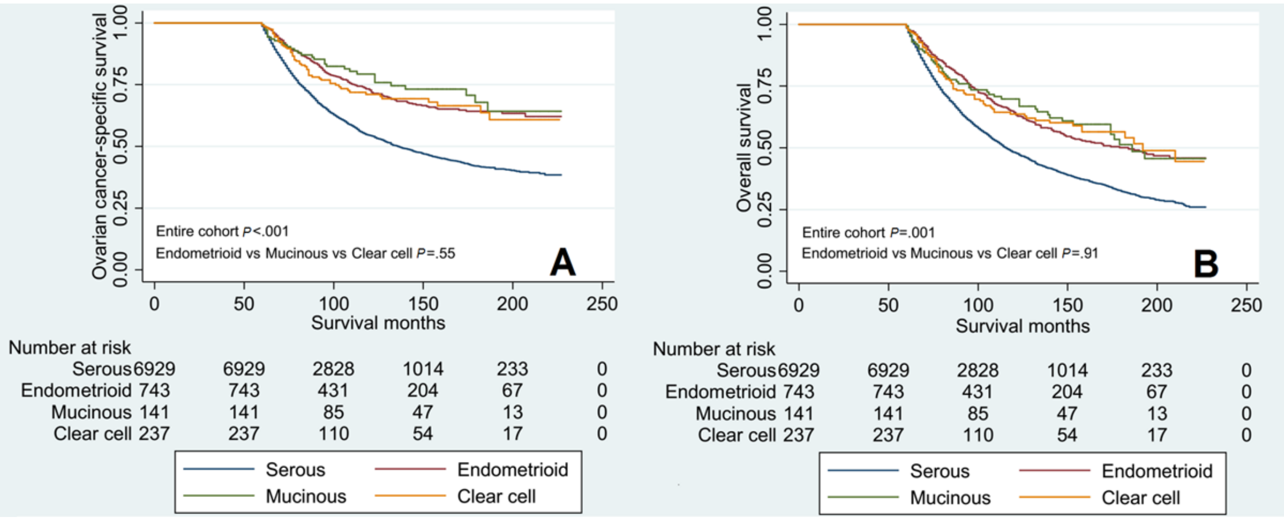


Table 2. Univariate and multivariate survival analyses of ovarian cancer–specific survival in long-term survivors of the epithelial ovarian cancer diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

Variables	Univariate survival analysis		Multivariate survival analysis	
	Hazard ratio (95% CI)	*P* value	Hazard ratio (95% CI)	*P* value
Age (years)				
<50	1 (reference)	Reference	1 (reference)	Reference
50-64	1.137 (1.037-1.246)	.006	1.091 (0.995-1.196)	.06
≥65	1.457 (1.323-1.606)	<.001	1.361 (1.234-1.500)	<.001
Race				
White	1 (reference)	Reference	—[a]	—
Black	0.949 (0.804-1.119)	.53	—	—
Other	0.913 (0.797-1.044)	.18	—	—
American Joint Committee on Cancer stage				
III	1 (reference)	Reference	1 (reference)	Reference
IV	1.355 (1.252-1.467)	<.001	1.224 (1.125-1.333)	<.001
Nodal status				
Negative	1 (reference)	Reference	1 (reference)	Reference
Positive	0.847 (0.784-0.916)	<.001	0.844 (0.781-0.912)	<.001
Unknown	1.511 (1.339-1.705)	<.001	1.309 (1.149-1.490)	<.001
Histological subtypes				
Serous	1 (reference)	Reference	1 (reference)	Reference
Endometrioid	0.515 (0.446-0.595)	<.001	0.534 (0.462-0.617)	<.001
Mucinous	0.436 (0.309-0.615)	<.001	0.454 (0.322-0.641)	<.001
Clear cell	0.550 (0.426-0.711)	<.001	0.563 (0.436-0.727)	<.001

[a]—: not determined.

Table 3. Univariate and multivariate survival analyses of overall survival among long-term survivors of the epithelial ovarian cancer diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

Variables	Univariate survival analysis		Multivariate survival analysis	
	Hazard ratio (95% CI)	*P* value	Hazard ratio (95% CI)	*P* value
Age (years)				
<50	1 (reference)	Reference	1 (reference)	Reference
50-64	1.188 (1.091-1.293)	<.001	1.149 (1.055-1.251)	.001
≥65	1.763 (1.615-1.924)	<.001	1.668 (1.527-1.821)	<.001
Race				
White	1 (reference)	Reference	—[a]	—
Black	0.970 (0.838-1.123)	.69	—	—
Other	0.916 (0.812-1.034)	.16	—	—
American Joint Committee on Cancer stage				
III	1 (reference)	Reference	1 (reference)	Reference
IV	1.349 (1.257-1.448)	<.001	1.222 (1.132-1.319)	<.001
Nodal status				
Negative	1 (reference)	Reference	1 (reference)	Reference
Positive	0.853 (0.796-0.915)	<.001	0.863 (0.805-0.925)	<.001
Unknown	1.484 (1.330-1.655)	<.001	1.298 (1.154-1.459)	<.001
Histological subtypes				
Serous	1 (reference)	Reference	1 (reference)	Reference
Endometrioid	0.601 (0.533-0.677)	<.001	0.632 (0.561-0.713)	<.001
Mucinous	0.566 (0.432-0.740)	<.001	0.604 (0.461-0.791)	<.001
Clear cell	0.606 (0.487-0.754)	<.001	0.624 (0.501-0.776)	<.001

[a]—: not determined.

Figure 4. The evaluation of the proportional hazards assumption in ovarian cancer-specific survival (A and C) and overall survival (B and D) among the different histological subtypes of the epithelial ovarian cancer from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

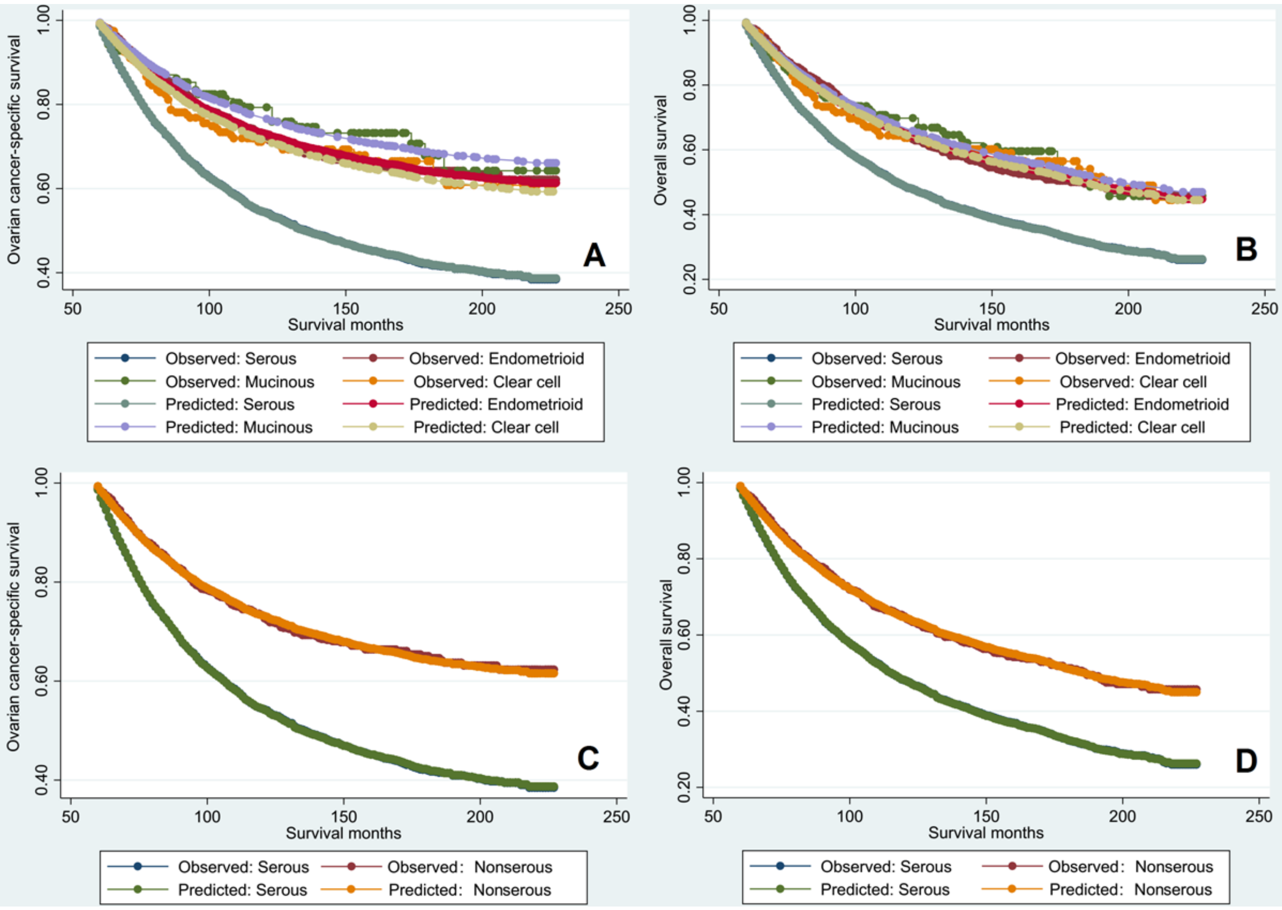


Figure 5. Ovarian cancer-specific survival curves (A) and overall survival curves (B) between serous cancer and non-serous cancer from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

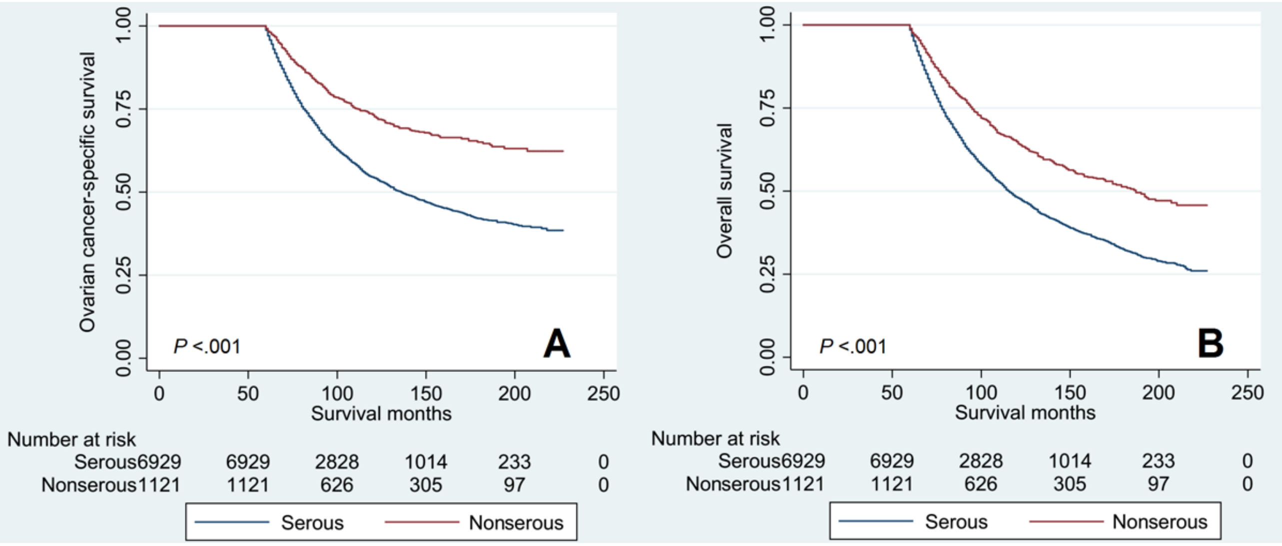


Table 4. Stratified analyses of the multivariable-adjusted hazard ratios and 95% CIs for ovarian cancer–specific survival and overall survival by histological subtype (serous vs nonserous) among long-term survivors of the epithelial ovarian cancer diagnosed from 2000 to 2014 using the Surveillance, Epidemiology, and End Results cancer data of the United States.

Variables (serous vs nonserous)	Ovarian cancer–specific survival		Overall survival	
	Hazard ratio (95% CI)	*P* value	Hazard ratio (95% CI)	*P* value
Aged <50 years	2.381 (1.861-3.046)	<.001	2.088 (1.679-2.596)	<.001
Aged 50-64 years	1.809 (1.514-2.161)	<.001	1.516 (1.304-1.763)	<.001
Aged ≥65 years	1.636 (1.311-2.041)	<.001	1.414 (1.188-1.683)	<.001
White patients	1.797 (1.580-2.044)	<.001	1.569 (1.407-1.749)	<.001
Black patients	1.383 (0.799-2.395)	.25	1.088 (0.692-1.712)	.72
Patients of other race	3.672 (2.294-5.879)	<.001	2.276 (1.609-3.219)	<.001
American Joint Committee on Cancer stage III disease	1.715 (1.503-1.958)	<.001	1.507 (1.347-1.684)	<.001
American Joint Committee on Cancer stage IV disease	2.861 (2.102-3.894)	<.001	1.990 (1.575-2.515)	<.001
Nodal negative disease	1.832 (1.578-2.128)	<.001	1.593 (1.403-1.809)	<.001
Nodal positive disease	1.850 (1.475-2.319)	<.001	1.522 (1.264-1.833)	<.001

Discussion

Principal Findings

Herein we used the SEER database to assess the role of histological subtypes in predicting the survival outcome among long-term survivors (≥5 years) of advanced EOC. Our results indicate that ovarian cancer remains the primary cause of death among long-term ovarian cancer survivors. Moreover, patients with endometrioid, clear cell, and mucinous tumors showed a significant improvement in OCSS and OS compared to those with serous tumors. This study provides a unique opportunity to determine the characteristics of long-term survivors of advanced EOC.

There exist limited studies that have explored factors associated with long-term survival in EOC [6]. Such studies have reported that long-term survival is associated with various factors such as younger age at diagnosis, earlier clinicopathologic stage, absence of ascites, lower grade, earlier stage, nonserous histology, and lower CA125 levels [3-5,19,20]. In our study, we used a population-based cohort, and our results indicate that younger age, stage III disease, and nonserous cancers were associated with long-term survival in EOC. Our results add to the current knowledge on the prognostic factors for the long-term survivors of EOC. In addition, epidemiological factors such as low body mass index, not smoking, parity, and individual exhauster-scored conditions have been associated with long-term survival in EOC [5,21]. However, owing to the limitation of the SEER database, we could not identify these epidemiological factors.

In our previous studies, we have found a markedly increased mortality rate among patients with stage III-IV mucinous and clear cell cancers, but better survival among those with serous and endometrioid cancers [13,22]. These results concur with those reported by previous studies on stage III-IV EOC [13,15,18,20,23,24]. The aggressive behavior and impaired response to taxanes and platinum-based chemotherapy in the case of mucinous and clear cell carcinomas may be the core reason for these findings [16,25,26]. However, a study using the California Cancer Registry and including patients diagnosed with EOC between 1994 and 2001 reported that nonserous subtypes, including endometrioid, clear cell, and mucinous carcinomas, were significant predictors of long-term survival [3]; this study included patients with early-stage EOC, and it may hence not reflect the true long-term survival characteristics of patients with advanced-stage EOC.

The prognostic role of histological subtypes on the survival outcome among long-term survivors of advanced EOC has been explored by limited studies. A previous study by Son et al [27] reported that 91% of deaths occurred within 8 years, and that survival for 8 years may represent the prognostic inflection point for long-term survival in advanced EOC. However, only 11 patients survived for >8 years in the Son et al's [27] study. In our study, approximately 80% of ovarian cancer–related deaths occurred in <5 years. Among long-term survivors (who survived for ≥5 years) (n=8050), 3874 patients died of any causes during follow-up, and the majority of patients died from ovarian cancer–related disease, particularly those with the serous subtype. Our results suggest that although the peak of ovarian cancer–related deaths occurred within 5 years, intensive follow-up is required for long-term survivors.

Several studies, including ours, have indicated that the survival outcome of clear cell and mucinous cancers were significantly inferior to that of serous cancers in advanced-stage disease [12-16]. However, in this study, the OCSS and OS for clear cell and mucinous cancers were significantly longer than those for serous cancers in long-term survivors, suggesting that the prognostic effect of the histological subtype on EOC survival changed upon extensive follow-up. Therefore, surveillance options tailored depending on the nature of the histological subtype of EOC should be considered in future studies. The mechanisms underlying this more aggressive course in early, but not in long-term, outcomes for mucinous and clear cell cancers in advanced-stage disease have not been studied in detail. Failure to respond to chemotherapy could contribute to poorer survival in clear cell and mucinous cancers with respect to early outcome [28], while the risk of death in patients with clear cell and mucinous cancers may be significantly reduced upon extensive follow-up [3]. Genetic signatures could further our understanding of the potential biological differences between short- and long-term survivors. However, the current evidence lacks consistency, limiting the reproducibility and clinical use of molecular markers [6].

Strengths and Limitations

There were several limitations to our study. First, this is a retrospective study; hence, we could not exclude all potential selection biases. Second, information on chemotherapy regimens, administered dose, number of chemotherapy cycles, and completeness of chemotherapy were unavailable in the SEER database. Third, the size of residual tumors (before 2010), patterns of disease recurrence, and strategy of treatment after disease progression were also not recorded in the SEER database. Moreover, this database lacks a central review for histological subtype. On the other hand, the strengths of this study include its population-based design. This study involved a relatively large cohort of patients with EOC, with the data representing a real-world scenario. Furthermore, our results are expected to expand the current knowledge on the biological behavior of EOC by various histological subtypes after extensive follow-up. Further studies focusing on the prognostic factors regarding long-term survivors of EOC are needed.

Conclusions

In conclusion, our study suggests that ovarian cancer remains the primary cause of death among long-term ovarian cancer survivors. Moreover, the probability of death is significantly different among those with different histological subtypes of EOC. It is important for clinicians to individualize the surveillance program for long-term ovarian cancer survivors. Further studies using diverse cohorts are warranted to confirm our findings and expand our understanding.

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Conflicts of Interest

None declared.

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Abbreviations

AJCC: American Joint Committee on Cancer
EOC: epithelial ovarian cancer
HR: hazard ratio
OCSS: ovarian cancer–specific survival
OS: overall survival

SEER: Surveillance, Epidemiology, and End Results

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Original Paper

Prevalence of Multimorbidity of Chronic Noncommunicable Diseases in Brazil: Population-Based Study

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Abstract

Background: Multimorbidity is the co-occurrence of two or more chronic diseases.

Objective: This study, based on self-reported medical diagnosis, aims to investigate the dynamic distribution of multimorbidity across sociodemographic levels and its impacts on health-related issues over 15 years in Brazil using national data.

Methods: Data were analyzed using descriptive statistics, hypothesis tests, and logistic regression. The study sample comprised 679,572 adults (18-59 years of age) and 115,699 elderly people (≥60 years of age) from the two latest cross-sectional, multiple-cohort, national-based studies: the National Sample Household Survey (PNAD) of 1998, 2003, and 2008, and the Brazilian National Health Survey (PNS) of 2013.

Results: Overall, the risk of multimorbidity in adults was 1.7 times higher in women (odds ratio [OR] 1.73, 95% CI 1.67-1.79) and 1.3 times higher among people without education (OR 1.34, 95% CI 1.28-1.41). Multiple chronic diseases considerably increased with age in Brazil, and people between 50 and 59 years old were about 12 times more likely to have multimorbidity than adults between 18 and 29 years of age (OR 11.89, 95% CI 11.27-12.55). Seniors with multimorbidity had more than twice the likelihood of receiving health assistance in community services or clinics (OR 2.16, 95% CI 2.02-2.31) and of being hospitalized (OR 2.37, 95% CI 2.21-2.56). The subjective well-being of adults with multimorbidity was often worse than people without multiple chronic diseases (OR=12.85, 95% CI: 12.07-13.68). These patterns were similar across all 4 cohorts analyzed and were relatively stable over 15 years.

Conclusions: Our study shows little variation in the prevalence of the multimorbidity of chronic diseases in Brazil over time, but there are differences in the prevalence of multimorbidity across different social groups. It is hoped that the analysis of multimorbidity from the two latest Brazil national surveys will support policy making on epidemic prevention and management.

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KEYWORDS

multimorbidity; prevalence; health care; public health; Brazil; logistic regression

Introduction

It is estimated that around 70% of all deaths worldwide are caused by noncommunicable diseases (NCDs), mainly cardiovascular diseases (31%), cancers (16%), chronic respiratory diseases (7%), and diabetes (3%) [1]. In Brazil, cardiovascular diseases, cancers, chronic respiratory diseases, Alzheimer's disease and other dementias, diabetes mellitus, chronic kidney disease, cirrhosis, and other chronic liver diseases represented 62.4% of all deaths between 1990 and 2017 [2].

The co-occurrence of two or more chronic diseases in an individual is called multimorbidity [3-5]. Cross-country comparisons are challenging, essentially because there is no standard definition of what diseases should be considered for multimorbidity [3]. According to a literature review [5], the most common diseases are diabetes, hypertension, variations of heart disease, hyperlipidemia, and obesity, there being a high variability of coexisting additional diseases. Individuals with multimorbidity could have a higher risk of polypharmacy and of having difficulty in managing special diets, and consequently, these factors could intensify the demand on health care resources and increase the vulnerability of patients to safety issues [6-8]. The association between multimorbidity and socioeconomic and demographic variables has been explored in the literature [9-11] using single-cohort data for the Brazilian population [12-17]. Brazil is the sixth-largest country in the world in territory and the fifth largest in terms of population [18]. However, there is little evidence on which to base the incidence of multimorbidity of chronic NCDs using multiple cohorts of data for Brazil.

The objective of this study is to evaluate dynamic distributions of the 9 key NCDs among the Brazilian population using integrated cross-sectional population surveys over a period of 15 years using the Brazilian National Household Sample Survey (PNAD) and the Brazilian National Health Survey (PNS). Our study developed statistical analysis to explore the possible nonclinical risk factors associated with the prevalence of multimorbidity. This is the first study to explore the temporal changes in multimorbidity over an extended period of 15 years, representing the largest sample (N=795,271) of multimorbidity research undertaken to date in Brazil. In addition, this study evaluated the impact of sociodemographic issues, well-being, health insurance, and health care demands on multimorbidity. A recent smaller-scale study of chronic diseases based on a single telephone survey corroborated our findings, considering a small scale of covariates [19].

Methods

Study Design and Data

PNAD and PNS are multiple-stage complex surveys conducted and made available online by the Brazilian Institute of Geography and Statistics to assess the status of households in Brazil. The National Research Ethics Commission approved the research and the content provided by all participants. The research used a stratified sampling method based on interviews conducted in all states and regions of Brazil. PNAD uses a 3-stage self-weighted cluster sampling technique. In the initial stage, cities with a large population and those belonging to metropolitan regions are included and other cities belonging to the same geographic microregion are grouped into a stratum of approximately the same size and systematically selected with probabilities proportional to their size. In the second stage, the census sectors are systematically chosen based on the last census in 2010, and the third sampling stage selects households in each sector [20]. PNS also uses a three-stage stratified sampling approach, which is a subsample of the Master Sample of the Integrated Household Surveys System consisting of primary sampling units (PSUs). In the first stage, PSU selection is obtained by simple random sampling. The second stage includes the selection of households. The last stage randomly selects a resident who is 18 years of age or above to answer the survey [21].

In this study, 4 cross-sectional national-based surveys from PNAD (1998, 2003, and 2008) and PNS (2013) were integrated for the common variables. To ensure the accuracy of analysis, variables that had over 25% missing values were excluded.

Variables

NCD questions intend to measure current morbidity (self-declared), including back/column, arthritis/rheumatism, cancer, diabetes, bronchitis/asthma, high blood pressure (HBP, or hypertension), heart disease, chronic renal insufficiency (kidney failure), and depression. Multimorbidity means that the patient has two or more NCDs. Overall, 11 independent variables in each cohort (ie, gender, race/color, age group, region, literacy, employment, subjective well-being (SWB), health insurance, health service accessibility, health service need, and hospitalization) were considered for this study.

In the survey, literacy was used to assess educational background. Similarly, the study asked, "Have you had a job in the past 12 months?" to indicate participants' employment status. To analyze the spatial feature of multimorbidity over time, we divided the nation into five regions, which are North, Northeast, Midwest, Southeast, and South, using the Brazilian government's official rules on dividing the territory. Additionally, this study assessed the impacts of health service usage on multimorbidity. Understanding the distribution of multimorbidity among different groups can support health prevention policies to decrease multimorbidity and to save public expenditure on health services. We explored the recent usage of certain health services in the previous 2 weeks, the frequency of hospitalization in the past 12 months, and the frequency with which the same health center was visited. Most people in Brazil use public health services.

The ability to access private health care using health insurance represents the available financial resources for health management [22]. Consequently, this study was designed to use health insurance as an indicator of attitudes toward personal health management. A subject's well-being was presented in the surveys using a 5-point scale (1 for the best to 5 for the worst) and was used to present the participants' perception of their health. Some new variables were derived from the existing information in the database, based on the research objective (eg, group ages and group states in the official regions).

Statistical Analysis

The analysis of multimorbidity was conducted from three aspects, which are social demographic, region, and utilization of health services. All analyses were categorized by age and gender. Descriptive analysis and data visualization were performed to identify differences in the participants' behavior and to summarize each variable's overlap distribution used in this study across each cohort. The sample comprised 795,271 participants divided into 2 main groups with 679,572 adults (18-59 years of age) and 115,699 elderly people (≥60 years of age). The inclusion criterion was being 18 years old or older, and we excluded 1.2% of individuals who did not answer all the questions about the 9 chronic diseases analyzed. The other 11 questions for analysis were mandatory in the surveys without any missing data. Hypothesis testing was conducted to determine the association between multimorbidity and demographic, geographic, socioeconomic, and health characteristics. The occurrences of all combined NCDs on each participant were explored using frequency analysis, and the interimpacts of NCDs were also tested. The Pearson chi-square test was used to determine the association between all variables and the occurrence of multimorbidity. Logistic regression models were applied for analyzing the impacts on multimorbidity. To estimate the association with multimorbidity, odds ratios (ORs) were computed with 95% CIs. First, the binary logistic regression model (BLRM) was used to compare the probability of multimorbidity occurrence (with: 1; without: 0) for the associated sociodemographic risk factors, such as gender, race/color, age group, region, literacy, employment, and health insurance. Second, the BLRM was applied to analyze the impacts of multimorbidity/sociodemographic characteristics on health-related factors, such as the participant's well-being, health service accessibility, health service need, and hospitalization. This methodology enabled us to estimate the OR of each predictor variable, independent of all other variables in the model. *P* values (2-sided) with 95% CIs were used for statistical significance. The data were analyzed using SPSS Statistics and QGIS for map design.

Results

Descriptive Statistics of Multimorbidity

Overall, 18.3% of the participants had 2 or more NCDs in Brazil, and the prevalence of multimorbidity varied between 17.1% and 21% over the 15 years of this study from 1998 to 2013 (see the multimorbidity frequency tables in Multimedia Appendix 1). The results show that 1 in every 5 Brazilian adults of 18 years and above had, on average, multimorbidity in 1998 and 2013, with a ratio of 1 in 6 in 2003 and 2008. Figure 1 summarizes the descriptive statistics of multimorbidity according to gender, race, age, education, and employment. In general, the percentage of multimorbidity for females varied between 20.9% and 25.6% and was higher than that of males over the study period. The difference in the multimorbidity rate between the genders varied between 9.7% (1998), 8.8% (2003), 8% (2008), and 8.7% (2013). The occurrence of multimorbidity grew gradually with age over the 15 years. However, the percentage of multimorbidity for young people increased in 2013 by 0.2% compared with that in 2008. The age group of 18-29 years had the lowest multimorbidity rate (2.6%) in 2008, and for people aged 60 or over, multimorbidity was lowest in 2013 (41.1%). The gap in the occurrence rate of having more than two NCDs between the lowest and highest age groups shrank from 48.3% in 1998 to 37.3% in 2013.

The least educated in the sample population (people without education) had a higher rate of multiple chronic diseases than the highest educated group in every study period (Figure 1). The greatest difference (20.4%) in the multimorbidity rate between the least and most educated groups occurred in 1998, and the rate gradually declined in subsequent years apart from 2008. The unemployed group had higher rates of multimorbidity in comparison with employed people for each individual period. The rate for both employed and unemployed people was the lowest in 2003 and increased slightly from 2003. With regard to the geographical distribution of multimorbidity, the South and Southeast had a higher rate of multimorbidity compared to the North and Northeast, except in 1998, and the pattern was the same across gender groups (Figure 2).

Figure 1. Percentage of multimorbidity by year with sociodemographics, subjective well-being, and health service characteristics.

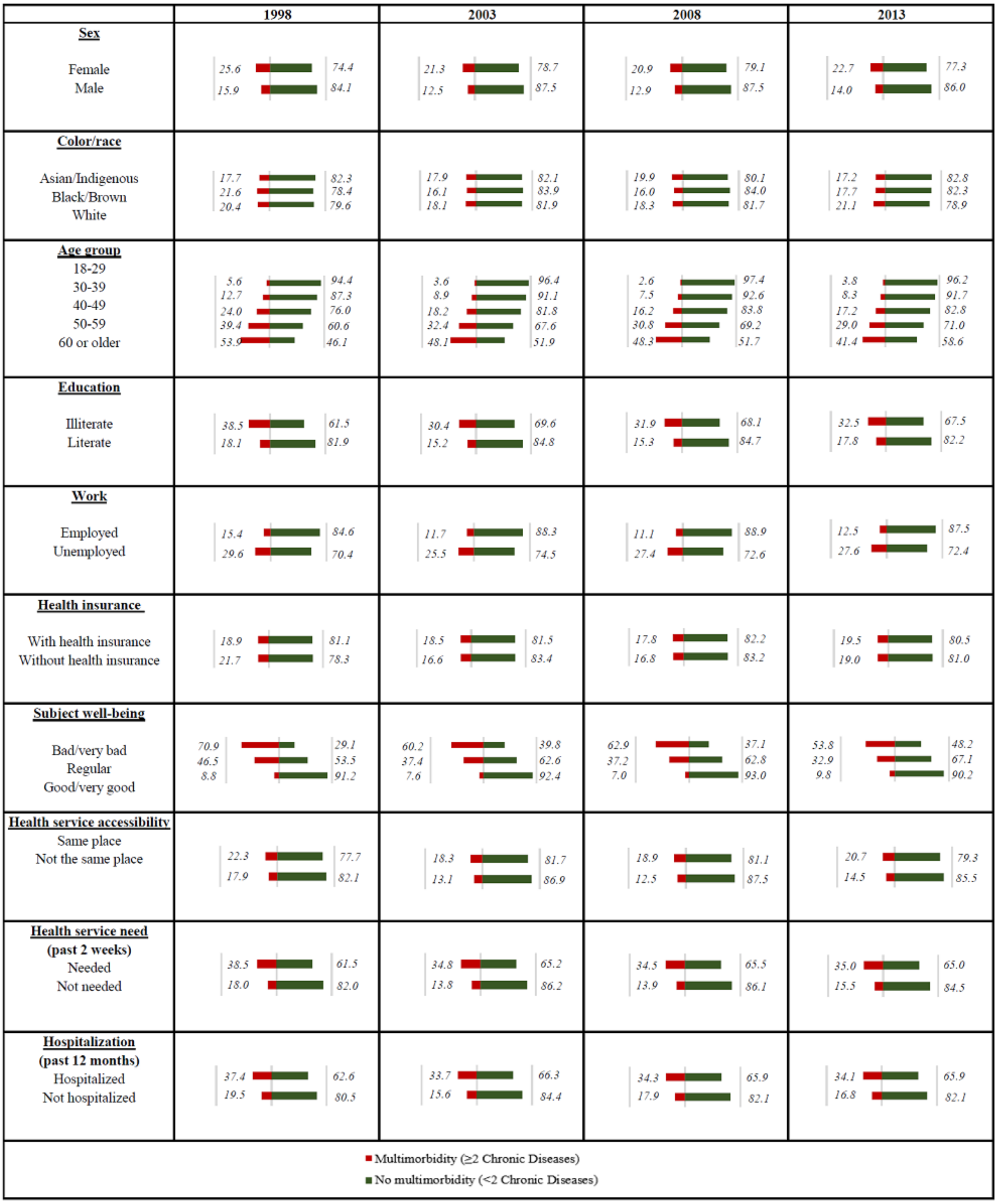
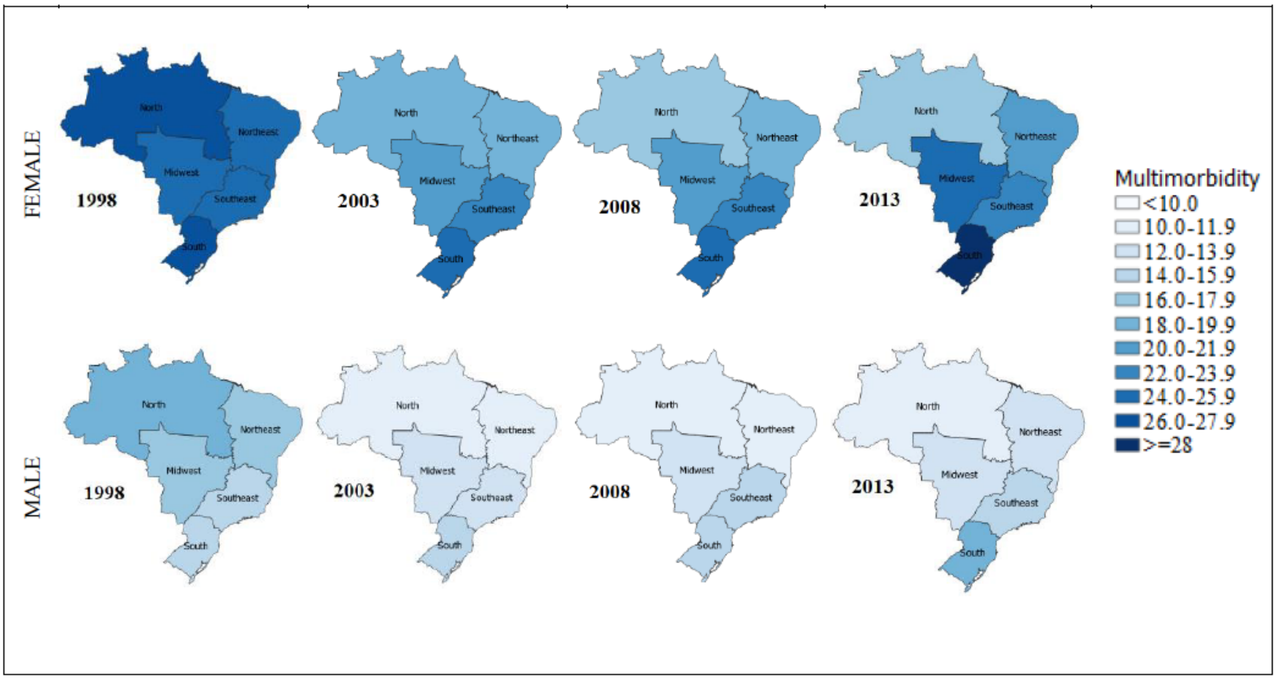
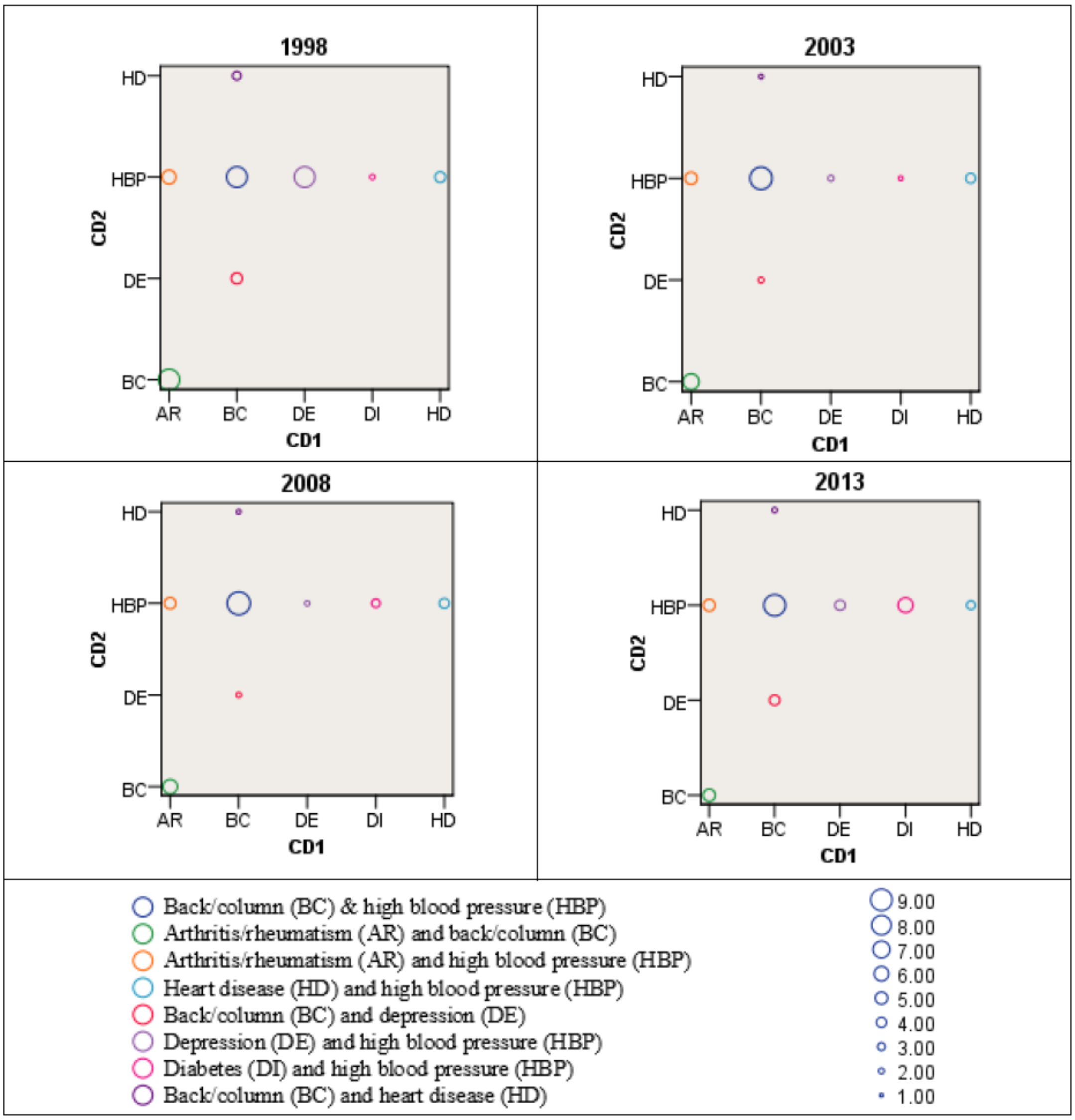


Figure 2. Percentage of multimorbidity in the 5 regions of Brazil by sex.



Pearson chi-square tests showed that multimorbidity was significantly associated with the risk factors considered over the 15-year period in Brazil (P<.001) except for health insurance in 2013. The covariates most associated with multimorbidity were age (0.415 in 2008) and SWB (0.483 in 1998). Clearly, participants with multiple NCDs considered their health status as bad or very bad more frequently than people without multimorbidity (Figure 1). The data also indicate that the demand for health services and hospitalization was higher among participants with multimorbidity. The minority of participants in the four cohorts declared they had visited health-related units, services, or professionals in the past 2 weeks or had been hospitalized in the past 12 months. Participants with back/column problems and HBP (7%) or column/back and arthritis/rheumatism (5.7%) were the most common of the multimorbidity population, as shown in Figure 3 (the frequency of each NCD calculated is shown in Multimedia Appendix 2). For multimorbidity with 3 chronic diseases, the most prevalent combination for the participants was arthritis/rheumatism, back/column diseases, and HBP (2.8%).

Figure 3. Most frequent CD combinations in Brazil. CD: chronic disease.



Multimorbidity Valuation Model

We developed BLRMs to evaluate the impact of sociodemographics (risk factors) on multimorbidity in Brazil and their associations with health-related variables. The parameter estimations of BLRM analysis are explained in the following sections.

Sociodemographic Analysis

Tables 1 and 2 show the OR of multimorbidity over the period of 1998-2013 for adults and for the elderly, respectively. The odds of multimorbidity for female adults increased by 73% compared with males (OR 1.73). For those over 60 years, the chance of having multimorbidity was 52% higher for women than for men. The ORs of multimorbidity for Black/Brown adult Brazilians (OR 0.91) and the elderly (OR 0.72) were relevantly smaller. However, there was little difference in the occurrence of multimorbidity between the Asian/indigenous group and Whites in Brazil (adults: OR 1.09; elderly: OR 1.03). Overall, the prevalence of multimorbidity increased with age. For instance, the group aged between 50 and 59 years had an almost 12 times greater chance (OR 11.89) of developing multiple chronic diseases compared with people between 18 and 29 years old. However, the odds for those over 60 years were almost 12 times higher (OR 19.77) than for those between 18 and 29 years.

Regression analysis showed that illiteracy is positively associated with multimorbidity, and the odds of unemployed people having multimorbidity increased 1.5 times compared to the employed adults (OR 1.47). With regard to the distribution of multimorbidity in Brazil by region, people from areas in the South showed a greater chance (adults OR 1.35; elderly OR 1.53) of having multimorbidity than did people from the North, on average, over the whole period. Overall, participants with multiple chronic diseases were more likely to be uninsured (OR 1.12), except the elderly group (OR 0.93). Note that individuals of all ages in Brazil are entitled to public health insurance.

Table 1. Results of the binary logistic regression model examining the association with multimorbidity for Brazilian adults (18-59 years old).

Characteristics	1998		2003		2008		2013		Overall	
	OR_{crude}[a]	$OR_{adjusted}$[b] (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)
Gender										
Male	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Female	1.83	1.77 (1.72-1.83)	1.97	1.82 (1.77-1.88)	1.79	1.60 (1.54-1.64)	1.88	1.79 (1.59-2.02)	1.86	1.73 (1.67-1.79)
P value	—[c]	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Race/color										
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Black/Brown	0.71	0.66 (0.52-0.83)	1.11	0.99 (0.82-1.21)	1.16	1.12 (0.95-1.33)	0.89	0.94 (0.60-1.47)	0.97	0.91 (0.76-1.08)
Asian/Indigenous	1.20	1.19 (1.14-1.23)	0.96	1.12 (1.08-1.16)	0.97	1.13 (1.09-1.67)	0.88	1.02 (0.91-1.15)	0.98	1.09 (1.05-1.13)
P value	—	<.001	—	<.001	—	<.001	—	.89	—	<.001
Age group (years)										
18-29	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
30-39	2.54	2.66 (2.54-2.79)	2.71	2.80 (2.65-2.96)	2.98	3.10 (2.93-3.29)	2.32	2.41 (1.94-2.98)	2.61	2.70 (2.55-2.85)
40-49	5.56	5.92 (5.65-6.20)	6.13	6.32 (6.00-6.65)	7.12	7.29 (6.91-7.70)	5.60	5.69 (4.64-6.99)	5.95	6.08 (5.77-6.40)
50-59	11.37	11.61 (11.05-12.20)	13.29	13.14 (12.48-13.84)	16.42	15.86 (15.01-16.76)	10.23	10.13 (8.25-12.44)	12.18	11.89 (11.27-12.55)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Education										
Literate	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Illiterate	2.30	1.39 (1.32-1.45)	1.84	1.20 (1.16-1.28)	1.94	1.23 (1.17-1.30)	1.83	1.13 (0.91-1.41)	2.02	1.34 (1.28-1.41)
P value	—	<.001	—	<.001	—	<.001	—	.28	—	<.001
Work										
Employed	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Unemployed	1.63	1.33 (1.29-1.38)	1.76	1.49 (1.44-1.54)	1.96	1.67 (1.61-1.73)	1.75	1.42 (1.26-1.60)	1.78	1.47 (1.42-1.52)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Region										
North	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Northeast	0.84	0.70 (0.64-0.77)	0.90	0.78 (0.72-0.85)	1.04	0.94 (0.87-1.02)	1.09	0.98 (0.83-1.15)	1.01	0.90 (0.85-0.95)
Southeast	0.66	0.59 (0.54-0.64)	1.07	0.91 (0.84-0.98)	1.30	1.16 (1.07-1.25)	1.32	1.20 (1.01-1.42)	1.10	0.99 (0.93-1.05)
South	0.84	0.80 (0.72-0.88)	1.35	1.23 (1.13-1.33)	1.59	1.48 (1.35-1.62)	1.87	1.74 (1.43-2.12)	1.42	1.35 (1.26-1.44)
Midwest	0.87	0.85 (0.77-0.94)	1.26	1.19 (1.10-1.30)	1.31	1.27 (1.16-1.39)	1.44	1.36 (1.14-1.62)	1.25	1.22 (1.15-1.30)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Health insurance										
With insurance	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Characteristics		1998		2003		2008		2013		Overall	
		OR_{crude}[a]	$OR_{adjusted}$[b] (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)
	Without insurance	1.26	1.29(1.25-1.35)	0.95	1.05(1.01-1.09)	1.04	1.10(1.06-1.15)	1.05	1.07(0.95-1.20)	1.06	1.12(1.08-1.16)
	P value	—	<.001	—	.02	—	<.001	—	.27	—	<.001

[a]OR_{crude}: crude odds ratio.

[b]$OR_{adjusted}$: odds ratio adjusted for gender, color/race, age group, literacy, work, region and health insurance.

[c]Not applicable.

Table 2. Results of the binary logistic regression model examining the association with multimorbidity for Brazilian elderly (≥60 years old).

Characteristics	1998		2003		2008		2013		Overall	
	OR_{crude}[a]	$OR_{adjusted}$[b] (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)
Gender										
Male	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Female	1.81	1.60 (1.52-1.68)	1.78	1.56 (1.49-1.64)	1.76	1.58 (1.51-1.65)	1.50	1.42 (1.22-1.65)	1.68	1.52 (1.44-1.60)
P value	—[c]	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Race/color										
White	1.00	1.00	1.00	1.00	1.00	1.00			1.00	1.00
Black/Brown	0.58	0.64 (0.47-0.85)	0.56	0.57 (0.43-0.75)	0.70	0.70 (0.57-0.87)	—	—	0.70	0.72 (0.57-0.91)
Asian/Indigenous	1.18	1.10 (1.03-1.17)	0.94	1.05 (0.99-1.11)	0.93	1.06 (1.01-1.11)	—	—	0.95	1.03 (0.97-1.09)
P value	—	<.001	—	<.001	—	<.001	—	—	—	<.001
Education										
Literate	1.00	1.00	1.00	1.00	1.00	1.00	—	—	1.00	1.00
Illiterate	1.49	1.32 (1.24-1.41)	1.11	1.15 (1.09-1.22)	1.05	1.12 (1.06-1.18)	—	—	1.18	1.23 (1.16-1.30)
P value	—	<.001	—	<.001	—	<.001	—	—	—	<.001
Work										
Employed	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Unemployed	1.79	1.55 (1.45-1.65)	1.98	1.70 (1.60-1.80)	1.90	1.66 (1.57-1.75)	1.54	1.42 (1.16-1.74)	1.76	1.53 (1.44-1.63)
P value	—	<.001	—	<.001	—	<.001	—	.001	—	<.001
Region										
North	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Northeast	0.88	0.84 (0.73-0.95)	0.83	0.82 (0.74-0.91)	0.87	0.83 (0.75-0.91)	1.38	1.34 (1.08-1.67)	1.06	1.01 (0.93-1.10)
Southeast	0.74	0.78 (0.69-0.89)	1.01	1.00 (0.90-1.11)	1.09	1.04 (0.94-1.14)	1.78	1.75 (1.40-2.18)	1.22	1.21 (1.11-1.33)
South	0.87	0.96 (0.84-1.11)	1.21	1.27 (1.13-1.42)	1.28	1.27 (1.14-1.41)	2.28	2.28 (1.77-2.92)	1.49	1.53 (1.39-1.69)
Midwest	0.89	0.96 (0.82-1.11)	1.16	1.20 (1.06-1.35)	1.22	1.20 (1.07-1.34)	1.64	1.63 (1.28-2.07)	1.29	1.31 (1.19-1.44)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Health insurance										
With insurance	1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00	1.00
Without insurance	1.27	1.14 (1.07-1.22)	0.92	0.93 (0.88-0.99)	0.85	0.87 (0.82-0.92)	0.86	—	0.94	0.93 (0.88-0.99)
P value	—	<.001	—	.02	—	<.001	—	—	—	.02

[a]OR_{crude}: crude odds ratio.

[b]$OR_{adjusted}$: odds ratio adjusted for gender, color/race, age group, literacy, work, region and health insurance.

[c]Not applicable.

SWB and Health Assistance

In general, the participants without multiple chronic diseases naturally considered their health status as either good or regular. However, the responses from the participants with multimorbidity showed that their SWB was almost 10 times more likely to be perceived as bad/very bad (adult OR 12.85; elderly OR 8.35) than good/very good in all study cohorts. Tables 3 and 4 shows the OR for adults and for the elderly, respectively. The odds of participants with multimorbidity using the same health care unit was about 30% greater than that of the other people. In addition, the participants with multimorbidity showed a 50% greater chance of needing health services (adult OR 2.73; elderly OR 2.16) and of being hospitalized (adult OR 2.29; elderly OR 2.37) compared with non-multimorbidity groups.

Table 3. Results of the binary logistic regression model examining the association with subjective well-being (SWB) and health service utilization for Brazilian adults (18-59 years old).

Status of variables	1998		2003		2008		2013		Overall	
	OR_{crude}[a]	$OR_{adjusted}$[b] (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)
SWB (bad/very bad)										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	21.32	13.90 (12.98-14.88)	17.29	12.81 (12.01-13.65)	24.04	18.17 (17.04-19.38)	12.08	10.02 (8.30-12.10)	17.70	12.85 (12.07-13.68)
P value	—[c]	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Health service accessibility										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	1.29	1.28 (1.23-1.33)	1.45	1.32 (1.26-1.38)	1.57	1.43 (1.38-1.49)	1.42	1.33 (1.17-1.52)	1.41	1.31 (1.26-1.36)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Health service need										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	2.90	2.67 (2.57-2.77)	3.35	2.82 (2.72-2.93)	3.42	2.98 (2.87-3.09)	3.06	2.62 (2.33-2.94)	3.16	2.73 (2.63-2.83)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Hospitalization										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	2.28	2.22 (2.11-2.33)	2.61	2.46 (2.35-2.58)	2.71	2.64 (2.52-2.77)	2.71	1.89 (1.61-2.22)	2.40	2.29 (2.19-2.39)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001

[a]OR_{crude}: crude odds ratio.

[b]$OR_{adjusted}$: odds ratio adjusted for gender, color/race, age group, literacy, work, region and health insurance.

[c]Not applicable.

Table 4. Results of the binary logistic regression model examining the association with subjective well-being (SWB) and health service utilization for Brazilian elderly (≥60 years old).

Status of variables	1998		2003		2008		2013		Overall	
	OR_{crude} [a]	$OR_{adjusted}$ [b] (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)	OR_{crude}	$OR_{adjusted}$ (95% CI)
SWB (bad/very bad)										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	11.66	11.4 9 (10.41-12.69)	7.61	8.81 (8.07-9.63)	7.60	9.16 (8.43-9.96)	4.95	6.23 (4.93-7.86)	7.24	8.35 (7.69-9.07)
P value	— [c]	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Health service accessibility										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	1.36	1.38 (1.30-1.48)	1.55	1.43 (1.34-1.52)	1.51	1.43 (1.35-1.51)	1.25	1.17 (0.98-1.40)	1.38	1.30 (1.23-1.38)
P value	—	<.001	—	<.001	—	<.001	—	.08	—	<.001
Health service need										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	2.56	2.59 (2.41-2.78)	2.78	2.62 (2.47-2.79)	2.58	2.46 (2.32-2.60)	1.81	1.71 (1.44-2.02)	2.26	2.16 (2.02-2.31)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001
Hospitalization										
Without multimorbidity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With multimorbidity	2.32	2.32 (2.14-2.52)	2.55	2.47 (2.29-2.66)	2.46	2.39 (2.23-2.56)	2.32	2.31 (1.86-2.88)	2.43	2.37 (2.21-2.56)
P value	—	<.001	—	<.001	—	<.001	—	<.001	—	<.001

[a] OR_{crude}: crude odds ratio.

[b] $OR_{adjusted}$: odds ratio adjusted for gender, color/race, age group, literacy, work, region and health insurance.

[c] Not applicable.

Discussion

Principal Findings

The main findings of this study were that in Brazil, multimorbidity was higher among women, people without education, and the unemployed. We confirmed that multiple chronic diseases grow considerably with age. Similarly, people with multimorbidity made greater use of health assistance in community services or clinics and of hospitalization. The people with multimorbidity often rated their SWB worse than people without multiple chronic diseases. These patterns were similar across all four cohorts analyzed. The literature indicates a higher prevalence of multimorbidity in groups of women, older people, and people with lower socioeconomic status in different countries [11,23,24], even though most studies are from Europe and North America.

The multimorbidity rate in Brazil gradually declined from 1998 to 2008, yet increased in 2013 by 2%, and was consistently characterized by gender, age, region, well-being, health service utilization, and health insurance across the 15-year period. Our study shows that the effect of multimorbidity has shifted little over the 15 years. Based on the expected population growth [20], we estimated that the multimorbidity rate would increase to 20.6% in 2020 and 21.9% in 2025, having considered the expected aging population (30.2 million in 2020 and 36.1 million in 2025), respectively. It is estimated that between 16% and 57% of adults in developed countries have multiple chronic conditions [25]. The Brazilian females had around 70% more chance of having multimorbidity than the males, and the ORs were considerably higher for women and grew with age in the period of 1998-2013.

We believe that differences in multimorbidity occurrences between gender and the higher use of health care services by individuals with multimorbidity will remain largely unchanged in the near future in Brazil, as the distribution between these groups is not expected to change [20]. Given the higher life expectancy for women (80.25 years in 2020 and 81.22 years in

2025) [20], multiple chronic diseases create additional expenses for the health care system [26]. In Switzerland, the total health care costs were 5.5 times higher for individuals with multimorbidity [27]. Participants who self-declared as Black/Brown presented less chance of multimorbidity in comparison to those who self-declared as White in this study. Race is not entirely a determinant factor worldwide [28], but it might reflect that social conditions and income are important factors associated with multimorbidity. Blacks/Browns in Brazil have lower income and less opportunity to access health insurance, and worse housing conditions [29]. This is the only study that has explored the association between multimorbidity and literacy in Brazil, and it is alarming that Brazilian adults without education have more chance of developing multimorbidity. These socioeconomic factors increase exposure to risks and may lead to a reduced awareness of health status and care.

A range of different combinations of diseases has been presented in the literature, including clusters with cardiovascular and metabolic diseases, mental health problems, and musculoskeletal disorders [5]. For the individual NCD, this study found that the two most common sources are arterial hypertension (HBP; 16.5%, 18.0%, 19.9%, and 23.9%) and diabetes (3.1%, 3.8%, 5.1%, and 7.2%) in the respective cohorts. However, the most common combination of three NCDs are (1) back/column with HBP, (2) arthritis/rheumatism with column/back, and (3) arthritis/rheumatism with HBP (4.3%). The VIGITEL survey [19] indicated that the occurrence of HBP and diabetes was 24.7% and 7.7%, respectively, using telephone survey data collected from 33,356 participants in 26 state capitals and federal districts in 2018. It confirms that our findings are also in line with the most recent statistics of morbidity in Brazil. Unemployment does increase the risk of multimorbidity and is comparable to another Brazilian study [13] in which the unemployed showed a greater prevalence of multimorbidity. Over the study period, the prevalence gradually increased in the South and declined in the North. The regional prevalence of multimorbidity was only statistically different in 2003 and 2008. We believe that it would be interesting to observe the culture, lifestyle, and socioeconomic factors in future studies to better understand the distribution variations by geographic region. Considering the economic factors across those regions, southern Brazil had greater economic development but its multimorbidity occurrences were also the highest in Brazil.

The analysis of health characteristics and behaviors has not been explored in previous multimorbidity Brazilian studies using data from PNAD and PNS. The SWB should reflect not only NCDs but also communicable diseases and other health problems included in this study. Yet, there was a significant relationship between the SWB and multimorbidity for all four cohorts. This is the first study to analyze the association between the prevalence of multimorbidity and the SWB in the Brazilian national population. Individuals with multimorbidity perceived their SWB to be much worse than that of other groups, even though no causal relationship could be established from cross-sectional surveys.

It is gratifying to note that people with multimorbidity could access a range of health care services via the insurance system, although it was unclear whether insurance was purchased before or after they had multiple NCDs. Globally, having a health plan can generate greater access to health care services to reduce the risk of health hazards and improve the quality of life [22]. According to the supplementary national health agency [30], only 47 million Brazilians have health insurance (22.6%) out of a total population of about 208 million inhabitants [20]. The lack of health insurance could be attributed to income, as a considerable proportion of the Brazilian population cannot afford health care plans, even people who have multiple chronic diseases. The number of individuals with voluntary private health insurance considerably varies between countries, such as 43% in Australia, 29% in Denmark, 86% in France, and 11% in the United Kingdom [22].

Brazilians with multimorbidity had about 30% more chance of using the same health care unit, three quarters of them used health services more frequently, and over half of them were hospitalized at least once. We believe these patterns will show up in big national survey data analysis over time and could support decision making on health management [31] by revealing the determinants of multimorbidity in terms of sociodemographic factors and health services. Taking a broader perspective, it is essential to consider the care of people with multimorbidity from the aspect of improving health management in primary care [6,32,33].

Limitations

Although our study explored patterns in the distribution of multimorbidity over a 15-year period (1998-2013) in Brazil, it also had several limitations. The self-reporting of chronic diseases could introduce bias (eg, the participant may not be aware of the disease or may not have been previously diagnosed by a doctor, or there may be over reporting), even though self-reporting is widely used in public health research [34]. Another limitation is that some survey questions changed over the period, yet this modification is unlikely to impact the outcomes of the study (eg, “Has any doctor ever given you the diagnosis of…” to “Has any doctor or health professional said that you have…”). Moreover, modifications in the data collection methodology could influence the geographic evaluation and the calculation of prevalence of NCDs by region.

This research evaluated the impact of multimorbidity on various outcomes that could lead to possible reverse causality, and future studies are needed to address this issue. Our findings indicate a possible influence of social conditions on health awareness and, consequently, an effect on the self-reporting of multimorbidity. Consistent with the prior literature [7,35], our study shows that multimorbidity in Brazil has led to a higher use of health care systems. Multimorbidity relates to physical inactivity, tobacco/alcohol use, and unhealthy diets. The lifestyle of individuals and families also needs to be considered in policies to minimize the risk of chronic diseases [36]. Multimorbidity is a complex health care situation that will tend to deteriorate with the co-occurrence of chronic diseases. Multiple health conditions are more common in disadvantaged groups and contribute to health inequalities [6]. Due to the economic status, it is possible that Brazilians from the North are less aware of their health condition compared with those from the South, which reinforces the need for preventative actions [37] and better health care services. Future studies will benefit from the availability of new population-based studies of multimorbidity patterns in Brazil founded on this study. It will be of pressing concern to explore further the relationships between unemployment, income, and chronic diseases as they relate to the difficulties of finding work or maintaining employment over time.

Conclusions

The distribution patterns of multimorbidity provide clear evidence of where there are differences in the prevalence of multimorbidity across different social groups. Our findings can help to shape existing public health policies to accommodate different preventative activities within health care services. This analysis also confirms that differences in the economic development model, including regional inequalities, education, and employment, have greatly damaged public health development in Brazil, a developing country. This study provides scientific evidence of preventative public health strategies in pandemic situations that are needed to significantly affect vulnerable groups with multimorbidity from both temporal and geographic perspectives.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Descriptive summary table: multimorbidity over time.
[DOCX File , 28 KB - publichealth_v7i11e29693_app1.docx]

Multimedia Appendix 2
Chronic disease prevalence in Brazilian adults over time (>18 years old).
[DOCX File , 19 KB - publichealth_v7i11e29693_app2.docx]

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Abbreviations

BLRM: binary logistic regression model
HBP: high blood pressure
NCD: noncommunicable disease
OR: odds ratio
PNAD: National Sample Household Survey
PNS: Brazilian National Health Survey
PSU: primary sampling unit
SWB: subjective well-being

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Original Paper

Evaluation of the National Tuberculosis Surveillance System in Sana'a, Yemen, 2018: Observational Study

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Abstract

Background: Tuberculosis remains a public problem that is considered one of the top causes of morbidity and mortality worldwide. The National Tuberculosis Control Program in Yemen was established in 1970 and included in the national health policy under the leadership of the Ministry of Public Health and Population to monitor tuberculosis control. The surveillance system must be evaluated periodically to produce recommendations for improving performance and usefulness.

Objective: This study aims to assess the usefulness and the performance of the tuberculosis surveillance system attributes and to identify the strengths and weaknesses of the system.

Methods: A quantitative and qualitative evaluation of the national tuberculosis surveillance system was conducted using the Centers for Disease Control and Prevention's updated guidelines. The study was carried out in 10 districts in Sana'a City. A total of 28 public health facilities providing tuberculosis services for the whole population in their assigned catchment areas were purposively selected. All participants were interviewed based on their involvement with key aspects of tuberculosis surveillance activities.

Results: The tuberculosis surveillance system was found to have an average performance in usefulness (57/80, 71%), flexibility (30/40, 75%), acceptability (174/264, 66%), data quality (4/6, 67%), and positive predictive value (78/107, 73%), and poor performance in simplicity (863/1452, 59%) and stability (15%, 3/20). In addition, the system also had a good performance in sensitivity (78/81, 96%).

Conclusions: The tuberculosis surveillance system was found to be useful. The flexibility, positive predictive value, and data quality were average. Stability and simplicity were poor. The sensitivity was good. The main weaknesses in the tuberculosis surveillance system include a lack of governmental financial support, a paper-based system, and a lack of regular staff training. Developing an electronic system, securing governmental finances, and training the staff on tuberculosis surveillance are strongly recommended to improve the system performance.

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KEYWORDS

evaluation; surveillance system; tuberculosis; Yemen

Introduction

Tuberculosis is an infectious disease caused by mycobacterium tuberculosis bacteria [1,2]. It remains a major cause of ill health, one of the top 10 causes of death worldwide, which has taken a higher ranking than HIV/AIDS [3]. According to World Health Organization (WHO) estimates, nearly 10 million people were infected with tuberculosis in 2019 [3]: 5.6 million men, 3.2 million women, and 1.2 million children. There were 1.4 million that died with tuberculosis among HIV-negative people, while 208,000 deaths were among HIV-positive people.

Tuberculosis can affect anyone anywhere, but almost 90% of those who fall sick with tuberculosis have been living in one of the 30 high tuberculosis burden countries. Eight countries account for two-thirds of the total, with India leading the count, followed by Indonesia, China, the Philippines, Pakistan, Nigeria, Bangladesh, and South Africa. The WHO Eastern Mediterranean Region contributes 819,000 (8.5%) of the people who developed the disease, with an estimated incidence rate of 114 per 100,000 populations [4].

Yemen has a moderate tuberculosis burden. According to WHO estimates, 14,000 patients with tuberculosis were reported in 2019, and the incidence rate was estimated as 48 per 100,000 population in 2019 [5]. The surveillance system must be evaluated periodically and produce recommendations for improving performance and usefulness. Therefore, this evaluation aims to assess the usefulness and performance of the tuberculosis surveillance system attributes and to identify the strengths and weaknesses of the system.

Methods

Study Design

A quantitative and qualitative evaluation was conducted to assess the performance of the tuberculosis surveillance system using the Centers for Disease Control and Prevention's (CDC) updated guidelines for Evaluating Public Health Surveillance Systems [6].

Study Setting and Duration

The study was carried out in 28 tuberculosis sentinel sites for the whole population in their assigned catchment areas in Sana'a City during October 1 to December 31, 2018.

Study Population

All participants have interviewed based on their involvement with key aspects of tuberculosis surveillance activities: seven managers and one data entry personnel at a central level and one tuberculosis coordinator and one lab supervisor at the governorate level, and at the peripheral level, 10 tuberculosis coordinators from the district level and 11 medical officers and 24 lab technicians from the health facilities.

Data Collection and Analysis

The National Tuberculosis Control Program (NTCP) documents (strategic plan, guidelines, annual reports, and databases) were reviewed to describe the system. In-depth interviews were used with participants based on their involvement with key aspects of tuberculosis surveillance activities. Verbal consent was obtained from all respondents who participated in the study. Semistructured questionnaires were used to collect information related to surveillance system attributes including flexibility, stability, simplicity, and acceptability at the four levels. The usefulness level was assessed using questions with (yes 1 or no 0) answers, while the other surveillance attributes were assessed using a three-point Likert scale (3 agree, 2 neutral, 1 disagree).

Scoring System

Specific indicators were used to assess each performance attributes.

The score percent was calculated by the following:

The overall score percent was calculated by the following:

The score percent of each attribute was interpreted as the following: greater than 80% was ranked as good, between 60% to 80% was ranked as average, and lesser than 60% was ranked as poor [7,8]. Data quality was assessed by reviewing documents such as quarter report, while the sensitivity and positive predictive value (PPV) were calculated using the following equation:

> Sensitivity = (true positive A / true positive A + false negative C) **(3)**
>
> Predictive value = (true positive A / true positive A + false negative B) **(4)**

The date was analyzed using Excel 2013 (Microsoft Corporation) and Epi Info version 7.2 (CDC) to calculate frequency and percentage.

Results

Desk Review Findings

Description of the Tuberculosis Surveillance System

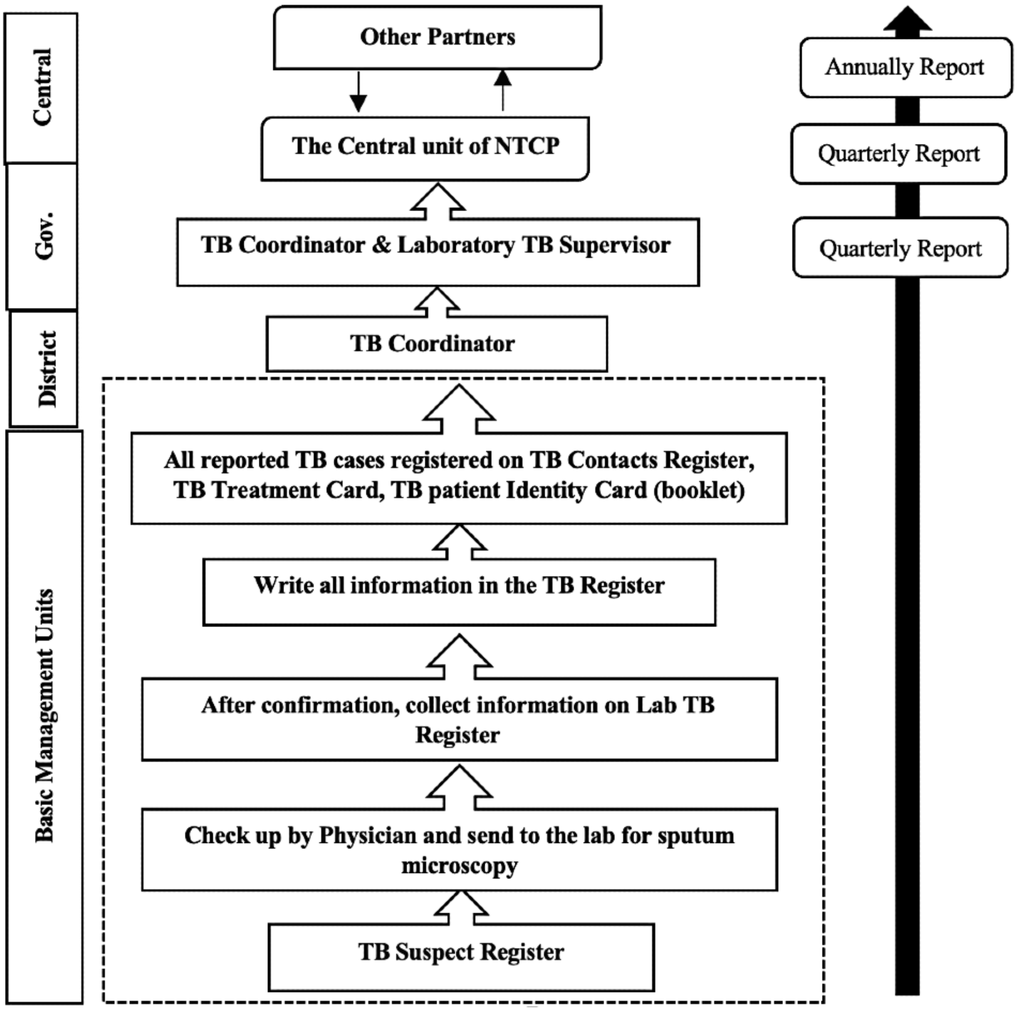
The NTCP was established in 1970 in the primary health care sector at the Ministry of Public Health and Population (MoPHP). The Tuberculosis Control Program is a tool for tuberculosis control strategy implementation within a national health system. As such, the NTCP, a vehicle for the directly observed treatment short course (DOTS) strategy since 1995, was used to reach the global targets for detection of at least 70% of cases and treatment success of at least 85%. The NTCP expanded the DOTS strategy gradually to cover all the existing 333 districts until the DOTS coverage in the population reached 100% by the end of December 2007. The MoPHP was established and organized as a central unit of the NTCP in the framework of a national health program in 1995 [9].

As of 2006, the NTCP has adopted the WHO Stop Tuberculosis Strategy and has initiated the development of components. In late 2015, the NTCP adopted the WHO End Tuberculosis Strategy as a national policy to prevent, manage, and control tuberculosis [10]. There are four tuberculosis centers located in major governorates (Sana'a City, Aden, Taiz, and Al Hudaydah). They provided outpatient clinical, radiological, and bacteriological culture services. The laboratory network of tuberculosis control consisted of 271 microscopy laboratories [11].

Data Flow of the Tuberculosis Surveillance System

The following diagram of data flow (Figure 1) describes four levels of responsibility to ensure tuberculosis prevention, care, and control services from peripheral basic management units to the center of the NTCP within the tuberculosis system. Each of these levels has well-defined tasks. The NTCP has 13 forms, registers, and reports. Those were designed for paper-based recording and reporting systems that are used by the surveillance department for management of data at all districts. The tuberculosis control program activities were highly dependent on international donors, the WHO, Japan International Cooperation Agency, and the Global Fund to Fight AIDS.

Figure 1. Data flow of the TB Surveillance System in Yemen. Gov: government; NTCP: National Tuberculosis Control Program; TB: tuberculosis.



Participants' Characteristics

A total of 54 participants were involved, 57% (n=31) were males and 43% (n=23) females. Almost half of the participants 50% (n=27) were lab technicians.

Findings From Qualitative Data

Usefulness

Table 1 shows that the overall score percent for usefulness was 71% (57/80), indicating an average rank. Only 40% (4/10) of participants mentioned that the tuberculosis surveillance data provided estimates of the tuberculosis magnitude, incidence, prevalence, and mortality, and helped in resource planning, prevention, care, and control.

Some participants mentioned:

> *The lack of reporting from the private sector leads to the presence of a gap between the estimated number of new cases and the number of actually detected cases.*

Table 1. The usefulness of the TB surveillance system by score, score percent, and rank in Sana’a City, 2018 (n=10).

Indicators	Score	Score percent	Rank
The system data provide estimates of the TB[a] magnitude, incidence, prevalence, and mortality	4	40	Poor
The system data were used to monitor trends of TB over time	10	100	Good
The system data can identify areas with anti-TB drugs failure	2	20	Poor
The system data were used for procurement of anti-TB drugs and laboratory reagents when needed	10	100	Good
The system data can be used to recognize the high-risk groups	10	100	Good
The system data helped in resource planning, prevention, care, and control	4	40	Poor
The system data were used to update and develop the national policy strategy for TB control	7	70	Average
The system data were used to assess the impact of interventions	10	100	Good
Overall	57	71	Average

[a]TB: tuberculosis.

The Tuberculosis Surveillance System Attributes

Flexibility

The overall score of flexibility was 75% (30/40) that reveals an average performance. Two out of four indicators of the flexibility attribute, “The system can accommodate any changes in reporting method” and “The system can integrate the surveillance of another disease,” had good rank. The indicator “The system can accommodate data changes with minimum cost and efforts” was poorly ranked (Table 2).

Table 2. The flexibility of the tuberculosis surveillance system by score, score percent, and rank in Sana’a City, 2018 (n=10).

Indicators	Score	Score percent	Rank
The system can accommodate with changes in case definition	7	70	Average
The system can accommodate any changes in reporting method	10	100	Good
The system can integrate the surveillance of other disease	10	100	Good
The system can accommodate data changes with minimum cost and efforts	3	30	Poor
Overall	30	75	Average

Stability

The overall stability of the system scored 15% (3/20), which indicates a poor performance. Both indicators of stability (“The system is stable after sponsors withdraw their support” and “The system does not require time to manage the data”) had a poor rank (Table 3).

Table 3. The stability of the tuberculosis surveillance system by score, score percent, and rank in Sana’a City, 2018 (n=10).

Indicators	Score	Score percent	Rank
The system is stable after sponsors withdraw their support	0	0	Poor
The system does not require time to manage the data	3	30	Poor
Overall	3	15	Poor

Simplicity

Regarding simplicity, out of 11 indicators, 6 indicators had a poor ranking. Two of the indicators had a good rank. The overall simplicity of the system scored 59% (863/1452), which indicates a poor performance (Table 4).

Table 4. The simplicity and acceptability attributes of the TB surveillance system by score, percent score, and rank in Sana'a City, 2018 (n=44).

Indicators	Score	Score percent	Rank
The system has standard case definitions for TB[a]	121	92	Good
The case definition for TB is easy to use	111	84	Good
Report forms are available	97	73	Average
Report forms are easy to fill	70	53	Poor
Data collection is not time consuming	61	46	Poor
Transmitting data to the central level is easy	59	45	Poor
Follow-up of cases is easy	48	36	Poor
Anti-TB drugs and laboratory reagents are available in a health facility to confirm diagnosis	99	75	Average
Staff received training for TB surveillance	64	48	Poor
Training courses are performed frequently	47	36	Poor
The system is responsive to suggestions	86	65	Average
Overall	863	59	Poor

[a]TB: tuberculosis.

Acceptability

Regarding the acceptability attribute, the statement related to willingness to participate in the tuberculosis surveillance system had an average rank of 88% (116/132). However, the satisfaction with the tuberculosis surveillance system had a poor rank of 44% (58/132). The overall acceptability score was 66% (174/264), which indicates average performance (Table 5).

Table 5. The acceptability attributes of the TB surveillance system by score, percent score, and rank in Sana'a City, 2018 (n=44).

Indicators	Score	Score percent	Rank
I am willing to participate in the system	116	88	Average
I am satisfied with the TB[a] surveillance system	58	44	Poor
Overall	174	66	Average

[a]TB: tuberculosis.

Findings From Quantitative Data

Data Quality

Regarding data quality, we have reviewed four tuberculosis reports; each report includes six format types. These formats were compared with the database. Four out of six forms were complete and accurate. However, the completeness and accuracy of the other two forms were zero. The overall data quality score was 67% (4/6), which ranked as average (Table 6).

Table 6. The completeness and accuracy of TB reports in Sana'a City, 2018.

Forms	Completeness (%)	Accuracy (%)
TB[a] case finding	100	100
Demographic characteristics	100	100
Sputum smear microscopy conversion	100	100
TB treatment outcomes	100	100
TB suspect	0	0
TB contacts	0	0
Overall	67	67

[a]TB: tuberculosis.

Sensitivity

The sensitivity of the tuberculosis surveillance system was 96%, which ranked as good. The sensitivity calculated by using the formula of (A / A + C) was as follows: sensitivity = 78 / 81 × 100 = 96% (Table 7).

Table 7. Distribution of direct smear microscopy and culture of tuberculosis cases to assess the sensitivity and positive predictive value in Sana'a City, 2018

DSM[a]	Culture, n		Total
	Positive	Negative	
Positive	78 (true positive A)	29 (false positive B)	107
Negative	3 (false negative C)	9 (true negative D)	12
Total	81	38	119

[a]DSM: direct smear microscopy.

Positive Predicative Value

The PPV of the tuberculosis surveillance system was 73%, which ranked as average. It was calculated by using the formula of (A / A + B), that is, the following: PPV = 78 / 107 × 100 = 73% (Table 7).

Strengths and Weaknesses of the Tuberculosis Surveillance System

Although the tuberculosis surveillance system had strength points that included the presence of an infrastructure system, qualified human resources, availability of antituberculosis drugs, and the presence of the coordination for tuberculosis activities at all levels, it had many weak points such as depending on external donors and a bureaucrat structure (a large number of hard copies) that lead to delay in its implemented activities in addition to a lack the motivation of human resources, lack of refreshment training for medical officers, poor coordination with other health sectors (private), and high turnover among medical officers at a peripheral level due to political crises and security situations.

Discussion

Principal Findings

Evaluation of any surveillance system is the cornerstone for its improvement and ensuring proper morbidity and mortality indicators. It is important to identify the weaknesses and strengths of the system and provide decision makers with evidence-based data to decide on its continuity.

Our study findings showed that the tuberculosis surveillance system was useful. It helps in monitoring trends of tuberculosis and estimates the need for antituberculosis drugs and laboratory reagents at all levels. These findings are similar to other studies in Afghanistan, Yemen, and Pakistan [7,8,12].

The flexibility of the tuberculosis surveillance system was ranked as average. It has been integrated with HIV and AIDS. The NTCP has a counseling clinic where each tuberculosis case was referred to undergo voluntary counseling and testing. Our findings are consistent with the results found in previous evaluations carried out in Pakistan and Zimbabwe [12,13].

Regarding the stability of the tuberculosis surveillance system, it was poor because of its total dependency on the donors in addition to the government's support for first-line antitubercuolosis drugs and the salary of the staff being completely suspended since 2014, as consequences of political and security crises. In addition, prolonged procedures to release funds from the Global Fund to implement tuberculosis control activities may lead to abandoning the activity implementation. Although, this finding is similar to what has been reported in Yemen and Zimbabwe [8,13]. Other studies showed stable tuberculosis surveillance systems [7,14].

The simplicity of the system was poorly rated for several reasons including data collection being time-consuming, the staff not receiving adequate training on tuberculosis surveillance, training courses not performed frequently, and report forms not easy to fill. Similar findings have been reported in Afghanistan and Zimbabwe [7,13]. However, this finding is not consistent with the findings in previous studies in Yemen, Pakistan, and South Africa [8,12,14].

This evaluation shows that the acceptability was average, as the focal points are willing to participate in the dengue surveillance system; however, they were poorly satisfied. This finding agrees with the findings of others in Afghanistan and Yemen [7,8] but disagrees with other studies in Harare City [15].

The data quality of the tuberculosis system was average. These findings were consistent with findings of other studies conducted in Harare City [15] but inconsistent with another study in the Republic of South Africa [14,16].

The sensitivity and the PPV of the system were good and average, respectively. These results are aline with a previous study in Afghanistan and Eden District [7,14]. However, they disagree with a study in Pakistan [12].

Limitations

This evaluation was carried out in Sana'a City and targeted only the health facilities providing tuberculosis services (purposive sample) due to time and funds constraints.

Conclusions

The tuberculosis surveillance system was found useful. Flexibility, PVP, and data quality were average. Stability, acceptability, and simplicity were poor. The sensitivity was good.

The main weaknesses in the tuberculosis surveillance system included a lack of governmental finances, a paper-based system, and a lack of regular staff training. Developing an electronic system, securing governmental financial support, and training the staff on tuberculosis surveillance are strongly recommended to improve the system performance.

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Conflicts of Interest

None declared.

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Abbreviations

CDC: Centers for Disease Control and Prevention
DOTS: directly observed treatment short course
MoPHP: Ministry of Public Health and Population
NTCP: National Tuberculosis Control Program
PPV: positive predictive value

WHO: World Health Organization

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Original Paper

Association of Substance Use With Behavioral Adherence to Centers for Disease Control and Prevention Guidelines for COVID-19 Mitigation: Cross-sectional Web-Based Survey

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Abstract

Background: Substance use is a risk factor for COVID-19 infection and adverse outcomes. However, reasons for elevated risk for COVID-19 in substance users are not well understood.

Objective: The aim of this study was to evaluate whether alcohol or other drug use is associated with adherence to Centers for Disease Control and Prevention (CDC) guidelines for COVID-19 mitigation. Preregistered analyses tested the hypothesis that greater use of alcohol and other drugs would be associated with lower CDC guideline adherence. A secondary objective was to determine whether substance use was associated with the likelihood of COVID-19 testing or outcome.

Methods: A cross-sectional web-based survey was administered to a convenience sample recruited through Amazon's Mechanical Turk platform from June 18 to July 19, 2020. Individuals aged 18 years or older and residing in Connecticut, Massachusetts, New Jersey, New York, or Rhode Island were eligible to participate. The exposure of interest was past 7-day use of alcohol, cigarettes, electronic cigarettes, cannabis, stimulants, and nonmedical opioids. The primary outcome was CDC guideline adherence measured using a scale developed from behaviors advised to reduce the spread of COVID-19. Secondary outcomes were likelihood of COVID-19 testing and a positive COVID-19 test result. All analyses accounted for the sociodemographic characteristics.

Results: The sample consisted of 1084 individuals (mean age 40.9 [SD 13.4] years): 529 (48.8%) men, 543 (50.1%) women, 12 (1.1%) other gender identity, 742 (68.5%) White individuals, 267 (24.6%) Black individuals, and 276 (25.5%) Hispanic individuals. Daily opioid users reported lower CDC guideline adherence than nondaily users (B=–0.24, 95% CI –0.44 to –0.05) and nonusers (B=–0.57, 95% CI –0.76 to –0.38). Daily alcohol drinkers reported lower adherence than nondaily drinkers (B=–0.16, 95% CI –0.30 to –0.02). Nondaily alcohol drinkers reported higher adherence than nondrinkers (B=0.10, 95% CI 0.02-0.17). Daily opioid use was related to greater odds of COVID-19 testing, and daily stimulant use was related to greater odds of a positive COVID-19 test.

Conclusions: In a regionally-specific, racially, and ethnically diverse convenience sample, adults who engaged in daily alcohol or opioid use reported lower CDC guideline adherence for COVID-19 mitigation. Any opioid use was associated with greater odds of COVID-19 testing, and daily stimulant use was associated with greater odds of COVID-19 infection. Cigarettes, electronic cigarettes, cannabis, or stimulant use were not statistically associated with CDC guideline adherence, after accounting for sociodemographic covariates and other substance use variables. Findings support further investigation into whether COVID-19 testing and vaccination should be expanded among individuals with substance-related risk factors.

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KEYWORDS

SARS-CoV-2; novel coronavirus; COVID-19; alcohol use; alcohol drinking; opioid use; stimulant use; nicotine; smoking; survey; substance abuse; addiction; mental health; pandemic

Introduction

The use of alcohol, tobacco, and other drugs has been identified as a risk factor for infection with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus responsible for the COVID-19 pandemic [1,2]. Substance use may increase risk through both biological and behavioral pathways [3]. First, chronic use compromises the immune system and major organs, including cardiac, pulmonary, and renal systems [4,5]. Second, potential behavioral pathways for COVID-19 infection include decreased inhibition, increased risk-taking behavior, and competing contingencies (eg, perceived need to obtain and use substances despite risk of exposure) [6]. A recent study found that substance use disorder diagnosis was associated with greater risk of coronavirus infection (adjusted odds ratio 8.7) and higher death rates [1]. While this finding may be partially explained by higher rates of medical comorbidities that confer increased risk for and severity of COVID-19 among individuals with substance use disorder, behavioral factors were not assessed [1].

Emerging data indicate changes in substance use and related problems in the United States during the pandemic. In a Centers for Disease Control and Prevention (CDC) survey, 13% of US adults reported initiating or increasing substance use to deal with COVID-19–related stress [7]. Another representative survey of US adults reported a 27% increase in average drinks per day and a 26% increase in frequency of binge drinking [8]. Smoking in young adults has shown signs of increased quit rates or reduced frequency overall, but increased quantity on use days [9,10]. Perhaps the starkest indicator is the increase in overdose deaths involving opioids, cocaine, and methamphetamine in 2020 [11,12].

The CDC recommends several behaviors to mitigate the spread of SARS-CoV-2, including avoiding close contact with others outside the household, handwashing, and wearing a face covering [13]. States have employed diverse mandates to control the spread of COVID-19, including limitations on social gatherings, business closures, and stay-at-home orders. Adherence to CDC guidelines and state mandates may be affected by substance use. For example, young adults under stay-at-home orders reported a higher number of in-person contacts outside the household on days they consumed alcohol [14]. Although other studies have assessed factors associated with adherence to COVID-19 mitigation behaviors, most have not addressed substance use [15,16]. Because the pandemic itself appears to be associated with increases in some types of substance use, understanding whether substance use is associated with lower adherence to CDC mitigation guidelines is pressing. Finding an association between substance use and suboptimal preventive behaviors would help to identify specific at-risk groups and to generate hypotheses on mechanisms underlying nonadherence to guidelines.

The objective of this study was to investigate links between use of specific substances and behavioral adherence to CDC guidelines in a sample of US adults surveyed in June and July 2020. Our main hypothesis predicted that greater substance use would be associated with lower CDC guideline adherence after accounting for demographic and contextual factors that have been associated with CDC guideline adherence or related health behaviors in previous studies, such as age and income [15-19]. Given that lower guideline adherence would have an expected association with COVID-19 exposure and infection, secondary analyses tested whether substance use was associated with the likelihood of receiving a COVID-19 test or with the outcome of testing.

Methods

Study Design and Data Source

This study was a deidentified, web-based, cross-sectional survey with a nonprobability sample. Participants were recruited using Amazon's Mechanical Turk (MTurk) platform. MTurk is a crowdsourcing platform with a built-in survey administration system that allows researchers access to a pool of >200,000 potential respondents, producing data of quality equal to or better than professionally sourced panels [20-23]. Our study focused on 5 northeastern states (Connecticut, Massachusetts, New Jersey, New York, and Rhode Island) that had the highest numbers of COVID-19 cases and deaths per capita in the United States at the time [24]. A pilot was released on May 27, 2020, for survey refinement. The final survey was released from June 18 to July 19, 2020, at which time the 5 states had restrictions on business capacity and social gatherings (see Table S1 in Multimedia Appendix 1). This study was an initiative of the Center for Addiction and Disease Risk Exacerbation to examine the link between substance use and disease [25].

Participants

Eligibility criteria were as follows: ≥18 years of age, residing in an eligible state (Connecticut, Massachusetts, New Jersey, New York, or Rhode Island), and holding an active MTurk account. Quotas based on age, gender, race, and ethnicity were used to ensure a diverse sample. Black and Hispanic individuals were oversampled owing to overwhelming evidence that such individuals have been disproportionately affected by the pandemic [26-30]. Race and ethnicity quotas were as follows: 40% non-Hispanic White, 25% Hispanic non-Black, 25% Black any ethnicity, and 10% non-Hispanic non-White. Within each racial/ethnic group, the following age quotas were applied: 10%, 18-25 years; 20%, 25-35 years; 20%, 35-45 years; 25%, 45-55 years; and 25%, ≥55 years. Percentages were allocated to each age range (which are preset in the MTurk system) to ensure broad representation of ages and specifically to avoid the underrepresentation of older adults often observed in web-based survey studies [31]. Within each cell type based on race/ethnicity and age, quotas stipulated equal numbers of men and women. Interested individuals completed a brief screening survey to assess demographics and were directed to the main survey if their quotas were not already filled. Participants provided written informed consent before beginning the survey. Participants were paid US $10 upon completion. This study was reviewed by the Brown University Institutional Review Board and was determined to be exempt from requiring Institutional Review Board approval as a minimal risk study per federal regulations.

Measurements

Sociodemographic Characteristics

Demographic characteristics included age, sex, gender identity, highest level of education, annual household income, and home ownership. These variables have demonstrated associations with adherence to COVID-19 prevention/mitigation behaviors in US adults in previous research [15-18] aside from home ownership, a proxy for wealth, which was chosen due to relations with health behaviors in other contexts [19]. Race and ethnicity were assessed with a two-item measure from the 2020 Household Pulse Survey [32]. Individuals indicated whether they were Hispanic, Latino, or of Spanish origin, and selected all races that applied. Participants were asked essential worker status, defined as “someone whose work is critical to business operations and/or meeting basic human needs and is required to attend work during the COVID pandemic” (yes/no/not sure).

Primary Outcome: CDC Guideline Adherence

The primary outcome was measured using a self-report questionnaire that we developed from the CDC’s recommendations for behaviors in which the public should engage to mitigate COVID-19 transmission (see Table 1). Participants rated how often they engaged in 13 recommended behaviors during the past 4 weeks on a scale from 0 (rarely or never) to 3 (always), with higher scores representing higher adherence. Parallel analysis and inspection of factor loadings supported use of the total item average as a unidimensional construct reflecting CDC guideline adherence. The internal consistency reliability was excellent (Cronbach α .91).

Table 1. Primary outcome: Centers for Disease Control and Prevention guideline adherence measure.[a]

During the past 4 weeks, how often did you…	Always	Usually	Sometimes	Rarely or Never
Wash your hands often with soap and water for at least 20 seconds especially after you have been in a public place, or after blowing your nose, coughing, or sneezing?				
Use hand sanitizer that contains at least 60% alcohol when soap and water was not readily available?				
Avoid touching your eyes, nose, and mouth?				
Avoid close contact with people who are sick?				
Remain at least 6 feet away from other people when in public?				
Stay home as much as possible?				
Use a cloth face cover over your nose and mouth when in public?				
Cover your mouth and nose with a tissue or use the inside of your elbow when you coughed or sneezed?				
Throw used tissues in the trash?				
Immediately wash your hands with soap and water for at least 20 seconds after coughing or sneezing?				
Clean and disinfectant frequently touched surfaces in your home (eg, tables, doorknobs, light switches, countertops, desks, phones, toilets, faucets)?				
Use detergent or soap and water to clean dirty surfaces before disinfection?				
When cleaning surfaces, how often did you use any of the following: a diluted household bleach, a solution that was at least 70% alcohol, or another EPA[b]-registered household disinfectant?				

[a]Participants rated how often they engaged in the recommended behaviors in this table during the past 4 weeks on a scale from 0 (rarely or never) to 3 (always), with higher scores representing higher adherence.

[b]EPA: Environmental Protection Agency.

Secondary Outcome: COVID-19 Exposure and Testing

COVID-19 testing and test results were the secondary outcomes. Testing history was assessed by asking “Have you been tested for the novel coronavirus or COVID-19?” (yes/no/not sure). Answering “yes” prompted these follow-up questions: “Have you had a nose swab test for the virus that causes COVID-19?” and “Have you had a blood test to see if you already had the virus (“serology”)?” Each of these were followed with the question, “If yes, what was your result?”

Substance Use

Substance use was recorded using the Timeline Followback method [33] for the 7 days preceding survey completion. If the participant endorsed any use of cigarettes, electronic cigarettes (e-cigarettes), cannabis, alcohol, opioids, or stimulants, the participant was asked to report whether the substance was used on each day in the past week. For opioids only, participants were instructed, "Do not report any drug that was taken as directed by a physician." Past 7-day frequencies of alcohol, cigarette, e-cigarette, cannabis, stimulant, and nonmedical opioid use were recoded to reflect no use, 1-6 days of use, and daily use.

Statistical Analysis

The analytic plan was preregistered and can be accessed online [34]. A descriptive analysis assessed the univariate distributions of demographic characteristics, substance use variables, COVID-19 testing, and the CDC guideline adherence outcome. Continuous data were reported as mean (SD), and categorical variables were reported as count (percentage). Distributional properties of outcomes informed model selection. Code and data analysis were generated using SAS software, Version 9.4 for Windows (Copyright 2016 by SAS Institute Inc), and R version 4.0.3 [35]. Independent variables accounting for CDC guideline adherence score were evaluated using a general linear model with a continuous outcome and categorical and continuous independent variables. Preregistered covariates tested for inclusion included age (continuous), education (high school or less [reference], some college/1-year degree, college graduate/4-year degree, graduate or professional degree), gender (cisgender female [reference], cisgender male, other gender identity, or prefer not to answer), race (White [reference], Black or African American, Asian, other or more than one racial identity), ethnicity (not Hispanic or Latino [reference], Hispanic or Latino), essential worker status (not essential worker or unsure [reference], essential worker), income (8 ordered categories, treated as continuous), household size (continuous, truncated at 6 maximum), dwelling ownership (no ownership [reference], 1=ownership), and COVID-19 test (no test or unsure [reference]; yes, test negative; yes, test positive). Covariates that were not related to CDC guideline adherence in omnibus Type III sums of squares tests were removed and models retested. Next, focal substance use variables reflecting no use, 1-6 days of use, and daily use of alcohol, cigarettes, e-cigarettes, cannabis, stimulants, and nonmedical opioids were added. Substance use variables that were not related to CDC guideline adherence were removed and models retested. Follow-up two-sided *t* tests compared daily use to 1-6 day and no use categories and 1-6 days of use to no use. Adjusted R^2 and ΔR^2 evaluated the proportion of variability in CDC guideline adherence accounted for by variables included in the models.

A secondary set of logistic regression models tested associations of covariates and substance use variables with the likelihood of COVID-19 testing and results. An initial logistic model evaluated the likelihood of COVID-19 testing (0=no test or unsure, 1=test). Differences in testing likelihood according to substance use frequency prompted post hoc analyses on possible explanatory factors. The post hoc analyses used independent two-sided *t* tests for continuous variables and Pearson χ^2 tests for categorical variables. A subset analysis among those who reported a COVID-19 test evaluated the likelihood of a positive test result (0=negative, 1=positive). Covariates that were not related to COVID-19 testing or COVID-19 test results in omnibus Type III sums of squares tests were removed and models retested.

Results

Demographic Characteristics of the Participants

Of the 3849 individuals who were assessed for eligibility, 1185 completed the entire survey (see Figure 1). Data sets were excluded from the analysis if the participant did not pass at least 2 of the 3 validity checks embedded in the survey, for example, Please select the response "strongly agree" (n=12) or if the participant endorsed implausible or mutually exclusive responses on demographic items (n=18). Duplicate data (ie, multiple responses from the same individual) were identified in 17 cases and were removed from the data set. Final models had 1084 participants after excluding participants with missing data for covariates. Demographic information for the evaluable data set including 1084 participants is provided in Table 2. Half of the study sample was males, and the mean age was 40.9 years. The majority of the sample consisted of Whites and had a college degree. Black individuals made up 24.6% (267/1084) of the sample and 25.5% (276/1084) of the participants identified as Hispanic. Approximately one-quarter of the sample had a history of COVID-19 testing. Of those who received a test, 15.8% (44/279) had a positive result. Of the 1084 participants, 700 (64.6%) reported substance use in the past 7 days. Cigarettes were the most common substance used daily, followed by alcohol and opioids. One-third of the sample reported nondaily alcohol use. The majority reported monosubstance use (382/1084, 35.2%), and alcohol was the most common single substance used (252/1084, 23.2%). Polysubstance use (2 or more substances) was reported by 318 individuals (29.3%). The most common combinations of substances were alcohol and opioids (41/1084, 3.8%), alcohol and cigarettes (36/1084, 3.3%), opioids and cigarettes (35/1084, 3.2%), and alcohol and marijuana (23/1084, 2.1%). Other polysubstance combinations were reported by <2% of the sample (<22 individuals per cell).

Figure 1. Sample selection of residents of Connecticut, Massachusetts, New Jersey, New York, and Rhode Island for a web-based survey of health behaviors and Centers for Disease Control and Prevention guideline adherence in June-July 2020.

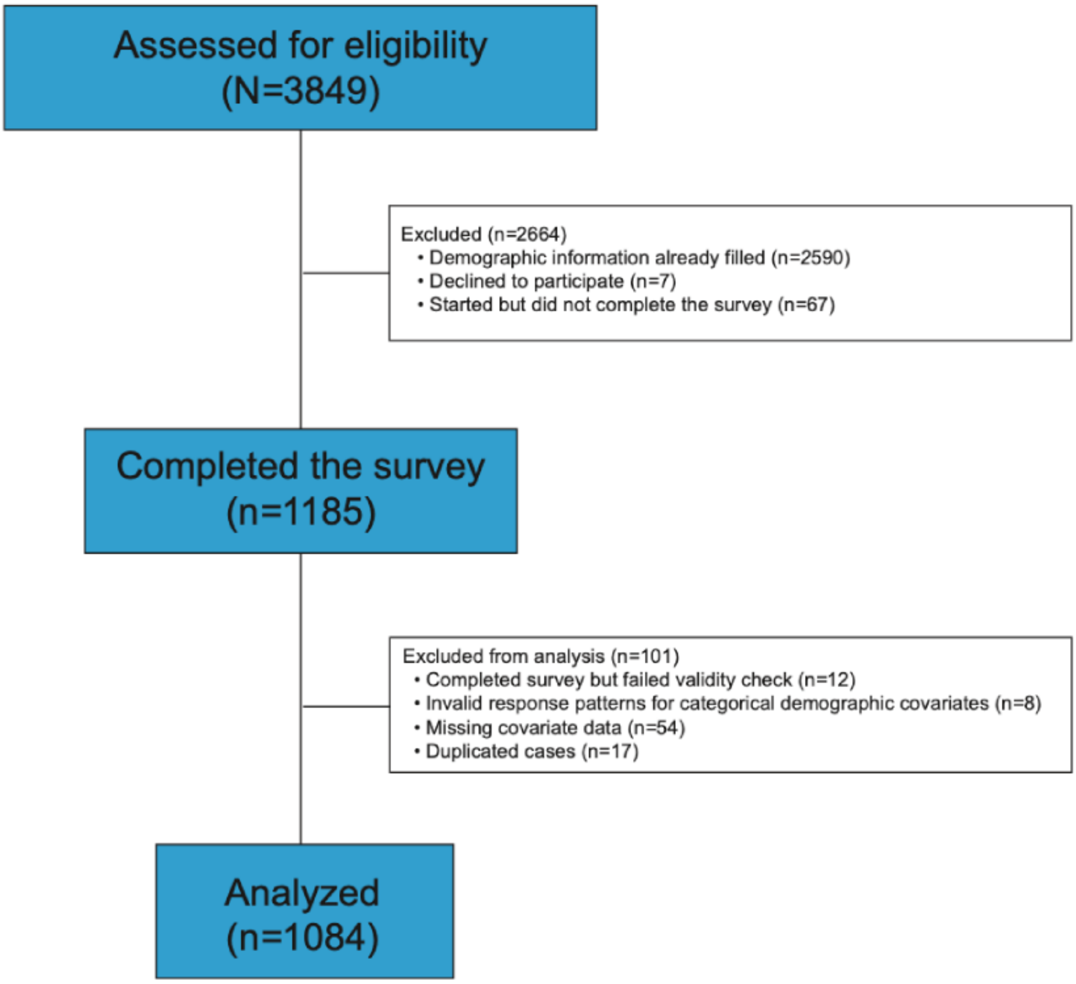

Table 2. Characteristics of the participants (N=1084) in the web-based survey of health behaviors and Centers for Disease Control and Prevention guideline adherence conducted in June-July 2020.

Variable	Value	Recode information
Age (years), mean (SD)	40.9 (13.4)	None
Sex (assigned at birth), n (%)		We created a combined sex and gender variable recoded to cisgender male if sex="male" and gender="man" and no other gender endorsed, cisgender female if sex="female" and gender="woman" and no other gender endorsed, and other for all other combinations.
Male	540 (49.8)	
Female	536 (49.5)	
Prefer not to answer	8 (0.7)	
Gender (select all that apply), n (%)		We created a combined sex and gender variable recoded to cisgender male if sex="male" and gender="man" and no other gender endorsed, cisgender female if sex="female" and gender="woman" and no other gender endorsed, and other for all other combinations.
Man	529 (48.8)	
Woman	543 (50.1)	
Nonbinary	6 (0.6)	
Transgender	4 (0.4)	
Other or prefer not to answer	9 (0.8)	
Race (select all that apply), n (%)		We created 4 race categories recoded to White if race="White" and no other race endorsed, Black or African American if race="Black or African American" and no other race endorsed, Asian if race=any of "Asian Indian | Chinese | Filipino | Japanese | Korean | Vietnamese | Other Asian" and no other race endorsed; and Other Race or More Than One for all other endorsed categories.
White	742 (68.5)	
Black or African American	267 (24.6)	
American Indian or Alaskan Native	26 (2.4)	
Asian Indian	34 (3.1)	
Chinese	31 (2.9)	
Filipino	6 (0.5)	
Japanese	3 (0.3)	
Korean	7 (0.6)	
Vietnamese	1 (0.1)	
Other Asian	15 (1.4)	
Native Hawaiian	2 (0.2)	
Guamanian or Chamorro	1 (0.1)	
Other Pacific Islander	5 (0.5)	
Ethnicity (select all that apply), n (%)		We dichotomized ethnicity to Not of Hispanic, Latino/Latina, or Spanish origin, and all other endorsed categories
Not of Hispanic, Latino/Latina, or Spanish Origin	808 (74.5)	
Mexican, Mexican American, or Chicano/Chicana	76 (7.0)	
Puerto Rican	42 (3.9)	
Cuban	14 (1.3)	
Another Hispanic, Latino/Latina, or Spanish origin	155 (14.3)	
Education, n (%)		None

Variable	Value	Recode information
College graduate	547 (50.5)	
Some college	215 (19.8)	
Professional degree	215 (19.8)	
High school or lower	107 (9.9)	
Annual household income, n (%)		Eight ordered categories were treated continuously.
Less than US $25,000	123 (11.4)	
US $25,000-$34,999	122 (11.3)	
US $35,000-$49,999	152 (14.0)	
US $50,000-$74,999	287 (26.5)	
US $75,000-$99,999	188 (17.3)	
US $100,000-$149,999	139 (12.8)	
US $150,000-$199,999	39 (3.6)	
US $200,000 and above	34 (3.1)	
Household size	3.06 (1.33)	None
Dwelling ownership (yes)	507 (46.8)	None
Essential worker, n (%)		Dichotomized to Yes and No or unsure.
No	641 (59.1)	
Yes	388 (35.8)	
Unsure	55 (5.1)	
Centers for Disease Control and Prevention adherence	2.20 (0.62)	None
COVID-19 testing history, n (%)		None
No test or unsure	805 (74.3)	
Yes	279 (25.7)	
COVID-19 test result (n=279), n (%)		Either a positive nasal or blood test was recoded as a positive COVID-19 test result.
Negative	235 (84.2)	
Positive	44 (15.8)	
Substance use, n (%)		
Cigarette use (past 7 days)		Recoded from Timeline Followback
None	865 (79.8)	
Nondaily (1-6 days)	66 (6.1)	
Daily (7 days)	153 (14.1)	
Electronic cigarette use (past 7 days), n (%)		Recoded from Timeline Followback
None	995 (91.8)	
Nondaily (1-6 days)	39 (3.6)	
Daily (7 days)	50 (4.6)	
Cannabis (past 7 days), n (%)		Recoded from Timeline Followback. Includes use of any form of cannabis
None	973 (89.8)	
Nondaily (1-6 days)	49 (4.5)	
Daily (7 days)	62 (5.7)	
Alcohol (past 7 days), n (%)		Recoded from Timeline Followback
None	643 (59.3)	
Nondaily (1-6 days)	356 (32.8)	

Variable	Value	Recode information
Daily (7 days)	85 (7.8)	
Opioids (past 7 days), n (%)		Recoded from Timeline Followback. Includes use of any opioids
None	858 (79.2)	
Nondaily (1-6 days)	180 (16.6)	
Daily (7 days)	46 (4.2)	
Stimulants (past 7 days), n (%)		Recoded from Timeline Followback
None	1015 (93.6)	
Nondaily (1-6 days)	42 (3.9)	
Daily (7 days)	27 (2.5)	

CDC Guideline Adherence

Covariates tested for inclusion are reported in Table 2. The following variables were statistically related to CDC guideline adherence and retained in the model: gender, ethnicity, essential worker status, income, and COVID-19 test. Covariates accounted for 7.1% of the variance in CDC guideline adherence (R^2=0.071, adjusted R^2=0.057). Unadjusted relations of substance use variables with CDC guideline adherence scores are provided in Table S2 in Multimedia Appendix 1. Cigarette, alcohol, opioid, and stimulant use were related to CDC guideline adherence scores in bivariate models. In the multivariable model including all substance use variables and significant covariates from Table 1, only alcohol consumption and opioid use were statistically related to CDC guideline adherence. The results of the final model are reported in Table 3. Participants who reported daily opioid use reported lower CDC guideline adherence than participants who reported 1-6 opioid use days or no opioid use. Likewise, participants who reported 1-6 opioid use days reported lower adherence than those who reported no use. Participants who reported 1-6 drinking days reported higher CDC guideline adherence than participants who reported daily drinking or no drinking, whereas daily drinkers and nondrinkers did not differ statistically on CDC adherence. The final model retaining only significant covariates, alcohol use, and opioid use accounted for 12.9% of the variance in CDC guideline adherence (R^2=0.129, adjusted R^2=0.120), where the covariate model reported above had accounted for 7.1% of the variance in CDC guideline adherence. Thus, when considering influences on CDC adherence, alcohol and opioid use contributed nearly as much to understanding adherence as did the combination of gender, ethnicity, essential worker status, income, and COVID-19 test.

Table 3. General linear model of associations between substance use and Centers for Disease Control and Prevention guideline adherence, accounting for covariates in the full sample of survey participants (N=1084).

Variable	Unstandardized estimate	95% CI
Intercept	2.26	2.19 to 2.37
Gender		
Cisgender female	Ref[a]	Ref
Cisgender male	−0.17	−0.24 to −0.10
Other gender identity or prefer not to answer	−0.42	−0.62 to −0.21
Hispanic or Latino (Ref: No)	−0.05	−0.13 to 0.03
Essential worker (Ref: No)	−0.04	−0.13 to 0.04
Income	0.02	0.004 to 0.04
COVID-19 test		
No test or unsure	Ref	Ref
Negative test	0.10	0.01 to 0.19
Positive test	−0.02	−0.21 to 0.17
Alcohol use (past 7 days)		
Daily versus none	−0.07	−0.20 to 0.06
1-6 days versus none	0.10	0.02 to 0.17
Daily versus 1-6 days[b]	−0.16	−0.30 to −0.02
Opioid use		
Daily versus none	−0.57	−0.76 to −0.38
1-6 days versus none	−0.32	−0.43 to −0.22
Daily versus 1-6 days[b]	−0.24	−0.44 to −0.05

[a]Ref: reference category.

[b]Indicates reference groups and additional models for substance use variables where reference groups were switched to allow for additional comparisons.

COVID-19 Testing

The relation of CDC guideline adherence with COVID-19 testing was also evaluated and found to be not statistically related. Of the covariates in Table 2, the following were related to the likelihood of COVID-19 testing: age, education, race, ethnicity, essential worker status, income, and household size. Of substance use variables, only opioid use was statistically related to testing likelihood. The results of the final model are reported in Table 4. For a daily opioid user, the odds of reporting COVID-19 testing were 3.35 times as large as the odds for a nonuser and 1.61 times as large as the odds for a participant who used opioids on 1-6 days.

Table 4. Logistic regression model of associations between substance use and any COVID-19 testing, accounting for covariates in the full sample of survey participants (N=1084).[a]

Variable	Unadjusted prevalence and percentage testing within category, n (%)	Odds ratio (95% CI)
Age	N/A[b]	1.01 (1.00-1.02)
Education		
Graduate or professional degree	64 (29.8)	Ref[c]
College graduate/4-year degree	162 (29.6)	0.70 (0.47-1.05)
High school or less	19 (17.8)	0.45 (0.23-0.86)
Some college/2-year degree	34 (15.8)	0.41 (0.24-0.69)
Hispanic or Latino	118 (42.8)	1.67 (1.18-2.37)
Not Hispanic or Latino	161 (19.9)	Ref
Racial identity		
White	165 (23.2)	Ref
Asian	9 (11.7)	0.66 (0.31-1.44)
Black or African American	89 (37.2)	1.60 (1.12-2.30)
Other or more than one	16 (27.6)	1.26 (0.63-2.52)
Essential worker	164 (42.3)	2.22 (1.60-3.09)
Not essential worker	115 (16.5)	Ref
Income	N/A	0.85 (0.77-0.94)
Household size	N/A	1.33 (1.17-1.50)
Opioid use		
Daily versus none	32[d] (69.6[d])	3.35 (1.63-6.86)
1-6 days versus none	93[e] (51.7[e])	2.08 (1.39-3.11)
Daily versus 1-6 days	*154[f] (18.0[f])*	*1.61 (0.78-3.34)*

[a]Italicized text indicates reference groups and additional models for substance use variables where reference groups were switched to allow for additional comparisons. Unadjusted prevalence values are provided for categorical variables only.

[b]N/A: not applicable.

[c]Ref: reference category.

[d]Daily.

[e]1-6 days.

[f]None.

Following the finding that daily and nondaily opioid users were more likely to receive a COVID-19 test, we conducted 2 post hoc analyses on factors that might plausibly lead to higher testing rates in opioid users. First, we asked whether opioid users had significantly higher rates of comorbid medical conditions known to increase the risk of COVID-19 in their households by comparing the count of how many of the following conditions were endorsed by the participants: autoimmune disease, cardiovascular disease, cerebrovascular disease, chronic lung disease, diabetes, immune compromise, or kidney disease. Independent *t* tests showed no difference in this count of medical conditions between daily users versus nonusers (t_{902}=–0.016, *P*=.98) or between nondaily users versus nonusers (t_{1036}=–1.333, *P*=.18). Second, we asked whether engagement in medication-assisted treatment (MAT) for opioid use disorder was associated with a higher likelihood of receiving a COVID-19 test. In the total sample, MAT was endorsed by 61% (28/46) of daily opioid users, 32.2% (58/180) of nondaily opioid users, and 2.1% (18/858) of nonusers. Among opioid users, 40.7% (57/140) of opioid users not engaged in MAT received a COVID-19 test, whereas 79% (68/86) of opioid users engaged in MAT received a COVID-19 test. This difference was significant (Pearson χ^2_1=31.8, *P*<.001). In summary, MAT engagement was associated with higher rates of COVID-19 testing in nondaily and daily opioid users. The likelihood of a positive result was evaluated among the subset who received a COVID-19 test. The following Table 2 covariates were statistically related to a positive result: ethnicity, household size, and dwelling ownership. Of substance use variables, only stimulant use statistically related to testing likelihood. The results of the final model are reported in Table 5. For a daily stimulant user, the odds of reporting a positive COVID-19 test among those who were tested was significantly higher for daily users than that for either nonusers or those who reported use on 1-6 days. There was no statistically significant difference in receiving a positive COVID-19 test for nondaily stimulant users versus nonusers.

Table 5. Logistic model of associations of stimulant use with positive COVID-19 test result, accounting for covariates, in the subset of participants reporting a COVID-19 test (n=279).[a]

Variable	Unadjusted prevalence and percentage testing within category, n (%)	Odds ratio (95% CI)
Hispanic or Latino	28 (23.7)	2.00 (1.96-4.19)
Not Hispanic or Latino	16 (9.9)	Ref[b]
Household size	N/A[c]	1.49 (1.08-2.07)
Dwelling ownership	15 (11.2)	0.45 (0.21-0.95)
No dwelling ownership	29 (20.0)	Ref
Stimulant use		
Daily versus none	12[d] (70.6[d])	10.49 (3.19-34.44)
1-6 days versus none	5[e] (18.5[e])	1.44 (0.49-4.25)
Daily versus 1-6 days	27[f] (11.5[f])	7.29 (1.66-32.05)

[a]Italicized text indicates reference groups and additional models for substance use variables where reference groups were switched to allow for additional comparisons. Unadjusted prevalence values are provided for categorical variables only.

[b]Ref: reference category.

[c]N/A: not applicable.

[d]Daily.

[e]1-6 days.

[f]None.

Discussion

Principal Results

This study tested the hypothesis that heavier substance use would be associated with lower adherence to CDC guidelines to reduce the spread of COVID-19. Our geographic focus was 5 states that had experienced the highest rates of COVID infection and deaths at the time of the survey [24]. Our hypothesis was partially supported in that daily drinkers reported lower adherence than those who drank 1-6 days per week, and daily opioid users reported lower adherence than those who used opioids 1-6 days per week or not at all. However, we did not observe statistical associations of cigarettes, e-cigarettes, cannabis, or stimulant use with CDC guideline adherence, after accounting for sociodemographic covariates and other substance use variables.

Use of some substances was related to the likelihood either of receiving a COVID-19 test or of receiving a positive test. The odds of COVID-19 testing were 3.35 times as large for daily opioid users as for nonusers and 2.08 times as large for nondaily opioid users as for nonusers. Post hoc analyses showed that opioid users did not have significantly higher rates of comorbid medical conditions than nonusers, but they did report high rates of engagement in MAT for opioid use disorder. In turn, MAT was associated with significantly higher rates of COVID-19 testing in opioid users. Although speculative, it is possible that engagement in MAT increased contact with the health care system and thereby increased testing rates in opioid users. In addition, among those who received a COVID-19 test, odds of a positive test were significantly higher in daily stimulant users than those who used stimulants less frequently or not at all. There is a large body of research linking the use of amphetamine, methamphetamine, and other stimulants to HIV transmission, largely through risky sexual behavior [36-38]. Although sexual contact is not central to COVID-19 transmission, it may be that stimulant users had a riskier pattern of in-person contacts (eg, more frequent or less observant of distancing) that increased their risk of COVID-19 infection.

Cigarette use was associated with CDC guideline adherence in unadjusted analyses; yet, this variable became nonsignificant after adjusting for sociodemographic characteristics and other substance use. This pattern suggests that other characteristics or behaviors associated with cigarette use are driving the finding. Null results observed for e-cigarette, cannabis, and stimulant use should be interpreted within the limits of the study design and sample size. The prevalence of nondaily or daily e-cigarette, cannabis, and stimulant use was less than 6%. For these substances, the study may not have had sufficient power to detect differences in CDC adherence scores.

In the final model, gender, income, and COVID-19 test history were the demographic covariates that remained significant after the inclusion of substance use variables. Women reported higher adherence than men and those with other gender identities, and income showed a positive linear association with adherence. These findings are consistent with previous research [15,17]. Participants with a negative COVID-19 test reported higher adherence than those who had not had a test or were unsure. There was no difference in the adherence between those reporting a negative versus positive test result. The reason for this finding is unclear but may involve higher vigilance in those who had received a negative test result. Although we oversampled Black and Hispanic individuals to ensure representation, neither race nor ethnicity was a significant predictor of CDC guideline adherence after accounting for substance use.

Substance use is a known risk factor for COVID-19 infection [1]. A major implication of our findings is that lower behavioral adherence to CDC guidelines may be one mechanism by which substance use increases risk for COVID-19 infection. These findings should not be used to further stigmatize these individuals, who already face considerable stigma and adversity in social, occupational, and health care settings. Rather, results reinforce the need for outreach efforts and interventions that support behavioral adherence, COVID-19 testing, and vaccination for this population. Limited previous research has addressed this topic. We did not replicate the finding that use of e-cigarettes and combustible cigarettes was associated with COVID-19 testing and positive diagnosis [39]. However, that study was limited to individuals aged 13-24 years, which differs from our adult population.

Interestingly, individuals who drank 1-6 days per week reported higher CDC guideline adherence relative to nondrinkers and daily drinkers who did not differ statistically from each other. This finding may be in line with other observational research linking moderate or occasional alcohol consumption to health behaviors such as physical activity [40,41]. This interpretation is speculative as alcohol quantity was not included in the model, and therefore, nondaily drinkers, nevertheless, may have engaged in heavy episodic drinking. Given the present findings regarding alcohol consumption and COVID-19, further work in this space is warranted.

Limitations

The limitations of this study include the use of a nonrepresentative convenience sample, self-report data, and a novel CDC adherence scale that has not yet been validated. The survey did not explicitly assess the number or timing of COVID-19 tests that participants had received. Absence of data on the timing of testing is a significant limitation particularly with regard to understanding the relation with substance use. Analyses accounted for frequency but not quantity of substance use or specific patterns of polysubstance use, both of which are potentially important factors that warrant attention in future research. Our findings may not generalize to the US population as a whole. For effects with large confidence intervals, findings should be interpreted as informing directionality for future research rather than representing a reliable estimate of their magnitude in the sampled population.

Conclusions

In a convenience sample of adults living in the northeastern United States, we found that daily use of alcohol or opioids was significantly associated with lower adherence to CDC guidelines for reducing the spread of COVID-19, after accounting for sociodemographic characteristics and other substance use. However, use of cigarettes, e-cigarettes, cannabis, or stimulants was not associated with adherence. We also found that daily use of nonprescribed opioids was associated with higher odds of COVID-19 testing and that daily use of stimulants was associated with higher odds of a positive COVID-19 test result. The strengths of this study include the calendar-based assessment of several common classes of substances and the racial, ethnic, and age diversity of the sample. The findings of this study point to a need for public health efforts to support behavioral adherence and to expand COVID-19 testing and vaccination in individuals with high levels of alcohol, opioid, or stimulant use.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplemental tables.
[DOCX File , 17 KB - publichealth_v7i11e29319_app1.docx]

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Abbreviations

CDC: Centers for Disease Control and Prevention
e-cigarette: electronic cigarette
MAT: medication-assisted treatment
MTurk: Mechanical Turk

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Original Paper

Impact of the COVID-19 Pandemic on Objectively Measured Physical Activity and Sedentary Behavior Among Overweight Young Adults: Yearlong Longitudinal Analysis

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Abstract

Background: The COVID-19 pandemic has impacted multiple aspects of daily living, including behaviors associated with occupation, transportation, and health. It is unclear how these changes to daily living have impacted physical activity and sedentary behavior.

Objective: In this study, we add to the growing body of research on the health impact of the COVID-19 pandemic by examining longitudinal changes in objectively measured daily physical activity and sedentary behavior among overweight or obese young adults participating in an ongoing weight loss trial in San Diego, California.

Methods: Data were collected from 315 overweight or obese (BMI: range 25.0-39.9 kg/m^2) participants aged from 18 to 35 years between November 1, 2019, and October 30, 2020, by using the Fitbit Charge 3 (Fitbit LLC). After conducting strict filtering to find valid data on consistent wear (>10 hours per day for ≥250 days), data from 97 participants were analyzed to detect multiple structural changes in time series of physical activity and sedentary behavior. An algorithm was designed to detect multiple structural changes. This allowed for the automatic identification and dating of these changes in linear regression models with CIs. The number of breakpoints in regression models was estimated by using the Bayesian information criterion and residual sum of squares; the optimal segmentation corresponded to the lowest Bayesian information criterion and residual sum of squares. To quantify the changes in each outcome during the periods identified, linear mixed effects analyses were conducted. In terms of key demographic characteristics, the 97 participants included in our analyses did not differ from the 210 participants who were excluded.

Results: After the initiation of the shelter-in-place order in California on March 19, 2021, there were significant decreases in step counts (−2872 steps per day; 95% CI −2734 to −3010), light physical activity times (−41.9 minutes; 95% CI −39.5 to −44.3), and moderate-to-vigorous physical activity times (−12.2 minutes; 95% CI −10.6 to −13.8), as well as significant increases in sedentary behavior times (+52.8 minutes; 95% CI 47.0-58.5). The decreases were greater than the expected declines observed during winter holidays, and as of October 30, 2020, they have not returned to the levels observed prior to the initiation of shelter-in-place orders.

Conclusions: Among overweight or obese young adults, physical activity times decreased and sedentary behavior times increased concurrently with the implementation of COVID-19 mitigation strategies. The health conditions associated with a sedentary lifestyle may be additional, unintended results of the COVID-19 pandemic.

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KEYWORDS

COVID-19; young adults; physical activity; sedentary behavior; activity monitor; public health; wearable; activity monitors; wrist worn; sedentary; lifestyle; pandemic

Introduction

Beginning in March 2020, many states in the United States implemented public health restrictions to reduce the transmission of SARS-CoV-2 and the incidence of COVID-19, including mandatory stay-at-home orders that have forced individuals to alter their family, work, education, and social routines. As a result, health behaviors are likely to have been affected [1,2]. These health behaviors include engaging in physical activity and minimizing sedentary behavior; their benefits across the life span have been well documented [2-5]. Importantly, increasing evidence suggests that these health behaviors are also associated with the risk of SARS-CoV-2 infection and the development of serious COVID-19 [2,4,5], thus making the understanding of how these health behaviors might have changed in response to COVID-19 mitigation strategies, including the introduction of the tiered reopening strategy at the end of August 2020 [6], a critical area of research.

The temporary closures of businesses and shifts from conducting in-person occupational and educational activities to conducting such activities in remote settings may have introduced new barriers to engaging in physical activity and reducing sedentary time, including limiting access to recreation spaces, increasing screen time [2,7], and altering sleep patterns [4]. Alternatively, the reductions in the time spent on other activities, such as commutes and social gatherings, may have increased the time available for engaging in physical activity. Therefore, it is unclear if changes in daily behavior are mitigating or exacerbating the separate, ongoing health crises of low physical activity and high sedentary behavior [2,5,8].

COVID-19 morbidity and mortality rates have been highest in patients who are older; are overweight or obese; and have associated comorbidities, such as type 2 diabetes mellitus and cardiovascular disease [9,10]. This is the same population that benefits the most from engaging in risk-reducing health behaviors; even a 2-week period of physical inactivity and increased sedentary behavior can measurably increase the risk of developing comorbidities [11,12]. Although older age is an important risk factor for COVID-19 complications, young adults are not impervious to serious COVID-19, especially young adults who are overweight or obese [13,14]. In recent decades, this demographic has experienced serious declines in physical activity and increases in sedentary behavior [4,15-17].

A growing number of studies show that physical activity decreased while sedentary behavior increased during the period of time that COVID-19 mitigation strategies were in effect [2,7,12,18,19]. These findings, while significant, are limited by cross-sectional study designs, the frequent use of convenience sampling with the limited characterization of study populations, and self-reported data of limited reliability and validity [2,14-16]. In this study, we add to the growing body of research on the health impact of the COVID-19 pandemic by examining longitudinal changes in objectively measured daily physical activity and sedentary behavior among young adults aged 18 to 37 years that have occurred prior to and throughout the ongoing pandemic (November 1, 2019, to October 30, 2020).

Methods

Participants and Setting

Our analyses used data from the Social and Mobile Approaches to Reduce Weight (SMART) 2.0 trial—an ongoing, 24-month (96 weeks), parallel-group randomized control trial that is being conducted in San Diego, California. The SMART 2.0 trial targets weight loss in overweight or obese young adults aged 18 to 35 years by using multiple modalities, including an activity monitor, wireless scale, and app; text messaging; social media platforms with social networking capabilities; and technology-mediated health coaching. The intervention content in the SMART 2.0 trial focuses primarily on self-regulatory mechanisms that promote health engagement in physical activity, diet, and sleep to achieve weight loss.

Participants were aged from 18 to 35 years old at enrollment; were overweight or obese (BMI: range 25.0-39.9 kg/m^2); were affiliated with the University of California, San Diego; San Diego State University; or California State University, San Marcos; were Facebook users or were willing to begin using Facebook; and owned a smartphone. The exclusion criteria included having any comorbidities of obesity that require a clinical referral (ie, pseudotumor cerebri, sleep apnea, orthopedic problems, and type 2 diabetes), having psychiatric or medical conditions that prohibit compliance with the study protocol, or experiencing a cardiovascular event within 6 months of enrollment. Participants were also excluded if they were being treated for malignancy (other than nonmelanoma skin cancer), experienced an eating disorder, were planning to undergo weight loss surgery or engage in any other weight loss interventions or programs within 24 months of enrollment, or were pregnant or were actively planning to become pregnant within 24 months of enrollment.

All participants provided written informed consent prior to enrollment. Incentive payments of US $20, US $25, US $25, and US $30 were provided to participants at the 6-, 12-, 18-, and 24-month follow-up measurement visits, respectively. All participants' study data were deidentified. The study procedures were approved by the University of California, San Diego, Institutional Review Board (approval number: 181862). The trial was sponsored by National Institutes of Health (grant NIH 5R01HL136769-01A1) and was registered with ClinicalTrials.gov (trial number: NCT03907462). The funder had no role in the research.

Demographic information was gathered through a self-reported survey at baseline, as shown in Table 1. All participants received weight loss goals that they were instructed to attempt to achieve throughout their participation in the study (ie, all participants were actively receiving the intervention). All participants were given the Fitbit Charge 3 (Fitbit LLC)—a wrist-worn activity monitor that measures physical activity, sleep, and heart function. They were instructed to wear the device daily. The device contains a triaxial accelerometer, optical heart rate monitor, altimeter, and vibration motor. The Fitbit uses a proprietary algorithm to determine activity levels, which are defined as vigorous, moderate, light, or sedentary [20]. Studies have shown that the Fitbit has an accuracy rating of 85.4% in distinguishing activity levels, specifically in distinguishing sedentary and light activity from moderate-to-vigorous activity [21]. Evidence has also shown that the Fitbit has acceptable levels of accuracy for measuring the number of daily steps taken [22,23]. The data from these devices were retrieved and aggregated by using the Fitabase software developed by Small Steps Labs LLC [24]—a third-party research platform designed to collect data from multiple Fitbit devices over time.

Table 1. Baseline characteristics of the participants in the Social and Mobile Approaches to Reduce Weight 2.0 trial who wore a Fitbit device for more than 250 days over the course of 1 year in California (N=97).

Characteristics	Participants, n (%)
Sex	
Male	39 (40)
Female	58 (60)
Hispanic or Latino origin	
Yes	40 (41)
No	57 (59)
Race	
White or Caucasian	54 (56)
Black or African American	4 (4)
Asian	28 (29)
American Indian or Alaska Native	8 (8)
Native Hawaiian or Pacific Islander	1 (1)
Other	15 (16)
Highest level of education	
Less than high school	0 (0)
High school graduate	8 (8)
Some college or associate degree	44 (45)
College graduate or baccalaureate degree	21 (22)
Master's degree	24 (25)
Professional or vocational degree	0 (0)
Doctoral degree	0 (0)
Current relationship status	
Single or casually dating	44 (45)
In a committed relationship	33 (34)
Living in a marriage-like relationship	4 (4)
Married	15 (16)
Separated	0 (0)
Divorced	1 (1)
Income over the last 12 months (US $)	
<5000	28 (29)
5000-11,999	8 (8)
12,000-15,999	6 (6)
16,000-24,999	10 (10)
25,000-34,999	13 (13)
35,000-49,999	11 (11)
50,000-74,999	12 (12)
75,000-99,999	5 (5)
≥100,000	4 (4)
Number of children aged under 18 years that live in your home	
0	75 (77)
1	13 (13)

Characteristics	Participants, n (%)
2	6 (6)
3	3 (3)
Number of adults that live in your home, including yourself	
1	15 (16)
2	33 (34)
3	19 (20)
4	18 (19)
5	4 (4)
6	7 (7)
10	1 (1)
What university are you affiliated with?	
University of California, San Diego	77 (79)
San Diego State University	6 (6)
California State University, San Marcos	14 (14)
What is your affiliation?	
Staff	32 (33)
Student	72 (74)

The variables of interest included minutes of moderate-to-vigorous physical activity (MVPA; ≥3 metabolic equivalents of task [METs]), minutes of light physical activity (<3 METs), step counts (ambulation), and minutes of sedentary behavior (<1.5 METs). Data were acquired from Fitabase at the minute level for heart rate and at the daily level for all other metrics of interest (amount of time spent in sedentary, light, moderate, and vigorous activity; total number of steps; amount of time spent asleep). Heart rate data were analyzed, and aphysiologic data were removed (defined as unlikely heart rates of >200 beats per minute or <50 beats per minute). A new metric for the total number of minutes with a given heart rate per day was calculated and used as a proxy measure for wear time. This metric was further adjusted to create a variable for day wear. This was done by subtracting the number of sleep minutes calculated by the Fitbit's proprietary algorithm for each calendar day (ie, the number of minutes from 12 AM to 11:59 PM that usually spans 2 sleep periods). The days that were included in the analysis were those in which participants achieved a day wear time of ≥600 minutes. The data were cleaned by using heart rate as an arbiter. Participant's data were valid if they had a wear time of ≥600 minutes per day for at least 250 days in the year [25,26].

Statistical Analysis

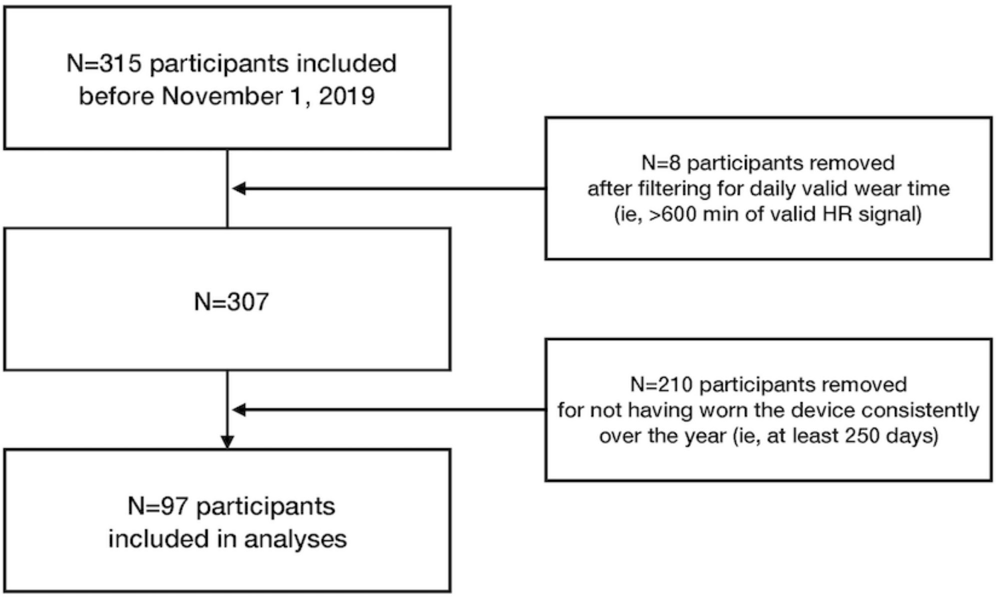
Changes in physical activity outcomes were first identified by using an algorithm that was designed to detect multiple structural changes in time series [27] and implemented within the R package *strucchange* (R Foundation for Statistical Computing). This method allows for the automatic identification and dating of structural changes in linear regression models with CIs. The optimal number of breakpoints in regression models was estimated by using the Bayesian information criterion and residual sum of squares; the optimal segmentation corresponded to the lowest Bayesian information criterion and residual sum of squares. To further quantify the changes in each outcome during the periods identified, linear mixed effects analyses were conducted. These analyses were implemented with the package *Lme4*, and posthoc comparisons among periods were conducted with the package *emmeans*. The mixed effects models included a random intercept, and posthoc comparisons were adjusted via the Bonferroni method. Finally, the four time series for steps, MVPA, light physical activity, and sedentary time were plotted with the package *ggplot2* by using a generalized additive model function. All statistical analyses were conducted by using R version 3.6.1 (R Foundation for Statistical Computing). The code and data used for the analyses are fully available on the Open Science Framework website [28]. The statistical significance of results was determined based on 2-tailed 95% CIs with predefined cutoffs. The data were stratified by date (ie, dates from November 1, 2019, to October 30, 2020). Descriptive statistics (proportions, means, and SDs) were used to define key demographic characteristics. Generalized additive models were conducted to analyze changes in each outcome variable over time.

Results

Summary of Participants

Data from a total of 315 participants were evaluated to determine their inclusion in this study. Among them, 8 participants were excluded after filtering for valid days based on our wear time criteria, as these 8 participants wore their devices for less 10 hours (600 minutes) per day. Afterward, 210 participants were excluded for having inconsistent wear times over the year. Specifically, these participants had less than 250 out of the valid 365 days' (68.5%) worth of data. These rather strict cutoff criteria (ie, 250 days) were used in order to reflect an entire year of consistent wear time. A total of 97 participants had at least 250 valid days' worth of monitoring data from November 1, 2019, to October 30, 2020, and were included in the analyses (Figure 1).

Figure 1. Flow diagram of participants in the Social and Mobile Approaches to Reduce Weight 2.0 trial who were included in the final analysis. HR: heart rate.



Demographic Characteristics

Table 1 shows the unadjusted study sample characteristics of the 97 participants included in the final analysis. The average age of the study population was 26.5 years (SD 8.5 years). Further, 41% (40/97) of participants identified as Latino or Hispanic, 44% were people of color (43/97), and 60% (58/97) identified as female. On average, participants had 45 minutes (SD 15 minutes) of MVPA, 6200 steps (SD 2000 steps), 367 minutes (SD 67 minutes) of sleep, and 1020 minutes (SD 108 minutes) of sedentary time per day throughout the analysis. The 97 participants included in the analyses did not differ from the 210 participants who were excluded in terms of the key demographic characteristics reported.

Changes in Physical Activity and Sedentary Behavior

Many of the breaks in activity occurred concurrently with the implementation of pandemic mitigation strategies in San Diego County, including the closing of schools, gyms, recreation spaces, parks, beaches, and other businesses in mid-March 2020; the reopening of outdoor spaces at the end of April 2020 and in early June 2020; and the introduction of the tiered reopening strategy at the end of August 2020. As shown in Figure 2, there was a marked decrease in step counts, light physical activity times, and MVPA times, as well as an increase in sedentary times, in March 2020 when compared to those in the prior months. For step count, the structural break detection algorithm indicated that 3 breaks in the time series occurred—one between December 20, 2019, and January 20, 2020; one between March 11 and March 13, 2020; and another between June 8 and June 18, 2020. Additionally, 3 structural breaks were also detected for MVPA. These occurred between January 1 and 14, 2020; between March 7 and 10, 2020; and between June 13 and 18, 2020. Further, 2 structural breaks were detected for light physical activity. These occurred between March 14 and 16, 2020, and between June 9 and 14, 2020. For sedentary behavior, 2 breaks occurred—one between March 7 and 14, 2020, and another between June 1 and June 16, 2020. Taken together, these results suggest that a significant increase in step counts and MVPA times occurred at the beginning of the year after the holiday season, a net decrease in physical activity outcomes occurred in mid-March (between March 10 and 16), and a new increase in physical activity times and decrease in sedentary behavior times occurred in the first 2 weeks of June. Multimedia Appendix 1 provides further information on these models.

The results from linear mixed effect models confirmed significant differences in each outcome among the following three periods: November 2019 to end of February 2020 (period 1), the beginning of March 2020 to the end of May 2020 (period 2), and the beginning of June 2020 to October 2020 (period 3; Figure 3).

Figure 2. Changes in the mean (A) step count, (B) light PA time, (C) MVPA time, and (D) sedentary time. Three breaks in the time series are highlighted at the end of December 2019, mid-March 2020, and July 2020 among participants of the Social and Mobile Approaches to Reduce Weight 2.0 trial who wore a Fitbit (Fitbit LLC) device for more than 250 days over the course of 1 year in California. MVPA: moderate-to-vigorous physical activity; PA: physical activity.

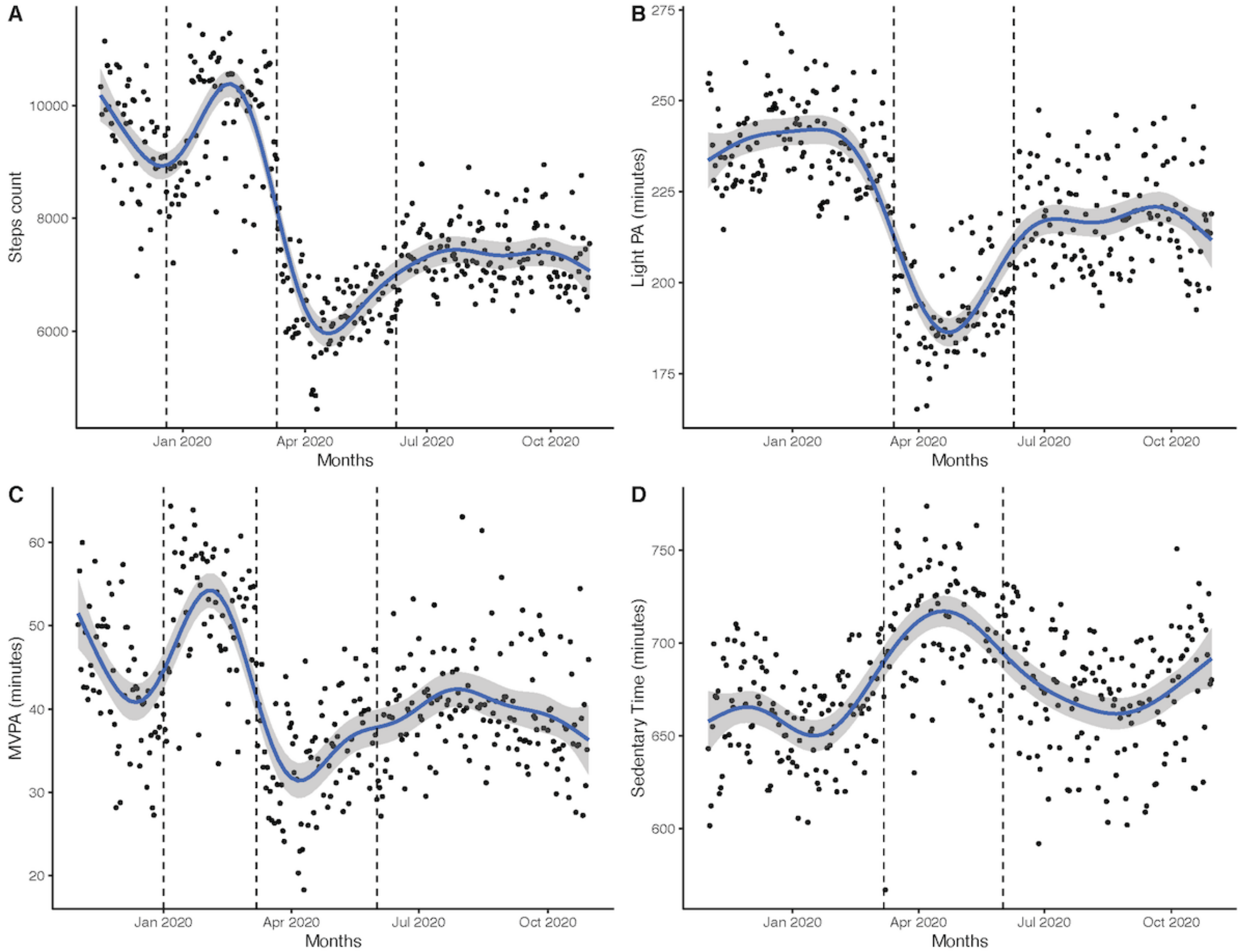
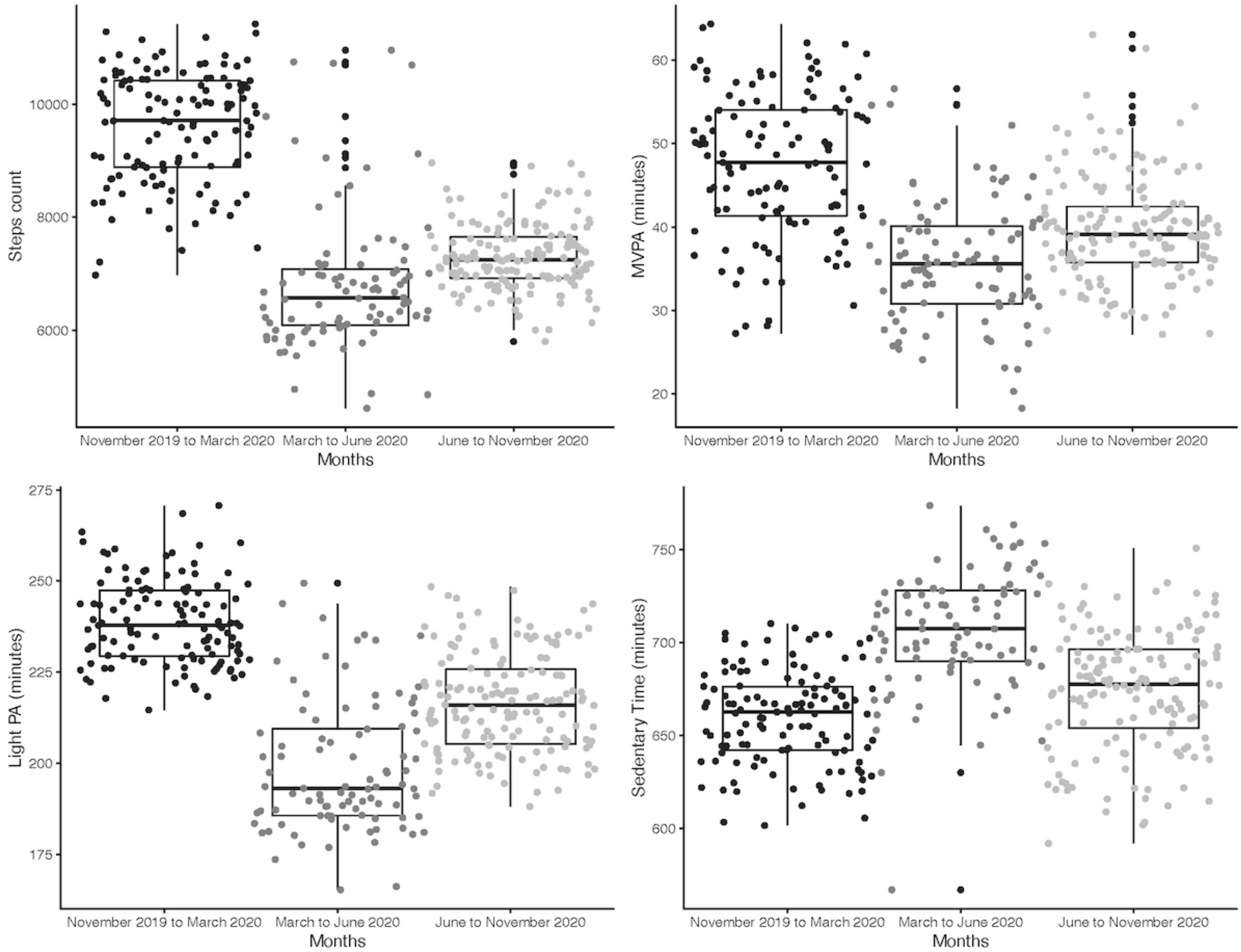


Figure 3. The results from linear mixed effect models confirmed significant differences in (A) step counts, (B) MVPA times, (C) light PA times, and (D) sedentary times across the three periods (November 2019 to the end of February 2020, the beginning of March to the end of May, and the beginning of June to October 2020) among participants of the Social and Mobile Approaches to Reduce Weight 2.0 trial who wore a Fitbit (Fitbit LLC) device for more than 250 days over the course of 1 year in California. MVPA: moderate-to-vigorous physical activity; PA: physical activity.



The average daily numbers of steps per day were 9641 (SE 251; period 1), 6769 (SE 253; period 2) and 7299 (SE 251; period 3) for the three time periods. A significant drop of 2872 steps per day was observed between periods 1 and 2 (95% CI 2734-3010), a significant increase in step count occurred between periods 2 and 3 (+529 steps per day; 95% CI 396-663), and the average number of steps in period 3 was still significantly lower than that in period 1 (−2343 steps per day; 95% CI −2223 to −2463).

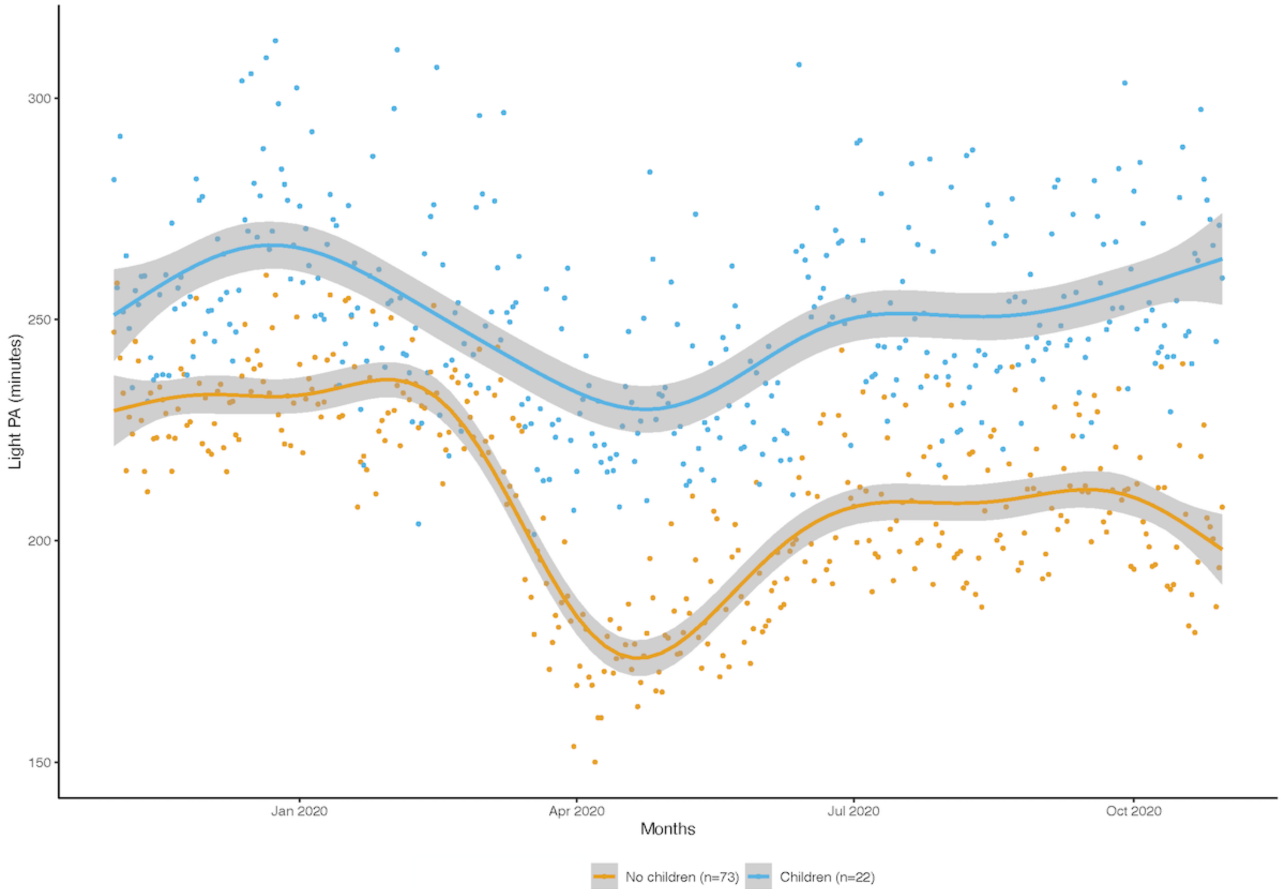
Similar patterns of results were observed for the other outcomes. The average number of minutes of MVPA per day was 47.6 minutes (SE 2 minutes) in period 1, 35.4 minutes (SE 2 minutes) in period 2 (−12.2 minutes; 95% CI −10.6 to −13.8), and 39.9 minutes (SE 2 minutes) in period 3 (+4.5 minutes compared to minutes in period 2; 95% CI 2.9-6).

The average number of minutes of light physical activity per day was 239 minutes (SE 5 minutes) in period 1, 197 minutes (SE 5 minutes) in period 2 (−41.9 minutes; 95% CI −39.5 to −44.3), and 216 minutes (SE 5 minutes) in period 3 (+19.1 minutes compared to minutes in period 2; 95% CI 16.7-21.4).

The average number of minutes of sedentary behavior per day was 659 minutes (SE 10 minutes) in period 1, 712 minutes (SE 10 minutes) in period 2 (+52.8 minutes; 95% CI 47-58.5), and 678 minutes (SE 10 minutes) in period 3 (−34 minutes compared to minutes in period 2; 95% CI −28.4 to −39.6).

The times series highlighted that these patterns of changes were relatively similar across subgroup comparisons, including those between males and females; between single and committed participants; between participants with annual incomes of below and above US $25,000; and between participants with and without children (Multimedia Appendix 2), with one exception. The declines in light physical activity times among participants with children (n=22) were lower than those among participants without children (n=73; Figure 4). Light physical activity was significantly different between these two groups during period 2 (−45.4 minutes for the participants without children; 95% CI −79.98 to −10.90) as well as during period 3 (−43.63 minutes for the participants without children; 95% CI −78.01 to −9.25).

Figure 4. Changes in the mean light PA times of participants of the Social and Mobile Approaches to Reduce Weight 2.0 trial who wore a Fitbit (Fitbit LLC) device for more than 250 days over the course of 1 year in California. The declines in light physical activity times among participants with children (n=22) were lower than those among participants without children (n=73). PA: physical activity.



Discussion

Principal Findings

In our study, we analyzed a complete year's worth of objective, high-resolution data to assess the impact that mitigation strategies associated with the COVID-19 pandemic have on physical activity and sedentary behavior in young adults. We observed that after the initiation of the shelter-in-place order in California, there were significant decreases in step counts, light physical activity, and MVPA, as well as significant increases in sedentary behavior. The decreases were greater than the expected declines observed during winter holidays, and they have not returned to the levels observed prior to the initiation of shelter-in-place orders. The length of the time series used in this study provides valuable insight into the effects of COVID-19 mitigation strategies. Specifically, strategies that include reducing access to recreation spaces and gyms and shifting to remote, web-based work rather than commuting to work or school are likely causes of the reductions in physical activity and increases in sedentary behavior observed within our study population [2-4,29]. These mitigation strategies, while important for reducing the spread of infectious disease, may further exacerbate the ongoing and separate health crises of low physical activity and high sedentary behavior that are present in the young adult population.

Our findings are in line with the findings from the existing literature to date, which has relied on self-report surveys and vary in length, ranging from 24-hour recalls [30] to 6-month self-recall physical activity reports [2,31]. Decreases in step counts, MVPA, and light physical activity and increases in sedentary behavior have been reported [17,19,30]. There have also been reports of increased activity in several populations; however, these patterns are unequal, as they depended on access to spaces for physical activity as well as whether these populations met the recommended level of physical activity prior to the initiation of pandemic mitigation strategies [32,33]. Most data have found that over 30% of adults have reported declines in physical activity in response to strict lockdown ordinances [2,34]. Our results expand the research in this area by revealing the magnitudes of the declines in physical activity and increases in sedentary behavior throughout key moments within the pandemic. This analysis captures the scope of the predicted declines in physical activity (November 2019 through the end of February 2020) resulting from holidays impacting work, family, education, and social routines and the daily behaviors associated with these declines. These were analyzed in relation to the initial mitigation strategies that were implemented from the beginning of March through May 2020. Such strategies included the March 19, 2020, stay-at-home order, which resulted in the closing of gyms, beaches, parks, and recreation spaces, and the subsequent opening of beaches and parks on April 27, 2020. We also identified a period of increased activity, which occurred from June 2020 through October 2020. This coincided with the June 12, 2020, reopening of some gyms and businesses and the tiered reopening system that took effect on August 31, 2020, during which physical activity and sedentary behavior levels were still lower than those from before the pandemic.

Our results showed that these trends were consistent across gender, partner status, income, and whether participants had children, underscoring the strong effect of COVID-19 mitigation strategies across all subgroups. The pronounced decreases in physical activity highlight a need for further investigation into the reasons for these declines; while many local restrictions resulted in the closures of gyms and other recreational areas, even the strictest stay-at-home orders all allowed for outdoor physical activity, and many gyms continued to conduct operations and classes outdoors. Additionally, considerable reductions in commuting time resulting from work and school being conducted remotely provided many individuals with increased leisure time. It is likely, then, that reductions in activity were due to changes in lifestyle activity associated with occupational and transportation-related physical activity and due to individuals being unable or unwilling to adapt to routines that accommodate for COVID-19–related restrictions, though more research on this is needed.

Our findings highlight a vast need for interventions that focus on increasing physical activity and decreasing sedentary behavior in young adults and the need for these interventions to highlight problem-solving and adaptations to changing conditions. Importantly, increasing evidence suggests that physical activity can reduce the risk of SARS-CoV-2 infection and the development of serious COVID-19 [2,4,5]. Given these risks, the increases in screen time associated with remote work and school, and the significant deleterious effects that the COVID-19 pandemic has on mental health, maintaining and increasing physical activity are key strategies for reducing some of the greatest mental and physical health risks associated with the COVID-19 pandemic. The World Health Organization has predicted that more global health emergencies will occur in the future [35]; the success of future health behavior interventions may depend on their ability to adapt to changing conditions at the global and individual levels.

The strengths of this study include the use of objective data from an existing cohort that has been longitudinally observed over the course of an entire year. This provided us with the ability to segment and examine expected declines in physical activity due to holidays and unexpected declines resulting from COVID-19 mitigation efforts. The limitations include the use of a sample that was recruited entirely from San Diego, California. This makes our findings potentially less generalizable to all young adults in other regions. The participants were also a part of an ongoing weight loss study and were seeking to lose weight, which may further limit the generalizability of our results to those attempting to lose weight and those who are motivated to use a Fitbit to support their weight loss. Additionally, due to the conservative cutoff criteria used for valid days and consistent wear times, our analysis included a smaller sample size compared to the original study's larger sample size.

Conclusion

In summary, our findings support the observation that health behaviors in young adults have been significantly impacted by COVID-19 mitigation strategies. The strategies used to mitigate and control the spread of SARS-CoV-2, while important, have unintended consequences that may continue to become increasingly apparent in the young adult population following the COVID-19 pandemic. As the pandemic continues, this population will be faced with a different lifestyle from the one before the pandemic—one in which the need for improved health behaviors should be emphasized beyond the pandemic and as pandemic fatigue [27] continues to negatively impact lifestyle decisions. Future interventions aimed at young adults should include varied options for physical activity, including options for conducting physical activities at home and in the community, as well as strategies for decreasing sedentary behavior, as most activities of daily living now occur in a home environment.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Structural break detection results.
[PDF File (Adobe PDF File), 129 KB - publichealth_v7i11e28317_app1.pdf]

Multimedia Appendix 2
Time series data.
[PDF File (Adobe PDF File), 929 KB - publichealth_v7i11e28317_app2.pdf]

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Abbreviations

MET: metabolic equivalent of task
MVPA: moderate-to-vigorous physical activity
SMART: Social and Mobile Approaches to Reduce Weight

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Original Paper

Impact of the COVID-19 Pandemic on the Health Status and Behaviors of Adults in Korea: National Cross-sectional Web-Based Self-report Survey

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Abstract

Background: The COVID-19 pandemic has radically shifted living practices, thereby influencing changes in the health status and behaviors of every person.

Objective: The aim of this study was to investigate the impact of COVID-19 on the self-reported health status and health behaviors along with any associated factors in adults in the Republic of Korea wherein no stringent lockdown measures were implemented during the pandemic.

Methods: We conducted a web-based self-reported survey from November 2020 to December 2020. The study participants (N=2097) were identified through quota sampling by age, sex, and geographical regions among residents aged 19 years or older in Korea. The survey collected information on basic demographics, changes in self-reported health status, and health behaviors during the COVID-19 pandemic. Self-reported health status and health behaviors were categorized into 3 groups: unchanged, improved, or worsened. A chi-square test and logistic regression analyses were conducted.

Results: With regard to changes in the self-reported health status, the majority (1478/2097, 70.5%) of the participants reported that their health was unchanged, while 20% (420/2097) of the participants reported having worser health after the COVID-19 outbreak. With regard to changes in health behaviors, the proportion of participants who increased tobacco consumption was similar to that of those who decreased tobacco consumption (110/545, 20.2% vs 106/545, 19.5%, respectively), while the proportion of those who decreased their drinking frequency was more than twice as many as those who increased their drinking frequency (578/1603, 36.1% vs 270/1603, 16.8%, respectively). Further, those who decreased their exercising frequency were more than those who increased their exercising frequency (333/823, 15.9% vs 211/823, 10%, respectively). The factor that had the greatest influence on lifestyle was age. In the subgroup analysis, the group aged 20-29 years had the highest number of individuals with both a worsened (100/377, 26.5%) and an improved (218/377, 15.7%) health status. Further, individuals aged 20-29 years had greater odds of increased smoking (6.44, 95% CI 2.15-19.32), increased alcohol use (4.64, 95% CI 2.60-8.28), and decreased moderate or higher intensity aerobic exercise (3.39, 95% CI 1.82-6.33) compared to individuals aged 60 years and older. Younger adults showed deteriorated health behaviors, while older adults showed improved health behaviors.

Conclusions: The health status and the behavior of the majority of the Koreans were not found to be heavily affected by the COVID-19 outbreak. However, in some cases, changes in health status or health behavior were identified. This study highlighted that some groups were overwhelmingly affected by COVID-19 compared to others. Certain groups reported experiencing both worsening and improving health, while other groups reported unchanged health status. Age was the most influential factor for behavior change; in particular, the younger generation's negative health behaviors need more attention in terms of public health. As COVID-19 prolongs, public health interventions for vulnerable groups may be needed.

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KEYWORDS

COVID-19; health status; health behavior; self-reported online survey; pandemic; epidemiology; public health; sociodemographic factors; health interventions; lockdown

Introduction

The COVID-19 pandemic has radically shifted living practices around the world. Governments have implemented social distancing measures, urged employees to work from home, and banned mass gatherings to prevent the spread of COVID-19 [1,2]. Individuals have been isolated owing to self-quarantine measures in the case of suspected or confirmed COVID-19 cases [1,2]. Social isolation and restrictions on daily activities influence health behaviors such as smoking, alcohol consumption, and physical activity [3-19]. This contributes to mental health illnesses [18] and physical health problems, including chronic diseases, which may worsen the overall health status [19].

Several studies have been conducted regarding the impact of the COVID-19 pandemic on health status and behaviors. Previous studies have shown that most of the health statuses, including self-reported physical health and mental health, tended to worsen [11] and health behaviors also deteriorated due to COVID-19. Several studies have shown that there has been an increase in the amount of smoking [3-5], an increase in relapse to smoking [6], and an increase in alcohol consumption [3,7,9-12,20] during the COVID-19 pandemic. Binge-eating behaviors and reduced level of exercise have also been reported [13], suggesting that the COVID-19 pandemic has led to poor health behaviors. However, positive behavioral changes have also been reported in some studies, such as people who were less active before the COVID-19 pandemic performing more exercises [14], or trying to quit smoking [15,16], or smoking less during the lockdown periods [17].

Previous studies have reported that social isolation during COVID-19 generally had an unfavorable impact on health status and behaviors; however, it also motivated individuals to take self-guided actions to improve their health. Although changes in health status and health behavior are complex and multifaceted, these previous studies have focused on specific populations [4,18], extreme circumstances such as lockdown or disasters [3,5,12,14,15], and certain health conditions and health behaviors [6,10,11,13,17]. Therefore, in the ongoing COVID-19 situation, it was difficult to understand the overall changes in health status and behavior caused by the restriction of physical activity and mental stress. However, it is important to identify the factors related to changes in health status and behaviors in terms of identifying high-risk groups requiring intervention. Several studies have reported that demographic factors, socioeconomic level, residential area, and disease status are related to lifestyle changes due to COVID-19 [21-23]. The objective of this study was to investigate whether the COVID-19 pandemic has induced changes in self-reported health status and health behaviors in 2020 in a country without stringent lockdown measures. We also identified the factors associated with changes in self-reported health status and health behaviors such as smoking, alcohol consumption, and exercise.

Methods

Participants and Recruitment

This cross-sectional survey was initiated on November 9, 2020. At the time of the survey, the total population of Korea according to the 2020 census by Statistics Korea was 51,780,000 [24], and we tried to calculate a representative sample size on behalf of the Korean population. Assuming 95% CI, 2.2% margin of error, and standard deviation of 0.5%, the estimated sample size was 1984, and we decided to gather more than 2000 participants. The total study participant recruitment period took 4 weeks from November 9 to December 4, 2020. This study was performed with technical support from Gallup Korea, a global social research company, and conducted in all regions of Korea. The study participants were identified through quota sampling by age, sex, and geographical regions among residents aged 19 years and older in the Republic of Korea. Korea is distributed geographically into 16 administrative distributes. Based on the 2015 National Statistical Office census data, this study was designed to sample 2000 people according to the population structure and a systematic random sampling method was implemented. In the web-based survey, the appropriate number of samples was allocated according to the population distribution for each of the 16 administrative district units, and the number of participants by age and gender was assigned to each unit. The estimated sample error of our study was 2.5% at 95% CI.

The survey was conducted as follows: the study participants were informed of the purpose of the study, they consented to participate, and they were directed to an encrypted website to complete the survey. The study was conducted anonymously, but to prevent duplicate questionnaires, the study participants used a mobile phone–based verification system. When the respondents enter their cell phone number before responding, the passcode is transmitted, and the passcode is used to identify the owner of the cell phone based on the information of the telecommunication company, thereby avoiding duplicate questionnaires. The questionnaire in this study consisted of multiple-choice questions, and there were no missing values in the case of the respondents who completed the survey because it was impossible to move to the next page if a response was omitted. Further, the questionnaire on 1 page consisted of about 10 questions on average, and if the study participant answered the same or similar answers to the questions on 1 page, a pop-up was set up to confirm whether the answers were certain before moving on to the next page. As a result, 1280 people dropped out of the study, including those who declined during the survey or refused to respond to the survey before they initiated the survey. Of the 3377 participants who consented to partake, 2097 completed the study and the dropout rate in the study was 37.9% (2097/3377). Those who completed the survey received an electronic device worth US $5.

The inclusion criteria included being ≥19 years old and physically healthy and mentally stable enough to read, understand, and answer the questionnaire. Further, to sample a representative group representing Koreans, we excluded those who were not residing in Korea from the study. Those who did not speak Korean were excluded from the study because they could have limitations in understanding the consent form or in reading and answering questions. The study protocol was approved by the Institutional Review Board of Seoul National University Hospital (IRB E-2011-102-1173). This study follows the guidelines of the STROBE (STrengthening the Reporting of OBservational studies in Epidemiology) checklist.

Survey Measures

The web-based survey collected information on basic demographics, changes in self-reported health status, and health behaviors during the COVID-19 pandemic. The demographic variables included sex, age, region, household income, education level, supplementary private health insurance, marital status, occupation, and presence of chronic diseases. Participants were categorized into 5 age groups (20-29 years, 30-39 years, 40-49 years, 50-59 years, and >60 years), and 3 groups as per the area of residence (Seoul metropolitan area, Daegu-Gyeongbuk province, and others) according to the incidence of COVID-19 epidemic in the area. Household income was classified into 4 groups (US $2000, US $2000-$3999, US $4000-$5999, ≥US $6000), and education level was categorized into 3 groups (high school graduate and undergraduate, college/university graduate or associate degree, and master's degree or above). Lastly, marital status was categorized into 3 groups (single, married, and divorced or widowed), while occupation was categorized into 4 groups (office worker, manual worker, self-employed, and housewife/student/unemployed).

In accordance with the previous studies on self-reported health status [25,26], the study participants were asked to report their health status 1 year before (prior to the COVID-19 outbreak) and their current health status (after the COVID-19 outbreak) to identify the changes associated with the COVID-19 pandemic. Questions about self-reported health status were obtained by using the original questionnaire of short form-36 items, and reference time was added as a footnote to reduce the recall bias of respondents. Self-reported health status was measured on a 5-point Likert scale from 1 (poor) to 5 (excellent) and then further categorized into 3 groups (unchanged, improved, or worsened). "Unchanged" was defined as a case in which the responses before and after were identical, "improved" as a case in which the health status improved after compared to before, and "worsened" as a case where the health status deteriorated after compared to before. Questions on smoking, alcohol consumption, and moderate or higher intensity aerobic exercise were partially derived from the Centers for Disease Control and Prevention's National Health Interview Survey. We had to generate questions about the changes before and after the COVID-19 outbreak for our study, and for the quantitative comparison of changes, we had to separately analyze the amount of smoking, drinking, and exercise before and after the COVID-19 outbreak. Detailed questions are provided separately in Multimedia Appendix 1. The changes in smoking, drinking, and exercise were classified into 3 groups (increased, decreased, or unchanged) through questions on the amount of smoking, drinking, and exercise 1 year before (before the onset of COVID-19) and now.

Statistical Analysis

A chi-square test was performed to compare the categorical variables such as changes in health status, smoking, alcohol consumption, and exercise at moderate intensity or higher before and after the COVID-19 outbreak. Logistic regression analyses were conducted to identify the factors associated with improving or worsening health behaviors. Demographic factors included in these regression analyses were sex, age, region, household income, education levels, supplementary private health insurance, marital status, occupation, and presence of chronic diseases. The results of the logistic regression analyses were presented with 95% CIs and adjusted odds ratio (aOR). Statistical significance was defined as a two-tailed P value <.05. All statistical analyses were performed using Stata version 23 (StataCorp LLC).

Results

Baseline Characteristics of the Participants

Table 1 shows the baseline characteristics of the participants. Of the 2097 participants, 1058 (50.5%) were men and 1039 (49.5%) were women. The study participants were evenly distributed across 5 age groups. Among them, 401 (19.1%) lived in the Seoul metropolitan area, 196 (9.4%) lived in the Daegu-Gyeongbuk province, and 1500 (71.5%) lived in other areas. Of the 2097 participants, 192 (9.2%) had an household income <US $2000, 1498 (71.4%) were university graduates, 1718 (81.9%) held supplementary private health insurance, 755 (36%) were singles, 1251 (59.7%) were married, 1110 (52.9%)

were office workers, followed by 582 (27.8%) housewives, students, or unemployed, and 1081 (51.6%) participants had more than one preexisting chronic condition. Among the 2097 participants, 545 (26%) were smokers and 1603 (76.4%) regularly consumed alcohol (Table 1).

Table 1. Baseline characteristics of the participants (N=2097).

Variable	Values, n (%)
Sex	
Men	1058 (50.5)
Women	1039 (49.5)
Age (years)	
20-29	377 (18)
30-39	411 (19.6)
40-49	485 (23.1)
50-59	479 (22.8)
≥60	345 (16.5)
Region	
Seoul metropolitan area	401 (19.1)
Daegu-Gyeongbuk province	196 (9.4)
Others	1500 (71.5)
Household income (USD)	
≤$2000	192 (9.2)
$2000-$3999	684 (32.8)
$4000-$5999	610 (29.2)
≥$6000	600 (28.8)
Educational status	
High school graduate and under	359 (17.2)
College/university graduation or associate degree	1498 (71.4)
Master's degree or above	240 (11.4)
Supplementary private insurance	
Yes	1718 (81.9)
No	379 (18.1)
Marital status	
Single	755 (36)
Married	1251 (59.7)
Widowed/divorced	91 (4.3)
Job	
Office worker	1110 (52.9)
Manual worker	212 (10.1)
Own business	193 (9.2)
Housewife/student/unemployed	582 (27.8)
Chronic illness	
Yes	1081 (51.6)
No	1016 (48.5)
Change of health status	
Getting worse	420 (20)
Unchanged	1478 (70.5)
Getting better	199 (9.5)
Smoking	

Variable	Values, n (%)
Yes	545 (26)
No	1552 (74)
Drinking	
Yes	1603 (76.4)
No	494 (23.6)

Changes in Health Status and Behaviors During the COVID-19 Pandemic

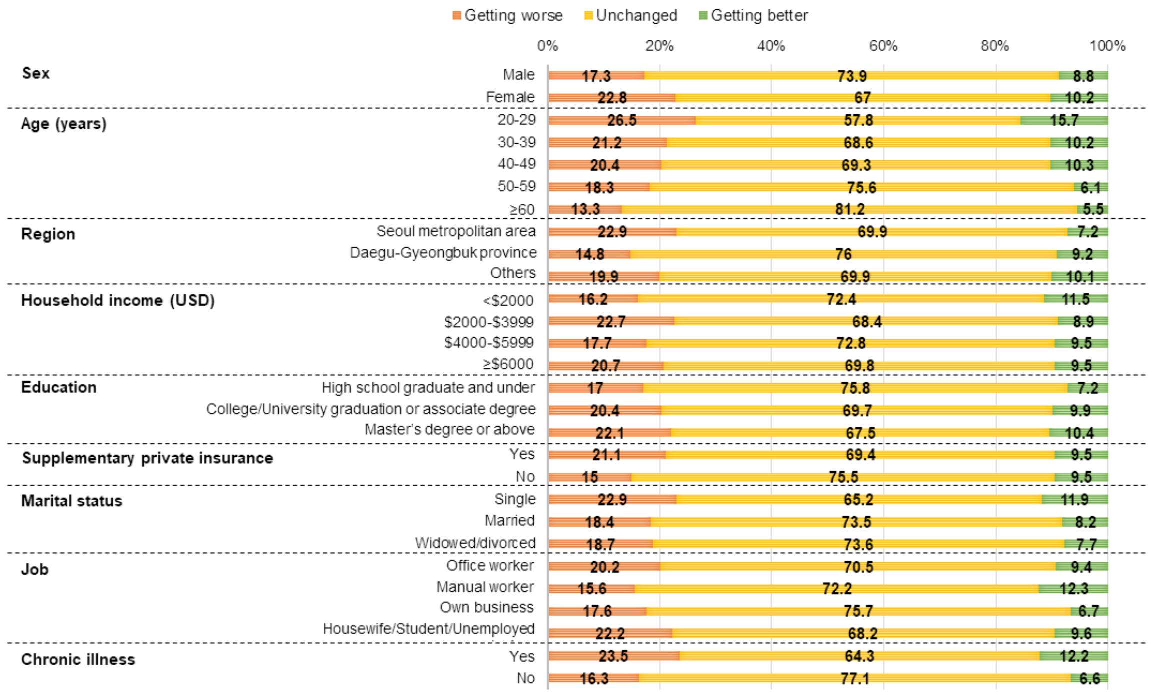
Regarding changes in health status before and after COVID-19, 1478 (70.5%) of the 2097 participants reported their health was unchanged, and 420 (20%) participants reported that their health status was worser than before. Among the 2097 participants, 199 (9.5%) responded that their health status improved. When asked about health behavior, among 545 smokers, 110 (20.2%) reported that their smoking frequency had increased while 106 (19.5%) reported that their smoking frequency had decreased, and these proportions were almost similar. With regard to drinking, 578 (36.1%) participants reported a decrease in drinking frequency while 270 (16.8%) reporting an increase—more than double the number of people decreased their drinking frequency. Decreased moderate or high-intensity aerobic exercise was reported by 333 (15.9%) participants whereas 211 (10%) reported an increased frequency in exercising after the onset of the pandemic (Figure 1).

Figure 1. Changes in the health status and behaviors of the adults in Korea during the COVID-19 pandemic.

Changes in Self-reported Health Status During the COVID-19 Pandemic in Subgroup Analyses

Women reported having both worser health (237/1039, 22.8%) and better health (106/1039, 10.2%) than men (183/1058, 17.3% and 93/1058, 8.8%, respectively; *P*<.001). Regarding age groups, the 20-29 years age group had the highest number of individuals with both a worsened (100/377, 26.5%) and an improved (59/377, 15.7%) health status. However, participants aged 60 years and older reported having the least of either worse (46/345, 13.3%) or improved (19/345, 5.5%) health status. Among the participants with supplementary private health insurance, 21.1% (363/1718) reported that their health had become worse (*P*=.03). We found that 22.9% (173/755) of the singles were more likely to gain a worser health status than those who were married (230/1251, 18.4%) and divorced or widowed (17/91, 18.7%). However, 11.9% (90/755) of the singles were more likely to have an improved health status than married (102/1251, 8.2%), divorced, or widowed (7/91, 7.7%) participants as well. Participants with preexisting chronic diseases (254/1081, 23.5%) reported having a worser health status more than those without (166/1016, 16.3%) (*P*<.001) (Figure 2).

Figure 2. Changes in the health status of the adults in Korea by subgroup during the COVID-19 pandemic. The change in health status was surveyed by 2097 participants.



Factors Associated With Worsening Health Behaviors

Age was the main risk factor for increased smoking; the aOR of increased smoking was higher among participants aged 20-29 years (aOR 6.44, 95% CI 2.15-19.32) than that among those who were aged 60 years and older. Further, age was the greatest risk factor for increased alcohol use; the aOR of increased drinking was the highest among participants aged 30-39 years (aOR 4.64, 95% CI 2.60-8.28). Further, individuals aged 20-29 years (aOR 3.39, 95% CI 1.82-6.33) had greater odds of decreased moderate or higher intensity aerobic exercise than those aged 60 years and older. Participants with preexisting chronic diseases were more associated with worsening of all health behaviors than those without, revealing increased smoking (aOR 2.07, 95% CI 1.28-3.36), increased alcohol consumption (aOR 1.44, 95% CI 1.09-1.90), and decreased moderate or higher intensity exercise (aOR 1.51, 95% CI 1.28-1.79). The area of residence, lower monthly household income, higher education level, and marriage status were also associated with worsening health behaviors (Table 2).

Table 2. Factors associated with worsening health behaviors.[a]

Variable	Increased smoking[b]	Increased alcohol consumption[c]	Decreased moderate or higher intensity aerobic exercise[d]
Sex			
Men	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Women	1.16 (0.66-2.02)	1.00 (0.75-1.32)	1.21 (0.90-1.65)
Age (years)			
20-29	*6.44 (2.15-19.32)*	*3.23 (1.64-6.40)*	*3.39 (1.82-6.33)*
30-39	*3.74 (1.52-9.25)*	*4.64 (2.60-8.28)*	*2.45 (1.41-4.27)*
40-49	1.94 (0.82-4.63)	*3.98 (2.31-6.85)*	*2.02 (1.24-3.29)*
50-59	1.69 (0.71-4.04)	*2.10 (1.21-3.66)*	1.53 (0.97-2.43)
≥60	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Region			
Seoul metropolitan area	1.22 (0.72-2.05)	*1.74 (1.26-2.39)*	1.04 (0.73-1.48)
Daegu-Gyeongbuk province	0.73 (0.33-1.61)	0.69 (0.40-1.18)	0.63 (0.35-1.11)
Others	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Household income (USD)			
≤$2000	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
$2000-$3999	0.70 (0.24-2.05)	1.01 (0.56-1.84)	1.23 (0.68-2.24)
$4000-$5999	0.40 (0.13-1.22)	0.73 (0.39-1.35)	1.28 (0.69-2.36)
≥$6000	*0.30 (0.10-0.94)*	0.90 (0.48-1.66)	1.20 (0.65-2.24)
Educational status			
High school graduate and undergraduate	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
College/university graduation or associate degree	0.90 (0.48-1.68)	0.86 (0.57-1.29)	*1.70 (1.09-2.64)*
Master's degree or above	1.82 (0.77-4.26)	0.82 (0.47-1.44)	*2.23 (1.40-3.55)*
Supplementary private insurance			
Yes	1.70 (0.83-3.51)	1.14 (0.76-1.73)	1.28 (0.85-1.94)
No	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Marital status			
Single	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Married	1.62 (0.86-3.02)	*1.61 (1.10-2.34)*	1.34 (0.87-2.06)
Widowed/divorced	*2.95 (1.01-8.66)*	1.94 (0.90-4.19)	1.42 (0.64-3.16)
Job			
Office worker	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Manual worker	1.27 (0.65-2.50)	1.20 (0.74-1.94)	0.87 (0.52-1.48)
Own business	1.29 (0.61-2.74)	*1.60 (1.09-2.20)*	1.52 (0.88-2.62)
Housewife/student/unemployed	0.59 (0.24-1.44)	0.86 (0.58-1.27)	1.29 (0.89-1.88)
Chronic illness			
Yes	*2.07 (1.28-3.36)*	*1.44 (1.09-1.90)*	*1.51 (1.28-1.79)*
No	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)

[a]Values in italics indicate statistically significant values.

[b]Change in smoking behavior was surveyed by 545 current smokers.

[c]Change in alcohol consumption was surveyed by 1603 participants who answered that they regularly consumed alcohol.

[d]Change in exercise behavior was surveyed by 2097 participants.

Factors Associated With Improving Health Behaviors

Regarding age, the aOR of decreased smoking for improving health behaviors was higher among participants aged 60 years and older (aOR 3.38, 95% CI 1.06-10.78) than that among those who were aged 20-29 years, whereas the aOR of increased moderate or higher intensity aerobic exercise for improving health behaviors was the highest among the latter. Higher monthly household income and education level, that is, those who had attained at most a high school diploma or less, were also associated with improving health behaviors (Table 3).

Table 3. Factors associated with improving health behaviors.[a]

Variable	Decreased smoking[b]	Decreased alcohol consumption[c]	Increased moderate or higher intensity aerobic exercise[d]
Sex			
Men	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Women	1.35 (0.79-2.3)	1.14 (0.91-1.42)	1.19 (0.88-1.60)
Age (years)			
20-29	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
30-39	1.6 (0.66-3.88)	0.71 (0.49-1.02)	*0.55 (0.33-0.89)*
40-49	1.71 (0.69-4.25)	0.7 (0.48-1.04)	*0.56 (0.33-0.95)*
50-59	1.86 (0.72-4.82)	0.93 (0.61-1.41)	*0.50 (0.28-0.87)*
≥60	*3.38 (1.06-10.78)*	0.99 (0.62-1.58)	0.54 (0.29-1.01)
Region			
Seoul metropolitan area	0.97 (0.57-1.65)	0.81 (0.61-1.06)	0.69 (0.46-1.04)
Daegu-Gyeongbuk province	0.94 (0.44-2.01)	0.83 (0.58-1.21)	1.14 (0.71-1.82)
Others	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Household income (USD)			
≤$2000	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
$2000-$3999	1.12 (0.35-3.53)	1.54 (0.97-2.45)	1.44 (0.97-2.13)
$4000-$5999	1.05 (0.32-3.43)	*1.77 (1.10-2.84)*	1.45 (0.98-2.15)
≥$6000	1.41 (0.43-4.62)	*1.91 (1.19-3.09)*	*2.12 (1.25-3.60)*
Educational status			
High school graduate and undergraduate	*3.22 (1.18-8.79)*	0.81 (0.53-1.24)	0.94 (0.51-1.71)
College/university graduation or associate degree	2.45 (0.99-6.04)	0.68 (0.49-0.94)	1.02 (0.63-1.63)
Master's degree or above	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Supplementary private insurance			
Yes	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
No	0.67 (0.33-1.34)	1.15 (0.86-1.55)	0.82 (0.54-1.24)
Marital status			
Single	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Married	0.78 (0.42-1.45)	*0.68 (0.50-0.92)*	1.12 (0.73-1.73)
Widowed/divorced	0.21 (0.04-1.05)	0.53 (0.28-1.02)	0.72 (0.28-1.82)
Job			
Office worker	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Manual worker	1.65 (0.88-3.12)	1.32 (0.91-1.91)	0.73 (0.40-1.32)
Own business	0.72 (0.33-1.57)	0.77 (0.51-1.15)	1.43 (0.87-2.37)
Housewife/student/unemployed	1.53 (0.70-3.30)	0.95 (0.72-1.27)	0.85 (0.58-1.24)
Chronic illness			
Yes	1.15 (0.73-1.81)	1.10 (0.89-1.37)	0.98 (0.73-1.32)
No	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)

[a]Values in italics indicate statistically significant values.

[b]Change in smoking behavior was surveyed by 545 current smokers.

[c]Change in alcohol consumption was surveyed by 1603 participants who answered that they regularly consumed alcohol.

[d]Change in exercise behavior was surveyed by 2097 participants.

Discussion

This study investigated whether the COVID-19 pandemic induced changes in self-reported health status and behaviors in adults in Korea, wherein stringent lockdown measures were not implemented. Most participants in this study reported an unchanged health status around 1 year before and after the COVID-19 epidemic. More participants reported that they became worse than those who reported they became better, which is consistent with the results of previous studies [11]. Both self-reported worsening and improving of health status were common in younger age groups. In addition, young age was a major risk factor for deterioration of health behaviors. From this, it is estimated that specific populations were experiencing varied impacts whereas other groups were not affected at all during the pandemic.

Contrary to previous studies that found an increased prevalence of smoking during the COVID-19 pandemic [3-5], this study found that previously identified increases in smoking among smokers were, in most cases, unchanged from prepandemic levels. Several studies showed increased alcohol consumption during the initial phase of the pandemic [10-12,27]; however, after social distancing measures were adopted, studies noted a reduction in alcohol consumption [8,28]. Similarly, our results reported that more participants had decreased alcohol intake than those who had increased alcohol intake during the pandemic.

Tailoring public health responses to targeted groups may be important for mitigating health behavioral problems during the COVID-19 pandemic. Previous studies showed that smoking was associated with an increased risk of COVID-19 progression [29,30]. Thus, it is important to identify the population groups who are more likely to engage in smoking as part of the COVID-19 risk management at the population level. This study revealed that reduction in smoking was associated with older age whereas an increase in smoking was associated with younger age, which aligned with previous findings that older smokers were more likely to quit than younger smokers during the pandemic [22]. Furthermore, being divorced or separated was also associated with an increase in smoking [22,31]. In contrast with what was previously found, financially stable individuals were less likely to smoke more [31], whereas highly educated individuals were reported to be less sensitive to reducing the frequency of their smoking, which aligned with that reported in earlier studies [32]. Lastly, preexisting chronic diseases were shown to be associated with increased smoking, as noted in previous studies [33,34].

Marital status had a significant association with alcohol consumption, showing an increased level for couples that were married. This was contrary to previous findings that single [35] and younger individuals [21,36] were more likely to consume more alcohol. Interestingly, individuals with a higher household income were more likely to report decreased alcohol consumption during the pandemic. This was in contrast to previous findings from the United Kingdom and the Pan American Health Organization that reported individuals with a higher household income had an increase in alcohol use [21,37]. Individuals living in the areas hit harder by COVID-19 were found to drink with higher frequency, which may be explained by the fear of COVID-19 infection [21]. Moreover, increased drinking during the pandemic was associated with psychological factors such as stress and noncompliance with social distancing measures as reported by a previous study [38]. Other factors, including self-employment and the presence of preexisting chronic conditions, were associated with an increase in alcohol use during the COVID-19 pandemic, aligning with an earlier study that demonstrated that job insecurity was more prevalent in those who were self-employed [23]. Furthermore, being married was also associated with a reduction in alcohol use. These results differ from those of previous studies that suggested single people drank more or that marital status was not associated with changes in alcohol consumption [9,35,36].

The COVID-19 pandemic might significantly affect body weight–related behaviors, including reduced levels of physical activity [39,40]. In particular, it was previously reported that decreased physical activity was remarkably widespread among obese populations and a higher body mass index was associated with an increased risk for COVID-19 hospitalizations and deaths [41-43]. This highlights the importance of physical activity for all groups during the COVID-19 pandemic. We found that amounts of exercise increased in the middle-aged populations but decreased in the younger age groups. Mandated work-from-home conditions may have contributed to the drop in physical activity and exercise among younger groups, while exercise promotions among middle-aged groups may have contributed to their consequential increase [44]. Individuals with college or university degrees or above were more likely to experience a reduction in exercise during the pandemic compared to those with a high school diploma or lower academic degree. This demonstrates that individuals with advanced degrees can be targeted for improvement in physical activities [45]. In contrast to the previous research that suggested individuals from higher-income households experienced a decrease in weight gain protective behaviors [46], we found that individuals with higher-income households actually experienced more of these behaviors during the pandemic. Lastly, having a preexisting chronic condition was significantly associated with reduced exercise. The chronic disease itself may cause a lack of physical activity; therefore, more attention should be paid to increasing regular exercise among patients with chronic diseases, especially during this pandemic.

The results on the health status and behaviors clearly outline the implications for public health both before and after the COVID-19 outbreak. Although the impact of the pandemic on health behaviors may vary widely by population group, the majority of the people did not notice significant changes. However, in some risk groups, health behaviors worsened, such as exercising less, drinking more alcohol, and smoking more cigarettes. Taken together, these findings demonstrate a need for public health interventions to manage health behaviors as the COVID-19 pandemic continues. Additionally, there is a need for follow-ups for those with chronic diseases to better understand their changes in health status and behaviors during the COVID-19 period.

Our study has several limitations. First, as participants were asked to compare their health status and behaviors 1 year ago to their current status and behaviors, recall bias may happen. In addition to this, intentional distortion of answers could not be ruled out. To reduce the recall bias as much as possible when scheming the items, the reference points were presented. Since most of the participants responded in November 2020, rather than simply suggesting “1 year ago,” the footnote below the question indicated “November 2019, before the outbreak of COVID-19 outbreak.” “The present” is also indicated as November 2020, after the COVID-19 outbreak. Second, since it is a self-report questionnaire, the results may vary depending on the person's perception. Third, since this study is a cross-sectional study, the causal relationship is unknown. Finally, since we only included a representative sample of the Korean population, our results may not be generalizable to other populations. Considering that Korea has never implemented lockdown measures, this study has successfully identified overall changes in health status and behavior and related factors during the pandemic under nonextreme circumstances. In addition, this study is meaningful in providing information on groups vulnerable to changes in health behavior due to COVID-19.

In conclusion, this study identified changes in health status and behavior and factors related to changes before and after the onset of COVID-19 in addition to confirming the characteristics of the group with worsened health status and behaviors. In particular, younger generation’s negative health behaviors need more attention in terms of public health. As COVID-19 prolongs, public health interventions for vulnerable groups may be needed.

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Authors' Contributions

EK, HL, JYL, and YCH conceptualized this study. EK and JYL curated the data. EK conducted the formal analysis. YCH acquired the funds. EK, HL, and JY carried out the investigations. EK, HL, JYL, and YCH performed the methodology. EK and JHS administered the project. YCH collected all the resources. EK used the developed software to conduct formal analysis. JYL and YCH supervised this study. JY and HL visualized this study. EK, HL, JY, and JYL wrote the original draft. EK, HL, JHS, JY, JYL, and YCH performed the writing-review and editing. JYL and YCH contributed equally as corresponding authors. All the authors approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Self-reported health status questionnaire.
[DOCX File , 22 KB - publichealth_v7i11e31635_app1.docx]

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Abbreviations

aOR: adjusted odds ratio
STROBE: STrengthening the Reporting of OBservational studies in Epidemiology

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Original Paper

The Impact of Public Health Events on COVID-19 Vaccine Hesitancy on Chinese Social Media: National Infoveillance Study

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Abstract

Background: The ongoing COVID-19 pandemic has brought unprecedented challenges to every country worldwide. A call for global vaccination for COVID-19 plays a pivotal role in the fight against this virus. With the development of COVID-19 vaccines, public willingness to get vaccinated has become an important public health concern, considering the vaccine hesitancy observed worldwide. Social media is powerful in monitoring public attitudes and assess the dissemination, which would provide valuable information for policy makers.

Objective: This study aimed to investigate the responses of vaccine positivity on social media when major public events (major outbreaks) or major adverse events related to vaccination (COVID-19 or other similar vaccines) were reported.

Methods: A total of 340,783 vaccine-related posts were captured with the poster's information on Weibo, the largest social platform in China. After data cleaning, 156,223 posts were included in the subsequent analysis. Using pandas and SnowNLP Python libraries, posts were classified into 2 categories, positive and negative. After model training and sentiment analysis, the proportion of positive posts was computed to measure the public positivity toward the COVID-19 vaccine.

Results: The positivity toward COVID-19 vaccines in China tends to fluctuate over time in the range of 45.7% to 77.0% and is intuitively correlated with public health events. In terms of gender, males were more positive (70.0% of the time) than females. In terms of region, when regional epidemics arose, not only the region with the epidemic and surrounding regions but also the whole country showed more positive attitudes to varying degrees. When the epidemic subsided temporarily, positivity decreased with varying degrees in each region.

Conclusions: In China, public positivity toward COVID-19 vaccines fluctuates over time and a regional epidemic or news on social media may cause significant variations in willingness to accept a vaccine. Furthermore, public attitudes toward COVID-19 vaccination vary from gender and region. It is crucial for policy makers to adjust their policies through the use of positive incentives with prompt responses to pandemic-related news to promote vaccination acceptance.

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KEYWORDS

COVID-19; vaccine; hesitancy; social media; China; sentiment analysis; infoveillance; public health; surveillance; Weibo; data mining; sentiment; attitude

Introduction

At the end of 2019, the first case of COVID-19 was reported in Wuhan, China. The disease spread rapidly throughout China, after which it soon evolved into a global pandemic. By the end of May 2021, the total number of confirmed cases globally exceeded 100 million, and the cumulative number of deaths was >3 million with a mortality rate of approximately 2.07% [1]. Although the rate was lower than that of severe acute respiratory syndrome coronavirus 1 and Middle Eastern respiratory coronavirus (9.5% and 34.4%, respectively), it cannot be ruled out that COVID-19 has stronger transmissibility than either one of those viruses [2,3]. The rapid spread of COVID-19 has brought unprecedented challenges to each country worldwide in terms of social, economic, cultural, and political aspects.

Vaccination is considered the most effective and safest way to provide immunity against new infectious diseases. According to statistics, the current kinds of vaccines worldwide can save more than 3 million lives related to >20 diseases every year [4]. To control the worldwide spread of COVID-19, a call for global vaccination against COVID-19 is required [5]. In mid-March 2020, China's recombinant COVID-19 vaccine was approved, and clinical trials were initiated [6]. Thus far, at least 13 different COVID-19 vaccines have been put into use throughout the world, including the Sinopharm COVID-19 vaccine [7]. However, with the continuous development of the internet worldwide, the antivaccine campaign is also spreading rapidly through social media platforms, thus causing a threat to optimal global vaccine delivery [8-10].

Social media has played a key role in information dissemination during the COVID-19 pandemic. Through social media, important epidemic-related information can be easily disseminated, and people across the world can quickly obtain relevant disease-related information, participate in the discussions, and express their own views about COVID-19 [11,12]. In the meantime, misinformation, defined as erroneous or incorrect information, has also been widely spreading during the pandemic [13]. Although misinformation about COVID-19 is posted more than evidence-based information on social media [14], scientific information has had more reposts than the false information [14], and the platforms have responded to much misinformation identified by fact-checkers [15].

Weibo is one of the representative social media platforms with most users in China, which has more than 500 million active users and more than 700 billion views [12,16-19]. It has become one of the primary social platforms for Chinese internet users to disseminate and acquire health information [20]. Up to June 2020, China had nearly 1000 million netizens, accounting for 67% of all Chinese citizens [21,22]. According to the 2020 annual report released by Weibo, users checked COVID-19–related information 16.1 billion times every day during the outbreak [23]. Particularly regarding the COVID-19 vaccine, more than 100,000 Weibo users participated in the discussion with a cumulative reading of more than 500 million times [24]. Given its popularity and the massive information contained within the site, Weibo can be considered an appropriate data source to investigate the public attitudes toward the COVID-19 vaccine.

For sentiment analysis during public health emergencies, many studies have used web crawlers, text-mining, and other technologies to collect information regarding a variety of public opinions from the internet [25]. In addition, some studies have used the web text data in accordance with different phases, classified these data on the basis of the theme and emotion [26,27], and adopted various visualization tools to investigate the public sentiment, thus proving that the social media can be applied to measure the public attention toward public health emergencies [27]. With the ongoing COVID-19 pandemic worldwide and successful entry of its related vaccines on the market, some studies have begun to focus on the information on social media to analyze the acceptance of vaccines by the public, emphasizing that the public's attitude on health issues are strongly influenced by social media [28].

However, many studies have not yet analyzed the sentiments of the Chinese population nationwide through their statements on domestic social media sites such as Weibo. While a number of studies have been conducted abroad on social media platforms, such as Twitter and Facebook [9,29-31], we do not yet clearly know the current sentiments and attitudes of the population toward COVID-19 vaccination in China. Furthermore, only a few studies have investigated the relationship between the social media context and public sentiment toward vaccination [32]. Clear and concise sentiment analysis of textual information on Weibo will not only improve the monitoring of public opinions on the internet but also effectively allow for the application of the results of emotional psychology studies to provide early warnings of unusual occurrences. The study of such psychological indicators is a very important guide for government policies at this particular stage [33-37] and would enable national governmental departments to better understand the attitude of the public toward vaccination, thus advancing collaboration with multiple parties more effectively to increase the vaccination rate of COVID-19.

This study aimed to investigate the public sentiment of COVID-19 vaccines and to evaluate gender and regional variations in this sentiment. The feasibility of social sentiment analysis on the basis of web-based data of hot-spot events and whether the same approach can be used in the future to keep track of public opinions on the internet during the vaccination period was assessed. The aim of this process was to provide a realistic grasp of the dynamic psychology of the public and highlight the leading role of the national government departments. The study also highlights the essential role of national governmental departments in moderating public sentiment through social media.

Methods

Methods Overview

Based on the public nature of the Weibo platform, this study used Python for data mining and sentiment analysis of the resulting text to crawl and analyze public comments published by Weibo users on the issue of COVID-19 vaccination, thus allowing the identification of the sentiment tendencies of the resulting text.

Data Collection

Processing

Python 3.9.2 (Python Software Foundation) [38] and related libraries were utilized to simulate logging and then capture the required data. The data obtained containing the identifier (ID) of the post, the context of the post, the post time, the repost times, the number of "likes," the gender of the person posting, the location of this person, and the posting person's birthday were saved as multiple csv files. Owing to the anticrawler mechanism of Weibo, outliers beyond the setting date or keyword ranges were excluded.

Inclusion Criteria

Data were captured from the search results of Weibo with the keyword "COVID-19 Vaccine (新冠 疫苗)" between October 18, 2020, and May 15, 2021 (inclusive of both dates). As the general search criteria, the captured posts could refer to any approved COVID-19 vaccines globally. However, the search results may tend to the vaccine that is available in China. Since the availability of the vaccine to the Chinese public can be dated back to mid-October 2020 [39], the chosen time period is believed to cover the process from vaccine development to the mass vaccination scheme.

Exclusion Criteria

Given that the study focused on the public opinion in China, any texts written in languages other than Chinese and those from users whose locations were outside China were excluded. Any posts consisting of only symbols or numbers were also excluded.

Data Cleaning

Text Cleaning

First, the text contains no Chinese characters, namely posts written in other languages, or posts consisting of only symbols or numbers were removed. Then, posts with missing information, such as location or date, duplicated posts and those from public accounts were also removed [40].

Relevance-Based Cleaning

Because of the specific writing style of social media, the relevance between the context and study topic is a vital issue to be considered [41]. In this part, a "base text" is set to describe the proven determinants of COVID-19 vaccine acceptance in China [42] and compared with each crawled post to obtain their similarity. Cosine similarity, which is conceived as a powerful approach in natural language processing (NLP), was performed to measure the similarity between the crawled post and base text as formulated in the following model:

in which A_i and B_i are the *i*th item of the word frequency vector of the extracted keyword list via term frequency–inverse document frequency (TF–IDF) from the base text and crawled posts, respectively. After a trail contained 1000 randomly chosen posts, a threshold of 0.025 was set to distinguish the relevant post from the irrelevant ones, which attained an accuracy rate of 94.1% (941/1000). The model was then applied to the data set, and irrelevant posts were excluded.

Sentiment Analysis

Sentiment analysis is an NLP-based method to detect subjectivity in text, extracting and classifying opinions and sentiments [43]. SnowNLP [44], which is a specialized Python library for Chinese language processing and has been used in social media text mining for medical studies, especially COVID-19–related studies, given its feasibility and accuracy [21,45-47], was used to perform sentiment analysis.

In total, 15,000 randomly chosen posts were annotated manually, each of them was coded by 2 researchers, one of whom annotated independently and the other double-checked, of which 12,000 and 3000 posts were randomly split into the training and test sets. The training set included 9084 positive and 2916 negative posts ("neutral" was not used as a category owing to its limited research significance [45]).

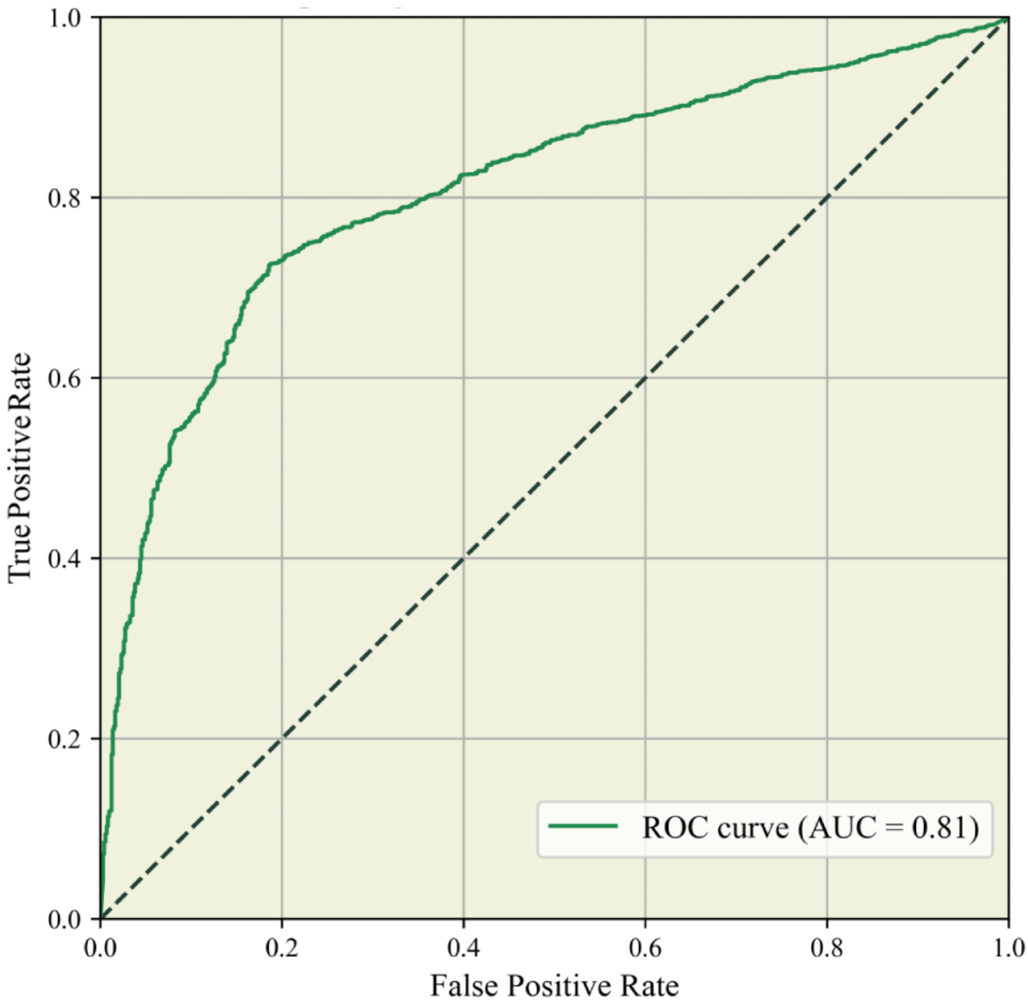
The process of SnowNLP includes word segmentation, stop word removal, and naïve Bayes classification. The key model is shown below:

where:

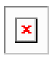
$$P(T) = P(T|c_1) \cdot P(c_1) + P(T|c_2) \cdot P(c_2)$$

in which T is the eigenvector of the text, and c_i is the *i*th emotion category, in this case, positive and negative. The posts are divided into those with probabilities higher than the threshold (positive category) or negative otherwise. Given the unbalanced distribution of labels in the training set, a receiver operating characteristics (ROC) curve was introduced [48] to evaluate the model (Figure 1). The area under the ROC curve (AUC) was then computed to measure the outcome of the classifier. After training, the threshold was set as 0.5889, for which the AUC yielded 0.81.

Figure 1. Receiver operating characteristic curve of the fitted SnowNLP model. AUC: area under the receiver operating characteristic curve; ROC: receiver operating characteristic.



After training the model, the emotions in the posts were computed. The sentiment score, *S* was calculated using the following equation:



in which #*Pos* and #*Neg* are the number of positive and negative posts, respectively. A sentiment score ranged from 0 to 1, indicating the most negative to the most positive.

Results

A total of 340,783 posts, including both original and reposted posts, and user-related information were retrieved. After cleaning, 156,223 posts were included in the analysis. According to the statistics, more female than male posters were noted, and more positive than negative posts were identified. Table 1 shows the number of posts and users.

Table 1. Descriptive statistics of total posts.

Topics	Posts or users, n (%)
Users (n=98,600)	
Male users	45,812 (46.5)
Female users	52,788 (53.5)
Total posts (n=156,223)	
Posts from male users	84,353 (54.0)
Posts from female users	71,870 (46.0)
Positive posts	93,660 (60.0)
Negative posts	62,563 (40.0)

As shown in Figure 2, the overall public positivity tends to fluctuate over time. The decline in positivity was consistent with the reported information about the side effects of the COVID-19 vaccine or other vaccines in general. In the week after October 18, 2020, a total of 59 people in South Korea were reported to have died after receiving the influenza vaccine, and at the same time, a rapid decline in the overall user's positivity for the COVID-19 vaccine occurred a short time after that report. In terms of gender, both men and women presented positive attitudes about the COVID-19 vaccine across most of the study periods, and the fluctuation patterns of the emotional score between male and female users is generally similar. Interestingly, although the trend of male and female emotional fluctuations was generally consistent, the overall positivity was weaker among female users than among male users most of the time. During the period from February 21 to March 21, 2021, China Central Television (CCTV) announced that pregnant and lactating women should postpone vaccination. Unlike male users, female user positivity for the COVID-19 vaccine decreased rapidly during this week (February 21-27, 2021) but began to rise again in the week.

Considering the 2 outbreaks in Shenyang, Liaoning Province, in January 2021 and Ruili, Yunnan Province, in March 2021, we present the heat map of the normalized sentiment score across all regions and provinces of China in heat maps by focusing on the period from 2 weeks before the outbreak to 4 weeks after the outbreak (Figure 3). Since the outbreak in these 2 regions, the sentiment about vaccination in this region and its surrounding regions had increased significantly, whereby vaccination positivity gradually declined 2 weeks after the outbreak was reported. In terms of the outbreak in Shenyang (upper panels in Figure 3), vaccination positivity increased not only in its own province but also in Northeast China and even throughout the country. Similarly, after the outbreak was reported in Ruili, Yunnan Province, the sentiment toward vaccination in Guizhou Province, a neighbor of Yunnan, also increased significantly.

Figure 2. The variation in public sentiment toward COVID-19 vaccines over time between male and female users (a higher sentiment score indicates higher positivity toward COVID-19 vaccines).

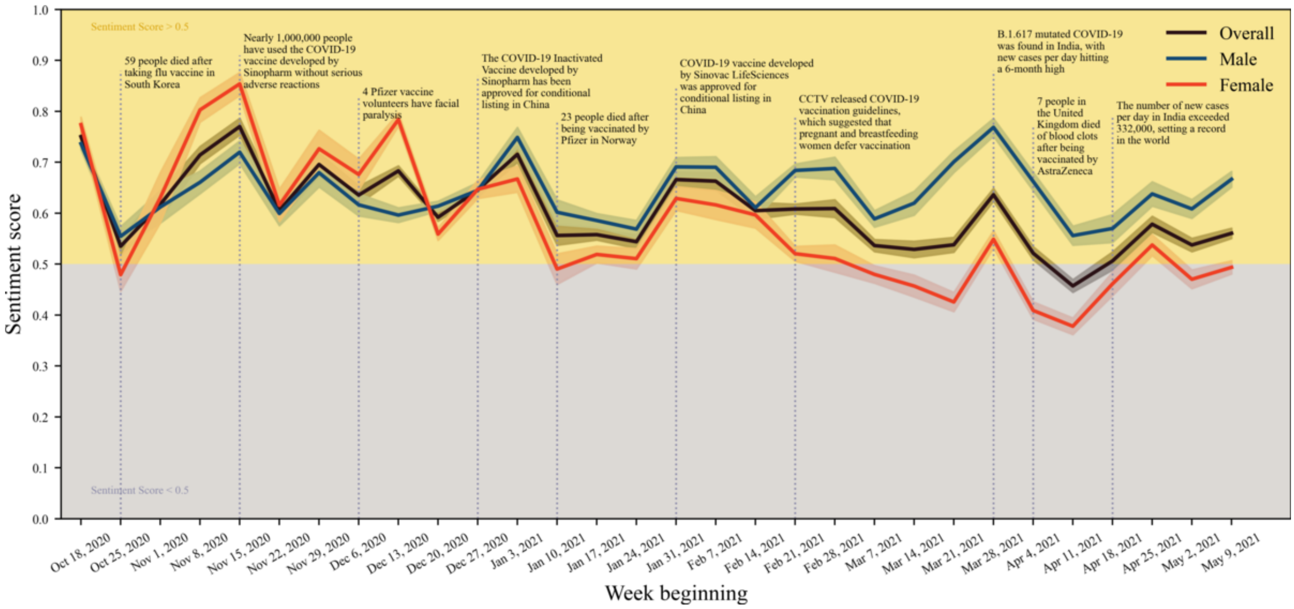


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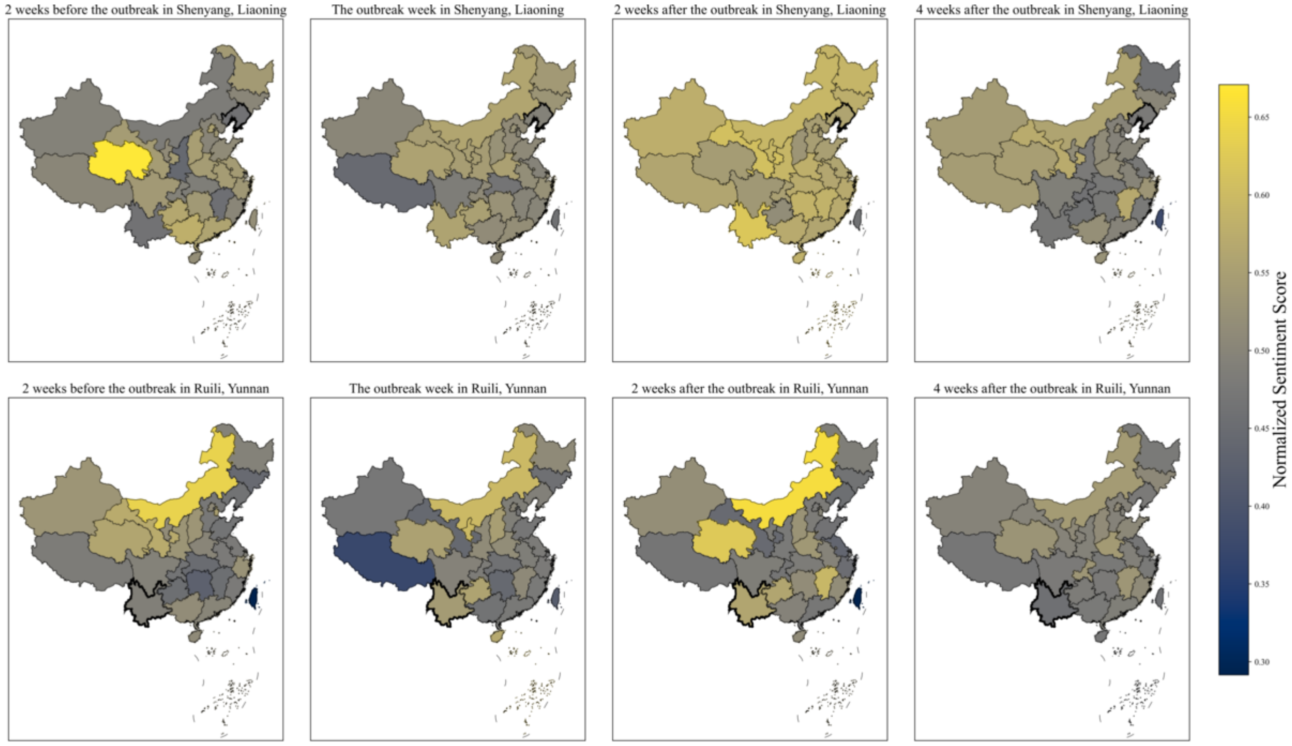
Figure 3. Variation in public positivity toward COVID-19 vaccines before and after the outbreak period in Ruili and Shenyang (the boundaries of provinces with the outbreak are highlighted in bold blacked lines).



Discussion

Principal Findings

COVID-19 vaccine hesitancy is a worldwide phenomenon and is a crucial issue to be solved in the fight against the pandemic. In China, we found that gender-specific emotional responses to vaccines could be influenced by various major public events over time, and the degree of influence varied by gender with women as the more vaccine-hesitant group. Furthermore, public positivity changed significantly in the weeks before and after the COVID-19 outbreak. A fairly substantial body of previous research demonstrating that women experience and express more intense emotion than men with regard to both positive and negative emotions can be found [49-51]. Recent media studies further indicate that female users are more likely to seek emotional support from web-based communities, while male users tend to provide information-related help [52,53]. Moreover, the difference in vaccine acceptance between genders has been reported in some previous studies focusing on flu vaccines, for which vaccine acceptance is greater in men than in women [54-56]; these findings also support our results. This study confirmed the emotional tendency of male and female users toward COVID-19 vaccines on social media, thus extending the literature on gender differences to the specific context of public health events. The findings also inspire policy makers for refined strategies in negative sentiment management. Interestingly, although previous studies show that women are more vaccine-hesitant [54-56], some studies have reported that vaccine coverage may be higher in women than in men [54]. The reason for this difference could result from women visiting preventive health care services and physicians more frequently [57]. Therefore, the policy maker should pay more attention to female communities' sentiments concerning major public health events and at the same time monitor the vaccination coverage to provide the in-time responses.

We found that the emotional tendencies of the pubic are dynamic, and positive and negative tendencies exist with respect to expressed emotional tendencies by the public. Every time a vaccine-related adverse event occurs, it may cause a decline in positive sentiment among Chinese internet users on Weibo, which is highly contagious on social media. Meanwhile, spreading false and appalling information on Weibo, which may bring about feelings of depression and anxiety for certain groups of people [58,59]. Therefore, when a COVID-19 emergency occurred in their particular region, people's sense of fear and self-protection led to increased positive emotions toward vaccination. Interestingly, during the outbreak in Shenyang, Liaoning, the positivity increased in this epidemic region and throughout the whole country. Even though the scenario could have resulted from the outbreak in other provinces in that period, we cannot rule out the possibility that regional outbreaks may affect national positivity. Furthermore, after the outbreak of the epidemic in Shenyang, Liaoning Province, Yunnan Province was the province with one of the most significant increases in vaccination positivity. Therefore, the public positivity of COVID-19 vaccines in previous epidemic regions may have a retrospective effect on vaccination positivity. As the situation of the outbreak improved, people began to gradually decrease the release of positive emotions again owing to decreased vigilance. Future studies should consider the use of social media to guide the public sentiment after the epidemic outbreak is over.

Although other emerging studies have investigated the intention toward COVID-19 vaccination using methods such as questionnaires, limitations such as the existence of some bias by inferring the perceptions and attitudes of the group with only a small sample still exist [60-64]. Sentiment analysis through the use of big data offers a more direct way to monitor the emotion of the citizens. Further studies should focus on the relationship between the positivity and the case rate growth or death rate.

With the popularity of the internet and economic development, social media has become a medium for people to express their emotions and opinions. For government officials and public health professionals, understanding public sentiment is critical to develop policies for infectious disease prevention and control and health care resource allocation. In the context of a global COVID-19 outbreak, the vaccine is an important measure to establish herd immunity against COVID-19 in an open border setting [65]. Therefore, understanding public sentiment about vaccines is an effective way for the government to promote COVID-19 vaccination in a rational and orderly manner. Exploring the factors and behaviors that influence positivity between different genders and different regions through the use of internet-based data can provide relevant information for government departments that are trying to assist in decision-making and providing health services. It also reminds relevant departments to establish public opinion and sentiment monitoring networks to understand the dynamics of public attitudes toward vaccines, predict changes in sentiment, and plan vaccine production and resource allocation rationally. This process is crucial for the government to better understand public sentiment through social media and to convey information accurately and timely, which will also answer vaccine-related queries and increase vaccination motivation.

Sentiment analysis can reveal differences between cities and regions, and when combined with current COVID-19 vaccine postings on social media and dynamic microblog postings based on geolocation data, can be used as a decision support point for government agencies. This type of analysis can also provide effective and real-time recommendations to government agencies that are based on the average number of microblogs per city and region and emotional tendencies; if this number is well above a significant peak, the information can be quickly reported to official agencies. Our text sentiment analysis tool can be an extension of this research, capturing the relevant information needed in real-time.

Limitations

This study has some limitations. First, our data collection was conducted only on one social media platform, Weibo. The opinions of those who did not use Weibo were not included. Second, the coding process was not completely independent, which may cause bias in the training process. Third, the gender and location information were self-reported by the users, which is a common issue in studies based on social media such as twitter [66]. Fourth, owing to the anticrawler mechanism of Weibo, a small proportion posts randomly lost during crawling. Fifth, sentiment may not be the only factor affecting vaccination acceptance. Local governments may take advantage of social media in promoting vaccination, but other challenges such as misinformation and the allocation of vaccines still exist.

Conclusions

The public opinion is closely related to public health events in China. When positive news about COVID-19 vaccines occurs, the public will be more positively sentimental about the vaccine and vice versa. This sentimental reaction appears to be gender-specific, by which men tend to be more open-minded than women. In terms of regional differences, the positivity of a province and its surrounding (and even the whole country) in which a pandemic occurs, was shown to increase and then decrease back to normal after 2-4 weeks. It is crucial for the government to adjust vaccination policies promptly in response to the public health events to promote massive vaccination via dynamic monitoring public sentiments.

Authors' Contributions

ZZ and WKM conceptualized and designed the study. ZZ contributed to methodology, data collection, visualization, and project administration. ZZ, GF, JX, and YZ analyzed the data and drafted the manuscript. JH, JL, BA, CJPZ, and WKM reviewed and edited the manuscript. All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

AUC: area under the receiver operating characteristic curve
CCTV: China Central Television
NLP: natural language processing
ROC: receiver operating characteristic
TF–IDF: term frequency–inverse document frequency

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Original Paper

COVID-19 Vaccine Hesitancy on Social Media: Building a Public Twitter Data Set of Antivaccine Content, Vaccine Misinformation, and Conspiracies

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Abstract

Background: False claims about COVID-19 vaccines can undermine public trust in ongoing vaccination campaigns, posing a threat to global public health. Misinformation originating from various sources has been spreading on the web since the beginning of the COVID-19 pandemic. Antivaccine activists have also begun to use platforms such as Twitter to promote their views. To properly understand the phenomenon of vaccine hesitancy through the lens of social media, it is of great importance to gather the relevant data.

Objective: In this paper, we describe a data set of Twitter posts and Twitter accounts that publicly exhibit a strong antivaccine stance. The data set is made available to the research community via our AvaxTweets data set GitHub repository. We characterize the collected accounts in terms of prominent hashtags, shared news sources, and most likely political leaning.

Methods: We started the ongoing data collection on October 18, 2020, leveraging the Twitter streaming application programming interface (API) to follow a set of specific antivaccine-related keywords. Then, we collected the historical tweets of the set of accounts that engaged in spreading antivaccination narratives between October 2020 and December 2020, leveraging the Academic Track Twitter API. The political leaning of the accounts was estimated by measuring the political bias of the media outlets they shared.

Results: We gathered two curated Twitter data collections and made them publicly available: (1) a streaming keyword–centered data collection with more than 1.8 million tweets, and (2) a historical account–level data collection with more than 135 million tweets. The accounts engaged in the antivaccination narratives lean to the right (conservative) direction of the political spectrum. The vaccine hesitancy is fueled by misinformation originating from websites with already questionable credibility.

Conclusions: The vaccine-related misinformation on social media may exacerbate the levels of vaccine hesitancy, hampering progress toward vaccine-induced herd immunity, and could potentially increase the number of infections related to new COVID-19 variants. For these reasons, understanding vaccine hesitancy through the lens of social media is of paramount importance. Because data access is the first obstacle to attain this goal, we published a data set that can be used in studying antivaccine misinformation on social media and enable a better understanding of vaccine hesitancy.

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KEYWORDS

vaccine hesitancy; COVID-19 vaccines; dataset; COVID-19; SARS-CoV-2; social media; network analysis; hesitancy; vaccine; Twitter; misinformation; conspiracy; trust; public health; utilization

Introduction

The opposition to vaccination dates back to the 1800s, immediately after the English physician Edward Jenner created the first vaccine in human history. The opponents to the vaccine were vocal and could be found in all segments of society: religious communities protested the unnaturalness of using animal infection in humans, parents were concerned about the invasiveness of the procedure, and vaccinated people were often illustrated with a cow's head growing from their neck [1]. Although vaccination is an effective way to prevent diseases such as diphtheria, tetanus, pertussis, influenza, and measles, almost 1 in 5 children still do not receive routine lifesaving immunizations, and an estimated 1.5 million children still die each year of diseases that could be prevented by vaccines that already exist [2]. These fatalities are not only caused by objective reasons, such as lack of access to vaccines due to poverty, but also by the unwillingness and fear regarding vaccines from the parents of these children. The term "vaccine hesitancy" refers to delay in acceptance or refusal of vaccines despite availability of vaccine services [3]. Vaccine hesitancy has emerged as a factor in vaccine delay and refusal for adults. A common example is the annual seasonal influenza vaccine. It has been observed that greater hesitancy, both general and specific to the influenza vaccine, is associated with lower vaccine uptake [4,5]. A variety of factors contribute to vaccine hesitancy, including safety concerns, religious reasons, personal beliefs, philosophical reasons, and desire for additional education [6]. During the COVID-19 pandemic, although the inoculation of large populations is increasingly important, antivaccine narratives are spreading rapidly, endangering public health, human lives, and the social order.

With the rise of social media, the dissemination of information (and hence, potentially, misinformation) has become easier than ever before. Unsurprisingly, antivaccine activists have also begun to use platforms such as Twitter to share their views. As a result, their activism has expanded its jurisdictions to include web-based propaganda. Compared with traditional communication channels, social media offers an unprecedented opportunity to spread antivaccination messages and allow communities to form around antivaccine sentiment [7]. Social media can amplify the effects of antivaccination misinformation; multiple studies have shown links between susceptibility to misinformation and both vaccine hesitancy and a reduced likelihood to comply with health guidance measures [7-10]. Based on these findings, vaccine-related misinformation on social media may exacerbate the levels of vaccine hesitancy, creating pockets with low vaccination rates in the United States and globally; this can hamper progress toward vaccine-induced herd immunity and can potentially increase the number of infections related to new COVID-19 variants, possibly leading to vaccine-resistant mutations. For these reasons, understanding vaccine hesitancy through the lens of social media is of paramount importance. Because data access is the first obstacle to attain this goal, to enable the research community, we built and made public a social media data set of antivaccine content, vaccine misinformation, and related conspiracies. Although researchers have been collecting data related to COVID-19 vaccines [11], per our knowledge, there are no public data sets focused specifically on the historical activities of antivaccination accounts on Twitter.

Here, we present a data set that focuses on antivaccine narratives on Twitter. The data set consists of two complementary collections: (1) the *streaming collection* contains tweets collected using the Twitter Streaming application programming interface (API) from a set of antivaccine keywords, and (2) the *account collection* contains historical tweets from approximately 70,000 accounts that engaged in spreading antivaccination narratives. Additionally, we present initial statistical analyses of the data, including the frequencies of hashtags, analysis of the news sources, the most likely political leaning of the accounts, and geographic distribution.

The published data set includes tweet IDs of publicly available posts, in compliance with the Twitter Terms of Service [12]. This collection builds on the previously published data sets by DeVerna et al [11], which is focused on general vaccine narratives, and it complements the previous work by Chen et al [13] and Lamsal [14], who published some of the largest Twitter data sets related to COVID-19 discourse to date. The complete data set in the form of a list of tweet IDs is openly available on GitHub [15].

Methods

Tracked Keywords for the Streaming Collection

To create a set of keywords that indicate opposition to vaccines, we used a snowballing sampling technique similar to that of DeVerna et al [11]. We started from a small set of manually curated keywords used exclusively in the context of strong vaccine hesitancy that appear on Twitter, such as *#vaccineskill* or *#vaccinedamage*. Using the Twitter Streaming API and the set of seed keywords, we collected the data for one day (October 18, 2020), after which we extracted other keywords that co-occurred with the seed keywords. We added the newly collected keywords to the list of seed keywords, checking them manually for relevance. We then repeated this step several times until we exhausted all the significant co-occurrences and narrowed our selection to approximately 60 keywords. The Twitter API can be queried with a substring of a longer keyword, and it will return the tweets that contain the substring. For example, the keyword *novaccine* will return the tweets that contain *novaccineforme*. We attempted to retain only the most informative and relevant stem words to capture most vaccine-related tweets and to avoid collecting less relevant tweets. The list of all keywords used to collect the streaming collection is listed in Table 1.

Table 1. Set of keywords used to collect the tweets in the streaming collection.

Keyword	Date on which tracking began
abolishbigpharma	12/30/2020
antivaccine	12/30/2020
ArrestBillGates	10/19/2020
betweenmeandmydoctor	12/30/2020
bigpharmafia	10/19/2020
bigpharmakills	12/30/2020
BillGatesBioTerrorist	10/19/2020
billgatesevil	12/30/2020
BillGatesIsEvil	10/19/2020
billgatesisnotadoctor	12/23/2020
billgatesvaccine	12/14/2020
cdcfraud	10/19/2020
cdctruth	10/19/2020
cdcwhistleblower	10/19/2020
covidvaccineispoison	12/23/2020
depopulation	10/19/2020
DoctorsSpeakUp	10/19/2020
educateb4uvax	10/19/2020
exposebillgates	12/30/2020
forcedvaccines	12/30/2020
Fuckvaccines	10/19/2020
idonotconsent	12/30/2020
informedconsent	12/14/2020
learntherisk	10/19/2020
medicalfreedom	12/30/2020
medicalfreedomofchoice	12/30/2020
momsofunvaccinatedchildren	12/30/2020
mybodymychoice	12/30/2020
noforcedflushots	12/30/2020
NoForcedVaccines	10/19/2020
notomandatoryvaccines	12/30/2020
NoVaccine	10/19/2020
NoVaccineForMe	10/19/2020
novaccinemandates	12/30/2020
parentalrights	12/30/2020
parentsoverpharma	12/30/2020
saynotovaccines	12/30/2020
stopmandatoryvaccination	10/19/2020
syringeslaughter	12/30/2020
unvaccinated	12/30/2020
v4vglobaldemo	12/30/2020
vaccinationchoice	12/30/2020

Keyword	Date on which tracking began
VaccineAgenda	10/19/2020
vaccinedamage	10/19/2020
vaccinefailure	10/19/2020
vaccinefraud	10/19/2020
vaccineharm	10/19/2020
vaccineinjuries	12/30/2020
vaccineinjury	10/19/2020
VaccinesAreNotTheAnswer	10/19/2020
vaccinesarepoison	10/19/2020
vaccinescause	10/19/2020
vaccineskill	10/19/2020
vaxxed	11/02/2020
yeht	11/02/2020

Collecting Tweets for Account Collection

First, we identified a randomly sampled set of approximately 70,000 accounts that appeared in the streaming collection and that engaged in antivaccine rhetoric between October and December 2020, either by tweeting some of the tracked keywords or by retweeting tweets that contained some of the tracked keywords. Then, for those accounts, we collected their historical tweets using the Twitter API. By leveraging Twitter's Academic Research product track, we were able to access the full archival search and overcome the limit of 3200 historical tweets of the standard API. In this way, we collected almost all the historical tweets of the most queried accounts.

Our collection relies upon publicly available data in accordance with the Content Redistribution clause under Twitter's Developer Agreement and Policy [12]. We released the data set with the stipulation that those who use it must comply with Twitter's Terms and Conditions. The complete data set is publicly available on a GitHub repository and is accessible on the web [15].

Calculating the Political Leanings of the Accounts

We calculate the political leaning of each account by measuring the political bias of the media outlets it shared. We use a methodology proposed in prior work [16-18], and we identified a set of 90 prominent media outlets and accounts that appeared on Twitter. Each of these outlets and their associated Twitter accounts were placed on a political spectrum (left, lean left, center, lean right, right) per ratings provided by the nonpartisan service AllSides [19]. For each account in the data set, we maintained a record of all retweets and the original tweets that contained a domain name affiliated with the selected media outlets. The political bias of each account was calculated as the average political bias of all media outlets it shared content from.

Identifying Low- and High-Credibility Media Sources

We leveraged *urllib*, the Python URL handling module, to parse the URLs found in the data set. Each URL was broken into several components, including the addressing scheme, network location, and path. A third-party data set that contains the domains associated with websites that share misinformation was used as a ground truth to tag the domain names [20]. For URLs that were not in the data set, we queried the Media Bias/Fact Check website [21] for further identification. Because URL shortening services such as Bitly [22] are widely used on Twitter, shortened URLs appeared frequently. We used *urlExpander* [23] to expand the shortened URLs and retrieve the full URLs where possible. Domain names of popular news aggregators and social networks such as Twitter, Facebook, Instagram, Periscope, and YouTube were ignored in the analysis.

Generating Geolocation Distribution Maps

To infer a tweet's geolocation, we used the information of the self-reported location of the account and matched it to a corresponding state in the United States. To calculate the average activity level per population, the absolute number of Tweets was normalized by the 2010 Census-reported population of that state as follows: $I = N_i/P_i \times 1{,}000{,}000$, where N_i is the number of tweets originating in state i and P_i is that state's population in 2010. This normalization provided information on the average number of collected tweets per million inhabitants. Note that we did not generate the geolocation map for the account collection, as it contains a relatively small number of accounts with self-reported locations.

Topic Network Analysis

A topic network was constructed to analyze the co-occurrence of hashtags in the streaming data set. Each node in the graph represented a hashtag, and an edge was added if two hashtags occurred in the same tweet. The node size was proportional to its degree of centrality, and the edge weight was the number of times two hashtags appeared together. For better visualization, nodes with fewer than 25 neighbors were ignored. To investigate the community structure of the network, we used the Louvain algorithm [24] on the topic network, which provided further insights about the links between antivaccine topics.

Results

The primary contribution of this study is the data set that we made publicly available. As of this writing (May 2021), we had collected over 137 million tweets organized in two collections. The streaming collection was gathered using the set of antivaccine keywords in Table 1. The account collection, on the other hand, contains the historical activities of accounts prone to spreading antivaccination narratives; thus, it is a significantly larger data set compared to the streaming collection. The basic statistics on the two data sets are shown in Table 2. The data set is available on GitHub [15] and was released in compliance with the Twitter Terms and Conditions. We are unable to provide the full text of the tweets; therefore, we are releasing the Tweet IDs, which are unique identifiers tied to specific tweets. Researchers can retrieve the full text and the related metadata by querying the Twitter API. Because the streaming data collection is still ongoing, the statistics shown below can vary in future versions of the data set. In the following sections, we will describe the streaming collection and account collection separately.

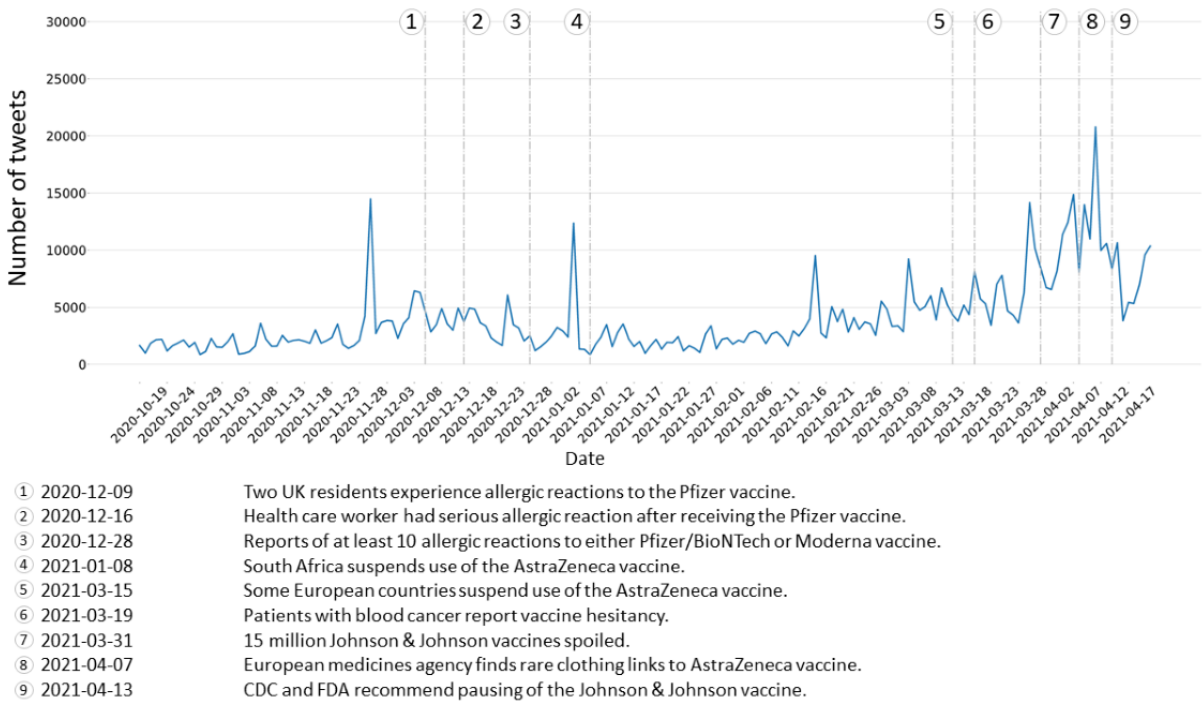
Table 2. Basic statistics on tweets collected in the streaming collection and account collection.

	Streaming collection	Account collection
Tweets, n	1,832,333	135,949,773
Accounts, n	719,652	78,954
Average number of tweets per account	2.5	1721.8
Verified accounts, n	9032	239
Accounts with location, n	5661	363
Date of oldest tweet	10/19/2020	3/6/2007
Date of most recent tweet	4/21/2021	2/2/2021

Streaming Collection

The streaming collection consists of 1.8 million tweets created by 719,000 unique accounts between October 18, 2020, and April 21, 2021. As shown in Figure 1, the number of relevant tweets in the streaming collection gradually increases from the start date. The chatter is relatively stable, with small spikes that do not often correspond to major announcements regarding vaccine research or vaccine authorization. We find this surprising, as the news usually drives the discussion on Twitter. Additionally, we observed a large spike in activity near the end of November 2020 that was not caused by any single event but rather by the increased activity of a small number of accounts.

Figure 1. Number of tweets over time in the streaming collection. The times of adverse events related to vaccines are marked by dashed vertical lines. Further descriptions of the news items are provided in the legend below the chart. CDC: US Centers for Disease Control and Prevention; FDA: US Food and Drug Administration.



The overwhelming majority of tweets originated from countries with predominantly English-speaking populations. Out of 1,832,333 tweets in the streaming collection, 1,245,986 (68%) originated in the United States, 229,041 (12.5%) in Great Britain, 100,778 (5.5%) in Canada, 21,987 (1.2%) in Ireland, and 20,155 (1.1%) in Australia; the rest of the tweets originated from other countries. In Figure 2, we show the geographical distribution of tweets in the United States. As expected, states with a large population, such as California, Texas, Florida, and New York, have more tweets in absolute terms (Figure 2, top). The number of tweets normalized by state population is depicted in Figure 2 (bottom), with the most tweets per capita originating from Hawaii, Alaska, and Maine, respectively.

Figure 2. Geographical distribution of the tweets from the streaming collection originating in the United States. The location of the tweets was inferred from the self-reported location of the account. Top: absolute number of tweets in each state; bottom: number of tweets normalized by the state population.

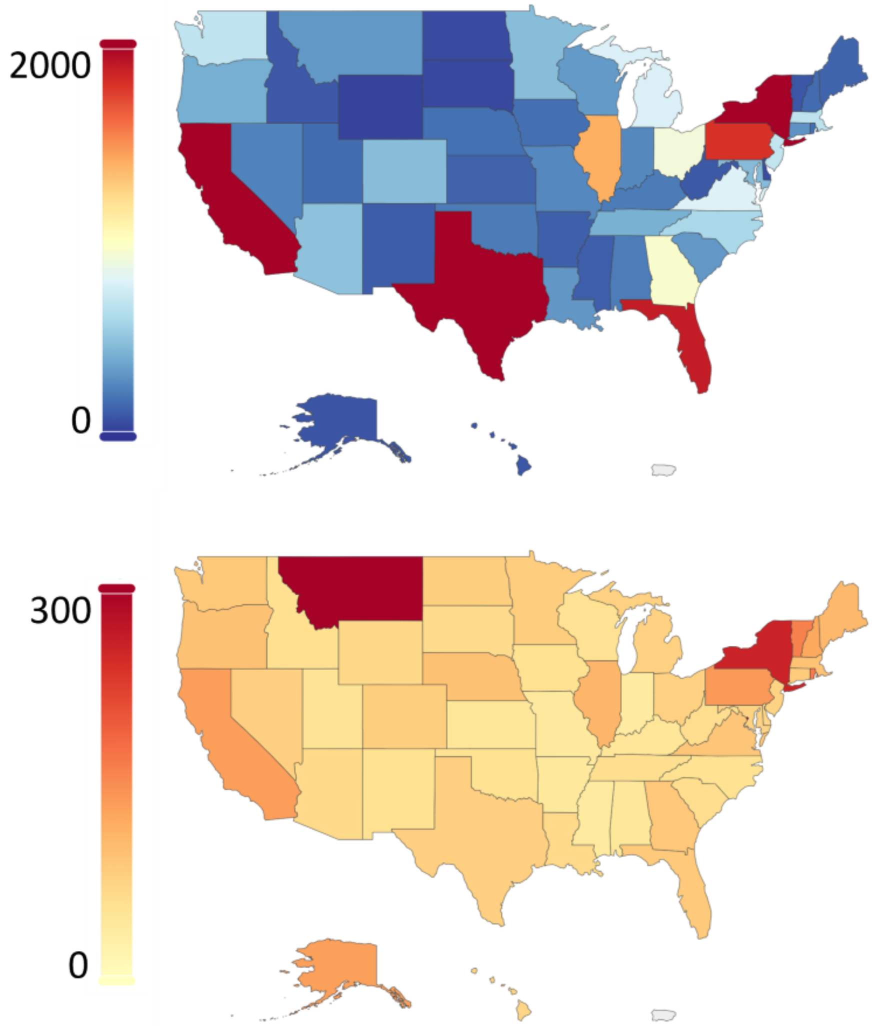


Table 3 lists the top 15 most tweeted hashtags in the streaming collection. The count column represents the total number of times a hashtag appears, and the proportion column quantifies the proportion of tweets that contain a specific hashtag out of all tweets with any hashtag. Note that many tweets contain no hashtags, and many tweets with a hashtag contain more than one hashtag. In addition to the most common general hashtags that we expected to find, such as *#vaccine* and *#covid19*, we observed a high proportion of hashtags that carry strong antivaccine sentiment, such as *#novaccineforme*, *#vaxxed* and *#vaccineinjury*. For example, *#novaccineforme* can be found in more than 25,000 tweets, accounting for 6.6% of all tweets in the streaming collection that contain any hashtags. A large set of common hashtags is related to some debunked conspiracy theories that claim there is a global plot by rich individuals to reduce the world population, often expressed through hashtags such as *#depopulation*, *#billgatesbioterrorist* and *#arrestbillgates*. Another set of very frequent hashtags appears benign on the surface. Hashtags such as *#learntherisk* and *#informedconsent* appear to communicate genuine concerns about the safety of the vaccines; however, those hashtags are usually decoys and are very often used by the same accounts that strongly oppose vaccination and that otherwise often use more explicit antivaccine hashtags.

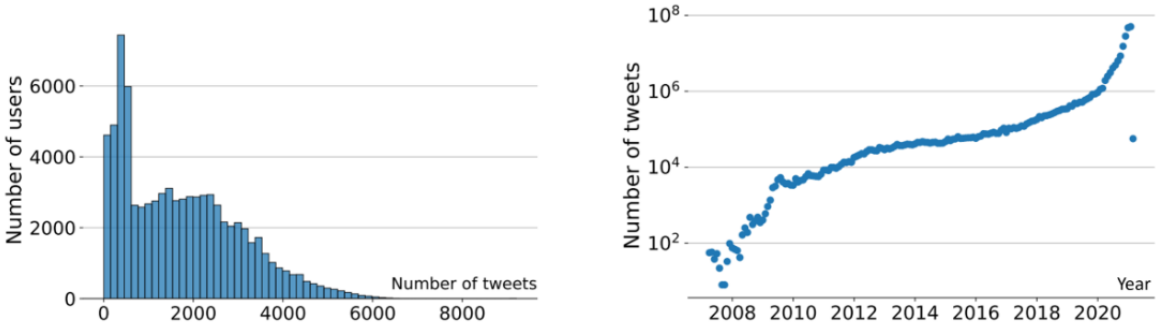
Table 3. Top 15 hashtags in the streaming data set. The count is the total number of times a hashtag appears, and the proportion quantifies the proportion of tweets that contain a specific hashtag out of all tweets with a hashtag.

Hashtag	Count, n	Proportion (%)
vaccine	41,069	10.66
vaccines	33,050	8.58
covid19	26,616	6.91
novaccineforme	25,642	6.66
learntherisk	23,340	6.06
billgatesbioterrorist	20,197	5.24
study	20,166	5.23
novaccine	19,410	5.04
mybodymychoice	19,166	4.97
informedconsent	16,578	4.30
depopulation	15,021	3.90
vaxxed	12,691	3.29
vaccineinjury	12,640	3.28
vaccination	10,873	2.82
arrestbillgates	9991	2.59

Account Collection

The account collection differs from the streaming collection, as it is focused on historical tweets from a set of accounts. The process of collecting the historical tweets is explained more in detail in the *Methods* section. The current account collection consists of more than 135 million tweets published by over 78,000 unique accounts, and it spans the period from March 3, 2007, to February 8, 2021. In Figure 3, we illustrate some of the most important statistics from this data collection. The left panel in Figure 3 shows the distribution of the number of tweets per account. Out of 78,954 accounts, 39,350 (49.8%) published fewer than 1500 tweets, 31,581 (40%) of the accounts have more than 2000 tweets, and 1184 (1.5%) have more than 5000 tweets. The right panel in Figure 3 shows the number of tweets over time. Most of the tweets originate in the year 2020, with the oldest tweet dating back to 2007. For 55,267 (70%) of the 78,954 accounts, the oldest collected tweet dates from 2020. There is a significant portion of accounts whose historical tweets date much earlier; for 14,211 (18%) of the 78,954 accounts, the earliest tweet was dated before 2018, and for 5368 (6.8%) of the accounts, the earliest tweet was dated before 2014. This relatively long-spanning collection of historical tweets at the account level may allow for a comprehensive temporal analysis of vaccine hesitancy development on Twitter over several years.

Figure 3. Tweets in the account collection. Left: distribution of tweets per account; right: distribution of tweets over time.



The 15 most common hashtags appearing in the account collection are displayed in Table 4. In addition to the common COVID-19–related hashtags, we observe many hashtags referring to US politics. During the period of the US 2020 presidential election and the political campaign, the accounts that appear in our collection were particularly active. Hence, we can see that many politically motivated narratives in the data originated during that period.

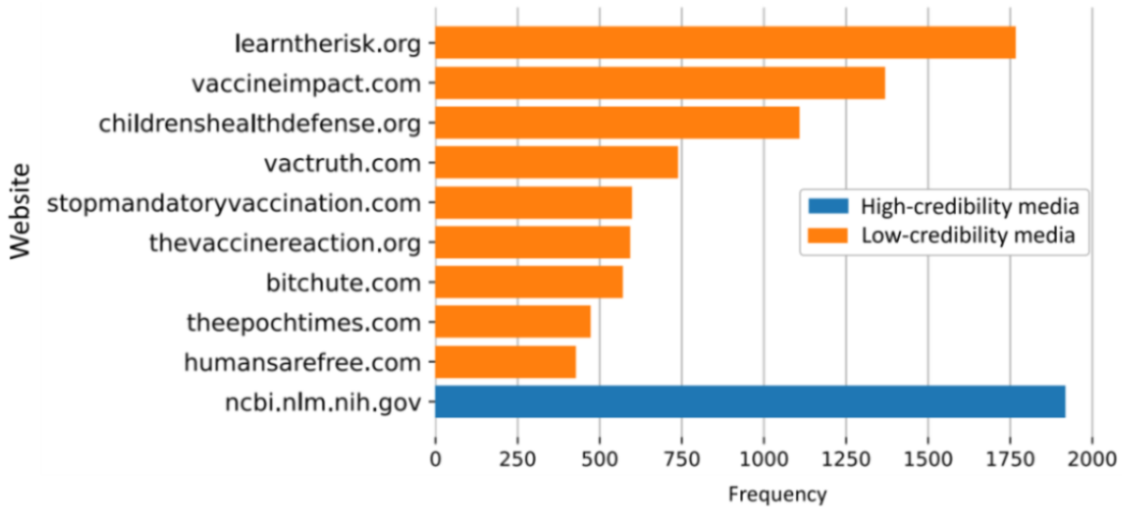
Table 4. Top 15 hashtags in the account collection. The count is the total number of times a hashtag appears, and the proportion quantifies the proportion of tweets that contain a specific hashtag out of all tweets with a hashtag.

Hashtag	Count	Proportion (%)
covid19	474,481	2.55
endsars	203,297	1.09
maga	164,332	0.88
coronavirus	158,574	0.85
trump	156,262	0.84
stopthesteal	121,069	0.65
trump2020	115,002	0.62
breaking	111,274	0.60
obamagate	110,046	0.59
covid	106,095	0.57
china	98,026	0.53
oann	96,943	0.52
antifa	79,157	0.43
biden	77,728	0.42
fakenews	66,599	0.36

News Sources in the Streaming Collection

Vaccine hesitancy is usually fueled by misinformation originating from websites with questionable credibility. In Figure 4, we list the top 10 URLs that can be found in the streaming collection, and we illustrate the number of times each appears. The vast majority of those websites can be found in the Iffy+ database of low credibility sites [20]. One of the most commonly shared sources is the website of an American antivaccine group called Learn The Risk; it is known for its campaigns against vaccination, which assert that vaccines are responsible for a large number of deaths of young children. It is followed by Vaccine Impact, a well-known news and information website that promotes pseudoscience; this website often shares antivaccination propaganda and promotes alternative medicine, holism, and alternative nutrition. The only website on the list with high credibility is the website of the National Center for Biotechnology Information (NCBI), a PubMed parent company.

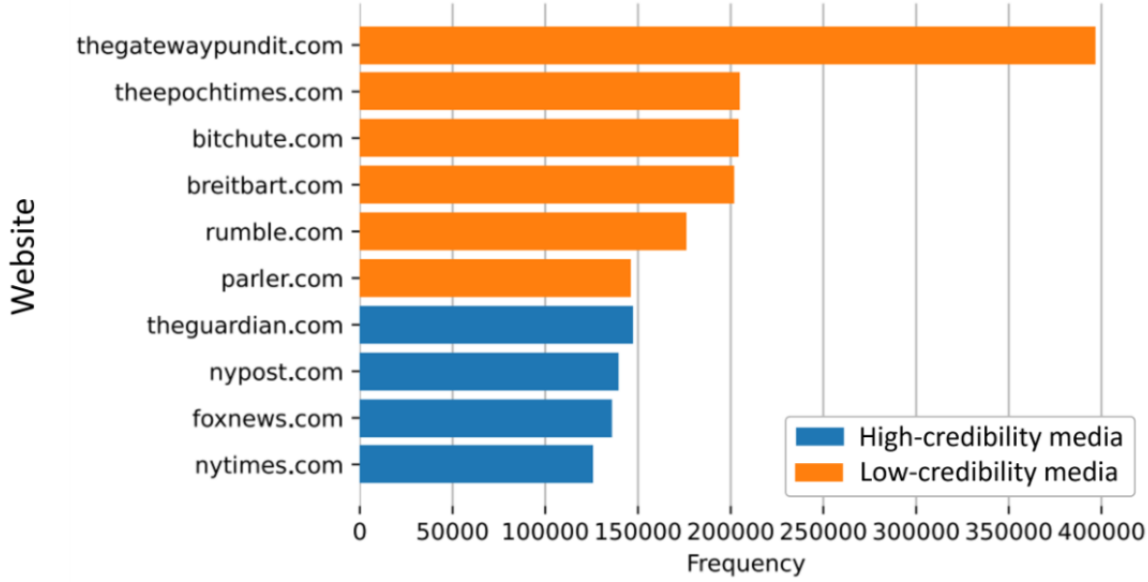
Figure 4. Top 10 news sources in the streaming collection. The URLs of the news aggregators and the large social platforms were omitted.



News Sources in the Account Collection

In Figure 5, we list the top 10 URLs that can be found in the account collection, and we illustrate the number of times each appears. Figure 5 shows that many far-right news media sites appear frequently in the account collection. The Gateway Pundit [25], which is known for publishing falsehoods, hoaxes, and conspiracy theories, occurs more than 400,000 times. Other far-right media outlets, such as Breitbart News [26] and the Epoch Times [27], also appear very often. Considering the sources that usually fall in the group of mainstream news media sites, such as Fox News [28] and the *New York Post* [29], conspiracy spreaders selectively quote reports from these sources to increase the credibility of often false claims.

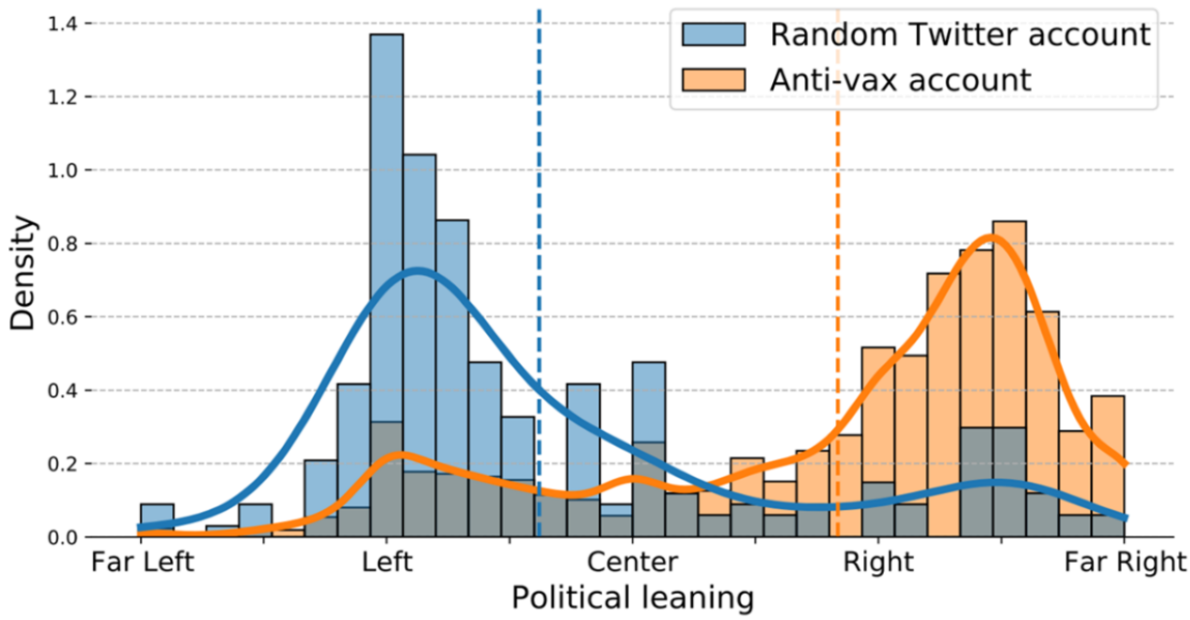
Figure 5. Top 10 URLs in the account collection. The URLs of the news aggregators and the large social platforms were omitted.



Political Leanings of the Antivaccination Accounts

In Figure 6, we show the distribution of political leanings of the accounts. The political leaning of an account was estimated based on its media diet (see the *Methods* section). The x-axis represents the account's political leaning and can take any value between "far left" and "far right." The y-axis is the normalized number of accounts with a corresponding political leaning. The political leaning of the accounts engaged in the antivaccination narratives is shown in orange. We observed a bimodal distribution with a significantly higher right peak. The blue bars illustrate the distribution of the political leanings for random Twitter accounts. The random Twitter accounts are a random sample of approximately 6000 accounts from the previously published Twitter data set related to the US 2020 Presidential election by Chen et al [30]. It has been previously shown that the Twitter users are younger on average and more likely to vote Democrat than the general public [31,32]. These results are not surprising, as they align with earlier studies showing that political orientation is a strong predictor of vaccine hesitancy in the United States [33,34].

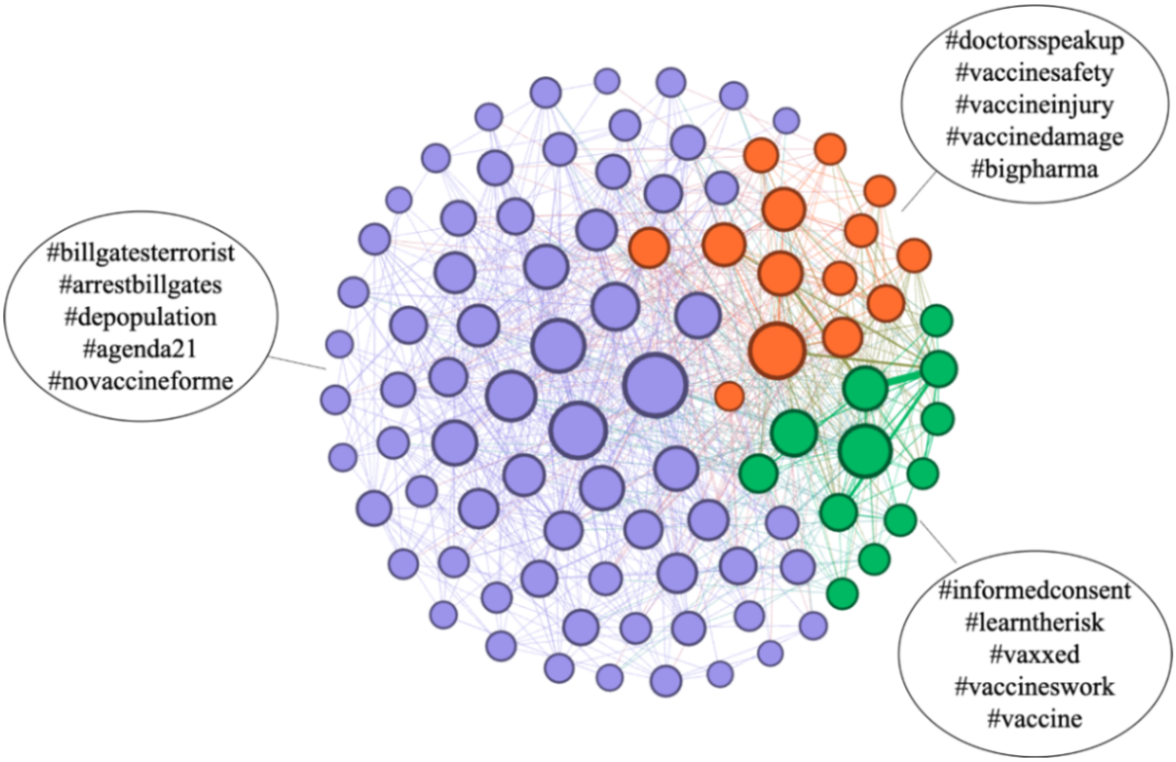
Figure 6. Distributions of the Twitter accounts based on their political leaning and attitude toward vaccination. The political leaning of each account was calculated from its media diet. Anti-vax: antivaccination.



Clusters of Antivaccine Narratives in the Streaming Collection

To obtain further insights into the provided data set, we explored the clusters of antivaccine narratives by identifying the antivaccine topics that usually co-occurred. We ran the Louvain community detection algorithm on the topic co-occurrence network, as described in the *Methods* section. The topic network is illustrated in Figure 7. We identified 3 distinct communities; all of them contained antivaccine keywords, but with different focuses on topics. The largest topic community, colored purple, focuses on debunked claims around the conspiracy narrative that the vaccine is a plot by rich people to reduce the world population. The second topic community, colored orange, mostly focuses on vaccine safety, as hashtags such as *#doctorsspeakup*, *#vaccinesafety*, and *#vaccineinjury* appear often. The smallest topic community, in green, contains a mixture of various hashtags that range from strongly antivaccine, such as *#informedconsent*, *#learntherisk*, and *#vaxxed*, to some neutral hashtags, such as *#vaccine*, to some provaccine hashtags, such as *#vaccineswork*.

Figure 7. An overview of the prominent hashtags in the data set, clustered into 3 communities. The nodes are the hashtags, and the links are drawn between two hashtags that appear together in the same tweet. Clustering was performed using the Louvain algorithm. For readability, we do not show all the node labels.



Discussion

Principal Findings

In this paper, we present a comprehensive data set consisting of tweets related to antivaccination narratives, organized in streaming and account collections. We characterized the data in several ways, including frequencies of prominent keywords, news sources, geographical location of the accounts, and political leaning of the accounts. The streaming collection consists of a random sample of tweets that contain any of the specific keywords promoting strong antivaccination sentiments. This is a common method used to collect Twitter data on vaccination hesitancy and other similar topics [35-42]. It is well understood by academics and is often used to provide useful insights about the chatter on the web about a particular topic in a specific period. The account collection was gathered using a relatively new method of collecting Twitter data by querying the historical activities from a set of tracked accounts. This collection was made possible after Twitter introduced the Academic Research product track API. In this way, by gathering massive amounts of historical tweets, researchers can characterize individual accounts rather than populations on average. This data set will be useful for scientists interested in the demographic and psychographic characteristics of Twitter users who are prone to spreading antivaccination narratives.

The news sources shared by the users in the streaming collection are predominantly websites with low credibility. However, the most shared URL is the website of the NCBI [25], which is part of the United States National Library of Medicine, a branch of the National Institutes of Health. NCBI houses PubMed, the largest bibliographic database for biomedical literature. This finding can create a false impression that the tweets from the streaming collection contain information from legitimate scientific sources. When we examined the context in which those papers were shared, we discovered that most of the papers from PubMed were cited with false and misleading conclusions. Sometimes, antivaccine advocates would share legitimate scientific papers documenting rare side effects of the vaccines, while overemphasizing the observed adverse effects and calling for vaccine boycotts. Sharing a scientific study in a tweet provides an illusion of credibility. Cherry-picking desirable sentences and relying on the fact that most of the audience will not make an effort to read a scientific paper in detail is a very effective strategy for manipulation.

It is often valuable to know the political affiliation of users who share antivaccine narratives. Knowing users' position on a political spectrum can be useful in identifying their most likely moral values and possible stances toward specific societal issues. This knowledge can be used to design appropriate future messaging and campaigns. We were able to identify the political affiliation for the accounts collection, as we had enough tweets for each account. Accounts that share common misinformation related to vaccines often share other conspiracy narratives, usually politically charged ones. The population susceptible to such narratives strongly skews conservative [18]; therefore, we expected that a large number of accounts in the account collection would be right leaning.

Limitations

Although the data sets give an overview of vaccine hesitancy on Twitter, potential limitations warrant some considerations. First, our streaming collection relies on a defined set of keywords. The antivaccine lingo is constantly evolving as the COVID-19 pandemic unfolds. Although we have made our best efforts to find the most representative keywords, they may not fully cover all antivaccine topics. The set of keywords we used was designed to capture the strongest antivaccine sentiments and may have missed various nuances in the multifaceted nature of vaccine hesitancy. Second, this data set should not be used to draw conclusions for the general population, as the Twitter user population is younger and more politically engaged than the general public [31]; this means that our data may be biased in various ways. Additionally, the keywords used for the collection were derived from the English vocabulary, highly biasing the geographical distribution of the tweets toward the English-speaking regions of the world. Finally, to prevent the spread of misleading COVID-19 information, Twitter has enacted specific rules and policies. The accounts violating these rules and policies may be banned by Twitter, making their tweets unreachable. At the time of writing, our estimate is that more than 40% of the accounts in the streaming collection and 30% of accounts in the accounts collection had been either banned or deleted. With each update of the streaming data set, we expect this proportion to change.

Conclusion

In addition to the streaming collection, which tracks tweets as they appear in real time, perhaps the most important contribution of this study is the account collection, a data set consisting of almost all historical tweets for a sample of users who were actively sharing antivaccination narratives. This data set can be used to provide further insights into the accounts that engage in antivaccine propaganda. Our intention in publishing this paper and data sets is to provide researchers with assets to enable further exploration of issues revolving around vaccine hesitancy and to study them through the lens of social media. The data sets collected and provided here could be useful for researchers interested in tracking the longitudinal characteristics of accounts engaging with antivaccine narratives. It can help provide better insights into the socioeconomic, political, and cultural determinants of vaccine hesitancy.

Use Notes

The data set is released in compliance with the Twitter Terms and Conditions and the Developer's Agreement and Policies [12]. Researchers who wish to use this data set must agree to abide by the stipulations stated in the associated license and conform to Twitter's policies and regulations.

Data Availability

The data are available at GitHub [15].

Acknowledgments

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Authors' Contributions

All authors conceived and designed the study. GM and YW collected and analyzed the data. All authors wrote and revised the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

API: application programming interface
DARPA: Defense Advanced Research Projects Agency
NCBI: National Center for Biotechnology Information

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Original Paper

Characteristics of and User Engagement With Antivaping Posts on Instagram: Observational Study

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Abstract

Background: Although government agencies acknowledge that messages about the adverse health effects of e-cigarette use should be promoted on social media, effectively delivering those health messages is challenging. Instagram is one of the most popular social media platforms among US youth and young adults, and it has been used to educate the public about the potential harm of vaping through antivaping posts.

Objective: We aim to analyze the characteristics of and user engagement with antivaping posts on Instagram to inform future message development and information delivery.

Methods: A total of 11,322 Instagram posts were collected from November 18, 2019, to January 2, 2020, by using antivaping hashtags including #novape, #novaping, #stopvaping, #dontvape, #antivaping, #quitvaping, #antivape, #stopjuuling, #dontvapeonthepizza, and #escapethevape. Among those posts, 1025 posts were randomly selected and 500 antivaping posts were further identified by hand coding. The image type, image content, and account type of antivaping posts were hand coded, the text information in the caption was explored by topic modeling, and the user engagement of each category was compared.

Results: Analyses found that antivaping images of the *educational/warning* type were the most common (253/500; 50.6%). The average likes of the *educational/warning* type (15 likes/post) were significantly lower than the *catchphrase* image type (these emphasized a slogan such as “athletesdontvape” in the image; 32.5 likes/post; *P*<.001). The majority of the antivaping posts contained the image content element *text* (n=332, 66.4%), followed by the image content element *people/person* (n=110, 22%). The images containing *people/person* elements (32.8 likes/post) had more likes than the images containing other elements (13.8-21.1 likes/post). The captions of the antivaping Instagram posts covered topics including “lung health,” “teen vaping,” “stop vaping,” and “vaping death cases.” Among the 500 antivaping Instagram posts, while most posts were from the *antivaping community* (n=177, 35.4%) and *personal* account types (n=182, 36.4%), the *antivaping community* account type had the highest average number of posts (1.69 posts/account). However, there was no difference in the number of likes among different account types.

Conclusions: Multiple features of antivaping Instagram posts may be related to user engagement and perception. This study identified the critical elements associated with high user engagement, which could be used to design antivaping posts to deliver health-related information more efficiently.

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KEYWORDS

anti-vaping; Instagram; user engagement; e-cigarettes; vaping; social media; content analysis; public health; lung health

Introduction

Around 2006, electronic cigarettes (e-cigarettes) became commercially available in the United States [1]. Since then, the prevalence of e-cigarette use (vaping) kept increasing, particularly among youth [2,3]. Due to the short history of e-cigarettes in the market, the long-term health effects of e-cigarette use are not well known [4]. However, multiple studies have shown an association between e-cigarette use and both physical and mental disorders [5-9]. In addition, more than 2000 e-cigarette or vaping product use–associated lung injury (EVALI) cases in the United States have been reported to the CDC since August 2019 [10].

The use of the internet to analyze, detect, and forecast diseases and predict human behavior relating to public health topics is known as infodemiology, which has become an essential part of health informatics research [11,12]. Social media data is a widely used web-based source for infodemiology studies [13-15]. As of 2019, there were approximately 247 million US social media users, representing 79% of the US population [16]. Recognizing the popularity of social media, e-cigarette manufacturers and stores post and share content promoting e-cigarettes on social media at no cost [17-19]. They increase the dissemination reach of their products by using popular hashtags or potentially by using computer programs to generate and post e-cigarette posts automatically and frequently [20-22]. On Twitter, there have been claims of multiple benefits of e-cigarette use [18,23-30]. In addition, e-cigarette companies and vape stores also increase the popularity of their products through celebrity sponsorship or by using fake user accounts to disseminate favorable views [20,21,27]. Social bot accounts have been shown to be used for promoting e-cigarettes and touting their “health benefits” on Twitter [31].

Although there are many provaping messages on social media, there are also posts about the potential adverse health effects of e-cigarette use [20,32-38]. Exposure to e-cigarette use on social media has been shown to be associated with e-cigarette use beliefs and vaping behavior [39]. Some government agencies started to recognize the unbalanced nature of information regarding e-cigarettes on social media and identified that more discussion about the negative health effects of e-cigarette use should be promoted [40,41]. The number of Twitter accounts about quitting smoking increased from 2007-2010, and almost half of the accounts were linked to commercial sites that promote different quit smoking products [30]. Sentiment and topic analyses showed that most of the health-related posts on Twitter are antivaping [42]. On YouTube, channels that post television/internet news content discuss the dangers of e-cigarettes more frequently than channels run by consumers or e-cigarette companies [43]. The most common negative health effects of e-cigarettes mentioned on YouTube include discussions about nicotine, and known and unknown health consequences related to e-cigarette use [28]. However, Instagram, a popular social media platform used by more than half of US youth [44], has rarely been investigated in terms of its antivaping content [45]. Our previous study showed that there are fewer antivaping posts than provaping posts on Instagram and highlighted the importance of regulating e-cigarette posts on Instagram [46]. However, we have only compared the overall differences between provaping and antivaping posts on Instagram. Antivaping content has not been well studied in the context of identifying effective communication methods to inform the public about the harms of e-cigarette use.

Therefore, we downloaded Instagram images that used antivaping hashtags. We selected 500 antivaping posts and analyzed their image type, image content, text information, and account type, as well as the user engagement associated with different categories. A full understanding of antivaping Instagram posts will aid in the identification of the essential post features related to higher user engagement and awareness, and further development of high-quality messages to inform Instagram users about the health risks of e-cigarette use.

Methods

Data Collection

We aimed to study vaping-related content posted on Instagram before the Food and Drug Administration announced a ban on cartridges and pods with specific flavors [47]. Therefore, posts using antivaping hashtags published from November 18, 2019, to January 2, 2020, were collected through Instagram’s application programming interface. The most frequently used antivaping hashtags identified from a previous study were used to extract data; these hashtags included #novape, #novaping, #stopvaping, #dontvape, #antivaping, #quitvaping, #antivape, #stopjuuling, #dontvapeonthepizza, and #escapethevape [46]. The Instagram images and the following metadata were collected: user ID, username, post date, follower count (the number of users that follow the account), following count (the number of users that the account follows), like count, comment count, media count (the number of posts that the accounts have), picture URL, caption, and hashtags. The combination of the Instagram user ID and post date were used to remove duplicate posts. The metadata including follower count, following count, like count, and comment count were updated one month later to get more accurate information.

Data Coding and Analysis

There were a total of 11,322 unique posts collected from Instagram during our study period from November 18, 2019, to January 2, 2020. From those posts, 1025 were randomly selected. Among the 1025 posts, 500 were antivaping posts as determined by hand coding, and these were used for further analysis. The attitude of each post toward e-cigarette use was determined by considering both image and caption content. Only the antivaping posts, which were about the potential health risks of electronic cigarette use or were against vaping behavior, were selected for further analysis. The coding of the images and their contents was similar to previous papers, with some modifications [29,46,48,49]. The posts were independently coded by two reviewers, and any differences were resolved by discussion. The reviewer agreement on classifying posts was 95.2%.

The image type, which identified the image themes, was categorized as one of the following: (1) advertisement (eg, a picture displaying discount information for quit vaping products); (2) catchphrase (eg, a picture emphasizing a slogan such as “athletesdontvape”); (3) product display (eg, a professional photo of an e-liquid container); (4) educational/warning (eg, images that state research results or facts about e-cigarettes; (5) events (eg, an image showing people attending a presentation or workshop related to e-cigarettes); (6) memes (eg, a picture created to deliver a message related to e-cigarettes while being comedic); (7) news (eg, a screenshot from a newspaper or television program of e-cigarette–related events); (8) notice (eg, a flyer about an upcoming e-cigarette–related presentation); (9) personal experience (eg, an image showing a person’s progress in quitting vaping); (10) vaping (eg, an image showing a person exhaling aerosols), and (11) others (images not falling into any previously defined category).

The content of Instagram images (ie, the objective elements shown in the images) was categorized into the following categories: (1) cartoon (as defined in the Master Settlement Agreement [19,50]); (2) text (eg, an image containing text information); (3) people/person (eg, an image with the major content of one or more people; (4) vaping (eg, an image displaying a person exhaling aerosols); (5) sign (eg, an image showing the sign of “no vaping allowed”); (6) product (eg, an image containing an e-cigarette device); and (7) others (images displaying items not falling into any category defined above). Each image might contain multiple content elements.

Since the attitudes of Instagram posts were determined based on both image and text content, the latent Dirichlet allocation (LDA) topic model was applied to the antivaping posts’ captions to analyze the text content of the antivaping posts [51]. Punctuation, stop words, and white spaces in the captions were removed to clean the data. Uppercase characters were converted to lowercase, and words were lemmatized to their stem form. Gensim (RARE Technologies Ltd) was used to identify frequent bigrams and trigrams. The optimal number of topics was determined based on topic coherence [52].

The posts were traced back to the posters’ Instagram accounts to determine the account type: (1) antivaping community (eg, a local government organization that is specifically against teens vaping); (2) personal, for example, a person who does not have either commercial (selling/promoting products) or professional (sharing professional knowledge) affiliations; (3) community (eg, a city account that uploads all their local news, which includes e-cigarette–related information), and (4) a business organization (eg, a company that promotes its essential oil products by claiming they can help with quitting e-cigarette use).

The number of likes was used to indicate the user engagement of each Instagram post. One-way analysis of variance and Tukey’s honestly significant difference (HSD) post hoc test were used to compare the means of likes for different categories of each feature, as well as the means of media_count and follower_count by using JMP Pro 15 (SAS Institute Inc). The correlations between media_count and follower_count for each account type were analyzed by Spearman correlation. Due to the large variation of real-life data, the top 5% and bottom 5% (outliers) of likes, media_count, and follower_count were removed from each category of each feature to compare the mean values [53].

Results

Characteristics of Antivaping Posts

Table 1 displays the distribution of the frequency of each image type. The most popular image type was *educational/warning* (253/500, 50.6%), followed by *memes* (n=36/500, 7.2%), *catchphrase* (n=35/500, 7%), *news* (n=29/500, 5.8%), *events* (n=28/500, 5.6%), and *vaping* (n=27/500, 5.4%). Further analysis compared the mean of likes among different image types (Table 1). Average numbers of likes for the *catchphrase* (mean 32.5) and *educational/warning* (mean 15) types were significantly higher than for *advertisement* posts (mean 8.2). In addition, the *others* type (mean 36.1) had significantly more likes than the *advertisement*, *vaping* (mean 15), *educational/warning*, and *notice* (mean 11.8) types.

Table 1. Image types of antivaping posts on Instagram (N=500).

Image type	Posts, n (%)	Mean likes (95% CI)
Advertisement	7 (1.4)	8.2 (2.8-13.6)
Catchphrase	35 (7)	32.5 (15.6-49.4)
Product display	15 (3)	18 (9.3-26.7)
Educational/warning	253 (50.6)	15 (13.6-16.4)
Events	28 (5.6)	22.6 (16.1-29.1)
Memes	36 (7.2)	18.3 (12.0-24.5)
News	29 (5.8)	19.4 (12.7-26.1)
Notice	10 (2)	11.8 (5.5-18.0)
Personal experience	9 (1.8)	25.1 (15.2-35.1)
Vaping	27 (5.4)	15 (8.9-21.0)
Others	51 (10.2)	36.1 (24.1-48.1)

To test if any image content element is associated with higher user engagement, the image content was analyzed. The analyses indicated that most of the antivaping posts contained *text* information (n=332, 66.4%), while *people/person* content appeared in 22% (n=110) of the posts. The proportions of posts containing each of the other image content elements were all close to 10% (*cartoon*: n=60, 12%; *media information*: n=45, 9%; *vaping*: n=55, 11%; *product*: n=54, 10.8%; *sign*: n=64, 12.8%; and *others*: n=53, 10.6%). Comparison of the means of likes among different image content types showed that the *people/person* content element (mean 32.8) had significantly more likes than the *cartoon* (mean 15.7), *media information* (mean 18.1), *text* (mean 16.2), *vaping* (mean 13.8), *product* (mean 19.2), *sign* (mean 15.4), and *others* (mean 21.1) elements.

Of the 500 antivaping posts, 483 contained captions. The LDA topic model was applied to those captions to reveal the content of Instagram antivaping posts. The identified popular topics were "lung health," "teen vaping," "stop vaping," and "vaping death cases" (Table 2).

Table 2. Caption analyses of antivaping Instagram posts.

Topic category	Keywords
Lung health	lung, ita, day, dona, make, time, healthy, start, week
Teen vaping	juul, nicotine, teen, kid, flavor, tobacco, youth, addiction, danger, school
Stop vaping	vape, stopvap, smoke, vap, novap, smoking, stop, quitsmok, tobacco, quitvap
Vaping death cases	vap, cigarette, product, health, year, people, case, death, state, report

Antivaping User Accounts

The selected 500 antivaping Instagram posts were posted by 393 unique Instagram accounts. Table 3 showed that the most popular account types were the *antivaping community* (n=177, 35.4%) and *personal* (n=182, 36.4%) account types. The rest of the posts were from *community* (n=99, 19.8%) and *business organization* (n=42, 8.4%) account types. Multiple posts might have been posted by the same Instagram account. On average, the *antivaping community* account type had the highest number of posts per account (1.69), followed by the *business organization* account type (1.31). The *community* and *personal* account types had an average number of 1.16 and 1.06 posts per account, respectively.

Statistical analyses showed that the *community* account type (mean 685) had significantly more followers than the *antivaping community* (mean 200; *P*<.001) and *personal* (mean 361.6; *P*<.001) account types. The number of followers for the *personal* account type was significantly more than for the *antivaping community* account type (*P*=.03). The *community* (mean 497.5) and *personal* (mean 361.6) account types posted significantly more images than the *business organization* (mean 145.8; *P*<.001 and *P*=.02, respectively) and *antivaping community* (mean 81.6; *P*<.001 and *P*<.001, respectively) account types. The numbers of posts by accounts and followers of the *antivaping community* (Spearman ρ=0.8230), *community* (Spearman ρ=0.7646), *business organization* (Spearman ρ=0.6601), and *personal* (Spearman ρ=0.5511) account types were all significantly correlated (all *P*<.001). However, no significant difference was observed in the mean number of likes across account types.

Table 3. Account type analyses of antivaping posts on Instagram.

Analyses	Community	Antivaping community	Personal	Business organization
Number of posts (N=500)	99	177	182	42
Percentage, %	19.8	35.4	36.4	8.4
Number of accounts (N=393)	85	105	171	32
Posts/account (average of 1.27 across all types)	1.16	1.69	1.06	1.31
Mean followers (95% CI)	685 (504.2-865.8)	200 (153.9-246.1)	364 (311.5-416.5)	354.9 (172.8-537.0)
Mean media (95% CI)	497.5 (365.0-630.0)	81.6 (60.4-102.8)	361.6 (304.6-418.5)	145.8 (76.0-215.5)
Correlation of followers and media (*P* value)	0.7646 (<.001)	0.8230 (<.001)	0.5511 (<.001)	0.6601 (<.001)
Mean likes (95% CI)	16.2 (12.7-19.6)	17.4 (14.9-20.0)	20.7 (18.1-23.3)	15.3 (11.7-19.0)

Discussion

Principal Findings

In this study, we found that the *educational/warning* antivaping Instagram images were the most common images, while the *catchphrase* images had the highest average number of "likes." Within different types of image content, the most popular element was *text*, while the *people/person* element had the most user engagement. The topics covered by the antivaping posts' captions included "lung health," "teen vaping," "stop vaping," and "vaping death cases." Most of the antivaping posts were from *antivaping community* and *personal* account types. However, the *antivaping community* account type had the highest average number of posts.

Comparison With Prior Work

Although *educational/warning* images were more popular than the other types, the *catchphrase* images and the *others* group had the most "likes." The *catchphrase* images were mainly associated with specific populations, such as athletes, parents, or high school students. These populations created slogans, which were also used as hashtags, to signal their social identity and their stance against vaping, such as #athletesdontvape and #itsnotcooltojuulinschool. Previous studies have shown that some provaping hashtags were created by vapers through a folksonomy process, and vaping communities might encourage the spread of specific vaping practices [54,55]. Therefore, the self-identification of antivaping Instagram users may have contributed to the higher user engagement of *catchphrase* images, offering a potentially effective approach to engaging populations with different identities to broaden the impact of antivaping education among the public.

The *others* image type included some unconventional pictures that did not fall into any other defined categories. Some of those images were not high quality, while others had links to vaping, or had antivaping-related information presented in the captions. For example, there was one image from a *personal* account that only had a few thousand followers. However, in the caption, the user described a traumatizing experience, explaining that their lungs were collapsing due to excessive vaping, which resulted in tens of thousands of "likes" and intense discussions about the harm of vaping. Therefore, the caption seemed to be a powerful feature for engaging users, although Instagram is a visual social media platform. The captions of the 483 antivaping posts all covered topics like "lung health," "teen vaping," "stop vaping," and "vaping death cases." Understanding how to use captions as part of an effective cessation strategy is very important, and our data suggested that using a storytelling approach to share a user's vaping experiences could be one option. These evidence-based messages could facilitate user interactions and appeal to fear, which has been recommended as a valid approach to raise awareness about health concerns [56].

Other than the image style and caption content, the impact that Instagram accounts have could also affect user interactions. There were 4 account types identified from the 500 antivaping posts. The *community* account type had the highest average numbers of followers (685) and posts (497.5). However, this account type posts images relating to various aspects of life rather than solely focusing on vaping-related information, which translated into a diluted frequency of antivaping posts (1.16 posts/account). In contrast, the *antivaping community* account type had the highest rate of antivaping posts (1.69 posts/account). However, this account type had a significantly lower number of followers, which could limit the impact of those accounts. There was no difference in the number of "likes" among the 4 different account types. One possible reason for this is that those accounts all publish posts with different image styles and caption content. Another possible reason might be that the exposure of Instagram users to antivaping posts may have been limited due to having fewer followers or infrequent posting, which may have caused the low number of "likes" observed for all account types.

Limitations

Creating high-quality post content might help overcome the limitations of account impact. In this study, we found that, among the types of image content compared, posts with a *people/person* element had the highest user engagement. However, we only compared limited numbers of image objects from a limited number of posts. A larger sample size might uncover a different ranking of image content as it relates to user engagement, which is one limitation of our study. In the future, deep learning methods will be used for image object detection. Similarly, the text content of collected images will be explored using deep learning techniques to generate image captions specific to our antivaping posts. Due to the small sample size of this study, we could not determine if saturation was reached when we were classifying the types of images and accounts. In addition, we used the average number of "likes" to indicate user engagement [49], but this does not indicate the user's support of vaping behavior [27]. Therefore, both the number and sentiment of comments should be analyzed to determine users' attitudes toward antivaping posts.

Conclusions

This study analyzed the features of antivaping Instagram posts that are related to user engagement and identified the most popular image type and the most active account type, which provided key insights into leveraging those features to develop and deliver antivaping messages efficiently on social media. Increasing the followers of antivaping accounts or encouraging accounts that already have a high impact (eg, influencers) to post antivaping information, as well as more frequent posts by public health entities, could potentially increase user engagement with antivaping posts and raise awareness about the risk of vaping among the public.

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Authors' Contributions

YG, ZX, and DL conceived and designed the study. YG and LS analyzed the data. YG wrote the manuscript. YG, CX, ZX, and DL assisted with interpretation of analyses and edited the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

EVALI: e-cigarette or vaping product use–associated lung injury
FDA: Food and Drug Administration
LDA: latent Dirichlet allocation
NIH: National Institutes of Health

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Original Paper

Population Health Surveillance Using Mobile Phone Surveys in Low- and Middle-Income Countries: Methodology and Sample Representativeness of a Cross-sectional Survey of Live Poultry Exposure in Bangladesh

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Abstract

Background: Population-based health surveys are typically conducted using face-to-face household interviews in low- and middle-income countries (LMICs). However, telephone-based surveys are cheaper, faster, and can provide greater access to hard-to-reach or remote populations. The rapid growth in mobile phone ownership in LMICs provides a unique opportunity to implement novel data collection methods for population health surveys.

Objective: This study aims to describe the development and population representativeness of a mobile phone survey measuring live poultry exposure in urban Bangladesh.

Methods: A population-based, cross-sectional, mobile phone survey was conducted between September and November 2019 in North and South Dhaka City Corporations (DCC), Bangladesh, to measure live poultry exposure using a stratified probability sampling design. Data were collected using a computer-assisted telephone interview platform. The call operational data were summarized, and the participant data were weighted by age, sex, and education to the 2011 census. The demographic distribution of the weighted sample was compared with external sources to assess population representativeness.

Results: A total of 5486 unique mobile phone numbers were dialed, with 1047 respondents completing the survey. The survey had an overall response rate of 52.2% (1047/2006) and a co-operation rate of 89.0% (1047/1176). Initial results comparing the sociodemographic profile of the survey sample to the census population showed that mobile phone sampling slightly underrepresented older individuals and overrepresented those with higher secondary education. After weighting, the demographic profile of the sample population matched well with the latest DCC census population profile.

Conclusions: Probability-based mobile phone survey sampling and data collection methods produced a population-representative sample with minimal adjustment in DCC, Bangladesh. Mobile phone–based surveys can offer an efficient, economic, and robust way to conduct surveillance for population health outcomes, which has important implications for improving population health surveillance in LMICs.

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KEYWORDS

mobile telephone survey; health surveillance; survey methodology; Bangladesh

Introduction

Background

Representative population-based surveys are important for measuring health outcomes and behavioral risk factors at the national and subnational levels [1]. These surveys can be used to provide key population health estimates, and if conducted at regular intervals, health trends can be monitored over time [1-3]. In low- and middle-income countries (LMICs), population health surveys are typically conducted using face-to-face household interviews due to methodological challenges, including a lack of representative individual sampling frames [4]. However, because of their high implementation costs and the time required, representative household surveys tend to be conducted only periodically [5]. In contrast, higher income countries (HICs) have developed and used annual telephone-based surveys, such as those for monitoring behavioral risk factor trends [6,7].

Telephone-based surveys are cheaper, faster, and can provide greater access to hard-to-reach or remote populations, particularly in the era of COVID-19, and hence are an appealing method for supplementing or replacing in-person household surveys in LMICs [8,9]. While sampling frames for probability-based telephone surveys have traditionally been limited to landlines in HICs, the growth of mobile phone ownership and the increasing number of mobile phone–only households has led to the development of dual-frame sampling designs [10,11]. However, in LMICs, the growth in mobile phone subscriptions has been exponential, with 22.9 subscriptions per 100 people in 2005 to 99.3 per 100 in 2020 [12]. This rapid increase has led to cellular networks leapfrogging landline infrastructure and mobile phones becoming the primary mode of communication [13].

High levels of phone ownership in LMICs provide a unique opportunity to implement novel data collection methods for population health surveys using mobile phones as a primary sampling unit [13]. However, there remain important methodological concerns regarding the use of mobile phone surveys in producing population-representative samples owing to sampling bias, coverage error, and low response rates [14]. For example, the sociodemographic profiles of mobile phone respondents have been shown to differ from those of face-to-face household survey respondents [15,16]. Recent systematic reviews identified only a few studies that were published using probability-based mobile phone survey methods in LMICs and reported a lack of consensus on the best implementation approaches and analytic methods to overcome methodological challenges in these populations [17,18].

In Bangladesh, where the mobile phone penetration rate is over 87% [19], phone-based surveys have been increasingly used for behavioral risk factor surveillance [20]. In urban areas, where the mobile phone penetration rate is even higher [21], these surveys have the potential to be especially useful for measuring population health outcomes. However, the population representativeness of these surveys has not been systematically evaluated and analytic methods such as poststratification adjustments have not been applied [20]. Therefore, the potential impact of sampling bias and coverage error on study findings and population estimates remains unknown.

Objectives

This study aims to address these critical methodological gaps to support the use of probability-based mobile phone survey methods for routine population health surveillance in LMICs. Here we describe the development of a mobile phone survey for measuring live poultry exposure in urban Bangladesh. Human-animal contact is a significant risk factor for the emergence of novel infectious diseases [22] and is, therefore, a key measure to capture in behavioral risk factor surveillance. Specifically, we provide an in-depth discussion of the methods covering sample design, questionnaire development, data collection, and poststratification analytic methods, as well as call outcome results, including response rates and population representativeness.

Methods

Study Design and Sampling

We conducted a population-based cross-sectional mobile phone survey between September and November 2019 to recruit a representative sample of adult males and females in North and South Dhaka City Corporations (collectively known as Dhaka City Corporation; DCC), in Dhaka, the capital of Bangladesh. The sampling frame was a list of mobile phone numbers from each of Bangladesh's 4 mobile phone operators (ie, Grameenphone, Robi Axia, Banglalink, and Teletalk). We restricted the phone numbers to those active in DCC, or if they could not be restricted to DCC, to those active in Dhaka district. Over 75% of the population of Dhaka district resides in DCC [23]. The phone numbers were provided by each mobile phone operator with permission from the Bangladesh Telecommunication Regulatory Commission.

We used a single-stage stratified probability sampling design to select participants. Before selection, the phone numbers were stratified by mobile operator and sampled in accordance with each operator's proportionate market share to maximize the precision of the sample and to ensure a representative distribution (Multimedia Appendix 1, Table S1) [24]. Within each operator list, simple random sampling was used to select phone numbers. At the time of contact, we screened each selected mobile phone respondent for eligibility, and we recruited an equal number of male and female respondents to allow for robust sex-specific analyses. Individuals were eligible for inclusion if they were at least 18 years of age, were current DCC residents, and had been residing in DCC for the past 1 year.

Questionnaire Development

The questionnaire was based on previous poultry exposure surveys conducted in urban China [25-28] but modified to the

Bangladeshi context through discussions with a 12-member advisory panel consisting of local experts in survey design, mobile phone surveys, and infectious diseases. Using a structured approach, the panel reviewed each survey question to assess the face and content validity of the items, as well as to identify areas for potential adaptation or modification and item reduction or addition. We conducted 2 rounds of review, and any items that did not achieve group consensus (defined as 60% agreement) were modified and re-examined until consensus was reached. Key revisions in this step centered on prioritizing and selecting items that were deemed feasible and reliable to ask participants during a phone interview. The questionnaire was translated into Bangla and independently reviewed by 2 native speakers familiar with the content to ensure comprehension and clarity; any translation disagreements were reviewed and further updated by the study team.

The final survey instrument comprised 5 sections and captured information on individual and household exposure to live poultry when purchasing at live bird markets (LBMs) and preparing food, prevention practices, influenza-like illness, and sociodemographics. LBMs were defined as a collection of stalls or vendors where the public could purchase live chickens, ducks, geese, or any by-products of these in an unprocessed form [29]. Specifically, the questions covered the following topics: frequency of LBM visits and the associated behaviors in markets, poultry processing practices during food preparation, uptake and adherence to hygiene practices, use of personal protective equipment (ie, gloves, facemask, and apron) during and after poultry exposure, self-reported influenza-like illness using a standard case definition [30], and household and individual-level sociodemographics. To minimize respondent burden when obtaining detailed information, where appropriate, the survey used a significant amount of branching logic. The questionnaire was thoroughly reviewed, and modifications were made as needed based on feedback from a pretesting phase (n=7) and a small-scale pilot (n=41). The final updated survey took approximately 10 to 15 minutes to complete.

Data Collection and Calling Procedure

We programmed both English and Bangla versions of the questionnaire into a customized computer-assisted telephone interview (CATI) platform developed by the Institute of Epidemiology, Disease Control and Research (IEDCR) in Dhaka, Bangladesh. This platform managed both the sampling and data collection processes, including complex form structure, automated repeat call attempts and interview rescheduling, automated strata monitoring of key variables (ie, mobile phone operator and sex of respondent) across interviewers, and pairing with a mobile phone app to facilitate automated dialing of each selected phone number. A team of 4 female data collectors was recruited to conduct the phone interviews, and data were entered into the CATI platform in real time. The data collectors received 4 days of training on the survey methods and questionnaire topics before the start of the pilot and data collection phases.

We conducted the survey between September and November 2019. In advance, we placed a Bangla-language newspaper advertisement in DCC's 2 most circulated newspapers to inform the public that they might receive a call from IEDCR regarding a health survey, that the phone numbers were randomly selected with the permission of the Bangladesh Telecommunication Regulatory Commission, and that participation was important for improving population health. Phone calls were made every day of the week between 8 AM and 8 PM (local time), except on Friday afternoons because of local religious observances, to limit the potential sampling bias that could result from recruiting only during weekdays and working hours.

Our team attempted calling each phone number up to 4 times to establish contact and conduct an interview with the respondent. Each unanswered call was automatically rescheduled for a different time of the day on a different day of the week over the following 7-day period. If the respondent was not reached after the maximum number of 4 call attempts, with at least one daytime and one evening call attempt, the phone number was classified as *no contact* and discontinued. At the first successful contact, we explained to the respondent the purpose of the study, the survey length, that participation was voluntary, and that all the information they provided would be kept confidential. Eligibility was confirmed and consent for survey participation was obtained at the time of the interview. When respondents were unable to complete the interview at the time of recruitment, we rescheduled the phone interview to a convenient time within the next 7 days. Once an interview was completed, or if a respondent declined, refused, or was ineligible, we discontinued the phone number from the call bank. In line with the IEDCR phone-based disease surveillance practices, no compensation was provided for participation. An overview of the recruitment process is provided in Multimedia Appendix 1, Figure S1.

Sample Size

A total of 1040 complete interviews (520 males and 520 females) were required to detect an 8% to 9% difference (65% vs 56% [26]) in live poultry exposure between strata, with 95% confidence and 80% power. The reason for explicitly stratifying by sex was to have sufficient statistical power to permit detailed exploration and identify notable differences in high-risk behaviors between males and females. This was important for ensuring appropriate and targeted risk-based implementation strategies.

Ethics Approval

This study received ethical approval from the committees of each of the participating research institutions: University of Toronto (protocol no. 37657), the Institute of Epidemiology, Disease Control and Research (IRB/2019/11), and the London School of Hygiene and Tropical Medicine (ref 17661). All the participants provided oral informed consent via phone.

Data Analysis: Response, Weighting, and Representativeness

The operational data for each phone number dialed and the corresponding details for call outcome status were summarized. We calculated the overall and mobile operator–specific response rates according to the American Association for Public Opinion Research (AAPOR) Response Rate-3 definition, which included those who were eligible and those estimated to be eligible in the denominator [31]. The number of persons estimated to be eligible was derived by assuming that the proportion of eligible individuals among those contacted was the same as for those who could not be contacted or who declined before their eligibility was determined.

The demographic data for completed interviews were summarized, and the sample distributions were compared with the Dhaka City Corporation demographic profile of the 2011 census [23]. To adjust for nonresponse and disproportionate stratified sampling by sex (ie, oversampling of females compared with the reference population), poststratification weights were calculated by age, sex, and education to align with the 2011 census. Weights were calculated using the census population fraction$_{ijk}$/study population fraction$_{ijk}$, where i was the age category, j was sex, and k was the highest completed education level. No extreme values were identified upon inspection. Participants with an invalid response to the weighting variables (ie, age, sex, and education) could not be assigned a weight and were, therefore, not included in the weighted analyses (n=16). The demographic distribution of the weighted data was summarized and compared with external data sources to assess the representativeness of the sample population for other key demographic variables, including marital status and region. All analyses were conducted in Stata 16.1 (StataCorp).

Results

Call Outcomes and Response Rates

Between September and November 2019, 5486 unique phone numbers were dialed. An overview of participant recruitment and outcome classifications is shown in Figure 1. Of the 5486 phone numbers dialed, 2051 (37.4%) were screened and determined to be ineligible. This included 288 (5.2%) phone numbers that were not in service, 49 (0.9%) respondents who were not in the eligible age range, 234 (4.3%) respondents who were not living in DCC, and 40 (0.7%) who had been living in DCC for less than 1 year. In addition, 1440 (26.2%) respondents were excluded because their sex-specific strata were complete; no information was obtained from 2259 (41.2%) phone numbers, including 1713 (31.2%) with no contact and 546 (10.0%) where the respondent declined to participate. Assuming that the mobile operator-weighted proportion of eligible individuals among those contacted and screened for eligibility was the same as for those who could not be contacted or who declined, 830 (36.7%) of these 2259 phone numbers were estimated to be eligible. Interviews were completed with 1047 (52.2%) respondents out of the 2006 eligible (known and estimated) phone numbers. The overall cooperation rate was 89.0%, based on the number of known eligible respondents contacted. Table 1 presents the call outcomes and response rates overall and by mobile phone operator.

Figure 1. Profile of participant recruitment and call outcome classification for the live poultry exposure mobile phone survey, Dhaka City Corporation, Bangladesh. DCC: Dhaka City Corporation.

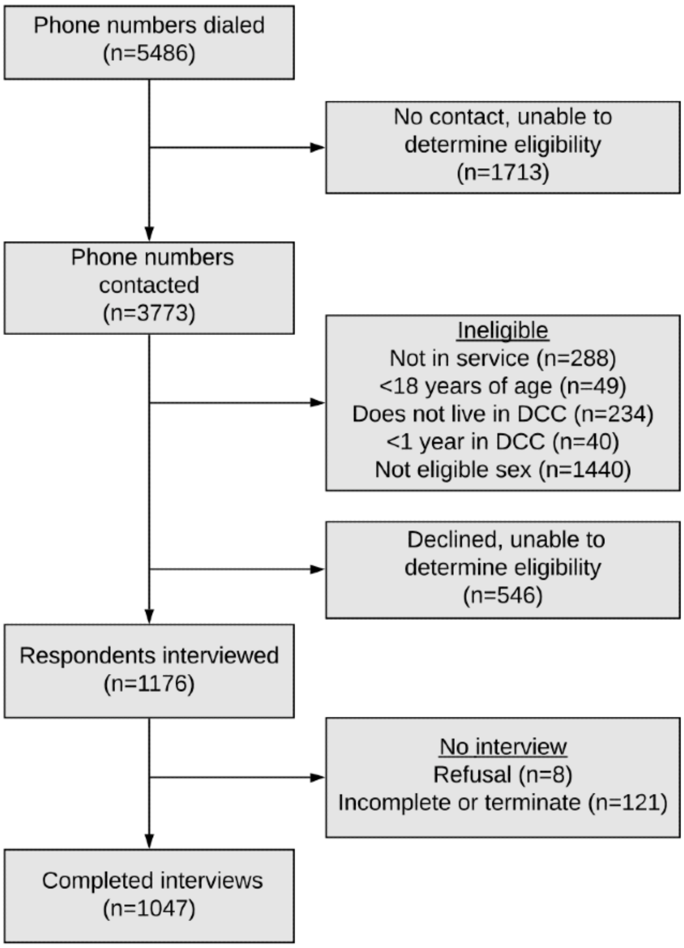

Table 1. Call outcome classification and response rates overall and by mobile phone operator for the live poultry exposure mobile phone survey, Dhaka City Corporation, Bangladesh.

Call outcome status	All, n (%)	Grameenphone, n (%)	Robi Axia, n (%)	Banglalink, n (%)	Teletalk, n (%)
Call outcomes					
Phone numbers dialed	5486 (100)	1901 (100)	2100 (100)	1346 (100)	139 (100)
Total ineligible	2051 (37.4)	697 (36.7)	932 (44.4)	367 (27.3)	55 (39.6)
Not in service	288 (5.2)	42 (2.2)	115 (5.5)	126 (9.4)	5 (3.6)
<18 years of age	49 (0.9)	15 (0.8)	13 (0.6)	18 (1.3)	3 (2.2)
Does not live in DCC[a]	234 (4.3)	89 (4.7)	31 (1.5)	113 (8.4)	1 (0.7)
Less than 1 year in DCC	40 (0.7)	20 (1.1)	5 (0.2)	13 (1.0)	2 (1.4)
Not eligible sex (strata complete)	1440 (26.2)	531 (27.9)	768 (36.6)	97 (7.2)	44 (31.7)
Total unknown eligibility	2259 (41.2)	663 (34.9)	817 (38.9)	723 (53.7)	56 (40.3)
No contact	1713 (31.2)	441 (23.2)	643 (30.6)	590 (43.8)	39 (28.1)
Declined (no eligibility screening)	546 (10.0)	222 (11.7)	174 (8.3)	133 (9.9)	17 (12.2)
Response rates					
Total eligible (known + estimated)	2006 (100)	831 (100)	575 (100)	553 (100)	47 (100)
No interview					
Refusal	8 (0.4)	0 (0)	2 (0.3)	6 (1.1)	0 (0)
Incomplete or terminated	121 (6.0)	54 (6.5)	39 (6.8)	26 (4.7)	2 (4.3)
No information (estimated eligible)[b]	830 (41.4)	290 (34.9)	224 (38.9)	297 (53.7)	19 (40.3)
Complete interviews (response rate)	1047 (52.2)	487 (58.6)	310 (54.0)	224 (40.5)	26 (55.4)

[a]DCC: Dhaka City Corporation.

[b]Estimated eligible number calculated using American Association for Public Opinion Research (AAPOR) guidelines [31], assuming that the proportion of eligible individuals among those who were contacted and screened is the same as for those who were unable to be contacted or declined.

Sample Characteristics and Representativeness

Compared with the DCC demographic profile from the 2011 census, the unweighted mobile phone survey sample overrepresented males aged 25 to 34 years as well as males and females with higher secondary education, while it underrepresented males and females aged 55 to 74 years and those with primary or lower than primary education. Given the stratified sampling design aimed at achieving equal representation of males and females, the overall unweighted sample overrepresented females and underrepresented males. After poststratification weighting on these key variables, the sample closely matched the population in terms of age, sex, and education (Table 2).

The weighted survey sample is representative of other demographic factors that were not used in the construction of the weights (Table 3). The overall sample shows a close match to the 2011 census figures for DCC by region, with slight discrepancies within the sex-specific strata. In terms of marital status, the survey slightly underrepresented single males and married females.

Table 2. Comparison of unweighted and weighted survey sample with 2011 census population benchmarks for the live poultry exposure mobile phone survey, Dhaka City Corporation, Bangladesh.

Characteristics	Unweighted sample			Weighted sample[a]			Census benchmarks[b]		
	Male (%)	Female (%)	All (%)	Male (%)	Female (%)	All (%)	Male (%)	Female (%)	All (%)
Age group (years)									
18-24	25.4	26.4	25.9	25.4	29.3	27.1	25.4	29.3	27.1
25-34	40.6	31.0	35.8	32.7	32.3	32.5	32.7	32.3	32.5
35-44	19.0	23.8	21.4	20.9	19.7	20.4	20.9	19.7	20.4
45-54	9.2	12.8	11.0	12.1	11.0	11.6	12.1	11.0	11.6
55-74	5.8	5.9	5.9	8.9	7.7	8.4	8.9	7.7	8.4
Sex									
Male	N/A[c]	N/A	50.0	N/A	N/A	57.5	N/A	N/A	57.5
Female	N/A	N/A	50.0	N/A	N/A	42.5	N/A	N/A	42.5
Education (highest completed)									
<Primary[d]	10.0	10.1	10.1	20.8	28.1	23.9	20.8	28.1	23.9
Primary	28.8	24.6	26.7	30.9	31.4	31.1	30.9	31.4	31.1
Secondary[e]	11.2	14.7	13.0	12.5	13.3	12.8	12.5	13.3	12.8
≥Higher secondary[f]	50.0	50.7	50.3	35.8	27.2	32.2	35.8	27.2	32.2

[a]Sample weighted by age, sex, and education to the Dhaka City Corporation demographic profile of the 2011 census.

[b]Census data for the 2011 Dhaka City Corporation demographic profile [23].

[c]N/A: not applicable.

[d]Primary indicates year 5 of school.

[e]Secondary indicates year 10 of school.

[f]Higher secondary indicates year 12 of school.

Table 3. Sample distribution compared with 2011 census population benchmarks for the live poultry exposure phone survey, Dhaka City Corporation, Bangladesh.

Characteristic	Weighted sample[a]			Census benchmarks[b]		
	Male (%)	Female (%)	All (%)	Male (%)	Female (%)	All (%)
Marital status						
Single, never married	27.0	12.1	20.6	29.7	11.6	22.1
Married	71.2	78.7	74.4	69.8	80.9	74.5
Other[c]	1.8	9.2	4.9	0.6	7.4	3.4
Region						
DCC[d] North	50.3	60.5	54.6	53.3	55.6	54.3
DCC South	49.7	39.5	45.4	46.7	44.4	45.7

[a]Sample weighted by age, sex, and education to the DCC demographic profile of the 2011 census.

[b]Census data for the 2011 DCC population, aged 20 to 74 years for marital status and all ages for region.

[c]Other includes widows or widowers and divorced individuals.

[d]DCC: Dhaka City Corporation.

Discussion

Principal Findings

This study provides empirical evidence that probability-based mobile phone surveys can achieve population-representative samples with relatively high response rates (1047/2006, 52.2%) in urban Bangladesh. Although the unweighted sociodemographic profile of the survey showed that mobile phone sampling slightly underrepresented older individuals and overrepresented those with higher secondary education compared with the census population, poststratification weighting on a key set of demographic variables (age, sex, and education) was sufficient to correct for these differences. Therefore, these findings support the use of mobile phone–based survey sampling and data collection methods for producing population-representative samples with minimal adjustment in urban areas that have high mobile phone penetration. This has important implications for improving population surveillance in LMICs.

A response rate of approximately 50% is lower than that of previous phone-based surveys conducted in Bangladesh [20,32] but is in line with the response rates achieved in surveys conducted through similar methods in other LMICs and is in fact higher than those typically achieved in HICs [16,33]. Several factors might have contributed to this lower rate compared with previous work, including changes in the methods of calculating response rates over time to provide more conservative estimates and general declines in response rates of population health studies over the past 30 years [31,34,35]. The use of airtime incentives has been found to improve response rates in interactive voice response surveys in Bangladesh [36] and could also be explored as a method to increase the rates in CATIs. The response rates were generally similar across mobile phone operators, except for Banglalink, which was considerably lower. This could be owing to differences in the geographic sampling frames between each operator, with Banglalink not restricted to DCC and instead sampling from phone numbers listed in Dhaka district. Overall, this supports the use of stratified sampling designs by mobile phone operators to appropriately capture subpopulation heterogeneity when conducting population-based surveys [37].

The unweighted demographic profile of our sample differed most from the census population by educational attainment. Overrepresentation of respondents with higher education is consistent across survey research methods, including those conducted in LMICs and HICs [14,16,38]. The impact of these differences on population-level estimates would be greatest in surveys where education is strongly associated with the outcome of interest [39]. However, the magnitude of this impact becomes negligible once weighted to the distribution of the reference population [15,39]. Previous research in LMICs has found that minimal adjustment of demographic factors is sufficient to reduce nonresponse and coverage error when conducting robust probability-based sampling [15]. In addition, comparisons with the census population showed that our weighted survey achieved a good representation of other characteristics, including region and marital status. The remaining differences between the census and the survey population distributions could be because our survey sample included only participants aged 18 to 74 years, whereas the published census figures include all ages for region and only ages 20 to 74 years for marital status. By conducting sex-stratified sampling, our study was sufficiently powered to explore sex-based subgroup analyses without generating extreme survey weights. Researchers intending to conduct similar mobile phone–based surveys with poststratification weights should determine subgroup analyses a priori to ensure that adequate stratified sampling is implemented.

Limitations

Although we demonstrated that population-based probability sampling using mobile phones can produce representative samples with minimal adjustment, this method had some limitations, as evidenced in this study. First, although comparisons to the census population can be used to evaluate the representativeness of the sample population, it does not preclude the potential for sampling bias due to coverage error. For instance, individuals who do not have mobile phones are likely different from those who do, based on factors such as socioeconomic status [40,41]. However, in DCC the mobile penetration rate was very high at over 87% [19], which suggests that impacts on population estimates due to coverage error were likely minimal in this urban area. Further work could examine this question in populations with lower mobile phone coverage or in nonurban settings where mobile phones may be shared within and between households, which would necessitate additional strategies to achieve a representative sample (eg, to randomly select an individual in a household using the same phone). The opposite is also of concern—potential bias introduced because of some individuals in the population having multiple mobile phone numbers. Recent studies quantifying this effect on the probability of selection have found that although the theoretical probability of inclusion for those with multiple phone numbers is greater than those with only one number, the likelihood of contacting any individual is extremely small in practice [13]. Although out of the scope of our analysis, this could be examined in future work by capturing information on mobile phone ownership and applying selection weights. The collection of additional household-based asset data to enable weighting by socioeconomic indicators, such as wealth index, could also be examined. In this survey, we only included education, which, while strongly correlated with relative wealth quintile, does not explicitly capture wealth [42]. However, examining the impact of increasing the survey length to capture household-based assets data on response rates is warranted. Finally, poststratification survey weighting should be conducted using recent reference population estimates. However, for DCC, the most recent census available is from 2011 [23]; therefore, any significant changes in the underlying population distribution during this time would not be reflected in the weights and could impact weighted population estimates.

Conclusions

In many LMICs, such as Bangladesh, the coverage of mobile phones is very high and includes a range of population subgroups. Mobile phone–based surveys can, therefore, offer an efficient, economic, and robust way to conduct surveillance for population health outcomes. We found that a mobile phone survey using a stratified probability sampling design produced a population-representative sample with minimal adjustment in urban Bangladesh. These results have important implications for improving population health surveillance methods in LMICs.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Additional information on mobile phone operators' proportionate market share and phone calling procedures.
[DOC File , 81 KB - publichealth_v7i11e29020_app1.doc]

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Abbreviations

CATI: computer-assisted phone interview
DCC: Dhaka City Corporation
HIC: higher income country
IEDCR: Institute of Epidemiology, Disease Control and Research
LBM: live bird market
LMIC: low- and middle-income country

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Original Paper

Digitization and Health in Germany: Cross-sectional Nationwide Survey

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Abstract

Background: Digital technologies are shaping medicine and public health.

Objective: The aim of this study was to investigate the attitudes toward and the use of digital technologies for health-related purposes using a nationwide survey.

Methods: We performed a cross-sectional study using a panel sample of internet users selected from the general population living in Germany. Responses to a survey with 28 items were collected using computer-assisted telephone interviews conducted in October 2020. The items were divided into four topics: (1) general attitudes toward digitization, (2) COVID-19 pandemic, (3) physical activity, and (4) perceived digital health (eHealth) literacy measured with the eHealth Literacy Scale (eHEALS; sum score of 8=lowest to 40=highest perceived eHealth literacy). The data were analyzed in IBM-SPSS24 using relative frequencies. Three univariate multiple regression analyses (linear or binary logistic) were performed to investigate the associations among the sociodemographic factors (age, gender, education, and household income) and digital technology use.

Results: The participants included 1014 internet users (n=528, 52.07% women) aged 14 to 93 years (mean 54, SD 17). Among all participants, 66.47% (674/1014) completed up to tertiary (primary and secondary) education and 45.07% (457/1017) reported a household income of up to 3500 Euro/month (1 Euro=US $1.18). Over half (579/1014, 57.10%) reported having used digital technologies for health-related purposes. The majority (898/1014, 88.56%) noted that digitization will be important for therapy and health care, in the future. Only 25.64% (260/1014) reported interest in smartphone apps for health promotion/prevention and 42.70% (433/1014) downloaded the COVID-19 contact-tracing app. Although 52.47% (532/1014) reported that they come across inaccurate digital information on the COVID-19 pandemic, 78.01% (791/1014) were confident in their ability to recognize such inaccurate information. Among those who use digital technologies for moderate physical activity (n=220), 187 (85.0%) found such technologies easy to use and 140 (63.6%) reported using them regularly (at least once a week). Although the perceived eHealth literacy was high (eHEALS mean score 31 points, SD 6), less than half (43.10%, 400/928) were confident in using digital information for health decisions. The use of digital technologies for health was associated with higher household income (odds ratio [OR] 1.28, 95% CI 1.11-1.47). The use of digital technologies for physical activity was associated with younger age (OR 0.95, 95% CI 0.94-0.96) and more education (OR 1.22, 95% CI 1.01-1.46). A higher perceived eHealth literacy score was associated with younger age (β=–.22, *P*<.001), higher household income (β=.21, *P*<.001), and more education (β=.14, *P*<.001).

Conclusions: Internet users in Germany expect that digitization will affect preventive and therapeutic health care in the future. The facilitators and barriers associated with the use of digital technologies for health warrant further research. A gap exists between high confidence in the perceived ability to evaluate digital information and low trust in internet-based information on the COVID-19 pandemic and health decisions.

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KEYWORDS

digital health; literacy; survey; attitude; usage; eHEALS; COVID-19; physical activity; general population; misinformation

Introduction

The COVID-19 pandemic contributed to the development of new technologies and accelerated the digitization of various domains of daily lives worldwide. One such domain focuses on digital aspects of public health. Digital public health describes the entire field of development and application of digital technologies in the context of public health, especially with regard to prevention and health promotion [1]. So far, digital technologies have shown potential for innovation, particularly in the area of individual health promotion, the use of health apps for prevention and early disease diagnosis, as well as for health education [2]. Digital technologies are thus likely to influence health-related decisions in the future [3].

Coincidentally, shortly before the onset of the COVID-19 pandemic (in August 2019), an innovative project was launched in the city of Bremen in Northern Germany. Specifically, Leibniz-Science Campus Digital Public Health Bremen (LSC DiPH) was established as a virtual network linking three local institutions with expertise on digital technology in medicine and public health (the Leibniz Institute for Prevention Research and Epidemiology-BIPS, the University of Bremen, and the Fraunhofer Institute for Digital Medicine-MEVIS) [4]. The general aims of LSC DiPH are to provide a platform for networking and to support interdisciplinary projects in the field of digital public health, focusing on prevention and health promotion.

This study was designed within the scope of LSC DiPH. Our objective was to explore the attitudes toward digitization in the health context using a nationwide survey of internet users selected from the general population in Germany. Such user-driven attitudes and preferences are of particular interest at the time of the worldwide COVID-19 pandemic that contributed to digitization in the health context. We were especially interested in the central aspects of digital public health [1], including personal use of digital technologies for obtaining health information and for supporting prevention and health promotion. Our study aimed to explore four main topics related to digitization in the health context. First, we aimed to investigate the attitudes toward current and future applications of digital technologies for health-related purposes, privacy of data online, and preferences for smartphone apps addressing prevention and health promotion. Second, owing to the overabundance of information on the COVID-19 pandemic online [5], we were interested in how the general population evaluates such information. Third, owing to contact restrictions during the COVID-19 pandemic that reduced the (analog) offers for performing physical exercise [6], we aimed to assess the interest in and actual use of digital alternatives for supporting physical activity. Fourth, we aimed to assess the digital (eHealth) literacy that is an essential requirement of dealing with digital technologies for health-related purposes [7]. In general, eHealth literacy describes the ability to seek, find, understand, and evaluate health-related information online [7]. Finally, we were interested in exploring the question of who uses digital technologies in the health context. In general, it has been shown that the privileged members of the general population (wealthier, younger, and more educated) have more access to and may receive a greater benefit from digital technologies [8]. Thus, we aimed to investigate the associations among sociodemographic factors and digital technology use in the health context.

Methods

Study Design

We performed a nationwide, cross-sectional survey using a representative sample of 1014 internet users selected from the general population living in Germany. Detailed information on the recruitment strategy is provided in Multimedia Appendix 1, Textbox S1.

Participants

The sample was recruited by the market research institute Kantar GmbH (Munich, Germany) from an existing panel. The participants were required to be internet users, aged 14 years or older, live in Germany, and able to complete the interview in German. Sociodemographic variables (age; gender; education; employment; household size [number of members]; household income; and residence by population size, region, and state) were collected to ensure that the sample was representative of the general population of Germany according to data from the Federal Statistical Office and the Microcensus. Ethical permission to perform the study was not required because the authors had no contact with the participants and obtained fully anonymized data from Kantar GmbH.

Procedure

The data were collected by Kantar GmbH using computer-assisted telephone interviews in October 2020. The participants were contacted by telephone using a random-digit-dial method. A dual-frame approach was used to ensure that both landline and mobile-only users were included. Each interview lasted about 15 minutes and was conducted in German.

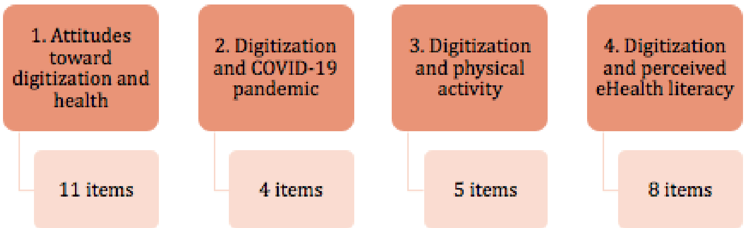
Survey Items

The interviews were conducted using a survey with 28 items divided into four topics (Figure 1).

All 28 items and answer options are reported in Multimedia Appendix 1, Table S1. The items were selected from existing and validated instruments in English or in German, which were adapted to the four topics and/or translated to German if translation was not available (see Multimedia Appendix 2).

Perceived eHealth literacy was measured with the German version of the eHealth Literacy Scale (eHEALS) [9]. eHEALS consists of eight items with statements that address the ability to locate, evaluate, and use internet-based resources for health-related purposes [10]. The items are rated on a 5-point Likert Scale (from 1=strongly disagree to 5=strongly agree). The overall sum score indicates the level of perceived eHealth literacy (from 8=lowest to 40=highest). eHEALS has acceptable psychometric properties [9,10].

Figure 1. Survey with 28 items divided into four topics.



Statistical Analysis

The statistical analysis was performed in IBM-SPSS24. First, the responses on all 28 items were analyzed using relative frequencies per item. This analysis was performed on raw responses unweighted by the sociodemographic factors because the survey data included some missing responses due to optional items. Specifically, the survey consisted of 13/28 mandatory items and 2/28 filter items that determined if the subsequent 5/28 optional items were asked or omitted. Furthermore, 8/28 eHEALS items had to be completely rated to compute the overall perceived eHealth literacy score for each participant and thus incomplete data had to be excluded from the analysis. To investigate the impact of the sociodemographic factors, we visually compared the responses on 13 mandatory items unweighted or weighted by the sociodemographic factors and report the weighted frequencies in Multimedia Appendix 1. Second, Cronbach α was computed to test the internal consistency of the unweighted responses on all eight eHEALS items. Third, three univariate multiple regression analyses (linear or binary logistic) were performed to investigate the associations among the sociodemographic factors and digital technology use. Each regression analysis included one dependent variable (the use of digital technologies for health or physical activity, or the perceived eHealth literacy score) and four independent variables (sociodemographic factors: age, gender, education, and household income). Variable coding and further details of these analyses are reported in Multimedia Appendix 1.

Results

Participants

The data from 1014 internet users were obtained via either landline (n=826, 81.46%) or mobile (n=188, 18.54%) telephones. The participants were recruited from all 16 states in Germany (Figure 2) with the majority residing in urban regions with up to 500,000 inhabitants (622/1014, 61.34%) and in the states of the former West Germany (829/1014, 81.76%; Multimedia Appendix 1, Table S2).

The sociodemographic characteristics of the 1014 participants are reported in Table 1. The participants (52% women) were aged 14 to 93 years (mean 54, SD 17). Of those, 66% completed up to tertiary (primary and secondary) education, 60% were either employed or seeking employment, 67% lived in 1-2–person households, and 45% reported a net household income of up to 3500 Euro/month (1 Euro=US $1.18).

Figure 2. Participant location by state in Germany.

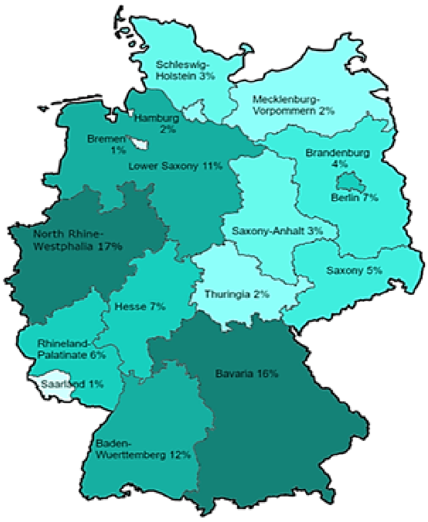


Table 1. Participant sociodemographic characteristics (N=1014).

Variable[a]	Participants n (%)
Gender	
Female	528 (52.07)
Male	486 (48.03)
Education	
Elementary/primary school	17 (1.68)
Vocational college or basic secondary	101 (9.96)
Secondary without tertiary entrance qualification	269 (26.53)
Secondary with tertiary entrance qualification	287 (28.30)
Tertiary	340 (33.53)
Employed	
Yes or seeking employment	607 (59.86)
No	407 (40.14)
Household size (members)	
1	239 (23.57)
2	436 (43.00)
3	162 (15.98)
4	123 (12.13)
5 or more	54 (5.33)
Household net income/month (Euro)[b]	
under 1500	94 (9.27)
1500 up to 2500	171 (16.86)
2500 up to 3500	192 (18.93)
3500 or more	370 (36.49)
no response	187 (18.44)

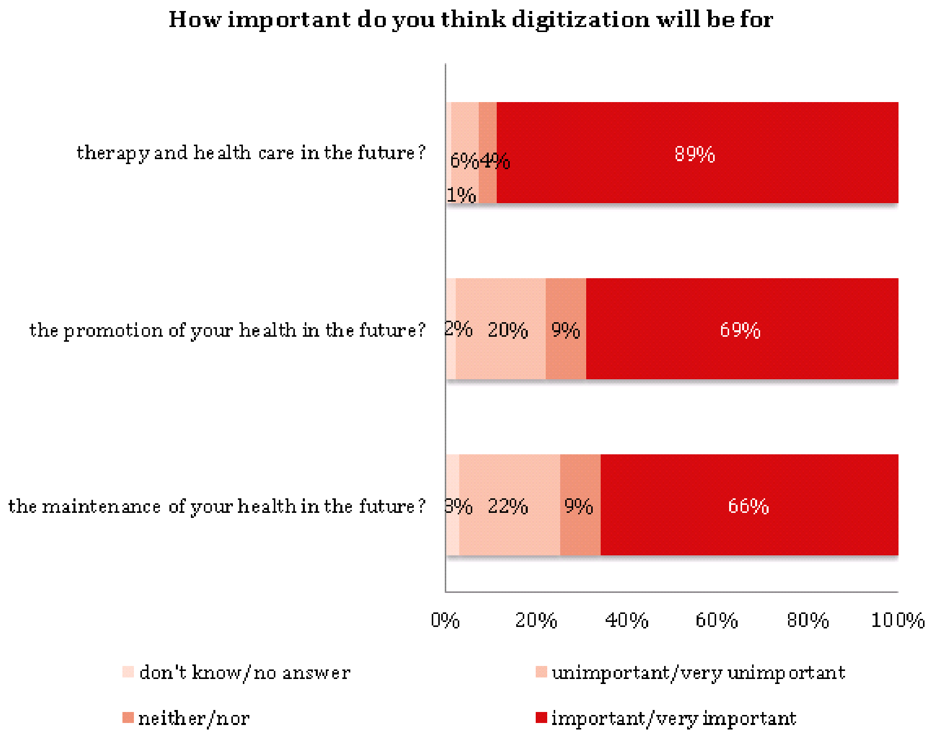
[a]Further characteristics are shown in Multimedia Appendix 1, Table S2.

[b]1 Euro=US $1.18 in 2020; the mean net household income in Germany was 3580 Euro/month in 2019-2020 [11].

Attitudes Toward Digitization and Health

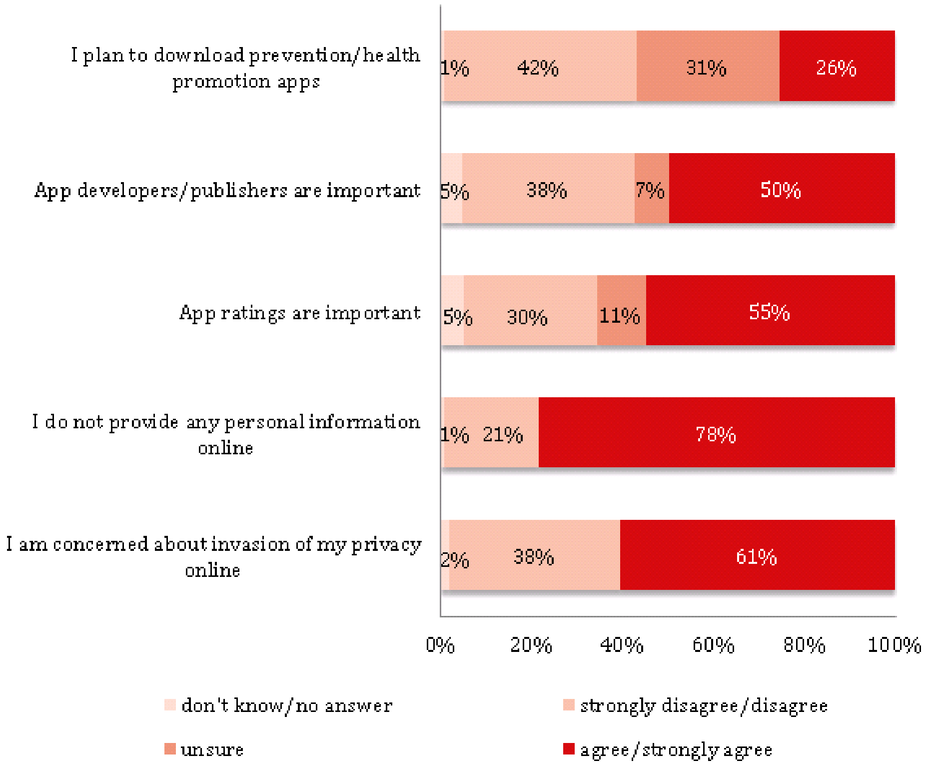
Over half of the participants (579/1014, 57.10%) reported having used digital technologies for health-related purposes. The majority noted that digitization will be important for therapy and health care (898/1014, 88.56%), health promotion (704/1014, 69.43%), and health maintenance (668/1014, 65.88%) in the future (Figure 3; Multimedia Appendix 1, Table S3 and Figure S1).

Figure 3. Digitization of health in the future (N=1014).



When asked about smartphone apps, 25.64% (260/1014) planned to download prevention/health promotion apps (Figure 4; Multimedia Appendix 1, Table S4 and Figure S2). The choice of apps depended on developers/publishers (507/1014, 55.00%) or ratings (558/1014, 55.03%). In terms of general internet use, 78.40% (795/1014) reported that they do not provide any personal information online and 60.55% (614/1014) were concerned about the invasion of their privacy online (Figure 4). The majority reported using social media platforms (868/1014, 85.60%). Among those who use social media (n=868), 593 (68.32%) typically access these platforms up to 10 times per day and 560 (64.52%) prefer messaging platforms such as Facebook Messenger, Viber, or WhatsApp (Multimedia Appendix 1, Table S4).

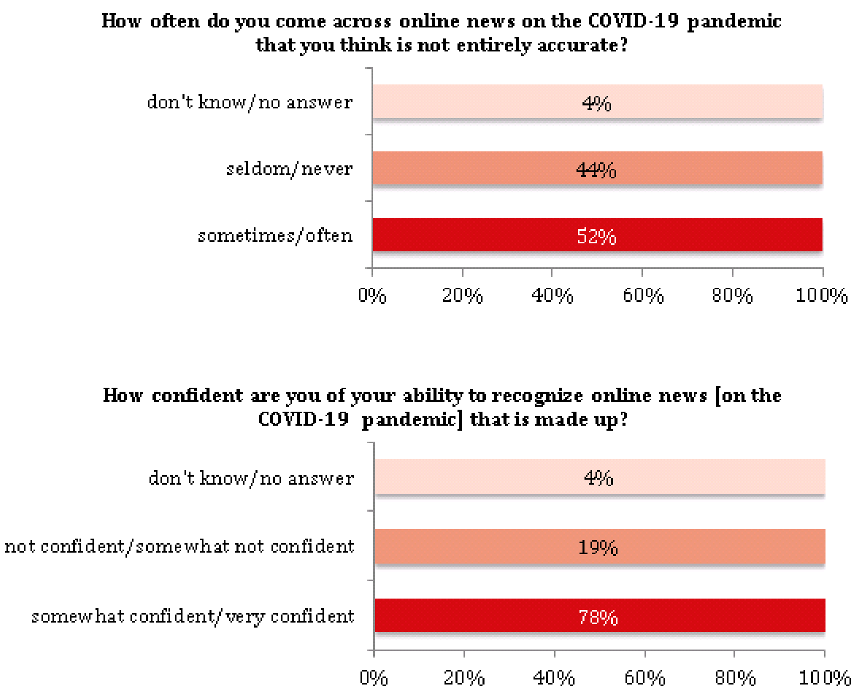
Figure 4. Digitization, smartphone apps, and internet use (N=1014).



Digitization and the COVID-19 Pandemic

Approximately half of the participants (532/1014, 52.47%) thought that the online news on the COVID-19 pandemic is, in some cases, not entirely accurate and the majority reported that they were confident in their ability to recognize such false online news (791/1014, 78.01%; Figure 5; Multimedia Appendix 1, Table S5 and Figure S3). Only a minority reported having shared false online news on the COVID-19 pandemic (56/1014, 5.52%) and 42.70% (433/1014) installed the contact-tracing app from the Robert Koch Institute in Germany by October 2020.

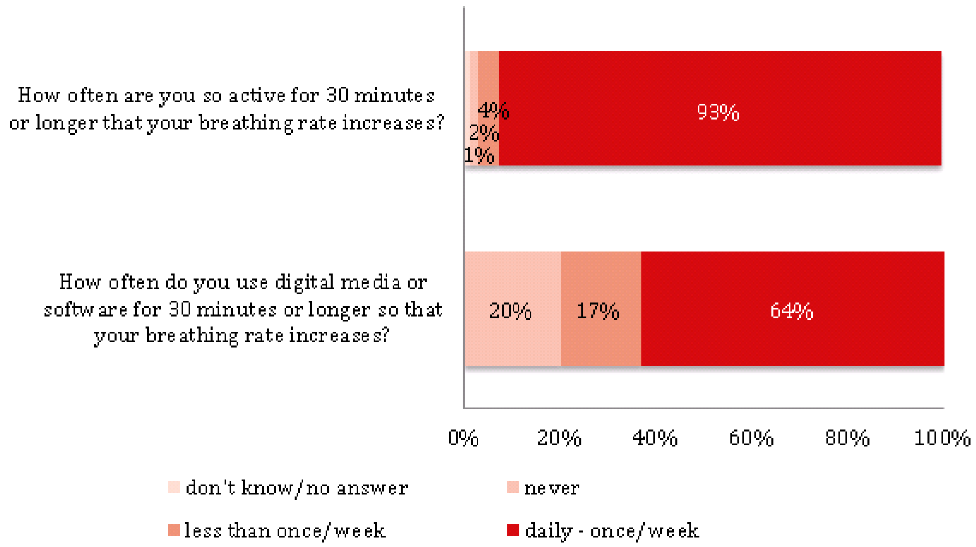
Figure 5. Digitization and COVID-19 pandemic (N=1014).



Digitization and Physical Activity

Although less than a quarter of the participants (220/1014, 21.70%) reported having used digital technologies to support moderate physical activity (ie, physical activity that leads to an increase in the breathing rate), most of these users (187/220, 85.0%) found such technologies easy to use (Multimedia Appendix 1, Table S6). In addition, most of these users (204/220, 92.73%) also reported that they regularly participate in moderate physical activity for 30 minutes or longer at least once a week and use digital technologies for such regular physical activity (140/220, 63.64%; Figure 6).

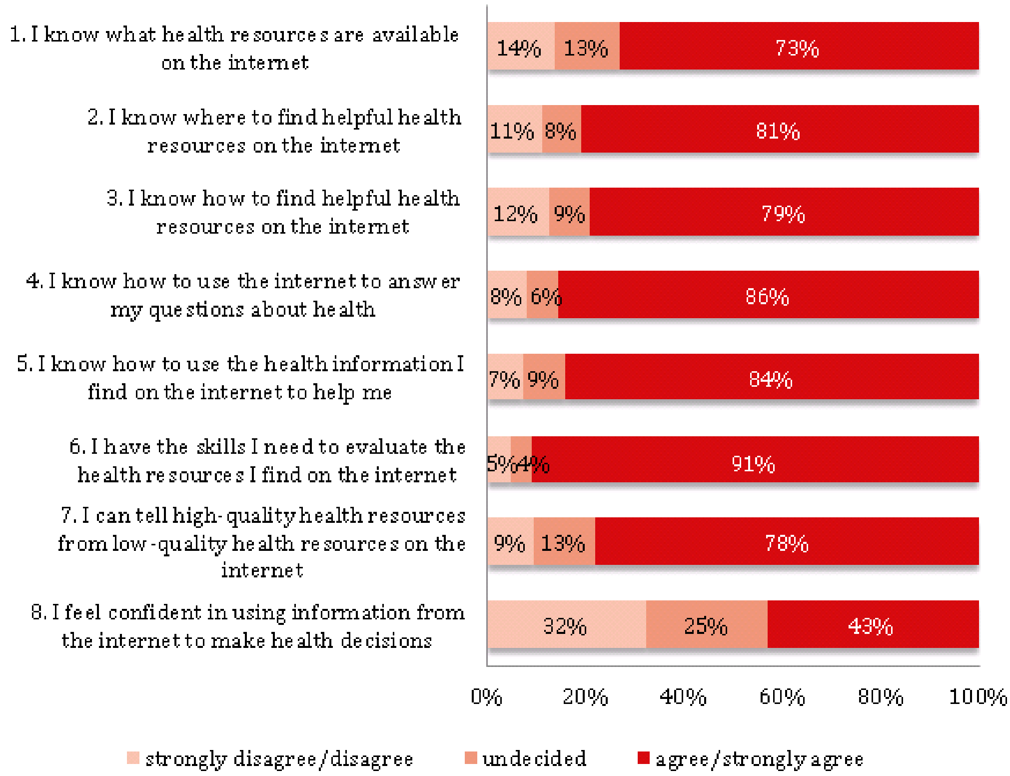
Figure 6. Digitization and physical activity (n=220).



Digitization and Perceived eHealth Literacy (eHEALS)

Complete responses on all eight items of the eHEALS were provided by 928 participants. The internal consistency of the responses was high (Cronbach α=.88; Multimedia Appendix 1, Table S7). The perceived eHealth literacy was high in our sample (eHEALS mean 31 points, SD 6; Multimedia Appendix 1, Table S8). Responses on eHEALS items 1 to 7 indicated that most participants (73%-91%) reported being able to locate, find, use, and evaluate health-related information online (Figure 7; Multimedia Appendix 1, Table S9). However, responses on eHEALS item 8 indicated that only 43.10% (400/928) were confident in using such online information for health-related decisions (Figure 7).

Figure 7. Digitization and perceived eHealth literacy (eHEALS; n=928).

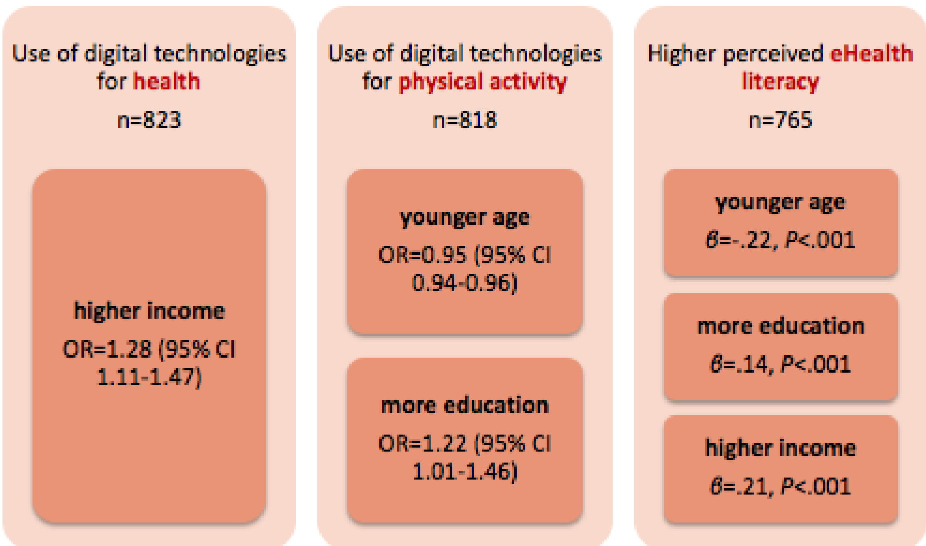


Sociodemographic Factors and Digital Technology Use

Three univariate multiple regression analyses were performed to investigate the associations among the sociodemographic factors and digital technology use. Participants who did not report their household income were excluded from each analysis. Odds ratios (ORs) with 95% CIs were computed using bivariate logistic regression analyses; β coefficients were computed using univariate multiple linear regression analysis. Variable coding and further details of these analyses are reported in Multimedia Appendix 1, Table S10.

All three regression analyses showed that the sociodemographic factors (age, education, and household income) were associated with digital technology use (Figure 8). The use of digital technologies for health was associated with higher income. The use of digital technologies for physical activity was associated with younger age and more education. Higher perceived eHealth literacy was associated with younger age, higher income, and more education.

Figure 8. Associations among sociodemographic factors and digital technology use. OR: odds ratio.



Discussion

Principal Results

This exploratory study reports a snapshot of attitudes toward digitization in the health context among internet users selected from the general population in Germany. The vast majority of our participants expected that digitization will affect health care and central aspects of public health (prevention and health promotion) in Germany. However, the interest in and actual use of digital technologies for health-related purposes was not yet widespread in late 2020. The users of digital technologies for physical activity found such technologies easy to use and actually used them regularly. The confidence in the ability to recognize false online news and the perceived eHealth literacy were high. However, the trust in online information on the COVID-19 pandemic and the confidence in internet-based health decisions were low. Younger, more educated, and wealthier participants were more likely to use digital technologies for health-related purposes and reported higher eHealth literacy. The main strength of our study is the large, representative sample (N=1014) with a wide age range from adolescence to late adulthood (14 to 93 years) selected from the general population in Germany. Thus, we were able to explore the attitudes toward digitization in the health context across different life stages. Some of our results confirm what is generally known about the users of digital technologies who tend to be more privileged (wealthier, more educated, and more digitally literate) [8]. However, our study also provides novel, interesting, and partially unexpected results that warrant further research. These include the low trust in health information online despite the high perceived eHealth literacy and the low interest in and prevalence of digital technology use for health promotion, such as for physical exercise.

Digitization and Health: Promises and Challenges

Widespread internet access and, in particular, the introduction of smartphones and other mobile devices since about 2009 have greatly contributed to the digitization of health [12]. Among others, digitization affects services, increases the availability of information, simplifies communication, and allows individual monitoring and self-measurement [1,13]. Indeed, our participants expected that especially therapy and health care services will be affected by digitization in the future. They also anticipated that digital technologies will be important to facilitate disease prevention and health promotion in the future. These could be achieved with the objective recording of data in everyday settings using increasingly affordable and user-friendly devices and digital apps [2]. Such data simplify monitoring of health and health-related behavior in daily life, and could positively reinforce behavioral patterns that contribute to a healthy lifestyle, including physical activity and nutrition [14]. In the long term, such data could be used for clinical decision-making [1]. However, rapid technological advancement is associated with several challenges on individual-, social-, and care-related levels, such as the ethical and legal aspects of data acquisition, storage, and application [1,13,15,16]. Aligned with these challenges, the majority of our participants expressed concern about their personal data and privacy online. Other issues such as the analog social environment, financial barriers, and digital competence and literacy [16] should also be considered in the future research on digitization and health. Furthermore, amid the ever-growing number of digital technology offers, in particular health-related apps, regulation is required in relation to safety, quality (ie, evidence-based content), and data protection (eg, introducing a quality score or label within the app store) to facilitate health decision-making among users of these offers [17,18].

Digital Technology Use

Digital technologies show great innovation potential, especially in the area of individual health promotion as well as in relation to health education [2]. However, less than 50% of our participants showed interest in smartphone apps for disease prevention and health promotion, the COVID-19 contact-tracing app, or digital technologies for physical activity in late 2020. This is surprising, because during the COVID-19 pandemic, the use of digital technologies for health-related purposes increased rapidly worldwide [15]. We can only speculate that the results of our study were affected by the timing of data collection that aligned with relaxing of contact restrictions in Germany between the European summer and late November 2020. Since various health-related activities, including organized sport and educational offers, were allowed “in person” at that time, the participants might have embraced such an analog lifestyle by showing less interest in digital technologies. However, it is possible that many returned to or started using digital technologies during the subsequent tightening of contact restrictions that followed in Germany during the European winter 2020 until summer 2021. Furthermore, preferences for apps addressing physical activity could also depend on other factors such as age. For example, a focus group study in Germany showed that older adults prefer to use simple-to-use fitness apps with few features, automated tracking of data, and active feedback to reach their goals [19]. A repetition of the present survey could be used to quantitatively investigate the influence of the COVID-19 pandemic and other factors on the use of digital technologies for physical activity promotion. Qualitative methods could be used to explore the more in-depth reasons that encourage or hinder the use of digital technologies for physical activity promotion depending on the sociodemographic characteristics of users.

Although used by the minority, the users reported that digital technologies were easy and frequently utilized for moderate physical exercise. Although digital technologies for physical exercise are already accepted [20], their development and effectiveness require systematic evaluation [1,14,20]. For example, effectiveness of digital technologies for physical activity promotion depends on engagement with such technologies [21]. In general, digital technologies could be useful at improving education (health literacy) on lifestyle-related disorders [22] and at fostering positive health behavior changes [14]. However, it remains unclear why only some digitally based health interventions work [23] and how such interventions support behavior change, including healthy lifestyle promotion, in real-world settings. Thus, evaluation studies with large samples are necessary to examine the effects of digital technologies on various aspects of health, including education, promotion of healthy lifestyle, and prevention. The focus of such studies could be on the clinical effectiveness of interventions with modern (digital) technologies relative to the traditional (analog) health interventions. However, social, economic, or ecological factors should also be investigated to understand the impact of digital technologies on health. In addition, the research and application of new study designs and methods for evaluation purposes is necessary to take into account the rapid development of digital technologies and continuous data collection.

Trust in Online Information and eHealth Literacy

Our data suggest that the general population in Germany used the internet for health education purposes (ie, to obtain information on the COVID-19 pandemic). However, the trust in such online information was low in our sample. This low trust could be associated with the so-called "infodemic" or abundance of correct and invented information on the COVID-19 pandemic available online [5]. The trust in online information also depends on digital competence and digital (eHealth) literacy that are important prerequisites for dealing with digital technologies for health-related purposes [5,24]. For example, those with low eHealth literacy have difficulties in recognizing invented, nonfactual information online [5]. According to an anonymous online survey conducted during the COVID-19 pandemic in late 2020 in Germany, approximately half of the 8500 participants selected from the general adult population reported limited eHealth literacy skills, in particular in terms of searching for and evaluating the reliability and relevance of health-related information online [24]. These findings closely align with results of another anonymous online survey of nearly 15,000 university students conducted in early 2020 in Germany [25]. Regardless of their high education status, the university students also reported difficulties with specific aspects of evaluation such as assessing the reliability and the commercial interests in the online information on the COVID-19 pandemic [25]. In contrast to these studies, our sample appeared to be more confident in their ability to evaluate the health resources online and reported a generally high level of perceived eHealth literacy. Such possible overestimation of eHealth literacy in our sample could be due to the different methods of data collection and tools utilized in different studies.

First, our results could be inflated by social desirability bias since our data were collected using computer-assisted telephone interviews rather than anonymous online surveys that were conducted in the other two studies in Germany [24,25]. Second, eHealth literacy was measured with the Digital Health Literacy Instrument in the other studies [24,25] and with eHEALS [9] in our study. Our data revealed that the responses on the eHEALS were highly consistent with the Cronbach α of .88 but also contradictory in some aspects: although many participants perceived their own eHealth literacy as high, less than 50% were confident in making health-related decisions based on information from the internet. Other studies that utilized eHEALS also reported similar Cronbach α coefficients [9,26] and high perceived eHealth literacy [9,26,27]. Similar to our results, the majority of participants in one of the studies [9] thought they had the skills to critically evaluate information online but only a minority felt confident in making health decisions based on such information. Interestingly, subjective (self-reported and perception-based) estimation of eHealth literacy was not associated with accurate judgments of the quality of a medical website or behavioral intentions beneficial to health [28]. Thus, high perceived eHealth literacy may be insufficient for making real-life decisions. Factors that promote or hinder behaviors and concrete actions related to eHealth literacy should be examined in further studies [29]. Furthermore, the reasons for low confidence in internet-based information and health decisions could be examined qualitatively. For example, internet users could report how they rate the health-related information on the internet, under what conditions they trust such information, and what factors would assist them with decision-making. Such qualitative data could then be used to design specific measures for evaluating online information with and for the general population in the context of participatory research.

Digital Divide

The use of digital technologies in the health context is associated with various ethical, legal, and social issues [13,30]. Our results confirm that privileged people (wealthier, younger, and more educated) tend to be more digitally literate and are more likely to use digital technologies for health-related purposes. These findings support the notion that a "digital divide" or the promotion of inequality via digital technologies is present in the health care context in Germany, similar to reports from other countries [8]. A debate regarding digital inequalities is not new [31,32] and various sociodemographic factors associated with digital technology use have already been identified in the health context [8]. The digital divide has become especially evident in the context of the COVID-19 pandemic that rapidly digitized health care [33]. Factors that continue to contribute to digital inequalities include poor internet access, low experience with and variable expectations toward digital health care, low digital literacy and technological skills of health care users and providers, inadequate means to purchase tools at a time of high economic instability, and a gap between digital health care offers and patient capability to access and effectively utilize such offers [33]. Since privileged people may disproportionately benefit from the advantages of digital technologies [13], interventions that address the digital divide should be designed to specifically target less privileged groups [32]. This is important to reduce the digital divide to better align access to and outcomes of digital health care, especially for the most vulnerable groups.

Limitations

There were several limitations of this study. First, the data were collected using a single source (quantitative survey) and relied on self-reports. Although the instrument was not validated, the survey items were selected from other existing, validated instruments and adapted to the purposes of this study. Second, there were very few items per topic, meaning that we were unable to gain detailed insight into the motivations for or against use and the types of digital technologies used for specific health-related purposes. Third, we did not weigh all data according to the sociodemographic factors due to the missing values on the optional items. However, weighing of responses on 13 mandatory items produced similar results to unweighted responses on these items (Multimedia Appendix 1, Figures S1-S3). Fourth, the associations among the sociodemographic factors and digital technology use for health-related purposes were relatively weak according to the univariate regressions. It is likely that such associations are complex and depend on further factors and/or on the interactions among multiple factors. Moreover, due to the cross-sectional design of our study, we were unable to investigate the causality in the associations among sociodemographic factors and digital technology use. Longitudinal studies with adequate follow-up are warranted to investigate how sociodemographic factors affect digital technology use.

Conclusions

Internet users in Germany expect that digitization will affect health care in the future. However, the interest in and actual use of digital technologies for health-related purposes was relatively low in Germany in late 2020. The use of digital technologies is generally accepted for some purposes such as for physical activity promotion, but depends on age, household income, and education. Despite the high perceived eHealth literacy, the trust in online information and in health decisions based on such information is low, as exemplified by the COVID-19 pandemic. Thus, there is a need to study the reasons for the low trust and the high confidence in the ability to evaluate health information online. Further research should also address the needs, preferences, and motivations of users to identify facilitators and barriers associated with digital technology use for health-related purposes.

Acknowledgments

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Authors' Contributions

KKDS: data processing and analysis, data visualization, writing—first draft, writing—review and editing. TJ, ES, JW: conceptualization, methodology and survey development, writing—review and editing. HZ: conceptualization, writing—review and editing.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Survey items, additional data, and results (Textbox S1, Tables S1-S10, Figures S1-S3).
[DOCX File , 173 KB - publichealth_v7i11e32951_app1.docx]

Multimedia Appendix 2
Survey item sources.
[XLSX File (Microsoft Excel File), 11 KB - publichealth_v7i11e32951_app2.xlsx]

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Abbreviations

eHEALS: eHealth Literacy Scale
LSC DiPH: Leibniz-Science Campus Digital Public Health Bremen
OR: odds ratio

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Original Paper

Demographics Associated With Stress, Severe Mental Distress, and Anxiety Symptoms During the COVID-19 Pandemic in Japan: Nationwide Cross-sectional Web-Based Survey

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Abstract

Background: With the spread of COVID-19, the deterioration of public mental health has become a major global and social problem.

Objective: The purpose of this study was to elucidate the relationship between the 3 mental health problems associated with COVID-19, that is, perceived stress, severe mental distress, and anxiety symptoms, and the various demographic factors, including occupation.

Methods: A nationwide web-based questionnaire survey was conducted in Japan from August 4 to 31, 2020. In addition to sociodemographic data, the degrees of perceived stress, severe mental distress, and anxiety symptoms associated with COVID-19 were measured. After performing a descriptive statistical analysis, factors related to stress, severe mental distress, and anxiety symptoms were analyzed using logistic regression analysis.

Results: A total of 8203 respondents submitted survey responses, among whom 34.9% (2861/8203) felt intense stress associated with COVID-19, 17.1% (1403/8203) were depressed, and 13.5% (1110/8203) had severe anxiety symptoms. The logistic regression analysis showed that each of the 3 mental health problems were prevalent in females, nonbinary gender, people in their 50s, 60s and older, respondents who visited psychiatrists, and those currently in psychiatric care. Severe mental distress and anxiety symptoms were associated with the number of effective lifestyle coping strategies during the lockdown period. Severe mental distress was only prevalent in teenagers and respondents in their 20s, as students tended to develop stress and severe mental distress. With regard to occupation, working in nursing care and welfare, education and research, and medical and health sectors was associated with stress; however, working in these occupations was not associated with severe mental distress and anxiety symptoms. Unemployment was associated with severe mental distress and anxiety symptoms. All 3 mental health problems were prevalent in part-time workers and those working in entertainment and arts sectors.

Conclusions: Gender, age, occupation, history of psychiatric visits, and stress coping mechanisms were associated with mental health during the COVID-19 pandemic, but their associations with stress, severe mental distress, and anxiety symptoms differed.

In addition, the actual state of mental health varied according to the respondents' occupation. It is necessary to consider the impact of the COVID-19 pandemic on mental health not only at the individual level but also at the occupational level.

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KEYWORDS

COVID-19; mental health; stress; depression; anxiety; occupation; public health; demographic factors; epidemiology; occupational health

Introduction

The global pandemic of the novel COVID-19 has continued since the unexplained advent of the pneumonia virus in Wuhan, China in December 2019 [1]. By the end of December 2020, 80 million cases were confirmed, with more than 1.7 million deaths globally [2]. Since then, various treatment methods, including vaccines, have been developed [3]; however, this unprecedented public health emergency of international concern has not yet been resolved. The effects of the COVID-19 pandemic are expected to continue in the future [4]. COVID-19 not only causes physical frailty but also gives rise to mental health problems [5]. Depression and anxiety have been reported to have increased among the public during the pandemic [6,7]. There are various causes of impaired mental health. Aside from anxiety regarding the disease, the policies employed by many countries to stop the spread of the infection (eg, quarantine, social distancing, isolation of infected people) have also affected people's mental health [8,9]. One of the main causes is the economic deterioration due to the stagnation of socioeconomic activities [10].

Studies related to mental health during the COVID-19 pandemic have gradually increased and continue to do so. Although there is a high degree of heterogeneity in studies of mental health during the COVID-19 pandemic due to differences in the situation of the infection in different countries, on average, approximately 30% of the general population have reported depressive and anxiety symptoms [11,12]. In a survey conducted in Japan in May 2020, 11.5% of the respondents reported serious psychological distress [13]. This may be because the number of infected people in Japan at that time was lower than that in the Western countries [2]. At the end of August 2020, when this survey was conducted, the number of people infected with COVID-19 in Japan was approximately 70,000, which was still lower than that in the Western countries [2]. However, the number of suicides in Japan started increasing from that period [14], and mental health issues related to COVID-19 have now become a major issue in Japan.

In previous studies, various factors such as gender, age, marital status, education, occupation and income, place of residence, contact history with patients with COVID-19, and comorbidities were associated with mental health problems such as stress, depression, and anxiety [15-18]. However, in many studies, stress has been measured with a general psychological scale, which differs from the perceived stress scale associated with COVID-19 [6,11]. Therefore, the relationship between various factors and each mental health problem related to COVID-19 such as perceived stress, depression, and anxiety has not been sufficiently investigated. Moreover, although the COVID-19 pandemic has had a great impact on society and people's behavior, there is a lack of occupational research on the same. Previous studies have often focused on specific occupations such as health care professionals and employment status [17]; however, a cross-sectional evaluation of mental health with respect to various occupations and considering it in combination with other attributes has not been conducted. Therefore, we conducted a nationwide web-based questionnaire survey in Japan to determine the relationship between various factors, including occupation, and perceived stress, severe mental distress, and anxiety symptoms, which are the 3 main mental health problems related to the spread of the COVID-19 pandemic.

Methods

Recruitment

From August 4 to August 31, 2020, we conducted a nationwide web-based questionnaire survey in Japan by using a web-based survey platform called SurveyMonkey [19]. Respondents were recruited through various news and social media sites such as Facebook and Twitter. Specifically, in addition to the snowball sampling method utilized by the researchers, announcements were made on the official websites of the laboratory and the University of Tsukuba. Additionally, major news media reported that this research was being conducted. The survey questionnaire was distributed among respondents who provided their informed consent after reading about the purpose of the survey on the first page and clicking on the check boxes. The survey was conducted anonymously, and no personally identifiable information was included in the data used for analysis. Furthermore, no exclusion criteria were established. Missing values for the social parameters are shown for each item. This study was approved by the Medical Ethics Committee of the University of Tsukuba (Registration 1546-1). Appropriate ethical considerations were applied during all the stages of this study.

Measures

We asked the respondents about their gender, age, occupation, and psychiatric outpatient history. We also enquired whether they experienced stress related to COVID-19 in the previous month. The response options included "strongly disagree," "disagree," "neither agree nor disagree," "agree," "strongly agree," and "other." We categorized those who chose the option "strongly agree" as those under severe stress related to COVID-19. Another question inquired whether the respondents felt that they or their families were at risk of infection, whether they were bullied or discriminated against, and whether self-confinement interfered with work or school. We also investigated the number of effective lifestyle coping strategies employed during the self-confinement period, such as maintaining a healthy rhythm of life, exercise, good eating habits, getting enough sleep, enjoying indoor activities, talking to friends, encouraging each other, reducing the amount of time spent watching television or surfing the internet, and getting the right information on COVID-19. The Japanese version of the 6-item Kessler Psychological Distress Scale (K6) and Generalized Anxiety Disorder-7 item (GAD-7) were used to measure severe mental distress and anxiety symptoms.

The K6 is a short, 6-item questionnaire developed for screening mood and anxiety disorders [20]. It evaluates mood and anxiety experienced in the last 30 days on a 5-point scale (ranging from 0 to 4). The total score for K6 ranged from 0 to 24. We used the Japanese version of K6, which has demonstrated confirmed reliability and validity [21]. Based on Kessler et al's recommendation [20], we adopted K6≥13 as the cut-off value, indicating a state of severe mental distress.

The GAD-7 is a self-administered questionnaire developed by Spitzer et al to assess the severity of generalized anxiety disorder by extracting a response set from the Public Health Questionnaire [22]. It consists of 7 items and evaluates the intensity of symptoms experienced in the past 2 weeks on a 4-point scale (0 to 3). The total score for GAD-7 ranged from 0 to 21. We used the Japanese version of GAD-7, which has exhibited robust reliability and validity [23]. The severity of the anxiety symptoms based on the GAD-7 score was assessed as follows: a score of 5-9 points indicated mild anxiety, 10-14 points indicated moderate anxiety, and ≥15 points indicated severe anxiety. We adopted GAD-7≥10 as the cut-off value indicating a state of anxiety symptoms.

Statistical Analysis

We first confirmed the response status of all respondents. Following this, we verified those who experienced severe stress related to COVID-19, those who were depressed (K6 score≥13), and those who had severe anxiety symptoms (GAD-7 score≥10). For these 3 indicators, we then excluded respondents with missing values and performed a chi-square test with Bonferroni correction (using the Bonferroni correction, .05 is divided by the number of statistical tests being performed, .05/15=0.00333; therefore, *P*<.003). Additionally, a residual analysis was carried out to see how the various factors, including occupation type, are interrelated. An adjusted standardized residual >3.29 or <–3.29 was considered significant (*P*<.001). Then, a logistic regression analysis was performed with each psychological indicator as a dependent variable and demographic factors, including occupation type, as independent variables (statistical significance was defined as *P*<.05). Variables that were reported to be associated with mental health during the COVID-19 pandemic, in previous studies, were included in the model. Nagelkerke's R^2 was calculated to check the goodness of fit of the logistic regression model. All statistical analyses were performed using the statistical package SPSS Statistics for Windows, version 22.0 (IBM Corp).

Results

Characteristics of the Respondents

The total number of consenting respondents was 8203. Table 1 lists the attributes of all respondents. Of the 8203 total responses, 4692 responses were from females. The age group was widely distributed from teenagers to those older than 60 years, but only 3.9% (324/8203) of the total respondents were aged 60 years and older. Unemployed people comprised 11.8% (971/8203) of the total respondents, and medical and health professionals comprised 11.7% (960/8203) of the employed people. Approximately 34.9% (2861/8203) of the respondents reported that they had been very stressed about COVID-19 over the previous month. During the spread of COVID-19, 52.8% (4333/8203) felt that they were at risk of infection, 46.4% (3808/8203) felt hindered by the lockdown, and 2.1% (175/8203) were bullied or discriminated against because they worked at a hospital that treats patients with COVID-19, which may have exposed them to the risk of infection.

Table 1. Characteristics of the respondents of a nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020 (N=8203).

Characteristic	Values, n (%)
Gender	
Female	4692 (57.2)
Male	2700 (32.9)
Nonbinary	128 (1.6)
Unknown	683 (8.3)
Age group (years)	
Teenage	178 (2.2)
20-29	1543 (18.8)
30-39	2106 (25.7)
40-49	2073 (25.3)
50-59	1296 (15.8)
≥60	324 (3.9)
Unknown	683 (8.3)
Occupation	
Unemployed	971 (11.8)
Medical and health	960 (11.7)
Education and research	754 (9.2)
Student	681 (8.3)
Information and communication systems	639 (7.8)
Other	531 (6.5)
Part-time job	494 (6)
Manufacturer	444 (5.4)
Entertainment and arts	415 (5.1)
Nursing care and welfare	392 (4.8)
Government job	343 (4.2)
Sales and wholesale	343 (4.2)
Infrastructure and construction	165 (2)
Finance and insurance	142 (1.7)
Food, beverage, and accommodation	96 (1.2)
Transportation	79 (1)
Agriculture, forestry, and fisheries	32 (0.4)
Unknown	722 (8.8)
History of psychiatric visits	
Currently going to the hospital	1148 (14)
History of hospital visit(s)	1823 (22.2)
None	4420 (53.9)
Other/unknown	812 (9.9)
Degree of stress associated with COVID-19	
Strongly agree	2861 (34.9)
Agree	3143 (38.3)
Neither agree nor disagree	286 (3.5)

Characteristic	Values, n (%)
Disagree	963 (11.7)
Strongly disagree	194 (2.4)
Other	756 (9.2)
Severe mental distress	
K6[a]≥13	1403 (17.1)
K6<13	5877 (71.6)
Unknown	923 (11.3)
Anxiety symptoms	
GAD-7[b]≥10	1127 (13.7)
GAD-7<10	5966 (72.7)
Unknown	1110 (13.5)
Experience during the spread of the COVID-19 infection	
Felt at risk of infection: yes	4333 (52.8)
Felt at risk of infection: no	3187 (38.9)
Felt at risk of infection: unknown	683 (8.3)
Hindered by the lockdown: yes	3808 (46.4)
Hindered by the lockdown: no	3712 (45.3)
Hindered by the lockdown: unknown	683 (8.3)
Being bullied or discriminated against: yes	175 (2.1)
Being bullied or discriminated against: no	7345 (89.5)
Being bullied or discriminated against: unknown	683 (8.3)
Number of effective lifestyle coping mechanisms employed during lockdown	
0	274 (3.3)
1-3	1934 (23.6)
4-6	2872 (35)
7-10	1467 (17.9)
Unknown	1656 (20.2)

[a]K6: 6-item Kessler Psychological Distress Scale.

[b]GAD-7: Generalized Anxiety Disorder-7 item.

Perceived Stress, Anxiety Symptoms, and Severe Mental Distress

Respondents without missing responses were divided into groups according to whether they experienced severe stress associated with the COVID-19 pandemic (excluding those who answered “other” on this question, 6363/8203, 77.6% of the respondents), whether they experienced severe mental distress (6424/8203, 78.3% of the respondents), and whether they experienced anxiety symptoms (6424/8203, 78.3% of the respondents). Tables 2, 3, and 4 present the characteristics of each group. In terms of gender, female respondents experienced the most COVID-19–related stress, whereas severe mental distress and anxiety symptoms were the highest in nonbinary respondents. According to age group, COVID-19–related stress was the highest among respondents in their 50s, whereas severe mental distress was the highest among teenagers, and anxiety symptoms were the highest among people in their 20s. Regarding occupation, stress was particularly high for those working in the medical and health fields. Furthermore, severe mental distress was the most common among the unemployed and students. Severe anxiety symptoms were also most commonly reported by the unemployed. Regarding the history of psychiatric visits, those who were currently seeing a psychiatrist comprised the highest percentages of those who reported severe stress, severe mental distress, and anxiety symptoms.

Table 2. Characteristics of those who reported experiencing COVID-19–related severe stress in the nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.

Variables	Severe stress related to COVID-19		
	Yes (n=2443), n (%)	No (n=3920), n (%)	*P* value[a]
Gender			<.001
Male	683 (30.1)[b]	1589 (69.9)[b]	
Female	1717 (43.1)[b]	2265 (56.9)[b]	
Nonbinary	43 (39.4)	66 (60.6)	
Age (years)			<.001
Teenage	36 (27.9)	93 (72.1)	
20-29	452 (35.5)	823 (64.5)	
30-39	655 (36.7)	1129 (63.3)	
40-49	689 (38.4)	1103 (61.6)	
50-59	490 (44.1)[b]	622 (55.9)[b]	
≥60	121 (44.6)	150 (55.4)	
Occupation			<.001
Information and communication systems	150 (27.5)[b]	396 (72.5)[b]	
Agriculture, forestry, and fisheries	9 (29)	22 (71)	
Transportation	20 (29.4)	48 (70.6)	
Student	182 (32)[b]	387 (68)[b]	
Manufacturer	122 (32.3)	256 (67.7)	
Government	100 (33.4)	199 (66.6)	
Unemployed	291 (37)	495 (63)	
Part-time job	160 (39.1)	249 (60.9)	
Finance and insurance	45 (37.2)	76 (62.8)	
Sales and wholesale	108 (37.5)	180 (62.5)	
Infrastructure and construction	59 (39.6)	90 (60.4)	
Food, beverage, and accommodation	28 (36.4)	49 (63.6)	
Other	179 (39.3)	277 (60.7)	
Entertainment and arts	149 (42.1)	205 (57.9)	
Nursing care and welfare	149 (44.2)	188 (55.8)	
Education and research	289 (44.2)	365 (55.8)	
Medical and health	403 (47.9)[b]	438 (52.1)[b]	
History of psychiatric visits			<.001
None	1392 (36.4)[b]	2429 (63.6)[b]	
History of hospital visit(s)	620 (39.7)	943 (60.3)	
Currently going to the hospital	431 (44)[b]	548 (56)[b]	
Number of coping mechanisms employed during self-confinement			.56
0-3	827 (38.4)	1326 (61.6)	
4-6	1054 (37.8)	1734 (62.2)	
7-10	562 (39.5)	860 (60.5)	

[a]With Bonferroni correction for the 15 tests, the threshold *P* value for significance was <.003.

[b]Significant at *P*<.001.

Table 3. Characteristics of those who reported experiencing severe mental distress in the nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.

Variables	Severe mental distress (6-item Kessler Psychological Distress Scale≥13)		
	Yes (n=1215), n (%)	No (n=5209), n (%)	*P* value[a]
Gender			<.001
Male	336 (14.6)[b]	1958 (85.4)[b]	
Female	824 (20.5)[b]	3196 (79.5)[b]	
Nonbinary	55 (50)[b]	55 (50)[b]	
Age (years)			<.001
Teenage	42 (32.3)[b]	88 (67.7)[b]	
20-29	356 (27.7)[b]	927 (72.3)[b]	
30-39	378 (21)	1421 (79)	
40-49	285 (15.7)[b]	1527 (84.3)[b]	
50-59	137 (12.2)[b]	986 (87.8)[b]	
≥60	17 (6.1)[b]	260 (93.9)[b]	
Occupation			<.001
Information and communication systems	85 (15.4)	466 (84.6)	
Agriculture, forestry, and fisheries	2 (6.5)	29 (93.5)	
Transportation	14 (20.6)	54 (79.4)	
Student	164 (28.7)[b]	407 (71.3)[b]	
Manufacturer	65 (17.1)	315 (82.9)	
Government	53 (17.7)	246 (82.3)	
Unemployed	231 (28.9)[b]	568 (71.1)[b]	
Part-time job	93 (22.6)	319 (77.4)	
Finance and insurance	17 (14)	104 (86)	
Sales and wholesale	56 (19.4)	233 (80.6)	
Infrastructure and construction	28 (18.8)	121 (81.2)	
Food, beverage, and accommodation	9 (11.5)	69 (88.5)	
Other	79 (16.8)	391 (83.2)	
Entertainment and arts	88 (24.7)	268 (75.3)	
Nursing care and welfare	58 (17)	284 (83)	
Education and research	93 (14.1)[b]	566 (85.9)[b]	
Medical and health	80 (9.4)[b]	769 (90.6)[b]	
History of psychiatric visits			<.001
None	469 (12.2)[b]	3387 (87.8)[b]	
History of hospital visit(s)	321 (20.3)	1259 (79.7)	
Currently going to the hospital	425 (43)[b]	563 (57)[b]	
Number of coping mechanisms employed during self-confinement			<.001
0-3	544 (25.1)[b]	1620 (74.9)[b]	
4-6	491 (17.4)	2329 (82.6)	
7-10	180 (12.5)[b]	1260 (87.5)[b]	

[a]With Bonferroni correction for the 15 tests, the threshold *P* value for significance was <.003.

[b]Significant at *P*<.001.

Table 4. Characteristics of those who reported experiencing anxiety symptoms in the nationwide web-based survey conducted that was to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.

Variables	Anxiety symptoms (Generalized Anxiety Disorder-7 item≥10)		
	Yes (n=996), n (%)	No (n=5428), n (%)	*P* value[a]
Gender			<.001
Male	308 (13.4)[b]	1986 (86.6)[b]	
Female	646 (16.1)	3374 (83.9)	
Nonbinary	42 (38.2)[b]	68 (61.8)[b]	
Age (years)			<.001
Teenage	22 (16.9)	108 (83.1)	
20-29	241 (18.8)[b]	1042 (81.2)[b]	
30-39	317 (17.6)	1482 (82.4)	
40-49	242 (13.4)	1570 (86.6)	
50-59	153 (13.6)	970 (86.4)	
≥60	21 (7.6)[b]	256 (92.4)[b]	
Occupation			<.001
Information and communication systems	64 (11.6)	487 (88.4)	
Agriculture, forestry, and fisheries	1 (3.2)	30 (96.8)	
Transportation	13 (19.1)	55 (80.9)	
Student	100 (17.5)	471 (82.5)	
Manufacturer	51 (13.4)	329 (86.6)	
Government	41 (13.7)	258 (86.3)	
Unemployed	198 (24.8)[b]	601 (75.2)[b]	
Part-time job	86 (20.9)	326 (79.1)	
Finance and insurance	13 (10.7)	108 (89.3)	
Sales and wholesale	45 (15.6)	244 (84.4)	
Infrastructure and construction	27 (18.1)	122 (81.9)	
Food, beverage, and accommodation	6 (7.7)	72 (92.3)	
Other	76 (16.2)	394 (83.8)	
Entertainment and arts	69 (19.4)	287 (80.6)	
Nursing care and welfare	49 (14.3)	293 (85.7)	
Education and research	85 (12.9)	574 (87.1)	
Medical and health	72 (8.5)[b]	777 (91.5)[b]	
History of psychiatric visits			<.001
None	351 (9.1)[b]	3505 (90.9)[b]	
History of hospital visit(s)	278 (17.6)	1302 (82.4)	
Currently going to the hospital	367 (37.1)[b]	621 (62.9)[b]	
Number of coping mechanisms employed during self-confinement			<.001
0-3	437 (20.2)[b]	1727 (79.8)[b]	
4-6	396 (14)	2424 (86)	
7-10	163 (11.3)[b]	1277 (88.7)[b]	

[a]With Bonferroni correction for the 15 tests, the threshold *P* value for significance was <.003.

[b]Significant at *P*<.001.

Logistic Regression Analysis of Perceived Stress, Severe Mental Distress, and Anxiety Symptoms

Tables 5, 6, and 7 show the results of the logistic regression analysis for each mental health problem. Women, nonbinary people, part-time workers, those working in entertainment and arts, people who had visited a psychiatrist in the past, and those who were currently under psychiatric care were more likely to have these mental health problems. Teenagers (*P*=.01) and people in their 20s (*P*<.001) exhibited a significantly higher probability of experiencing severe mental distress, and people in their 50s (*P*<.001) and 60s and older (*P*<.003) exhibited a significantly higher probability of experiencing severe stress related to COVID-19. In contrast, people in their 40s, 50s, and 60s and older exhibited a significantly lower probability of experiencing severe mental distress (*P*<.001) or feeling anxious (40s: *P*=.004; 50s: *P*=.04; 60s and older: *P*=.002).

In terms of occupation, respondents who felt highly stressed were more likely to be students (*P*=.03) and those working in sales and wholesale (*P*=.01), infrastructure and construction (*P*=.01), nursing and welfare (*P*<.001), education and research (*P*<.001), and medical and health sectors (*P*<.001). Students also exhibited a significantly higher probability of experiencing severe mental distress (*P*=.01), and people in sales and wholesale (*P*=.04) and infrastructure and construction (*P*=.02) also exhibited a significantly higher probability of feeling anxious. However, although unemployed persons did not exhibit a significantly higher probability of experiencing severe stress, they were highly likely to experience severe mental distress and anxiety symptoms (*P*<.001). Moreover, those who had employed effective lifestyle coping mechanisms during the lockdown period exhibited a significantly lower probability of experiencing severe mental distress or feeling anxious (*P*<.001).

Table 5. Logistic regression analysis of the COVID-19–related severe stress that was reported in a nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.[a]

Variable	Severe stress related to COVID-19	
	Odds ratio (95% CI)	*P* value
Gender		<.001
Male	1.000	N/A[b]
Female	1.693 (1.512-1.895)	<.001
Other	1.496 (1.002-2.236)	.049
Age (years)		<.001
Teenage	0.768 (0.492-1.198)	.24
20-29	1.034 (0.875-1.222)	.69
30-39	1.000	N/A
40-49	1.075 (0.936-1.234)	.31
50-59	1.335 (1.142-1.561)	<.001
≥60	1.505 (1.153-1.966)	.003
Occupation		<.001
Information and communication systems	1.000	N/A
Agriculture, forestry, and fisheries	1.190 (0.530-2.674)	.67
Transportation	1.171 (0.669-2.052)	.58
Student	1.368 (1.025-1.824)	.03
Manufacturer	1.307 (0.978-1.746)	.07
Government	1.278 (0.938-1.740)	.12
Unemployed	1.221 (0.956-1.560)	.11
Part-time job	1.399 (1.060-1.848)	.02
Finance and insurance	1.361 (0.895-2.069)	.02
Sales and wholesale	1.475 (1.084-2.007)	.01
Infrastructure and construction	1.660 (1.132-2.435)	.01
Food, beverage, and accommodation	1.301 (0.784-2.158)	.31
Other	1.486 (1.134-1.946)	.004
Entertainment and art	1.768 (1.327-2.354)	<.001
Nursing care and welfare	1.828 (1.368-2.443)	<.001
Education and research	1.946 (1.519-2.494)	<.001
Medical and health	2.313 (1.826-2.929)	<.001
History of psychiatric visits		<.001
None	1.000	N/A
History of hospital visit	1.186 (1.047-1.343)	.007
Currently going to the hospital	1.507 (1.296-1.751)	<.001
Number of effective coping mechanisms employed during self-confinement	0.986 (0.965-1.009)	.24

[a]Nagelkerke's R^2=0.050.

[b]N/A: not applicable.

Table 6. Logistic regression analysis of the severe mental distress reported in a nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.[a]

Variable	Severe mental distress (6-item Kessler Psychological Distress Scale≥13), n (%)	
	Odds ratio (95% CI)	*P* value
Gender		<.001
Male	1.000	N/A[b]
Female	1.652 (1.421-1.922)	<.001
Other	4.135 (2.700-6.333)	<.001
Age (years)		<.001
Teenage	1.780 (1.124-2.821)	.01
20-29	1.452 (1.194-1.767)	<.001
30-39	1.000	N/A
40-49	0.724 (0.604-0.868)	<.001
50-59	0.529 (0.423-0.663)	<.001
≥60	0.291 (0.173-0.491)	<.001
Occupation		<.001
Information and communication systems	1.000	N/A
Agriculture, forestry, and fisheries	0.467 (0.106-2.049)	.31
Transportation	1.604 (0.823-3.123)	.17
Student	1.550 (1.104-2.174)	.01
Manufacturer	1.359 (0.936-1.972)	.11
Government	1.167 (0.785-1.735)	.45
Unemployed	1.731 (1.282-2.337)	<.001
Part-time job	1.428 (1.007-2.026)	.046
Finance and insurance	0.818 (0.452-1.481)	.51
Sales and wholesale	1.472 (0.994-2.181)	.054
Infrastructure and construction	1.369 (0.833-2.250)	.22
Food, beverage, and accommodation	0.769 (0.362-1.633)	.49
Other	1.184 (0.830-1.689)	.35
Entertainment and art	1.856 (1.299-2.651)	.001
Nursing care and welfare	1.124 (0.764-1.655)	.55
Education and research	1.159 (0.827-1.624)	.39
Medical and health	0.717 (0.508-1.010)	.06
History of psychiatric visits		<.001
None	1.000	N/A
History of hospital visit	1.794 (1.524-2.111)	<.001
Currently going to the hospital	5.006 (4.215-5.945)	<.001
Number of effective coping mechanisms employed during self-confinement	0.869 (0.843-0.895)	<.001

[a]Nagelkerke's R^2=0.192.

[b]N/A: not applicable.

Table 7. Logistic regression analysis of the anxiety symptoms reported in a nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.[a]

Variable	Anxiety symptoms (Generalized Anxiety Disorder-7 item≥10)	
	Odds ratio (95% CI)	*P* value
Gender		<.001
Male	1.000	N/A[b]
Female	1.233 (1.054-1.442)	.009
Other	2.694 (1.746-4.157)	<.001
Age (years)		<.001
Teenage	1.083 (0.624-1.880)	.78
20-29	1.127 (0.910-1.396)	.27
30-39	1.000	N/A
40-49	0.753 (0.622-0.912)	.004
50-59	0.789 (0.632-0.984)	.04
≥60	0.471 (0.292-0.759)	.002
Occupation		<.001
Information and communication systems	1.000	N/A
Agriculture, forestry, and fisheries	0.310 (0.041-2.344)	.26
Transportation	1.933 (0.975-3.829)	.06
Student	1.439 (0.982-2.109)	.06
Manufacturer	1.360 (0.905-2.044)	.14
Government	1.212 (0.784-1.874)	.39
Unemployed	1.866 (1.350-2.581)	<.001
Part-time job	1.809 (1.249-2.619)	.002
Finance and insurance	0.871 (0.453-1.675)	.68
Sales and wholesale	1.576 (1.028-2.417)	.04
Infrastructure and construction	1.803 (1.082-3.033)	.02
Food, beverage, and accommodation	0.698 (0.287-1.693)	.43
Other	1.524 (1.049-2.214)	.03
Entertainment and art	1.896 (1.287-2.794)	.001
Nursing care and welfare	1.253 (0.827-1.899)	.29
Education and research	1.381 (0.963-1.981)	.08
Medical and health	0.902 (0.624-1.303)	.58
History of psychiatric visits		<.001
None	1.000	N/A
History of hospital visit	2.038 (1.713-2.425)	<.001
Currently going to the hospital	5.133 (4.293-6.136)	<.001
Number of effective coping mechanisms employed during self-confinement	0.898 (0.871-0.927)	<.001

[a]Nagelkerke’s R^2=0.147.

[b]N/A: not applicable.

Discussion

In this study, we conducted a nationwide web-based questionnaire survey in Japan to shed light on the association between 3 mental health problems related to the COVID-19 pandemic (perceived stress, severe mental distress, and anxiety symptoms) and various factors. The strength of this study is that perceived stress was evaluated subjectively in relation to the COVID-19 pandemic and that various occupations were taken into consideration in evaluating the same. A large portion of the sample experienced stress, severe mental distress, and anxiety symptoms. However, their characteristics and experiences were associated with these problems differently; occupation, in particular, seemed to have a significant impact on these differences. Approximately 73.2% (6004/8203) of the respondents experienced perceived stress related to the COVID-19 pandemic, and 34.9% (2861/8203) of the respondents experienced severe stress. In addition, 17.1% (1403/8203) of the respondents had a score of 13 or higher on the K6 depression scale, and 13.7% (1127/8203) had a score of 10 or higher on the GAD-7 anxiety scale. In a similar study conducted in Japan, 11.5% of the respondents had a K6 score of 13 or higher [13]; prior to this survey being conducted in April 2020, the Government of Japan declared a state of emergency in response to the first wave of the pandemic, and some prefectures were put on a mild lockdown. Given that this study was conducted during the second wave, wherein a subsequent state of emergency was not declared, it is not possible to make a simple comparison due to the difference in conditions. However, due to the prolongation of the COVID-19 pandemic, it has been suggested that the accompanying lifestyle changes may have an adverse effect on mental health. Nevertheless, compared to other countries, the proportion of people in Japan with severe mental distress was not high [24,25]. A similar trend was observed with regard to anxiety [26-28]. It is believed that these tendencies were because the spread of the infection was relatively controlled in Japan compared to other countries at that time.

The results of logistic regression analyses revealed that perceived stress, severe mental distress, and anxiety symptoms related to the COVID-19 pandemic are associated with factors such as gender, age, occupation, history of psychiatric visits, and stress-related coping mechanisms. Factors that have a common negative association with these 3 mental health problems include being a woman and having a history of psychiatric visits. Regarding age, the higher the age, the higher the COVID-19–related stress, whereas severe mental distress and anxiety symptoms were more severe in younger people. Furthermore, the existence of coping mechanisms contributed to the reduction in severe mental distress and anxiety symptoms. These associations have also been reported in previous studies [13,26,29-31].

In terms of occupation, different associations with perceived stress, severe mental distress, and anxiety symptoms that are associated with the COVID-19 pandemic were identified. Since people from the information and communication systems industry experienced relatively good mental health, they were used as a standard for making comparisons. With the spread of COVID-19, the information and communication systems sector has become even more important in the society [32,33]. It has also been reported that in Japan, the rate of people working from home in the telecommunications industry is higher than that for other occupations [34]. These factors may have positively influenced their mental health.

Meanwhile, students had high levels of stress and severe mental distress. Previous studies have also revealed that COVID-19 has adversely affected students' mental health [35]. In Japan, most schools are forced to close during emergencies. Subsequently, during the lockdown due to the COVID-19 pandemic, classes were conducted online [36]. Student suicide is known to be common at the beginning of the semester [37,38]. These results, coupled with the increase in suicide rate among students since the spread of the second wave of the COVID-19 infection in Japan [39], may have influenced the new web-based school setup during the pandemic. They comprised the category most hindered by the lockdown (see Multimedia Appendix 1).

After students, those from the sectors of the food, beverage, and accommodation; entertainment and arts; education and research; and part-time work comprised a large proportion of people who experienced stress due to the lockdown, though to varied degrees (see Multimedia Appendix 1). The food, beverage, and accommodation industry was one of the sectors that was significantly affected by the COVID-19 pandemic [40], and many felt that they were at risk of infection; however, there were no significant differences in stress (P=.31), severe mental distress (P=.49), or anxiety symptoms (P=.43). This may have been because the Japanese government initiated focused financial support for the food, beverage, and accommodation industry during the survey period [41], though it cannot be denied that this may also be because a relatively small number of people were affected. There were no significant differences in severe mental distress and anxiety symptoms among people working in the field of education and research. This may have been influenced by the fact that relatively few of them felt that they were at risk of infection during the period when this survey was conducted. Meanwhile, the entertainment and arts sectors reported high levels of perceived stress, severe mental distress, and anxiety symptoms. The COVID-19 pandemic was particularly devastating to these sectors due to the rules on social distancing in many countries, the ban on large-scale gatherings, and the need to refrain from going out for nonessential reasons [42,43]. In addition, the news in Japan about a celebrity's suicide that took place a month before the survey may have had an impact [44]. Furthermore, high levels of perceived stress, severe mental distress, and anxiety symptoms among people working in part-time jobs may be due to their unstable employment and vulnerable positions [45-47].

With regard to occupations such as sales and wholesale as well as infrastructure and construction, the percentage of those who responded that there was a problem due to the lockdown was lower than that in the industries listed above, but perceived stress and anxiety symptoms were higher. Although there was no significant difference, depressive tendencies were also observed. COVID-19 caused a chain of economic impacts in each sector due to supply chain turmoil; this result is believed to be a reflection of those impacts [48]. In the unemployed group, no increase in perceived stress associated with COVID-19 was observed, but severe mental distress and anxiety symptoms were high. We cannot rule out the possibility that the unemployed individuals in our study were unemployed before the spread of COVID-19, and it is possible that they had mental health problems regardless of COVID-19. A previous study reported that unemployment is associated with depression and reduced self-esteem [49]. However, due attention should be paid to the results of this study, as previous studies have also identified unemployment as a risk factor of depression during the COVID-19 pandemic [50].

Nursing care, welfare, medical care, and health care sectors were associated with increased stress due to COVID-19. Since these professions tend to confront COVID-19 directly, it is natural for people working in these sectors to feel the risk of infection and feel highly stressed. In addition, since prejudice and discrimination against health care workers have become a problem [51], the proportion of health care professionals who complained of discrimination was also large in this study. Interestingly, this was not associated with high levels of severe mental distress or anxiety symptoms in this study. There have been numerous reports of deterioration in the mental health of health care professionals during the COVID-19 pandemic [52]. The inconsistency between the results of this study and those of previous studies may be because this study included a small percentage of respondents who were actually engaged in the treatment of patients with COVID-19 [53]. This study did not collect information on whether respondents were infected with COVID-19 or had contact with patients with COVID-19. Our results may also have been affected by the fact that infection was relatively controlled in Japan compared to other countries at the time of the survey. Additionally, having adequate knowledge of COVID-19 [54,55] may also prevent the exacerbation of depression and anxiety.

The limitations of our survey are as follows. First, since it was a web-based questionnaire survey that allowed free participation, sampling bias and the effect of duplicate responses and missing values must be considered. We confirmed that responses were obtained from a wide range of people based on demographic factors such as occupation; however, the groups do not represent the general Japanese population. Second, although the spread of infection changes daily and varies across regions, we did not account for the impact of this in the study. Third, the details regarding the respondents' occupation, such as whether or not they worked from home, are not clear; therefore, its impact cannot be evaluated. Past studies have reported that worrying about not being able to work from home is associated with poor mental health [56]. Fourth, the actual economic status of each respondent was unknown. Economic status also affects mental health [57]. Fifth, since we did not inquire whether the respondents had ever been infected with COVID-19, we do not know the effect of the respondents' personal experiences with past infection on their mental health. Sixth, this study focused on perceived stress; however, it did not examine posttraumatic stress. Finally, it is difficult to evaluate the causal relationships since this study adopted a cross-sectional design.

Despite these limitations, the study found that COVID-19–related perceived stress, severe mental distress, and anxiety symptoms—the 3 mental health-related issues—tended to differ by occupation. These gaps indicate the complexity of changes in people's mental health during the COVID-19 pandemic. These results suggest that there may be 2 main mechanisms underlying mental health problems. One is the direct deterioration of mental health due to the accumulation of stress associated with COVID-19, which is represented by the remarkably high stress in the medical and health professions. This may include fear of infection and overwork in industries where the workload increased with the spread of infection. Burnout among health care workers has become a problem in Western countries, where the number of people infected with COVID-19 is high [58], and priority measures are needed to reduce COVID-19–related stress. The other is the indirect deterioration of mental health as a result of changes in the socioeconomic conditions due to COVID-19. As COVID-19 has become a more prolonged problem than natural disasters, changes in social structure and economic conditions have become more serious and uncertainty about the future is continually increasing. In our study, occupations with high COVID-19–related stress did not necessarily coincide with those experiencing severe mental distress. Although some degree of stress is assumed, it is suggested that those who are socially unstable or vulnerable to change may develop severe mental distress due to the indirect effects of the COVID-19 pandemic. As the second wave of the COVID-19 infection gradually subsides, these people may be excluded from the process of resuming economic and social activities, face severe realities, and may be exposed to a high risk of suicide. To prevent the increase in suicide cases caused by the COVID-19 pandemic, it is ideal to implement socioeconomic and mental health measures focusing on groups that experience high levels of severe mental distress and anxiety symptoms, as pointed out in this study.

In conclusion, gender, age, occupation, history of psychiatric visits, and stress-coping mechanisms were associated with mental health during the COVID-19 pandemic. In particular, in terms of occupations, a strong association with severe mental distress was noted in students, unemployed individuals, part-time workers, and people working in the entertainment and arts industry. Since mental health problems differ depending on the type of occupation, combatting the adverse effects of the COVID-19 pandemic requires more active socioeconomic and preventive mental health measures for those in fields/occupations that have been affected the most by the pandemic. In addition, it will be necessary to conduct further detailed research to clarify how the COVID-19 pandemic causes mental health problems not only at the individual level but also at the occupational level.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Differences in the experiences during the spread of the COVID-19 infection by occupation in a nationwide web-based survey that was conducted to examine the relationship between the COVID-19 pandemic and mental health in Japan in 2020.
[DOCX File , 17 KB - publichealth_v7i11e29970_app1.docx]

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Abbreviations

GAD-7: Generalized Anxiety Disorder-7 item
K6: 6-item Kessler Psychological Distress Scale

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Original Paper

Obesity-Related Communication in Digital Chinese News From Mainland China, Hong Kong, and Taiwan: Automated Content Analysis

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Abstract

Background: The fact that the number of individuals with obesity has increased worldwide calls into question media efforts for informing the public. This study attempts to determine the ways in which the mainstream digital news covers the etiology of obesity and diseases associated with the burden of obesity.

Objective: The dual objectives of this study are to obtain an understanding of what the news reports on obesity and to explore meaning in data by extending the preconceived grounded theory.

Methods: The 10 years of news text from 2010 to 2019 compared the development of obesity-related coverage and its potential impact on its perception in Mainland China, Hong Kong, and Taiwan. Digital news stories on obesity along with affliction and inferences in 9 Chinese mainstream newspapers were sampled. An automatic content analysis tool, DiVoMiner was proposed. This computer-aided platform is designed to organize and filter large sets of data on the basis of the patterns of word occurrence and term discovery. Another programming language, Python 3, was used to explore connections and patterns created by the aggregated interactions.

Results: A total of 30,968 news stories were identified with increasing attention since 2016. The highest intensity of newspaper coverage of obesity communication was observed in Taiwan. Overall, a stronger focus on 2 shared causative attributes of obesity is on stress (n=4483, 33.0%) and tobacco use (n=3148, 23.2%). The burdens of obesity and cardiovascular diseases are implied to be the most, despite the aggregated interaction of edge centrality showing the highest link between the "cancer" and obesity. This study goes beyond traditional journalism studies by extending the framework of computational and customizable web-based text analysis. This could set a norm for researchers and practitioners who work on data projects largely for an innovative attempt.

Conclusions: Similar to previous studies, the discourse between the obesity epidemic and personal afflictions is the most emphasized approach. Our study also indicates that the inclination of blaming personal attributes for health afflictions potentially limits social and governmental responsibility for addressing this issue.

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KEYWORDS

public health; computational content; digital research methods; obesity discourse; gene disorders; noncommunicable disease

Introduction

Background

The prevalence of obesity has increased worldwide, including China, the world's most populous country. A recent report on China indicated that 46.4 million women (14.9%) and 43.2 million men (10.8%) are obese, which reflects a major health challenge [1]. Obesity not only represents a cosmetic concern but also is a medical problem that increases the risk of other diseases and health problems [2]. Obesity itself is a disease that can cause premature disability and death by increasing the risk of cardiovascular diseases, metabolic disease, musculoskeletal disease, osteoarthritis, dementia, depression, and some types of cancers [2,3]. Being obese can increase the risk of many potentially serious health conditions. Because of the complexity of diseases associated with obesity, it is one of the most difficult public health issues our society should deal with.

News plays an important role in distributing reliable information for general readers or subscribed peer-publics. The current body of literature has adopted the framing theory for reporting news content, which highlights some aspects of themes in news stories to help define ill health problems [4-6]. The most applied thematic coverage is associated with increased societal attributions, while episodic coverage is related to increased individualistic responsibility and punitive treatment [5,7,8]. Considering obesity a key public health priority, news stories that report on obesity may impact and induce shifts in readers' perceptions of the obesity problem [4,5].

In this study, the obesity issue is addressed from two approaches: first, we face new concentrations of media power, leading to new inequalities and insecurities with respect to data geographies and different data-related practices [9]. Specifically, there are many nefarious motivations underlying the creation of disinformation by giving one major reason why a person or group might want to spread wrong information [6-8]. Previous nascent studies on media content have shown that computational methods facilitate digital journalistic data collection and metadata analysis [10-12]. Studies have shown the importance of machine computational algorithms in facilitating big data storage and analysis to empower beneficial information for extending the preconceived grounded theory [10,13].

Second, comparatively fewer studies on journalistic content analysis on health issues are in languages other than English [6]. Thus, 9 mainstream and digital journalistic content in Chinese with high browsing and circulation were examined. Our results may broaden the scope for learning public health information from news media in terms of languages and geographical comparison considerations.

Goals of This Study

This study examined the causes and strength of inferences associated with obesity by parsing meaning from unstructured data to guide decisions. The dual objectives of this study are to understand how obesity is covered in news along with the timeline of obesity communication and what journalistic discourse says about etiology, afflictions issues, and diseases associated with the burden of obesity. We draw upon recent advances in computational text analysis to develop a hybrid approach to the deductive analysis of large scale of digital course [14].

The analysis consists of comparisons between the digital journalistic work in Mainland China and its 2 neighboring territories with the condensed Chinese population, Taiwan, and Hong Kong. The comparison is meaningful by considering different governmental paths and socioeconomic developments in the Chinese civilization. The news content also highlights the media environment and public communication priority which potentially impact readers' perceptions of health care management.

Research Questions

The conceptual foundations of machine computation to text classification were used. A strategy for theory-assisted (driven and computer) classification of large text corpora with established categories was evaluated. Given the natural discourse on digital media, it is argued whether linguistic preprocessing can improve classification quality. Therefore, 6 research questions have been raised for studying the trend and patterns of obesity communication and mediated associations of obesity coverage for web-based readers:

1. What is the trend of coverage of the obesity epidemic and how has the pattern of digital journalistic stories developed over time?
2. What etiological factors are associated with obesity covered in the news?
3. What types of diseases linked with obesity are presented in the news coverage?
4. What type of etiology and disease linked with obesity have been ignored?
5. What is the strength of the correlation of observable variables (etiology and disease) linked with the burden of obesity by considering the total effect (a combination of direct and indirect variables)?
6. What type of message frames (thematic or episodic) does health-related news employ?

Methods

The Approach of Automated Content Analysis

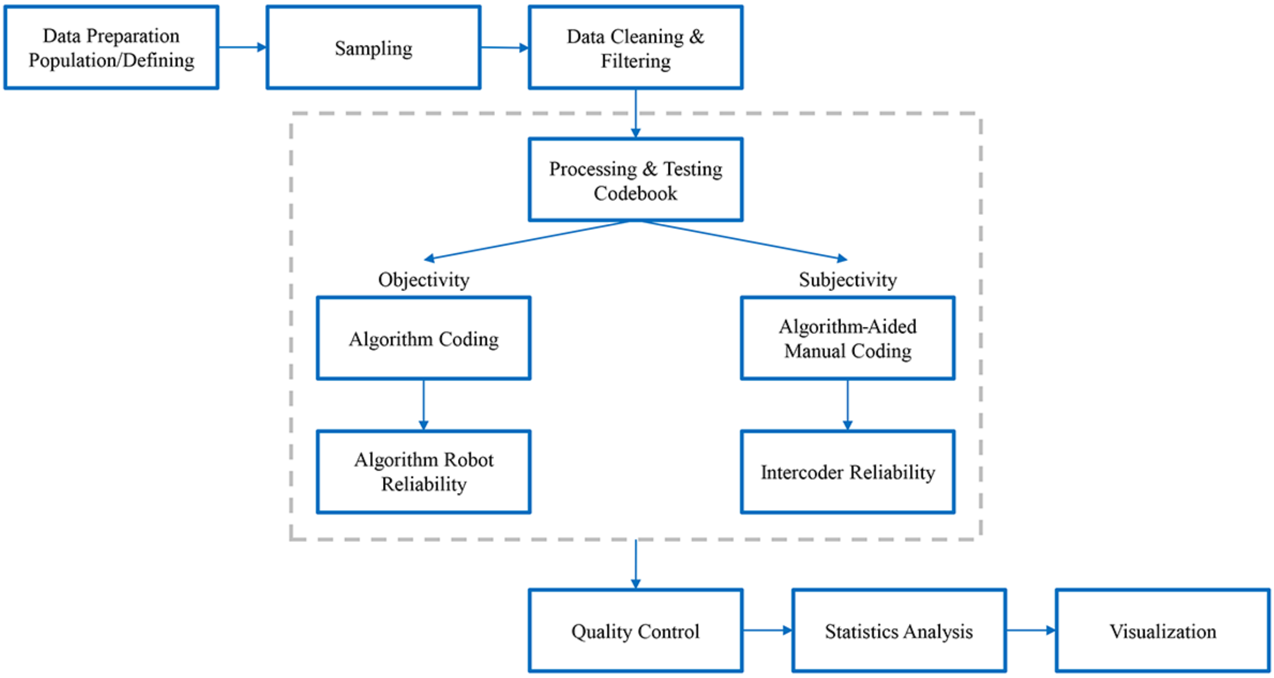
The study protocol included defining text documents of news by retrieving web-based sources and testing the depth and scale of the data. Previous studies emphasized the importance of combining computational and manual techniques to preserve the strengths of traditional content analysis and the innovative large-scale capacity of big data analysis [6,15,16]. Traditional content analysis provides systematic rigor and contextual sensitivity while the computational analysis maximizes the algorithmic accuracy of computational methods to yield more favorable results [17]. Thus, an approach of combining computational and manual methods throughout the data analysis process was used.

Machine computational algorithms were used with a proposed platform, DiVoMiner. The tool of text processing is a modern technique for automated content analysis. It has been designed to organize and filter large archives of documents on the basis of patterns of word co-occurrence and term discovery [16,18]. Specifically, DiVoMiner is a computational platform that integrates functions of data cleaning, filtering, analysis, and visualization from the perspective of social sciences. It is an operating system that allows users to monitor the data information and provide content analysis in a timely manner.

Automated content analysis to identify prominent issues has become a commonly used methodology, particularly in communication sciences [19-23]. The computational procedure began with customized news data preparation, storage, preprocessing, screening, and cleaning. The process of data filtering is imperative and important for organizing unstructured data to be processed in a manner to be further analyzed with validity [9,11]. The use of a computational algorithm facilitates detecting terms and topic-modeling while focusing on theory development and application [24-27].

One of the tasks was to make news articles more discoverable. Therefore, each article that contained a keyword, a phrase in a sentence, or an assertion about obesity were sampled and screened. The process involved pilot coding, subsequent modification, and double coding, which could improve coding efficiency and data quality [27,28]. Figure 1 shows the workflow of hybrid and automatic content analysis for computer-assisted classification of DiVoMiner.

Figure 1. The workflow of hybrid and automatic content analysis for computer-assisted classification of DiVoMiner.



Sampling News Media and Articles

The sampling criteria of digital journalistic work were in accordance with those of previous studies by considering the following three criteria: high circulation of news media, accessible with digital archives, and from the most populated cities with a severe obesity problem [6,7,16,28]. However, the newspapers were selected not only for a representation of what the mainstream newspapers offer its web-based readers but also for reasons in representing government-oriented (owned or business) news.

For example, 3 sampled newspapers in Mainland China focus on uncovering the potential impact of state influence on news production. It can be considered the mouthpiece of the government. Nevertheless, relative to state-owned and controlled media, business-oriented news agencies from Taiwan and Hong Kong are sampled to learn their editorial operation, which may fit into their desired investment profile [29,30]. The data span from January 1, 2010, to December 31, 2019, which would help understand the journalistic surveillance of obesity coverage for a decade.

Overall, 9 newspapers were selected: *Southern Metropolis Daily* (南方都市報), *Guangzhou Daily* (廣州日報), and *Beijing Evening News* (北京晚報) from Mainland China; *United Daily News* (聯合報), *Times Daily News* (中國時報), and *Liberty Times* (自由時報) from Taiwan; and *Apple's Daily News* (蘋果日報), *Oriental Daily* (東方日報), and *MingPao* (明報) from Hong Kong.

Keywords Developed for Automated Coding

The procedure of determining keywords included collecting and extracting words into the meaning group by the pkuseg—python. Thus, the word segmentation toolkit provides acceptable accuracy to meet the requirements of mediated associations in this study [16,28]. However, it is worth noting that Chinese words and words in the meaning group have a unique morphological system by selecting different settings on semiprefixes or semisuffixes [6,16]. For instance, the keywords related to an individual's weight included "obese" (過肥) or "overweight" (過重); multiple terms describing obesity included "too big" (太胖) or "excessive weight" (體重超標); the semiprefix "too" (太) denotes the level of obesity for "too fat" (太肥) or "too heavy" (太重); the semisuffix "-zi" (子) is able to nominalize an adjective "fat" (胖) into "pang-zi" (a fat man)

(胖子). Filters employed word segments such as obesity, obesity-related keywords, and alternative terms to create a logical phrase allowing search results to be more objective. The objectivity of journalistic data should not be viewed as an absolute, but rather as a performance that is grounded in practice.

Many Chinese lexicons for covering obesity and its causal link seem to be interchangeable in the codebook, despite the word "cause" being typically used to express how one factor assumes responsibility for its effects, while "lead to" is used to express the result of a certain action or event. Therefore, a tailored codebook containing keywords, phrases, causal link, etiological inference, and diseases potentially related to obesity has been developed for obesity-related communication from a journalistic perspective. The codebook was tested several times along with manual annotations in a fast, uncomplicated, but more efficient and satisfying way.

The drafted codebook consists of 13 target words, 13 etiologies, and 7 categories of noncommunicable diseases (NCDs) adapted from previous studies [2,3,6,28]. However, it was decided that any article that contained the keyword "obesity" and its related terms a minimum of 2 times was ideal to be considered valid samples. The threshold was decided in a data-driven manner because the existing supervised algorithms did not yield output variables satisfactorily. News articles that contained related terms at least 2 times can ensure valid terms. This also allowed researchers to uncover associations that could not have been found using analog research methods [30]. Additionally, objectivity is a core journalistic norm, which involves collecting and disseminating verifiable facts delivered in a detached manner [29,30]. Therefore, each article containing the keyword more than 1 time is viewed as evidence to lend weight to assertions and increase objectivity in news reports.

Our results include 11 target words, 11 etiologies, and 4 disease categories specifically related to obesity coverage. The revised codebook sustains the framing of obesity disorder as an NCD in the Chinese newspapers. A list of target words for obesity, causal link–related terms, and obesity with etiology and disease in Chinese with English translations is displayed in Multimedia Appendix 1.

Data Preprocessing

To ensure the validity and reliability of machine analysis, a manual procedure was used to ensure a more reliable computational process for the generated text, including frequent terms, topics, and causal links [31]. Therefore, 5 Chinese graduate students majoring in communications and new media were trained for over 10 hours to act as independent coders. Each coder was required to code 500 sampled with 20% of overlapping news stories by providing dichotomous judgments and to indicate uncertainty. If a news article provided a verbal statement that suggested a problem associated with excess weight, it was coded for the presence of a news claim. Coders discussed all disagreements and uncertainties with the first author during the final stage of the analysis.

Previous communication studies have recommended 80% agreement between coders as an acceptable minimum [6,14,16]. The reliability for each variable in this study indicated substantial agreement across coders (Cohen κ= 0.81-1.00; *P*<.001; 95% CI 0.704-0.908), indicating high confidence in the reliability of the test data. Taken together, previous studies guided the conceptualization of mediated association to capture explicit assertions of casual links [11,26,32]. Analogical reasoning on linguistic regularities for developing a more comprehensive and reliable association is imperative.

Etiology of Causality Assessment

Causality is one of the discourse analyses performed by extracting semantic relationships between cause and consequence for learning and predicting the structure of a sentence [33]. Analyzing causality is a common practice for studying the data corpus of machine learning [6,26]. Considering the widespread use and the complex nature of the Chinese language, DiVoMiner helped implement the taxonomy to measure the concept of causality. Specifically, based on the internal rules of mining text [31,34,35], DiVoMiner guided the machine to automatically label obesity and its related keywords. The classification results of algorithm coding generated by DiVoMiner were obtained simultaneously.

For correlation and total effect analysis, Python3 NetworkX was used to examine a network. The concept of obesity-related terms was considered as nodes while the article numbers were considered as weights. Betweenness centrality is the sum of the fraction by considering the shortest paths of all pairs in a network [36]. The greater edge centrality (EC) indicates that the terms are more connected. To explore the strength of the association between 2 variables, the width of an edge was calculated for each node. For instance, a node of "high calorie" shows high strength with the use of "heart attack." Several examples of conceptual terms analyzed by the DiVoMiner are shown in Multimedia Appendix 2.

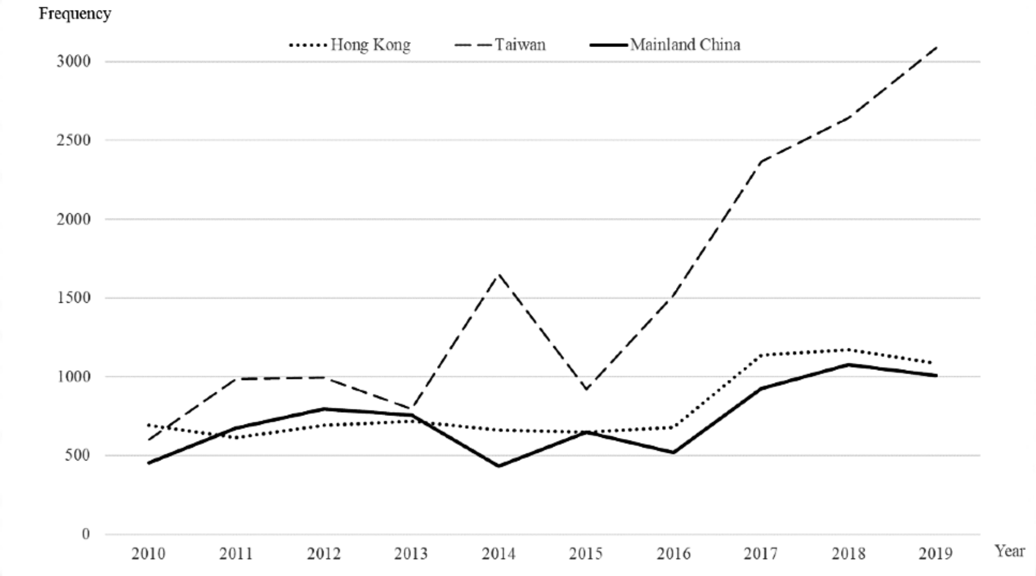
Results

Codebook and Data Trend

In total, 13 target words, 11 etiologies, and 4 categories of disease were closely related to obesity reports, which sustains the framing of obesity disorder as an NCD in the Chinese newspapers. Based on a contrast analysis of semantics developed, the episodic theme emphasized 6 variables, including an individual's behavior related to stress, tobacco use, overuse of alcohol, decreased physical activity, improper diet, and drug use. In comparison, the thematic theme included 5 variables including genetic disorders, environmental pollution, family status, poor economy, as well as social and economic systems. Four main types of diseases such as cardiovascular, metabolic, cancer, and autoimmune were identified as major pathogenic links with obesity in the news.

In all, 30,968 articles covering obesity along with the etiology of causal inference were identified from 2010 to 2019, which show a clear trend of increasing attention over time. To facilitate comparisons across media development process and cultures, the numbers and ranks of obesity-related articles were significantly different between Mainland China and the neighboring areas in Hong Kong and Taiwan (χ^2_{30}=1098.88, *P*<.001). The highest surge in obesity-related coverage in Mainland China was observed in 2018 and 2019, but it showed a big decrease in coverage in 2014 and 2016. Figure 2 shows an overview of the trend and development of obesity with causal claims in the news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Figure 2. Trend and development of obesity with causal claims in news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.



An overall analysis revealed that news articles related to the obesity epidemic peaked in 2019 (n=5183, 16.7%), followed by 2018 (n=4890, 15.8%) and 2017 (n=4432, 14.3%). The average coverage of obesity and its etiology and related diseases was 3097 articles per year. In comparison, above-average reports were observed in Taiwan's journalistic discourse. A trend of below-average reporting was found from within the years between 2010 and 2017 (range from 1746 to 2744 articles). The intensity of journalistic coverage of the obesity epidemic peaked in Taiwan (n=15,571), followed by newspapers in Hong Kong (n=8103) and Mainland China (n=7294). Table 1 displays the distribution of obesity-related news articles in Chinese newspapers in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Table 1. Distribution of obesity-related news articles in Chinese newspapers in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Year	Obesity-related news articles, n (%)			
	Mainland China (n=7294)	Taiwan (n=15,571)	Hong Kong (n=8103)	All (n=30,968)
2010	453 (6.2)	602 (3.9)	691 (8.5)	1746 (5.6)
2011	673 (9.2)	985 (6.3)	616 (7.6)	2274 (7.3)
2012	798 (10.9)	994 (6.4)	693 (8.6)	2485 (8.0)
2013	759 (10.4)	797 (5.1)	716 (8.8)	2272 (7.3)
2014	431 (5.9)	1652 (10.6)	661 (8.2)	2744 (8.9)
2015	650 (8.9)	922 (5.9)	650 (8.0)	2222 (7.2)
2016	519 (7.1)	1520 (9.8)	681 (8.4)	2720 (8.8)
2017	927 (12.7)	2367 (15.2)	1138 (14.0)	4432 (14.3)
2018	1077 (14.8)	2643 (17.0)	1170 (14.4)	4890 (15.8)
2019	1007 (13.8)	3089 (19.8)	1087 (13.4)	5183 (16.7)

Etiology of Obesity-Related Communication

The etiological attributes of obesity coverage were presented in 16,991 of 30,968 (54.9%) articles initially collected. The highest intensity of newspaper coverage on obesity-mediated causes was observed in Taiwan (n=8090, 47.6%), followed by Mainland China (n=5584, 32.9%) and Hong Kong (n=3317, 19.5%). Overall, there was a substantially stronger focus on 3 shared causative inferences of obesity such as stress (n=4483, 26.4%), tobacco use (n=3148, 18.5%), and genes (n=2418, 26.4%).

In comparison, one common causal attribute of obesity, social and economic system (n=7, 0.2%) received the least coverage in all newspapers. One etiology of causative conditioning, such as drug use, also received scarce coverage in Mainland China (n=47, 1.1%), while one causative agent of the poor social economy also received scarce coverage in Taiwan (n=24, 1.6%) and Hong Kong (n=12, 2.1%). In brief, the numbers and ranks of the shared causes of obesity between controlled news media and business-oriented news were significantly different (χ^2_{33}=348.48, P<.001).

The pattern of using episodic (personal) versus thematic (nonpersonal) agents in 3 areas is similar. Among a total of 16,991 articles, the episodic risk factor makes up the majority of causes of obesity, which were covered (n=13,587, 80.0%), compared to the influence of thematic conditions (n=3404, 20.0%). Specifically, the number of episodic themes associated with obesity were the highest in Taiwan (n=6563, 48.3%), followed by Mainland China (n=4283, 31.5%) and Hong Kong (n=2741, 20.2%). Etiological factors including stress, tobacco use, and alcohol overuse were strongly associated with obesity coverage in all newspapers.

On contrast analysis of semantic concepts, the number of thematic themes associated with obesity were also the highest in Taiwan (n=1527, 44.9%), followed by Mainland China (n=1301, 38.2%) and Hong Kong (n=576, 16.9%). Genetics contribute to 61.6%-80.7% of obesity with further news coverage. Table 2 shows a comparison of causal attributes of obesity in the news articles under 2 themes in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Table 2. Comparison of causal attributes of obesity in the news articles under 2 themes in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Causal attributes of obesity	News articles, n (%)			
	Mainland China	Taiwan	Hong Kong	All
Episodic theme	4283 (100)	6563 (100)	2741 (100)	13,587 (100)
Stress	1523 (35.6)	2046 (31.2)	914 (33.3)	4483 (33.0)
Tobacco use	944 (22.0)	1635 (24.9)	569 (20.8)	3148 (23.2)
Alcohol overuse	863 (20.1)	1121 (17.1)	430 (15.7)	2414 (17.8)
Lack of physical activity	500 (11.7)	1102 (16.8)	552 (20.1)	2154 (15.9)
Improper diet	406 (9.5)	590 (9.0)	262 (9.6)	1258 (9.3)
Drug use	47 (1.1)	69 (1.1)	14 (0.5)	130 (1.0)
Thematic theme	1301 (100)	1527 (100)	576 (100)	3404 (100)
Genetic disorders	801 (61.6)	1152 (75.4)	465 (80.7)	2418 (71.0)
Environmental pollution	348 (26.7)	278 (18.2)	76 (13.2)	702 (20.6)
Family status	63 (4.8)	71 (4.6)	19 (3.3)	153 (4.5)
Poor societal economy	88 (6.8)	24 (1.6)	12 (2.1)	124 (3.6)
Social and economic system	1 (0.1)	2 (0.1)	4 (0.7)	7 (0.2)

There were 4 main types of diseases including cardiovascular, metabolic, cancer, and autoimmune diseases associated with obesity communication in the Chinese newspapers. Among 30,968 articles initially collected, the news coverage of diseases linked with obesity were presented in a total of 20,111 articles (64.9%). The highest intensity of news coverage of the obesity mediated diseases was observed in Taiwan (n=10,622, 52.8%), followed by Mainland China (n=5432, 27.0%) and Hong Kong (n=4057, 20.2%).

Three disease categories were paid the most attention for coverage: cardiovascular diseases (n=8477, 42.2%), metabolic diseases (n=6869, 34.2%), and cancer (n=4762, 23.7%). Autoimmune diseases received relatively scarce reports associated with obesity (n=3, 0.0%), while the others were totally ignored (eg, musculoskeletal or neurological disorder).

The diseases associated with obesity also show a significant difference among the 9 newspapers (χ^2_{36}=83.74, P<.001). Table 3 displays the disease types associated with obesity in news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

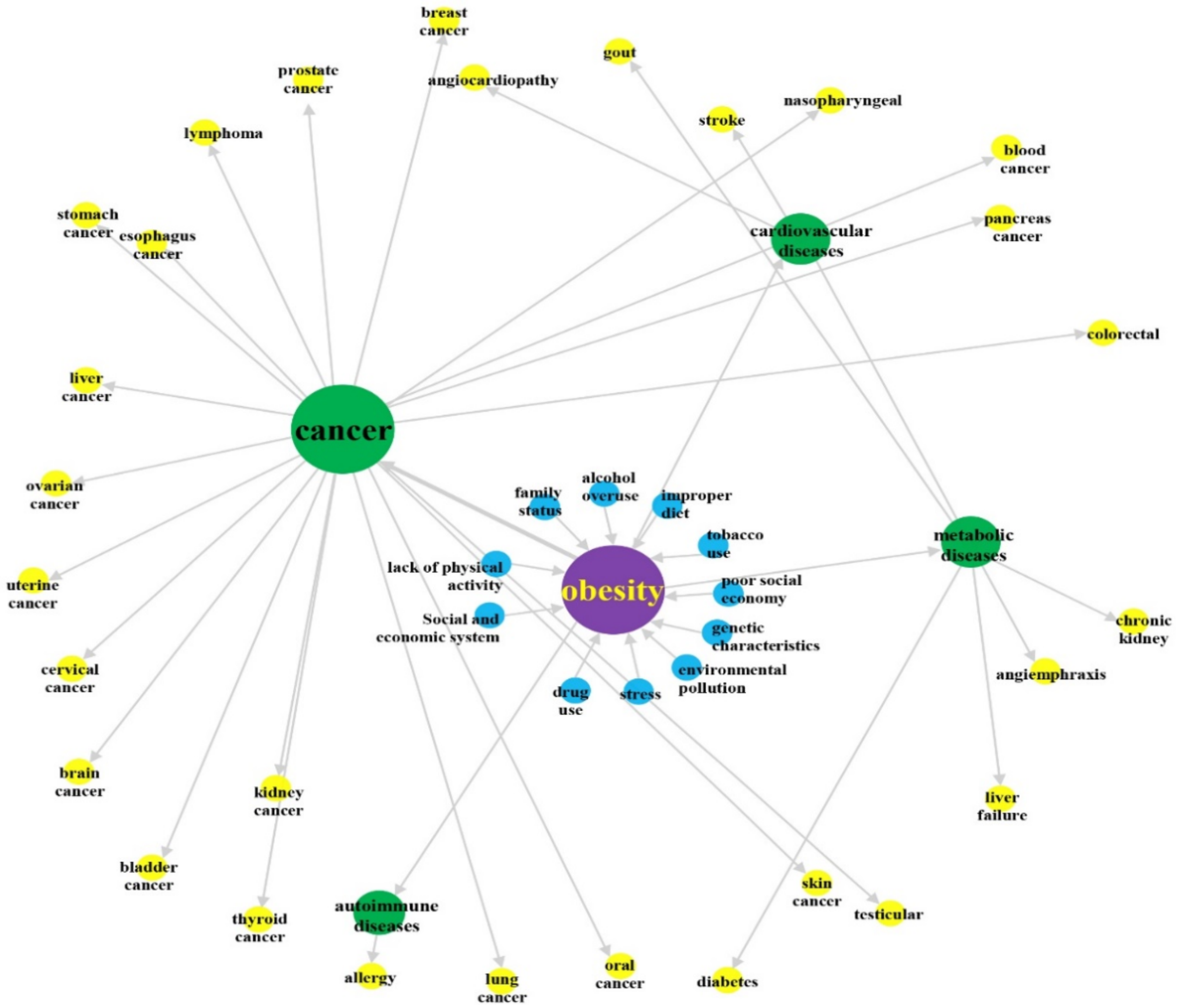
To examine the strength of disease etiology associated with obesity-related communication, a network analysis displayed a connection created by the aggregated interaction. As a result of the betweenness EC measurement, the rank-correlation between the causal effects and betweenness centrality was 0.17. Specifically, the aggregated interaction between the 2 terms "obesity" and "cancer" was the highest (EC=0.133), followed by the mediated relation between "obesity" and "metabolic diseases" (EC=0.030), and "obesity" and "cardiovascular diseases" (EC=0.024).

Table 3. Disease types associated with obesity in news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Disease types	Obesity-related news articles, n (%)			
	Mainland China (n=5432)	Taiwan (n=10,622)	Hong Kong (n=4057)	All (n=20,111)
Cardiovascular diseases	2306 (42.5)	4349 (40.9)	1822 (44.9)	8477 (42.2)
Metabolic diseases	1951 (35.9)	3593 (33.8)	1325 (32.7)	6869 (34.2)
Cancer	1175 (21.6)	2678 (25.2)	909 (22.4)	4762 (23.7)
Autoimmune diseases	0 (0.0)	2 (0.0)	1 (0.0)	3 (0.0)

The result shows that overweight and obesity are associated with an increased risk of 21 types of cancer and a total of 11 behavioral and environmental factors. An explanation for the different trends of the centrality measures as the network density increases is that renal cell cancer (RCC) is the major type of kidney cancer with increasing incidence; furthermore, obesity is one of the well-established risk factors for RCC, as covered in the news. In addition, several factors of an individual's behavior such as poor diet and too little physical activity are highlighted, while factors of environmental variables including pollution and poor societal economy are observed. Figure 3 displays a direct graph color-coded on the basis of the betweenness centrality of each vertex from the least (yellow) to the greatest (blue) with regard to etiology and NCDs associated with obesity in the news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.

Figure 3. A direct graph color-coded on the basis of the betweenness centrality of each vertex from least (yellow) to greatest (blue) with regard to etiology and noncommunicable diseases associated with obesity in the news articles in Mainland China, Hong Kong, and Taiwan from 2010 to 2019.



Discussion

Principal Findings

The high prevalence of obesity is associated with an enormous medical, social, and economic burden. Chinese news coverage on obesity along with etiology of causal inference shows a clear trend of increasing attention over time. This also suggests that chronic stress is strongly associated with obesity. The association between stress and obesity can lead to overeating of foods that are high in fat, sugar, and calories, which, in turn, can lead to weight gain. On analyzing the strength of the association between the observed disease burden and obesity-related coverage, we found that cardiovascular diseases were the most frequent disease type. In comparison, metabolic dysfunction and inflammation caused by obesity are ignored in the news, despite scientific evidence indicating that metabolic dysfunction caused by obesity contributes to a wide variety of disorders and effects on the nervous system [33].

It is also clear that digital news frequently links the concept of obesity with NCDs such as "cardiovascular diseases," "metabolic diseases," or "cancer." Current information circulates from the Chinese news serve as a wake-up call for the general public who have been slow to acknowledge that obesity is a disease and a dangerous disease paring with NCDs. Moreover, media content still emphasizes that obesity as merely a lifestyle issue or, worse, a moral failing due to lack of willpower. Thus, the communication or advice from the news reporting is usually just to eat less and exercise more which could be ineffective for most people with obesity, and those who do manage to lose weight tend to gain it back quickly. This is not a matter of will power but rather the body has evolved complex physiological processes to actively resist weight loss through metabolic, hormonal, and neurobehavioral changes [1-3].

Following a stronger focus on 2 shared causative attributes of obesity such as stress and tobacco use, another 3 causative inferences covering genetic disorders, overconsumption of alcohol, and decreased physical activity were also covered frequently. Four top causal inferences of obesity were about an individual's responsibility in handling stress, tobacco, alcohol, and decreased physical activity in all newspapers. To be specific, the causative inferences of alcohol intake linked to obesity were prominent in Mainland China, while stress, tobacco use, and decreased physical activity received more media attention in Hong Kong and Taiwan. The pattern in showing various causal inferences can be understood as an indication of a feature distinctive of obesity communication in the area.

Consistent with the existing literature [1,2,6], the obesity epidemic—according to news reports—is increasing the burden of several NCDs such as heart disease, diabetes, and cancer. News reports advise that obesity is associated with poor health outcomes, increasing the likelihood of developing NCDs and conditions including obstructive sleep apnea syndrome. At first glance, one might think that chronic illnesses are sufficient to identify interventions for analyzing causal language and the strength of the effect of NCDs on obesity. More combined and rigid scientific interventions should be investigated for reporting in the news because both individual and social transmission of obesity is apparent; populations achieve obesity through some combinations of mechanisms such as lack of exercise, genetic disorders, unhealthy lifestyle, and a poor food environment. Thus, a classification of obesity to being socially communicable should be acknowledged in the news.

The state-owned media may have certain advantages relative to commercial-driven news that the health educator may want to consider. For instance, Mainland China's state-owned media may have far greater reach of readership than business-oriented and private news organizations in Hong Kong and Taiwan. A market-driven newspaper such as Apple's Daily News from Hong Kong linked casual reasoning most frequently between decreased physical activity and obesity, followed by genetic characteristics and obesity concerns. In contrast, United Daily News from Taiwan focused more commonly on fat mass and obesity-associated genes, followed by lack of physical activity, as causal attributes for obesity. Similarly, Guangzhou Daily from Mainland China linked obesity with genetic disorders, followed by the consequence of lack of physical activity.

This study aims to understand how themes and scenarios about the outcomes and implications of news coverage on obesity are reconstructed and acted upon. The substance of investigative news reports should demonstrate the claim that the contemporary digital news media is best characterized as a narrative short communication prepared on the topic of obesity and its potential communicability. We nowadays face new concentrations of power, leading to new inequalities and insecurities with respect to data ownership, data geographies, and data interpretation. Learning the coverage of the obesity epidemic will likely change practice for health researchers, journalists, and medical professionals, as shifts will be seen in the incidence of obesity-related disease severity.

Comparison With Prior Work

The causal links in media texts can be made explicitly or implicitly. Over the past decade, numerous causal inferences and effects for interventions have been evaluated [3,8,10,21], but very little evidence exists about their long-term effectiveness. An algorithmic strategy can extract and classify complex semantic contents in lingual media discourse. Thus, millions of news texts at minimal added human effort afford researchers control over the process of theory-guided classification and with scientific findings.

Other viewpoints are consistent with previous reports. First, health news can play a positive role in promoting public health or a negative role in causing unnecessary fear [16,29]. The episodic coverage emphasized attributions of individualistic causal responsibility and the punitive treatment outnumbered the thematic coverage for increased societal attributions. The most severe issue with causal inferences of news reported was to blame individuals for their own health afflictions, but little consideration is given to larger social and environmental issues [5,6,8,16]. Thus, attributing obesity to a failure of personal responsibility may impair and limit social, economic, environmental, and governmental approaches for addressing it.

Second, Chinese news offered gene-based explanation of obesity disorder at the highest frequency (61.6% to 80.7%). It has been reported that news stories often misrepresent genetics by exaggerating the causal link between genes and obesity [34]. The single biomedical frame related to obesity issues in the news was highlighted, despite various causal factors that should be taken into consideration [8,34]. The news reports that offer gene-based explanations regarding obesity may make audiences believe that genetic influence is the primary cause of the obesity disorder, compared to news coverage that suggests that obesity is a consequence of one's unhealthy lifestyle [34].

Limitations and Challenges

Several limitations are noteworthy. The purpose of this study is to identify causal inference patterns in news coverage on obesity communication. There are challenges and limitations for categorizing a vast amount of news data and considering the news featured frame as mixed. In the changing scope of news reporting, significant issues within journalism as a professional field have emerged. Additionally, the readership complexity can be quite challenging in terms of suggesting interventions and fostering media education. The rapid diffusion of internet-based news on mobile devices has also created limitations for linking communication effects.

There are challenges with computational methods, including the lack of standards for automated content measures and their interpretation of information. Although the implicit causal inferences in this study may suggest or infer causation, the number of articles on obesity-related diseases may not be completely representative. These are all attributed to language complexity in similar research [9,32,34,37]. A variety of diseases can develop over the course of time; as a result, our findings limit the use of data for prediction and actions to improve the effectiveness of news education.

The experience gained with previous research and epidemiological problems such as obesity interventions should help expand the required health initiatives and increase the likelihood of preventing future generations from facing the consequences of obesity. Interventions including obesity communication is not straightforward but rather conditional on the confounders. As new features are being introduced and the programming languages continue to evolve, mixed methods such as advanced quantifying studies in data journalism, agent-based modeling, and experimental research of news study are suggested.

Conclusions

This study examined journalistic work on the impacts and effects of excess weight and its potential links of etiology and diseases from 2010 to 2019. Our results show the coverage of obesity evolving over time, the path it takes, and the words and phrases that surround the topic. A total of 21 cancers and 11 behavioral factors are identified to be associated directly with overweight- and obesity-related communication. Overall, the increasing trend of coverage illustrates the interaction of journalistic and public health concerns in supporting obesity communication.

News content associated with a given unhealthy behavior is presented in more than half of the articles. Concomitantly, the NCDs associated with the obesity epidemic are also found frequent in over 60% of the articles. Two frames were considered for a useful discussion concluding that the framework of obesity involves individual-level rather than societal etiologies. A more prevalent frame in future studies is proposed because our findings suggest far more complexity than is apparent for discussion.

With the increasing amount of web-based news and the incorporation of computational methods, it is possible to extract meaning from a large volume of data and to apply computational algorithms to unstructured data. In particular, few studies have focused on the Chinese data, which suffer from a heavy underrepresentation from empirical and theoretical research. Nevertheless, this study moves media analysis beyond the realm of the traditional content analysis by gathering metadata to support and contradict our suspicions.

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Authors' Contributions

AC designed the main concepts of this study; PS conceived the study and designed the codebook; AC, ML, and WJ performed data verification and conducted data analysis; and AC and WJ wrote and edited this paper. All authors approved and promoted the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Obesity-related keywords in Chinese and translation in English.
[DOCX File , 887 KB - publichealth_v7i11e26660_app1.docx]

Multimedia Appendix 2

Examples of conceptual terms in news media with English translation.
[DOCX File , 778 KB - publichealth_v7i11e26660_app2.docx]

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Abbreviations

EC: edge centrality
NCD: noncommunicable disease
RCC: renal cell cancer

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Original Paper

Novel Methods in the Surveillance of Influenza-Like Illness in Germany Using Data From a Symptom Assessment App (Ada): Observational Case Study

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Abstract

Background: Participatory epidemiology is an emerging field harnessing consumer data entries of symptoms. The free app Ada allows users to enter the symptoms they are experiencing and applies a probabilistic reasoning model to provide a list of possible causes for these symptoms.

Objective: The objective of our study is to explore the potential contribution of Ada data to syndromic surveillance by comparing symptoms of *influenza-like illness* (ILI) entered by Ada users in Germany with data from a national population-based reporting system called GrippeWeb.

Methods: We extracted data for all assessments performed by Ada users in Germany over 3 seasons (2017/18, 2018/19, and 2019/20) and identified those with ILI (report of fever *with* cough *or* sore throat). The weekly proportion of assessments in which ILI was reported was calculated (overall and stratified by age group), standardized for the German population, and compared with trends in ILI rates reported by GrippeWeb using time series graphs, scatterplots, and Pearson correlation coefficient.

Results: In total, 2.1 million Ada assessments (for any symptoms) were included. Within seasons and across age groups, the Ada data broadly replicated trends in estimated weekly ILI rates when compared with GrippeWeb data (Pearson correlation—2017-18: r=0.86, 95% CI 0.76-0.92; P<.001; 2018-19: r=0.90, 95% CI 0.84-0.94; P<.001; 2019-20: r=0.64, 95% CI 0.44-0.78; P<.001). However, there were differences in the exact timing and nature of the epidemic curves between years.

Conclusions: With careful interpretation, Ada data could contribute to identifying broad ILI trends in countries without existing population-based monitoring systems or to the syndromic surveillance of symptoms not covered by existing systems.

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KEYWORDS

ILI; influenza; syndromic surveillance; participatory surveillance; digital surveillance; mobile phone

Introduction

Background

Influenza is a disease that causes considerable morbidity and mortality each year [1] and has been the subject of research investigating the application of novel surveillance tools, including the potential use of data from web-based sources [2]. In many European countries, data on the syndromic surveillance of *influenza-like illness* (ILI) are collected via internet-based reporting tools run by national public health institutes [3]. In Germany, one such tool (*GrippeWeb*) collects data from voluntary participants, who are prompted to report, on a weekly basis, whether they have experienced any symptoms of an acute respiratory infection [4]. Such a tool is complementary to physician- and laboratory-based surveillance and helps to capture data from a population who have not or may not come into contact with the health care system, thus potentially providing a fuller picture of disease incidence within the population. Such population-based reporting tools might confer particular benefits during an epidemic or pandemic, if patterns of health care–seeking behavior change because of individuals' reluctance or inability to visit doctors or clinics [5].

Objectives

A growing number of studies have explored the potential contribution of additional web-based data sources to the surveillance of infectious diseases, including the aggregation of data from web-based newsfeeds [6,7] and analyses of Google search query data [8,9]. One additional possible source of data is from health-related smartphone apps. One such app, the symptom assessment tool Ada [10,11], collects basic demographic information and self-reported symptoms from users to suggest conditions that they may be experiencing. In this study, we compare ILI symptoms reported by Ada users in Germany with ILI symptom data reported to GrippeWeb to explore the potential contribution of data from the Ada app to syndromic surveillance.

Methods

Description of Ada

The symptom assessment app Ada can be downloaded and used free of charge. Users must declare that they are aged ≥16 years in order to create an account; however, account owners can assess symptoms on behalf of others, including those aged <16 years. Users provided their age, sex, and some basic medical history information before starting a *symptom assessment*, which begins with the question "*Let's start with the symptom that's troubling you the most*," followed by "*Do you have any other symptoms?*" Symptoms are initially entered into a free-text field, with users selecting the best fit from a list of medically curated terms. On the basis of the initially entered symptoms and other user-provided information, including age and sex, a probabilistic reasoning model determines which additional questions to ask (ie, the exact set of symptoms asked about varies from assessment to assessment). At the end of an assessment, users are provided with a list of up to 5 possible causes for their symptoms, as well as advice on possible next steps, for example, whether the condition could be managed at home or whether consulting a physician or hospital is recommended. The Ada app can assess an extensive range of symptoms and conditions covering various medical specialties, not only those related to respiratory illness.

Extraction of Ada Data and Definition of ILI

Data from all Ada assessments (ie, for any symptoms or complaints) completed by users in Germany between calendar week 27, 2017, and calendar week 26, 2020, were extracted; users may have completed only one or more than one assessment over this period. Users were classified as having ILI if they reported fever with *either* cough *or* sore throat (same ILI definition as used by GrippeWeb), either as initially entered symptoms (ie, users entered these terms directly or selected them from a dropdown list at the start of the symptom assessment), or in response to questions asked during an assessment. Questions were of the form: "*Do you have symptom x?*" where "*x*" *was fever, cough, or sore throat.*" Answer options were *yes*, *no*, or *I don't know*; only *yes* responses were used. For fever, users were additionally asked to state what temperature their fever was, or to state *I don't know*. *Yes* responses for fever were still used even if the users reported that they did not know what their temperature was.

Description of GrippeWeb

The GrippeWeb system has been described in detail elsewhere [4]. Briefly, participants who registered were asked to log in on a weekly basis and report if they had experienced any of the main symptoms of a new respiratory illness (any cough, head cold, sore throat, or fever) in the preceding week (retrospective reporting for up to 4 weeks is also possible). Participants were asked to respond even if they had not experienced any symptoms. To reduce the bias possibly introduced by people reporting only during weeks when they are ill, participants must report to the GrippeWeb system at least 5 times to be included in data analyses. Participants who reported less than 10 times, but who met the definition for an acute respiratory infection (report of fever, cough, or sore throat) on 50% or more of these occasions were also excluded from data analyses [4]. The minimum age for participation in GrippeWeb is 14 years; however, parents can report on behalf of children aged <14 years.

Calculation of Ada ILI Rates and Extraction of GrippeWeb ILI Rates

From calendar week 27, 2017 to calendar week 26, 2020 (ie, covering 3 flu seasons: 2017/18, 2018/19, and 2019/20), weekly raw Ada ILI rates were calculated by taking the number of assessments in which users met the definition of ILI, divided by the total number of assessments completed in Germany during that week. To account for differences between the age and sex of Ada users compared with the general population, the raw Ada rates were standardized (by age and sex) for the German population. German population size estimates were extracted from the United Nations Department of Economic and Social Affairs website [12]. Weekly standardized ILI rates were also stratified across 5 age groups (0-4, 5-14, 15-34, 35-59, and 60 years) by calculating 3-weekly smoothed averages and taking median values from the 3 seasons for each age group (2017/18, 2018/19, and 2019/20).

Weekly population-adjusted GrippeWeb ILI estimates for calendar week 27, 2017 to calendar week 26, 2020, were extracted manually from reports published on the GrippeWeb website [13]. This was done using a linear regression equation that predicted y-axis values (the population-adjusted ILI rates) for each calendar week. Using the same method, weekly age-stratified ILI estimates were extracted for the same age groups mentioned above, on the basis of data from the 2011/12 to 2016/17 seasons (three-weekly smoothed averages; median values from the 6 seasons), as reported in [4].

Data Analyses

We plotted Ada population-adjusted ILI rates alongside GrippeWeb rates in time series plots: overall and stratified by age. Owing to differing denominators, it should be noted that actual ILI rates were not directly comparable between the 2 data sources; in GrippeWeb, participants were prompted to report to the system each week regardless of whether they had symptoms, that is, the denominator included those with and without ILI symptoms. In contrast, in Ada, users only consulted and reported to the tool when they had symptoms. Furthermore, in addition to these symptomatic ILI users, the Ada denominator also included users who completed an assessment for any type of symptom, including those unrelated to respiratory illness.

The nature of the relationship between Ada and GrippeWeb data was explored using scatterplots, and correlations were explored using Pearson correlation coefficient—values for *r*, 95% CI, and *P* values at the significance level of .05. All plots and analyses were performed using Excel (Microsoft Inc) and Stata (StataCorp) version 11.

Ethics and Data Privacy

We analyzed pseudonymized health data for public health purposes according to the European General Data Protection Regulation. Ada users were duly informed of the use of their data (information available at any time in Ada's privacy policy). In addition, users maintained their right to object to such processing for reasons arising from their particular situation, as required by the General Data Protection Regulation. Raw numbers presented in this study are rounded to the nearest 10 for data privacy reasons.

Results

Description of Ada User Population

In total, 2,108,110 assessments (for any symptoms) performed by Ada users in Germany between calendar week 27, 2017, and calendar week 26, 2020, were analyzed. The quantity of data available for analysis varied over time for several reasons. These include the following: (1) user numbers can change from month to month depending on marketing activities and (2) owing to changes in Ada's data privacy and use policy, data for only a restricted subset of users were available for the period May 2018 to November 2019.

Table 1 provides an overview of the number of assessments completed per season and the demographic characteristics of Ada users. The median number of assessments completed per week was lower in the 2017/18 season than in 2018/19 and 2019/20, and the IQR was greater in the 2017/18 and 2019/20 seasons than in the 2018/19 seasons. Overall (over all seasons), a large majority of users were female (1,470,740/2,108,110, 69.77%) and aged between 15 and 34 years (1,556,490/2,108,110, 73.83%), with fewest users in the youngest age group (0-4 years: 18,150/2,108,110, 0.86%), followed by the oldest age group (>60 years: 49,980/2,108,110, 2.37%). There were fewer users in the age group of 5-14 years in seasons 2018/19 and 2019/20 than those in the 2017/18 seasons, most likely because of a change in the minimum sign up age from 13 to 16 years in May 2018. In total (over all seasons), 2.24% (47,300/2,108,110) of Ada users reported ILI. This proportion was slightly higher among male users (2.8%) than among female users (2%), and also varied by week and age group (see sections below on comparison of ILI rates).

Table 1. Number of assessments completed and demographics of Ada users in Germany, seasons 2017/18, 2018/19, and 2019/20[a].

Demographics	Season		
	2017/18	2018/19	2019/20
Total number assessments completed	565,880	625,130	917,100
Number assessments per week, median (IQR)	10,240 (400-15,240)	12,020 (10,840-13,310)	16,950 (14,750-19,970)
Sex, n (%)			
Female	389,700 (68.87)	442,490 (70.78)	638,550 (69.62)
Male	176,190 (31.14)	182,640 (29.21)	278,540 (30.37)
Age, n (%)			
0-4	4100 (0.72)	6070 (0.97)	7980 (0.87)
5-14	44,480 (7.86)	18,620 (2.97)	13,810 (1.51)
15-34	400,220 (70.73)	464,460 (74.3)	691,810 (75.43)
35-59	92,640 (16.37)	108,500 (17.36)	161,470 (17.6)
≥60	11,000 (1.94)	15,560 (2.49)	23,420 (2.55)

[a]A season begins in calendar week 27 of any given year and finishes at the end of calendar week 26 of the following year. Numbers rounded to the nearest 10 for data privacy reasons

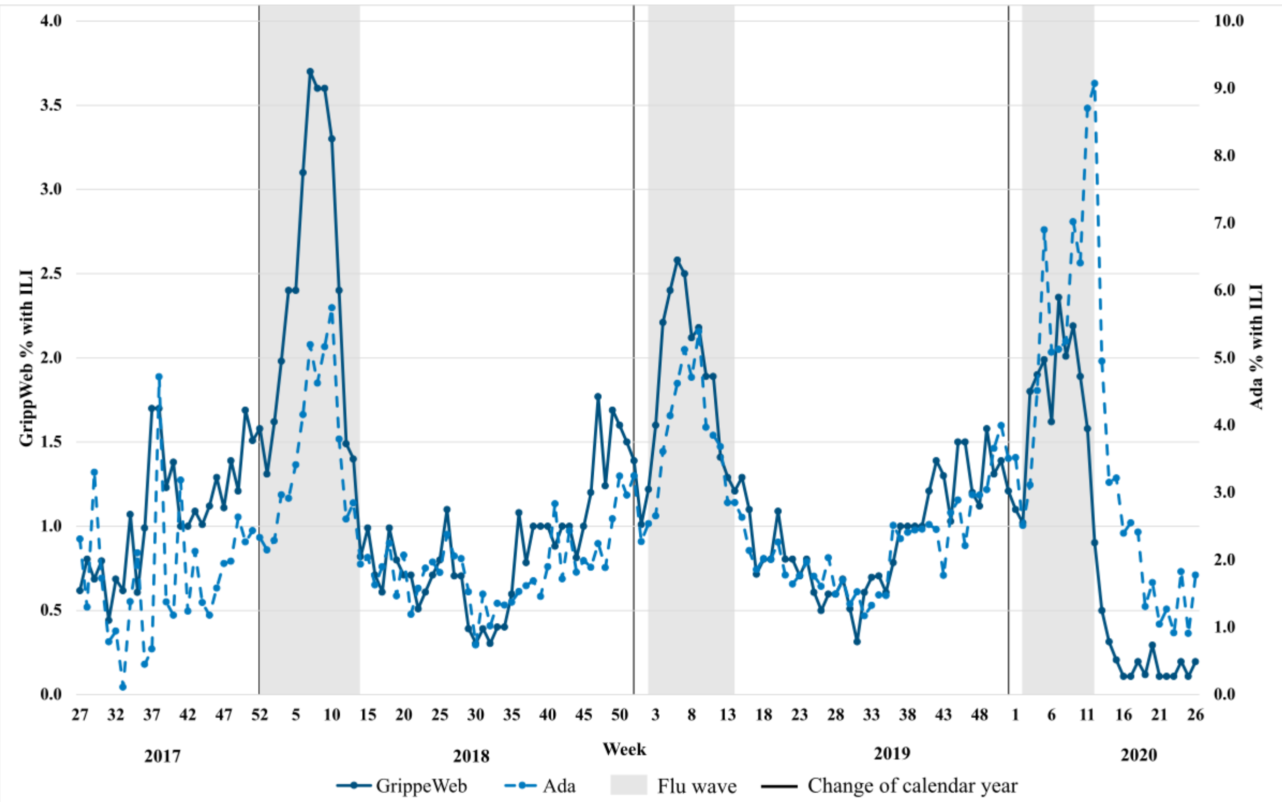
Description of GrippeWeb Users

Briefly, the number of reports on the GrippeWeb system has increased from approximately 800 per week in mid-2011 [4] to approximately 5000 per week in 2020 [14]. In 2017, 56% of participants were females and the sample represented the German population quite well across age groups, albeit with some overrepresentation of those aged 40-59 years and some underrepresentation of those aged 15-24 years and 60 years [4].

Comparison of Population-Adjusted ILI Rates Across Three Seasons

Figure 1 shows the weekly population-adjusted ILI rates estimated using Ada and GrippeWeb data for seasons 2017/18, 2018/19, and 2019/20 (recall that actual rates for Ada and GrippeWeb are not directly comparable and that we rather sought to compare trends in rates). The figure shows that within seasons, trends were broadly similar between the 2 data sources, albeit with specific differences. For example, although both data sources showed the start of the peak ILI season around the same time each year (with increases from week 2 in 2017/18 and 2018/19 and from week 3 in 2019/20), there were differences in the exact nature and timing of the peaks. In 2017/18, the GrippeWeb peak ILI rate was recorded in week 7, whereas the Ada peak was recorded in week 10. In 2018/19, peak ILI rates were recorded by GrippeWeb and Ada in weeks 6 and 9, respectively, and in 2019/20 in weeks 7 and 12, respectively. Results of Pearson correlation indicated that the Ada and GrippeWeb data were significantly correlated, with *P*<.001 in all 3 seasons. The correlation coefficient *r* for seasons 2017/18, 2018/19 and 2019/20 was 0.86 (95% CI 0.76-0.92), 0.90 (95% CI 0.84-0.94), and 0.64 (95% CI 0.44-0.78), respectively. Scatterplots of the population-adjusted Ada and GrippeWeb ILI rates for each individual season are shown in Multimedia Appendices 1-3.

Figure 1. Weekly population-adjusted influenza-like illness rates in Germany as estimated by GrippeWeb (solid line) and Ada (dashed line), calendar week 27, 2017 to calendar week 26, 2020. GrippeWeb data extracted from the report by Buchholz et al [13]. The flu wave period is defined each year by the Robert Koch Institute according to virological surveillance. ILI: influenza-like illness.



Looking at Figure 1 and comparing across seasons within a single data source, the GrippeWeb data showed higher peak ILI rates in 2017/18 compared with 2018/19 or 2019/20 (with the relative height of the *waves* being similar during these latter 2 seasons). This pattern was not seen in the Ada data, where the relative height of the waves was similar in 2017/18 and 2018/19, but higher in 2019/20 (with particularly high rates seen in weeks 11 and 12 of 2020). In 2020, both data sources showed a steep decline in ILI rates after week 11 (GrippeWeb) or week 12 (Ada). Between weeks 12 and 26 of 2020, ILI rates were low in both data sources; however, this trend was seen particularly in the GrippeWeb data when compared with corresponding weeks in previous years. ILI rates in the Ada data over these weeks in 2020 were slightly lower but broadly similar to those seen in previous years.

Comparison of Age-Stratified Population-Adjusted ILI Rates

Figures 2 and 3 show the age-stratified population-adjusted ILI rates estimated by GrippeWeb (median values from 6 seasons) and Ada (median values from 3 seasons), respectively. Across the 5 age groups, broad patterns were similar between the 2 data sources, with both showing the highest ILI rates among the youngest individuals (aged 0-4 and 5-14 years), with decreasing ILI rates with increasing age; the lowest ILI rates were observed among those aged 60 years in both data sources. Results of Pearson correlation for each age group indicated that the Ada and GrippeWeb data were significantly correlated, with *P*<.001 in all cases. The respective correlation coefficients for age groups 0-4, 5-14, 15-34, 35-59, and ≥60 were 0.93 (95% CI 0.88-0.96), 0.83 (95% CI 0.72-0.90), 0.89 (95% CI 0.82-0.94), 0.79 (95% CI 0.66-0.88), and 0.78 (95% CI 0.64-0.87). Scatterplots of the age-stratified ILI rates estimated by GrippeWeb and Ada are shown in Multimedia Appendices 4-8.

Figure 2. Population-adjusted age-stratified influenza-like illness rates as estimated by GrippeWeb (3 weekly moving averages, graphs show median values from 6 seasons 2011/12 to 2016/17). Data extracted from the study by Buchholz et al [4], as described in the Methods section. ILI: influenza-like illness.

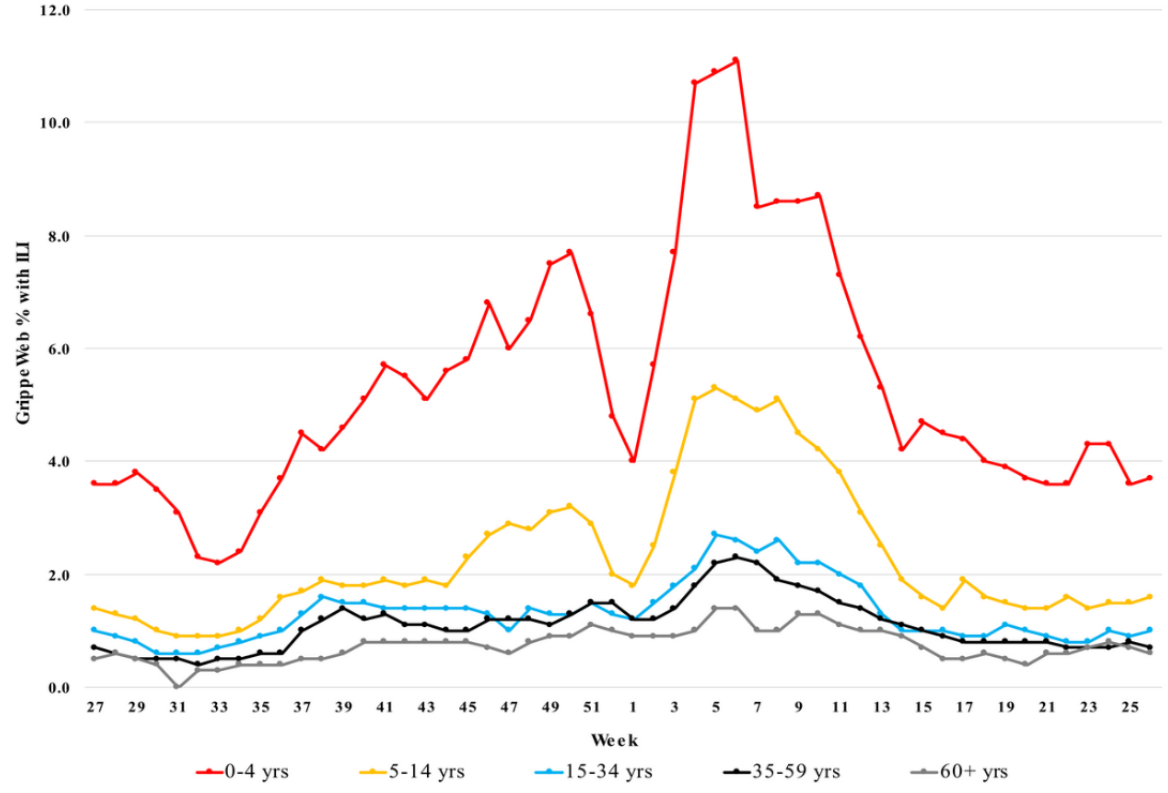
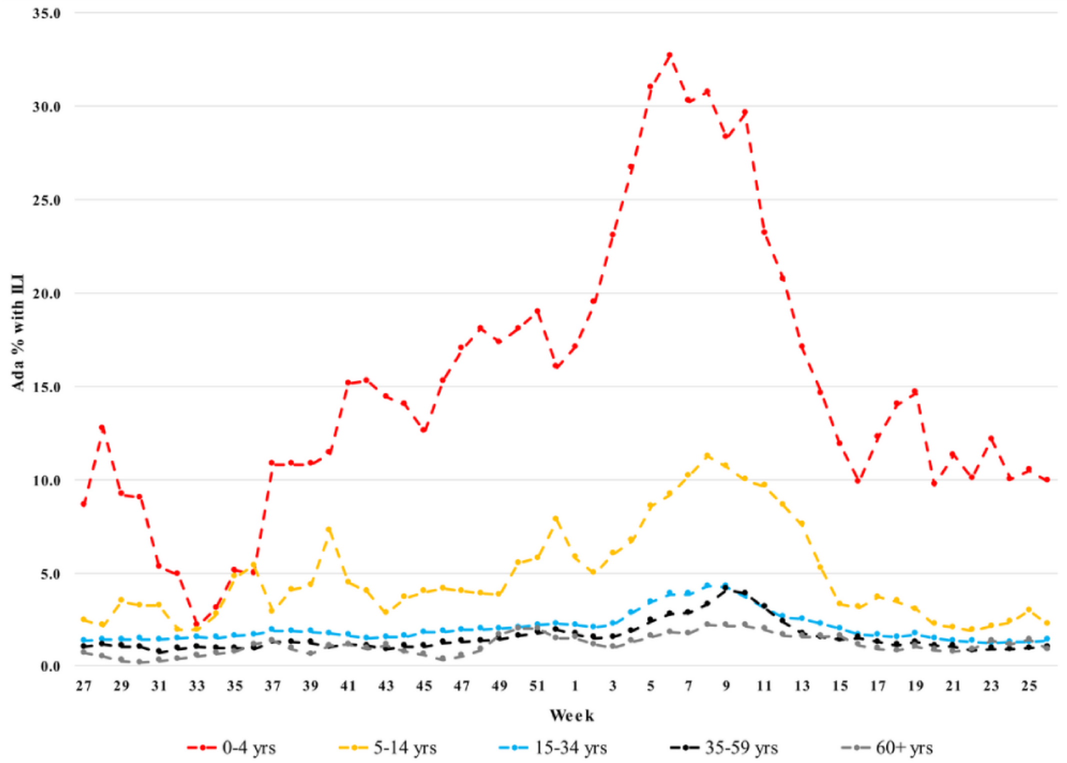


Figure 3. Population-adjusted age-stratified influenza-like illness rates as estimated by Ada (3 weekly moving averages, graphs show median values from 3 seasons 2017/18 to 2019/20). ILI: influenza-like illness.



Discussion

Principal Findings

In this analysis, we have shown that within seasons and across age groups, the Ada data broadly replicated trends in estimated weekly ILI rates for Germany when compared with data from GrippeWeb, with the latter system having previously been shown to correspond well with other sources of national influenza surveillance data [4,15]. This broad congruence is encouraging, particularly given the very different nature of the tools and the way in which they collect data, and points to the potential value of data from a tool such as Ada.

In addition to broad trends, however, the specific nature and timing of an epidemic curve are likely to be of interest to health service providers as they plan health care resources [16]. Comparing the data presented in this paper with data presented in the annual influenza surveillance reports for Germany, in 2 out of 3 seasons analyzed (2017/18 and 2018/19), GrippeWeb showed peak ILI rates a week earlier than was seen in health care system-based surveillance data [17,18]. This might be explained by a time lag between the onset of symptoms and the point at which an individual visits a physician (and the physician can notify the health authorities), and demonstrates the potential of web-based reporting systems to detect the start of epidemics earlier than traditional systems. In all 3 seasons, the timing of Ada's peak ILI rates corresponded with weeks during which the influenza epidemic was also reported to have peaked in national surveillance data. This overlap was encouraging, but in this retrospective analysis, Ada did not demonstrate the ability for early epidemic detection. That said, as Ada data can provide symptom trends in real time (without the time lag typical of national surveillance data), future analyses could explore a possible time benefit by prospectively comparing daily notification data with Ada data.

When comparing trends across seasons within an individual data source, GrippeWeb showed the highest ILI peaks in 2017/18, which was also reported in national surveillance data to be a particularly bad flu season in Germany, with less severe epidemics reported in 2018/19 and 2019/20 [14,18]. Ada detected the highest ILI rates in 2019/20, with lower intensity ILI peaks in 2017/18 and 2018/19. Various hypotheses have been suggested for this anomaly.

As Ada users consult the app when desired, the data are subject to variability, depending on how many users consult the app and for what symptoms in any given week (and this may in turn be influenced by marketing activities or other factors, such as public interest). An examination of trends in the symptoms initially entered into the app between January and April 2020 revealed that between March 12 and March 24, 2020 (covering dates in weeks 10, 11, and 12), there was a sharp increase in the proportion of initially entered symptoms, which were fever, cough, or sore throat. National influenza surveillance data showed that the influenza epidemic in Germany came to an end around this time [19]. However, this period corresponds with weeks when high SARS-CoV-2 case numbers were reported in Germany during the spring 2020 wave of the COVID-19 pandemic [20], and also with weeks when various COVID-19 control measures were introduced by the German government (eg, recommendations for social distancing and the closure of schools) [21].

It is possible that the sharp increase in the proportion of user-entered symptoms, which were fever, cough, or sore throat, was due to the detection of COVID-19 cases. However, sentinel surveillance data showed that the proportion of samples positive for SARS-CoV-2 in weeks 10, 11, and 12 was much lower (between approximately 0.5% and 1.5%) than the proportion positive for influenza viruses (between approximately 20% and 40%) [19]. Therefore, it seems unlikely that Ada ILI rates possibly caused by SARS-CoV-2 would have been higher than ILI rates caused by influenza (or other viruses). An alternative, more probable explanation is that users were more likely to consult Ada for ILI symptoms during these specific weeks because of heightened awareness or concern regarding their symptoms, as a result of the prevailing COVID-19 pandemic. Between weeks 12 and 26 of 2020, Ada ILI rates were slightly lower but broadly similar to those reported over corresponding weeks in previous years, whereas GrippeWeb rates were considerably lower in comparison to corresponding weeks in previous years. Low incidence of influenza was reported in the weeks following the start of the COVID-19 pandemic in March 2020 (and also over the winter 2020/21 season), and is thought to be an effect of nonpharmaceutical pandemic control measures (recommendations for social distancing, intermittent closure of schools and kindergartens, closure of shops and restaurants, etc). This reduction in ILI rates was only partially detected in the Ada data.

Other possible explanations for the high ILI peak seen in the Ada data in weeks 11 and 12 of 2020 include the possibility that a routine update to Ada's medical model around this time influenced the frequency with which questions related to ILI were asked. However, our examination of the nature of the change made indicates that this is likely to have had a much lesser impact than the user-driven changes that we observed when examining only the initially entered symptoms, which were unaffected by changes to the medical model.

Owing to a change in Ada's privacy policy, data for only a subset of users were available for the period May 2018 to November 2019, and it is possible that differences or biases between these users and those who consulted the app before or after this period contributed to some of the differences observed. In 2017/18, national sentinel surveillance data showed that ILI consultation rates among those aged 35-59 years were particularly high [17]. Given the predominance of young individuals aged 15-34 years in the Ada data and the smaller proportion of those aged 35 years, it is possible that our sample of users aged 35 years was not representative of adults in this age group, or that older age groups used the app in a different way to younger ones (eg, possibly being less concerned about or less likely to consult the app for ILI symptoms). These hypotheses might provide a partial explanation for the lower Ada ILI peak in 2017/18 compared with later seasons (ie, Ada may not have captured a possible higher ILI incidence among older age groups in the 2017/18 season).

Limitations

The limitations of the Ada data include that users are predominantly young and female, and that the data may be subject to fluctuations resulting from user behavior, marketing activities, or changes to Ada's medical models. For these reasons, the data must be interpreted with caution. The strengths of the Ada data include that they are real time and cover a broad range of symptoms. Their primary value may lie in providing initial information on broad ILI trends for countries without existing population-based monitoring systems or information on other symptoms not covered by existing syndromic surveillance systems, including those with noninfectious causes (eg, relating to the effects of pollution, food allergies, or other common conditions such as migraine). Further studies should validate the potential of tools such as Ada for the future of syndromic surveillance, making comparisons also to laboratory-confirmed surveillance data. The advantages of app-based systems include the rapid collection of data from a large pool of individuals. Tools that collect data in a standardized and systematic way (eg, the COVID Symptom Study [22]) could make rapid and impactful contributions, particularly during a pandemic.

Acknowledgments

The authors would like to thank all Ada users who consented to the analysis of their data for public health purposes. We would also like to thank the members of Ada Health's Medical Department for their comments on this study (Dr Ewelina Türk and Dr Merret Eiling). This study was funded by Ada Health GmbH.

Authors' Contributions

CC and AG developed the design of the study, based on the initial work done by AF. CC and FB performed data management and analysis, supported by AM. CC drafted the manuscript, and all authors contributed to the comments and assisted in editing the final version.

Conflicts of Interest

All authors are employees or former employees of Ada Health GmbH.

Multimedia Appendix 1

Scatterplot of weekly population adjusted GrippeWeb and Ada influenza-like illness rates for the period from week 27, 2017 to week 26, 2018.

[PNG File , 93 KB - publichealth_v7i11e26523_app1.png]

Multimedia Appendix 2

Scatterplot of weekly population adjusted GrippeWeb and Ada influenza-like illness rates for the period from week 27, 2018 to week 26, 2019.

[PNG File , 87 KB - publichealth_v7i11e26523_app2.png]

Multimedia Appendix 3

Scatterplot of weekly population adjusted GrippeWeb and Ada influenza-like illness rates for the period from week 27, 2019 to week 26, 2020.

[PNG File , 84 KB - publichealth_v7i11e26523_app3.png]

Multimedia Appendix 4

Scatterplot of weekly population-adjusted influenza-like illness rates among those aged 0-4 years. GrippeWeb data points represent median weekly values over six seasons (2011/12–2016/17), and Ada data points represent median weekly values over three seasons (2011/12–2016/17).

[PNG File , 95 KB - publichealth_v7i11e26523_app4.png]

Multimedia Appendix 5

Scatterplot of weekly population-adjusted influenza-like illness rates among those aged 5-14 years. GrippeWeb data points represent median weekly values over six seasons (2011/12–2016/17), and Ada data points represent median weekly values over three seasons (2011/12–2016/17).

[PNG File , 86 KB - publichealth_v7i11e26523_app5.png]

Multimedia Appendix 6

Scatterplot of weekly population-adjusted influenza-like illness rates among those aged 15-34 years. GrippeWeb data points represent median weekly values over six seasons (2011/12–2016/17), and Ada data points represent median weekly values over three seasons (2011/12–2016/17).
[PNG File , 89 KB - publichealth_v7i11e26523_app6.png]

Multimedia Appendix 7
Scatterplot of weekly population-adjusted influenza-like illness rates among those aged 35-59 years. GrippeWeb data points represent median weekly values over six seasons (2011/12–2016/17), and Ada data points represent median weekly values over three seasons (2011/12–2016/17).
[PNG File , 81 KB - publichealth_v7i11e26523_app7.png]

Multimedia Appendix 8
Scatterplot of weekly population-adjusted influenza-like illness rates among those aged 60+ years GrippeWeb data points represent median weekly values over six seasons (2011/12–2016/17), and Ada data points represent median weekly values over three seasons (2011/12–2016/17).
[PNG File , 85 KB - publichealth_v7i11e26523_app8.png]

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Abbreviations

ILI: influenza-like illness

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Original Paper

Digital SARS-CoV-2 Detection Among Hospital Employees: Participatory Surveillance Study

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Abstract

Background: The implementation of novel techniques as a complement to traditional disease surveillance systems represents an additional opportunity for rapid analysis.

Objective: The objective of this work is to describe a web-based participatory surveillance strategy among health care workers (HCWs) in two Swiss hospitals during the first wave of COVID-19.

Methods: A prospective cohort of HCWs was recruited in March 2020 at the Cantonal Hospital of St. Gallen and the Eastern Switzerland Children's Hospital. For data analysis, we used a combination of the following techniques: locally estimated scatterplot smoothing (LOESS) regression, Spearman correlation, anomaly detection, and random forest.

Results: From March 23 to August 23, 2020, a total of 127,684 SMS text messages were sent, generating 90,414 valid reports among 1004 participants, achieving a weekly average of 4.5 (SD 1.9) reports per user. The symptom showing the strongest correlation with a positive polymerase chain reaction test result was loss of taste. Symptoms like red eyes or a runny nose were negatively associated with a positive test. The area under the receiver operating characteristic curve showed favorable performance of the classification tree, with an accuracy of 88% for the training data and 89% for the test data. Nevertheless, while the prediction matrix showed good specificity (80.0%), sensitivity was low (10.6%).

Conclusions: Loss of taste was the symptom that was most aligned with COVID-19 activity at the population level. At the individual level—using machine learning–based random forest classification—reporting loss of taste and limb/muscle pain as well as the absence of runny nose and red eyes were the best predictors of COVID-19.

(JMIR Public Health Surveill 2021;7(11):e33576) doi:10.2196/33576

KEYWORDS

digital epidemiology; SARS-CoV-2; COVID-19; health care workers

Introduction

The COVID-19 pandemic is one of the greatest health challenges that societies around the globe have ever experienced. A range of instruments and ways to measure factors related to COVID-19 and the pandemic have been described [1-7]. COVID-19 presents a challenge for public health in general, while health care workers (HCWs) are at particular risk of acquiring COVID-19 [8]. Several studies using online forms have found they can be useful for tracking disease activity in different locations, including workplaces [9,10]. However, these technological platforms require timely, persistent, and ongoing engagement to generate valid and representative surveillance data [1]. In the context of collaboration and the collection of collective health information, digital epidemiology and participatory surveillance techniques have been demonstrated to be tools with great potential for helping to detect health threats [11-16]. Many strategies that involve daily reporting of symptoms through the voluntary participation of individuals have reported successful results [17,18]. Participatory surveillance by patients has been shown to have a complementary role in detecting syndromic clusters for several epidemiological challenges, such as COVID-19, seasonal influenza, or high-risk mass gatherings [17-22]. The implementation of novel techniques represents an additional opportunity for the rapid analysis of big data based on machine learning, thereby acting as a complement to traditional disease surveillance systems.

The objective of this work is to describe a web-based participatory surveillance strategy among HCWs in two Swiss hospitals during the first wave of the COVID-19 pandemic.

Methods

Study Design

A prospective cohort of HCWs was recruited in March 2020 at the Cantonal Hospital of St. Gallen and the Eastern Switzerland Children’s Hospital, Switzerland. Individuals aged 16 years and older were eligible. HCWs were enrolled in the study after accepting the electronic informed consent form. The anonymization of participants was carried out by using a management ID system with three levels; we anonymized the participants (user ID), surveys (survey ID), and their samples (order ID). No compensation was provided and participation was voluntary. A copy of the informed consent with all details about privacy and confidentiality is provided in Multimedia Appendix 1. The study was approved by the local ethics committee (Ethikkommission Ostschweiz; #2020-00502). All participants received a link via email to fill in a baseline questionnaire collecting data on pre-existing conditions at the start of the study. To improve the data quality and reduce reporting bias, mobile number validation was required; participants could only move forward if they input a token sent to their mobile phone. After completing the baseline form, participants became eligible to receive the daily SMS text message with an individualized link redirecting them to a secure web platform where they could fill in their symptom diary. To encourage participant engagement through the entire period, an SMS text message reminder was sent to those that did not fill in the symptom diary the day before. In the symptom diary, participants were asked about the type and severity of COVID-19 symptoms according to Table 1. Those that met SARS-CoV-2 testing criteria (ie, fever/feverishness, cough, shortness of breath, sore throat, or anosmia/ageusia) according to the Swiss Federal Office of Public Health (FOPH) were asked to schedule an appointment for a nasopharyngeal swab [23].

For validation purposes, the positivity rate of the online survey was compared to the positivity rate of HCWs undergoing SARS-CoV-2 polymerase chain reaction (PCR) testing at the study institutions (independent of study participation). We tested both isolated symptoms and various combinations, including the FOPH testing criteria.

Table 1. List of symptoms and consequences.

Survey question topic	Type
Sore throat	Symptom
Cough	Symptom
Shortness of breath	Symptom
Runny nose	Symptom
Headache	Symptom
Diarrhea	Symptom
Anorexia/nausea	Symptom
Fever	Symptom
Chills	Symptom
Limb/muscle pain	Symptom
Loss of taste	Symptom
Itchy red eyes	Symptom
Feeling weak	Symptom
Fever-related muscle pain	Symptom
Took medicines	Consequence
Sought health care	Consequence
Missed work	Consequence
Hospitalized	Consequence

Data Analysis

For the analysis of time trends of symptoms, we used a locally weighted running line smoother (locally estimated scatterplot smoothing [LOESS]) [24], which is a nonparametric smoother with Gaussian noise added in the sine wave. This algorithm estimates the latent function in a pointwise fashion. This method is a supervised machine learning approach and was carried out to generate a moving average for scatterplot smoothing among the data points. Its function can be expressed as the following:

$$\omega\,(\chi)=(1-|d|^3)^3$$

where *d* is the distance of the data point from the point on the fitter curve, scaled to lie in the range from 0-1. We then used a moving average with 7 days as the window size, aligned on the right.

The Spearman rank correlation coefficient was used to verify the statistical dependence between symptoms and test positivity, using a monotonic function described by the following formula [25]:

It is critical to identify significant temporal deviations throughout the period including the impact of seasonality in such high frequency data inputs. Therefore, we applied the Seasonal-Hybrid Extreme Studentized Deviate (S-H-ESD) algorithm [26], which uses a modified Seasonal-Trend decomposition procedure based on LOESS [27]. This technique allows for the identification of change points over time, recognizing when the signal frequency (FOPH classification) was positive (increasing) or negative (decreasing). The missing value was handled by spline interpolation, the maximal anomaly ratio was 0.1, and a piecewise median time window of 2 weeks was chosen.

Finally, to classify participants according to the probability of having symptoms compatible with COVID-19, we used the random forest algorithm. This is an ensemble learning method based on decision trees, which increases the accuracy of classification for both training and test data [28]. Specifically, this algorithm is a predictor consisting of an assembly of randomized base regression trees $\{r_n(\mathrm{x},\Theta_m,D_n),m \geq 1\}$, where $\Theta_1,\Theta_2,\ldots$ are independent and identically distributed (IID) outputs of a randomizing variable Θ. These random trees are pooled to form the following aggregated regression estimate [29]:

where denotes expectation with respect to the random parameter, conditionally on X and the data set D_n.

To explain how the random forest technique was used in this study, a summary of its parameters along with a prediction matrix for the model was generated. In addition, a receiver operating characteristic (ROC) curve was created to evaluate the binary classification of the model. We split the data, using 70% of entries for model training and 30% of entries for the test set. To determine which variables were more or less important for predicting the outcome, we used a boxplot chart.

Algorithms and techniques were programmed and deployed in R language, using the Exploratory [30] framework. The data collection system was developed using JotForm [31] as well as a proprietary solution and was hosted at Amazon Web Services, using EC2 and S3 instances. The SMS text messaging system used Twilio's [32] application programming interface to send out the messages.

Results

From March 23, 2020, to August 23, 2020, a total of 127,684 SMS text messages were sent, generating 90,414 valid reports among 1004 participants, achieving a weekly average of 4.5 (SD 1.9) reports per user. Female gender (n=755, 75.2%) was more prevalent than male (n=249, 24.8%) among participants, reflecting the general HCW population in these hospitals. The median age was 39 years, with a mean of 40.2 (SD 11.3) years. Figure 1 shows the temporal distribution of symptoms of respiratory infection over the study period, using LOESS regression. In total, 1.49% (n=15) of participants reported a positive PCR result during the study period. The first peak of the bimodal curves clearly parallels the reference curve of individuals in the hospital who tested positive, representing the first COVID-19 wave in the region. The second peak appears between July 2020 and August 2020, with a much lower signal in the reference curve of individuals who tested positive.

Regarding anomaly detection over time, Figure 2 shows whether a signal of symptoms was expected (based in the past trends) or if it represented a positive or negative anomaly, meaning a significant increase or decrease in the frequency of recorded symptoms. Table 2 indicates the change points that were statistically significant, including the difference observed when compared with the expected amount. The positive anomalies happened in three different periods; two of them occurred during the highest activity of the first wave and the third occurred between July and August, representing a possible second wave. However, as mentioned above, no second (or third) wave was seen in the reference curve.

Figure 1. Temporal distribution and LOESS regression of symptoms related to acute respiratory infection in health care workers at two hospitals in Switzerland. FOPH: cases documented by the Federal Office of Public Health; LOESS: locally estimated scatterplot smoothing.

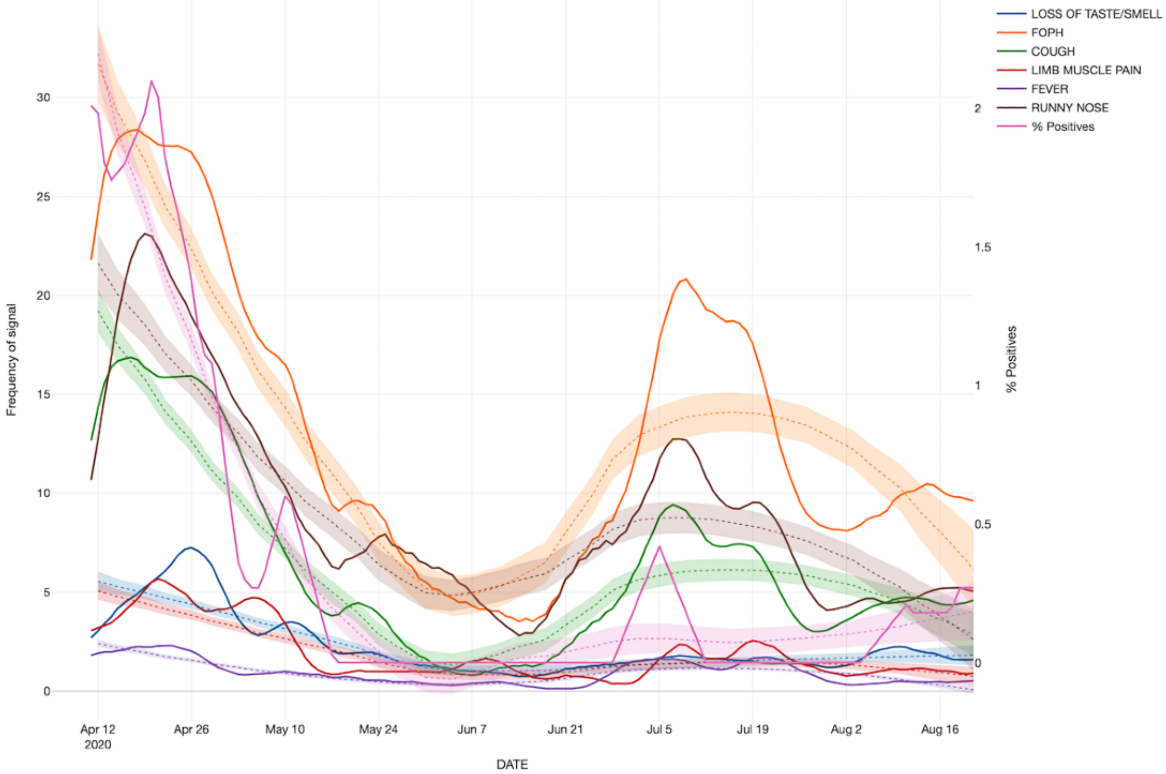


Figure 2. Temporal distribution of the FOPH proportion of positives, indicating which types of anomalies occurred in health care workers in two hospitals in Switzerland. FOPH: Federal Office of Public Health.

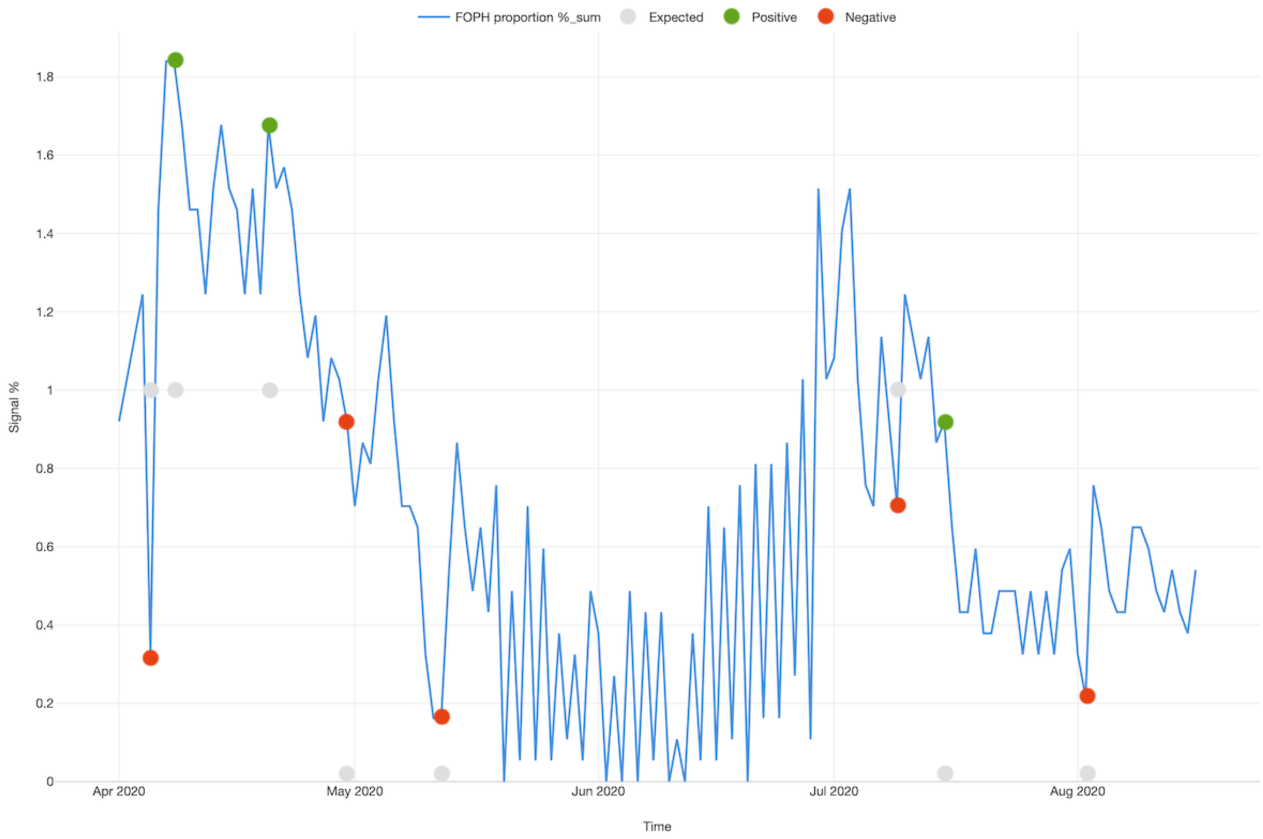


Table 2. Significant (*P*<.05) timepoints for anomaly detection in health care workers, Switzerland.

Date	Federal Office of Public Health proportion of positives	Expected	Difference from expected	Anomaly type
05/04/2020	.324675325	1	–.675324675	Negative
08/04/2020	1.83982684	1	.83982684	Positive
20/04/2020	1.677489177	1	.677489177	Positive
30/04/2020	.91991342	0	.91991342	Negative
12/05/2020	.162337662	0	.162337662	Negative
09/07/2020	.703463203	1	–.296536797	Negative
15/07/2020	.91991342	0	.91991342	Positive
02/08/2020	.216450216	0	.216450216	Negative

A correlation matrix between symptoms and a positive PCR test result for SARS-CoV-2 is shown in Figure 3, while in Figure 4, the significance matrix shows the positive and negative correlations, as well as the nonsignificant ones. The symptom with the strongest correlation with a positive PCR result was loss of taste. Conversely, symptoms such as red eyes or runny nose were negatively associated with a positive test (Table 3).

Figure 3. Correlation matrix using the Spearman method for symptoms and positive results in health care workers in two hospitals in Switzerland during the study period. FOPH: Federal Office of Public Health.

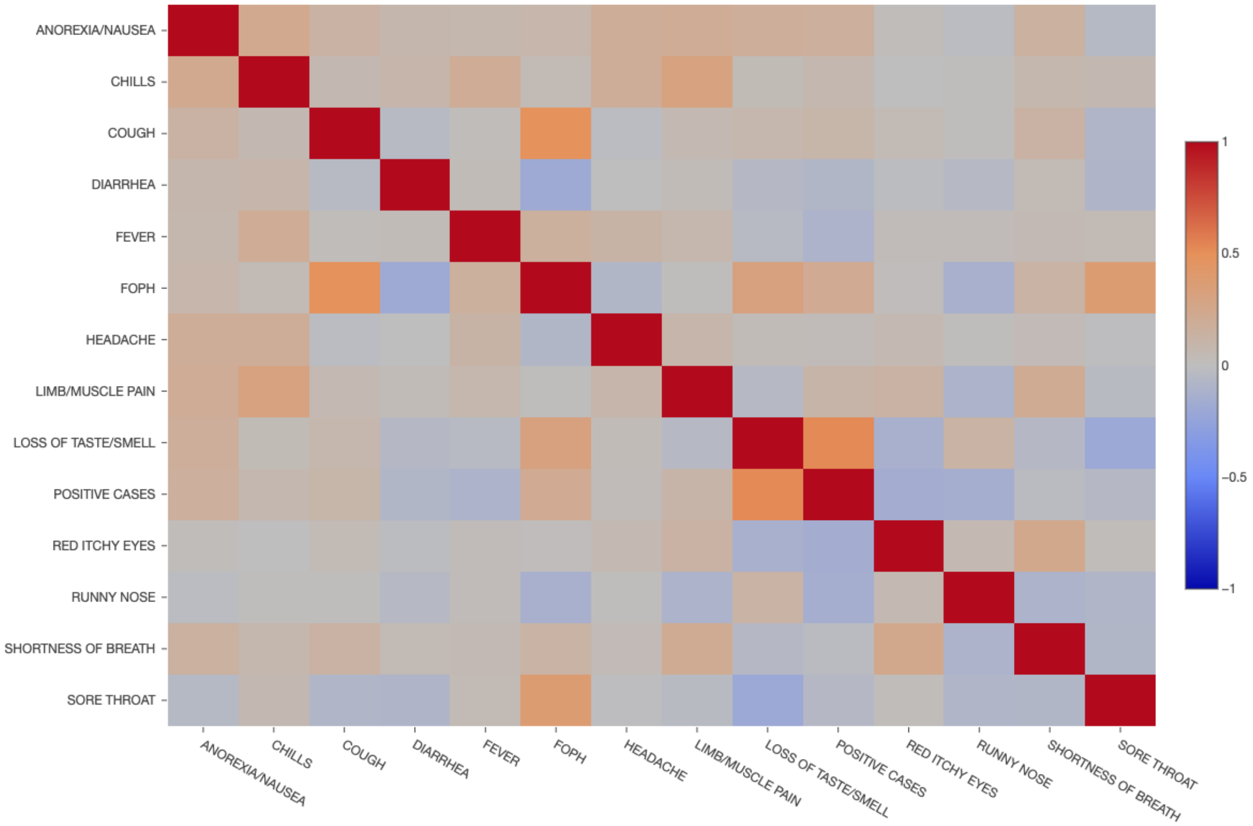


Figure 4. Significance matrix showcasing the positive and negative correlations between variables in health care workers in two hospitals in Switzerland during the study period. A larger dot represents a higher correlation.

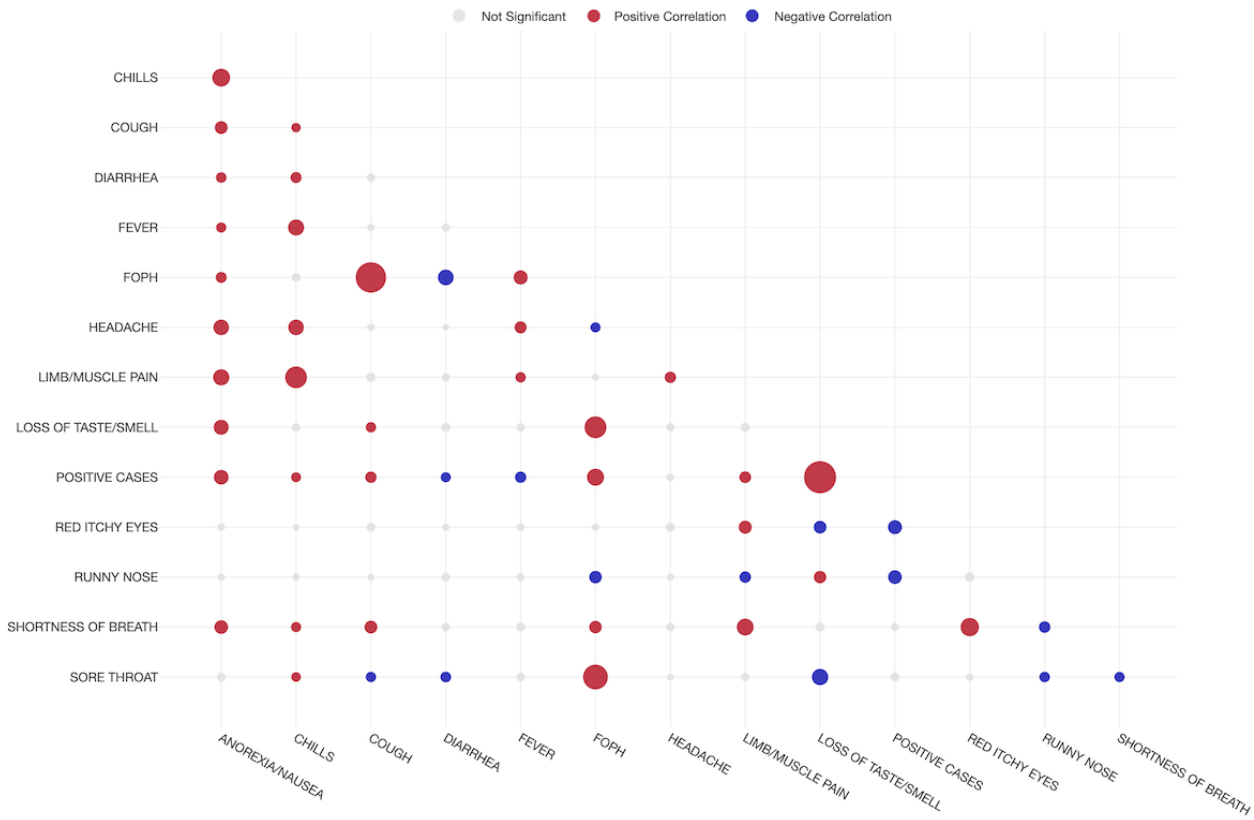


Table 3. Correlation between symptoms and positive cases in health care workers in Switzerland for the period of the study.

Symptoms	Correlation	Pairs	*P* value
Loss of taste	0.5274	Positive	<.001
Federal Office of Public Health definition	0.2189	Positive	<.001
Anorexia/nausea	0.1698	Positive	<.001
Limb/muscle pain	0.1103	Positive	<.001
Cough	0.1032	Positive	<.001
Chills	0.0731	Positive	.002
Headache	0.0279	Positive	.37
Red itchy eyes	–0.1560	Negative	.01
Runny nose	–0.1508	Negative	.001
Fever	–0.1025	Negative	.10
Diarrhea	–0.0770	Negative	.001

Finally, Table 4 shows the summary results from a random forest algorithm that was used to classify participants into SARS-CoV-2 positive and negative cases based on their indicated symptoms. The area under the ROC curve shows reasonable performance of the classification tree, with an accuracy of 88% for the training data and 89% for the test data (Figure 5). Nevertheless, while the prediction matrix showed good specificity (80.0%), sensitivity was low (10.6%; Table 5).

Figure 6 shows the importance of symptoms and their capacity to predict the expected outcome based on the random forest algorithm, considering a *P* value of <.05. Loss of taste and limb/muscle pain were the most important variables for prediction of a positive result, while runny nose and red eyes were negatively correlated with the same outcome. Fever was a very weak predictor of a positive result.

Table 4. Summary of the parameters of the random forest model.

Data set	Area under the curve	F_1 score	Accuracy rate	Misclassification rate	Precision	Recall
Training	.90375	.68027	.8839	.11604	.87719	.5555
Test	.87576	.66331	.89438	.10561	.91304	.5206

Figure 5. Receiver operating characteristic curve for the random forest model.

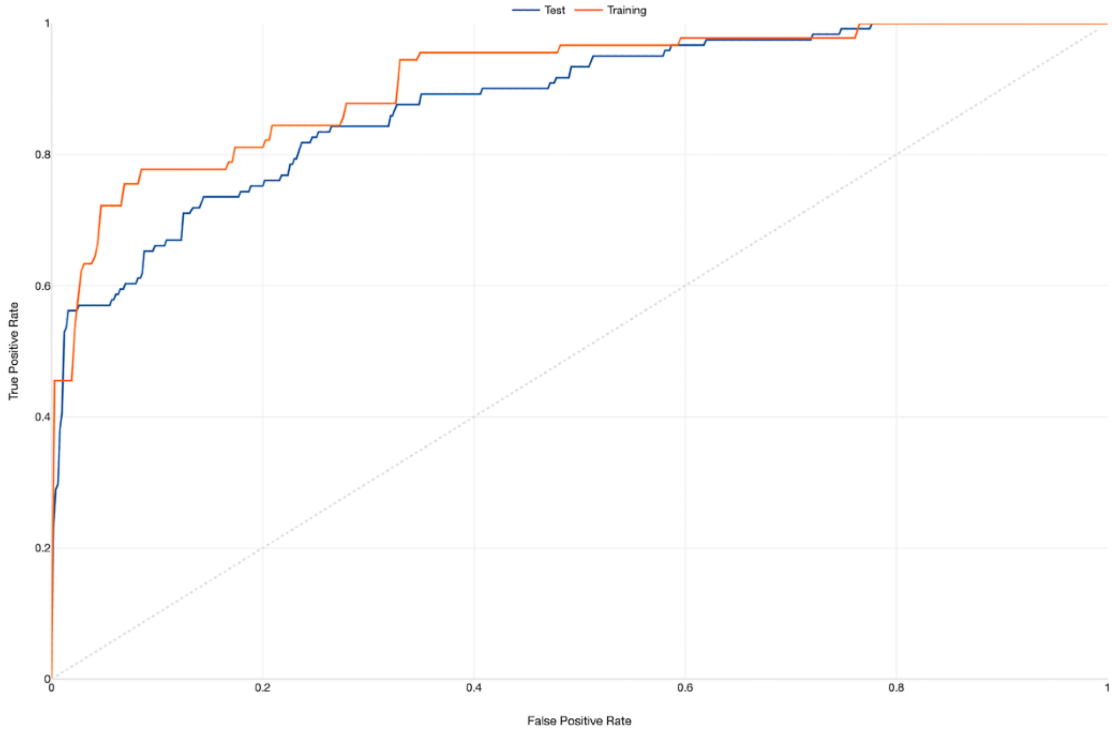
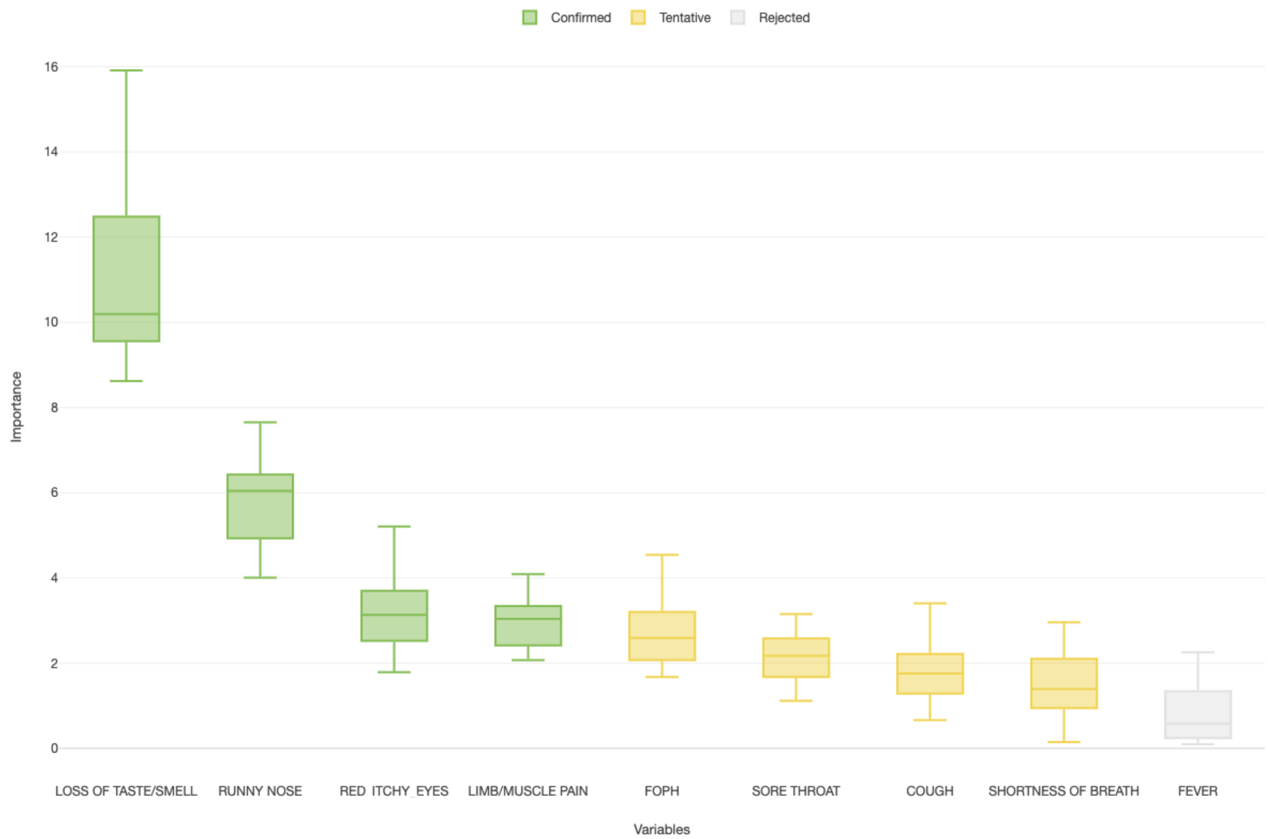


Table 5. Prediction matrix for the random forest model.

Data set and type (actual)	Data type (predicted)	
	TRUE, %	FALSE, %
Test		
TRUE	10.4	9.57
FALSE	.99	79.04
Training		
TRUE	12.35	9.88
FALSE	1.73	76.05

Figure 6. Boxplot of the importance of symptoms and their capacity to predict the expected outcome based on the random forest algorithm (*P*<.05). Loss of taste, limb/muscle pain, FOPH (Federal Office of Public Health), sore throat, cough, and shortness of breath were positively associated with the outcome. Runny nose and red itchy eyes were negatively associated with the outcome. Fever was neither positively nor negatively associated with the outcome.



Discussion

This study demonstrates the use of digital surveillance to monitor COVID-19 activity among HCWs. Loss of taste was the symptom that was most aligned with COVID-19 activity at the population level. At the individual level, using machine learning–based random forest classification, reporting loss of taste and limb/muscle pain as well as absence of runny nose and red eyes were the best predictors of COVID-19. The main strengths of the study are its high response rate and the comparison to a reference curve, which was based on documented PCR results in the same population.

Syndromic surveillance through participatory surveillance has been shown to be a feasible strategy to monitor COVID-19 activity [33], and is considered an important measure to inform the public health response to this pandemic [34]. Considering that engagement is a key element of a successful platform, our study—with an average response of 4.5 answers per week—has an excellent basis to produce valid and representative results. This high rate of engagement and participation is extraordinary when compared to other platforms [13,17,18,33], especially over a period of 5 months [35]. The easy-to-use survey, the defined population of HCWs from two different hospitals, and the regular interaction with study participants are potential reasons for this high response rate. It remains to be seen if these engagement indexes can be maintained when the study is scaled up to larger communities.

The temporal distribution of symptoms followed the trends represented in the first wave of COVID-19 in Switzerland [36,37]. However, the signals detected in July were not due to COVID-19, as shown by the reference curve. Interestingly, several HCWs tested positive for rhinovirus during this time period, suggesting that this was the reason for this wave. Of note, loss of taste, the most specific symptom of COVID-19, did not increase during this second wave.

Several other studies have shown that loss of taste is a good proxy for COVID-19 [38-41]. Although the specificity of this symptom is excellent, only about 20% of patients report loss of taste [42]. We conclude that the detection of loss of taste is very helpful to interpret findings at the population level, but less so at the individual patient level because of its low prevalence. The second most important positively associated symptom in our analysis was limb/muscle pain, which has also been noted by others [43]. Remarkably, runny nose and red eyes were very important negative predictors of COVID-19; this finding is particularly useful for when surveillance is performed during allergy season. However, both the sensitivity and specificity of a symptom depend on the background activity of other infections and allergies and might therefore be subject to change. The validity of a symptom may also change due to genetic adaptations in the dominant SARS-CoV-2 strain. During the study period, none of the new variants of SARS-CoV-2 (eg, B.1.1.7/Alpha) were circulating in Switzerland. Therefore, the symptoms described here cannot necessarily be extrapolated to a different circulating SARS-CoV-2 variant. However, syndromic surveillance through participatory surveillance may allow for the detection or validation of a different clinical presentation emerging from a new circulating strain. Indeed, a recent study describes small differences in COVID-19 symptoms in the general population in the United Kingdom depending on the variant [44].

Our study has a number of limitations. First, it was performed outside influenza season. Because influenza more often presents with constitutional symptoms than other respiratory viruses, distinguishing influenza from COVID-19 by analysis of symptoms is difficult. Second, we relied on participants self-reporting their symptoms, a method that is prone to bias. Third, generalizability of our data is limited because only one-fifth of the HCWs from our hospitals participated in the study; in addition, the spatial component could not be explored due to these same reasons. At the same time, this would be a very important parameter for evaluating whether SARS-CoV-2 is being regionally distributed, which would be useful to form a complete picture for disease surveillance purposes. The application of classification techniques based on machine learning, such as random forest classification, has its own limitations, as a large number of trees can make the algorithm too slow and ineffective for real-time predictions. In general, these algorithms are fast to train, but quite slow to create predictions once they are trained. A more accurate prediction requires more trees, which results in a slower model.

Nevertheless, we deem the presented surveillance tool highly useful in monitoring and predicting COVID-19 activity among our HCWs. Currently, we have expanded our HCW cohort to include over 5000 participants from over 20 institutions [45]. The analysis of data from different institutions will allow us to detect the clustering of cases in certain institutions, which might trigger targeted intervention measures in affected health care institutions. Additionally, these data allow for the detection of symptomatic HCWs who were either not tested or had a false-negative PCR result, and also for the discrimination of symptoms caused by SARS-CoV-2 from symptoms caused by other viruses, such as influenza. Further questions, which we aim to answer with the surveillance data generated in this larger cohort, include how long HCWs with documented SARS-CoV-2 infection (or vaccination) are protected against reinfection or how the emergence of viral variants might change the symptomatology of COVID-19.

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Authors' Contributions

OLN and PK conceived of the presented idea and wrote the manuscript with support from TE, CK, MS, DF, WA, and PV. OLN carried out the analysis. All authors revised the final version of the manuscript. PK supervised the project.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Informed consent (in German).
[PDF File (Adobe PDF File), 206 KB - publichealth_v7i11e33576_app1.pdf]

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Abbreviations

FOPH: Federal Office of Public Health
HCW: health care worker
LOESS: locally estimated scatterplot smoothing
PCR: polymerase chain reaction
ROC: receiver operating characteristic
S-H-ESD: Seasonal-Hybrid Extreme Studentized Deviate

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Original Paper

Using Google Trends to Inform the Population Size Estimation and Spatial Distribution of Gay, Bisexual, and Other Men Who Have Sex With Men: Proof-of-concept Study

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Abstract

Background: We must triangulate data sources to understand best the spatial distribution and population size of marginalized populations to empower public health leaders to address population-specific needs. Existing population size estimation techniques are difficult and limited.

Objective: We sought to identify a passive surveillance strategy that utilizes internet and social media to enhance, validate, and triangulate population size estimates of gay, bisexual, and other men who have sex with men (gbMSM).

Methods: We explored the Google Trends platform to approximate an estimate of the spatial heterogeneity of the population distribution of gbMSM. This was done by comparing the prevalence of the search term “gay porn” with that of the search term “porn.”

Results: Our results suggested that most cities have a gbMSM population size between 2% and 4% of their total population, with large urban centers having higher estimates relative to rural or suburban areas. This represents nearly a double up of population size estimates compared to that found by other methods, which typically find that between 1% and 2% of the total population are gbMSM. We noted that our method was limited by unequal coverage in internet usage across Canada and differences in the frequency of porn use by gender and sexual orientation.

Conclusions: We argue that Google Trends estimates may provide, for many public health planning purposes, adequate city-level estimates of gbMSM population size in regions with a high prevalence of internet access and for purposes in which a precise or narrow estimate of the population size is not required. Furthermore, the Google Trends platform does so in less than a minute at no cost, making it extremely timely and cost-effective relative to more precise (and complex) estimates. We also discuss future steps for further validation of this approach.

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KEYWORDS

gay, bisexual, and other men who have sex with men; spatial distribution; population size estimation; pornography; technology-aided surveillance

Introduction

Understanding the spatial distribution and population size of marginalized populations allows public health leaders to advocate for population-specific needs, plan and implement relevant treatment and prevention programs, and evaluate the population impact of interventions tailored to these groups [1]. Multiple data sources are needed to triangulate these estimates if we are to provide useful information to public health practitioners.

Gay, bisexual, and other men who have sex with men (gbMSM) are one population for whom sampling frame data are not available. Thus, population size estimation studies are common for this population. In fact, more than 100 gbMSM population size estimation studies have been conducted globally—each aiming to provide precise, accurate, and region-specific estimates [2]. These studies utilize a range of population size estimation methods (eg, census and enumeration, multiplier, capture-recapture, population survey, network scale-up, wisdom of the crowds) in recognition that any given method relies on difficult-to-meet or unvalidated theoretical assumptions or complex and difficult implementation strategies [1]. Nevertheless, various methods tend to converge around similar estimates in a given region. For example, Rich and colleagues estimated the size of the gbMSM population in Metro Vancouver by using the Canadian Community Health Survey, HIV testing service data, the multiplier method (ie, using prevalence of service use data from a representative population-specific data set and multiplying it by the number of people who used a service), and the "wisdom of the crowds" method (ie, asking people to guess). They found that the median of all estimates represented 2.9% of the Metro Vancouver census male adult population with an interquartile range of 1.1%-4.5% [3].

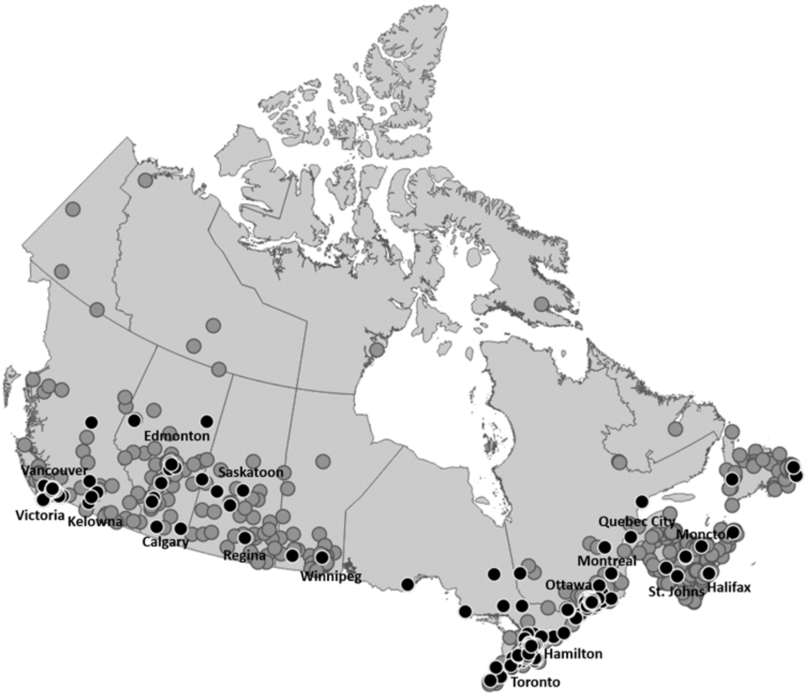
Regardless of the convergence of these estimates, it is difficult to create estimates that accurately reflect the population size of gbMSM in all regions (especially for subregions such as cities and towns)—even in a country with as robust a research infrastructure as Canada. This is largely due to the lack of census data and the paucity of representative samples that include sexual orientation measures. Therefore, while the spatial distribution of gbMSM is known to be heterogeneous, particularly with regards to rural and urban locations [4-6], it is very difficult to ascertain a population size estimate for many regions in Canada. For example, the Pacific AIDS Network in British Columbia estimated that the population share who were gbMSM was 2.6% (of total male population) provincewide, 5.3% in Vancouver Coastal Health Region (ie, the most urban region), and less than 2% in all other health regions [7]. It is unclear whether these differences arise from survey response rates, differences in service utilization, or some other confounder arising from the varying health needs and greater desire for anonymity among rural gbMSM. Different sources of data are undoubtedly expected to capture different populations, and many methods used (eg, clinic samples) cannot necessarily tie individuals to a specific geographic subregion.

Passive surveillance strategies such as social media or internet-based surveillance programs could help validate existing methods by addressing the issue of sampling bias [8,9]. The movement toward these passive approaches may make the process of sample size estimation easier. Such an approach would be consistent with efforts such as Google Flu, which used Google search queries to predict flu outbreaks and hospitalizations [10]. Similarly, the Food Safety project used Twitter data to identify and respond to food poisoning incidents [11]. Clearly, the use of social media and internet search data has public health utility and could therefore be used to help estimate the spatial distribution and population size of gbMSM in cities across Canada.

Methods

On October 26, 2020, publicly available Google Trends [12], based on internet search behavior between January 1, 2015 and January 1, 2020, was used to estimate the percentage of searches for "gay porn" (quotation marks not included) relative to the searches for "porn." The resultant data provided the relative proportion of searches for each given term. The data therefore control for population. Google Trends data also omit outliers (ie, individuals searching for the same term in a short period of time) [13]. These values were thus interpreted as the prevalence of gay porn searches, which we propose as a simply proxy indicator as a proof of concept for how Google Trends data might be leveraged to estimate the distribution of gbMSM. We acknowledge, of course, that only men do not search for porn and that the frequency of porn searches may vary geographically and between sexual orientations. Given that men and gbMSM, in particular, may be more likely to consume porn and that straight men and women may also search for gay porn, we believe this indicator should likely be interpreted as an overestimation of the prevalence of gbMSM in any given area [14,15]. Furthermore, gbMSM living in rural areas may be more likely to consume pornography (perhaps due to reduced access to sexual partners [16]). With consideration of the indicator's limitations, subregion breakdowns for available cities were extracted, resulting in prevalence estimates of the "gay porn" search term for 609 cities (See Figure 1). Coordinates for each city were retrieved using the Google Geocoding application programming interface [17], and a cartographic file was constructed with latitude, longitude, and our estimate of the prevalence of the "gay porn" search term. Additional cartographic files for census subdivision and provincial boundaries were also accessed via Statistics Canada [18].

Figure 1. Cities from Google Trends with prevalence estimates for the “gay porn” search term in Canada in 2015-2019. Gray circles represent cities with prevalence estimates >0%, while black circles represent cities with prevalence estimates of +1%.



All data files were uploaded into QGIS and projected to the NAD83 Statistics Canada Lambert Conformal Conic projection (EPSG 3347). Using the inverse distance weighting (IDW) interpolation tool, a raster was created. Standard settings were used for the IDW interpolation. The distance coefficient (p) was set to 2.0. in order to provide a map of the areas with the highest prevalence of the “gay porn” search term and the pixel size was set to 1000. Owing to overdispersion from a high number of 0 values, these values were omitted from the data set upon which IDW values were based under the assumption that the mechanisms producing 0% estimates are likely attributable to poor quality data from low search volume regions. As such, IDW-interpolated spatial distributions were calculated from data on 134 cities (21.9% of all 611 Canadian cities tracked by Google Trends).

In addition to the nationwide figure, subregional figures for selected Canadian cities were also captured and displayed at a 1:1210020 scale. Regression models were also constructed to examine the association between the prevalence of the “gay porn” search term and population density. Population density estimates were taken from the 2018 Canadian census for each of the 609 cities included. City-level data (noninterpolated) were used for the regression analysis, and the cities with 0 values were included. Moran’s I was calculated to assess for spatial autocorrelation between point estimates of the prevalence of the “gay porn” search term. Based on these results, we constructed a linear mixed-effects regression model with linear, exponential, Gaussian, and spherical spatial correlation structures. Minimal differences between the models were observed, but we selected the model with a spherical correlation structure that had the lowest Akaike information criterion value. As all data for this analyses were publicly available, this study did not require review by a research ethics board.

Results

The mean prevalence of the “gay porn” search term for all cities retrieved from Google Trends was 0.6% (SD 0.124). If the 0% prevalence estimates are removed, the estimated prevalence increases to 2.8% (SD 0.008). Data were right skewed, with only 6 Canadian cities having prevalence estimates of 5% or higher (ie, Vancouver, Rimouski, Saguenay, Côte Saint-Luc, Montreal, and Quebec). Several cities had estimates of 4% (Toronto, Ottawa, New Westminster, Victoria, Burnaby, Moncton, Dieppe, Fredericton, Halifax, Stratford, Sept-Iles, Mascouche, Gatineau, Drummondville, Longueuil, Sherbrook, and Brossard). Based on Moran’s I, the prevalence of the “gay porn” search term was spatially autocorrelated (observed=0.156, expected=–0.002, SD 0.008, $P<.001$). Regression results adjusted for the spatial correlation structure showed that higher population density was statistically related to the prevalence of the “gay porn” search term: each 100-person increase in population density was associated with a 0.07% increase in the prevalence of the “gay porn” search term (β=.00074, SE 0.000062, $P<.001$). The interpolated prevalence of the “gay porn” search term is provided in Figure 2. A histogram of the raster values generated from the IDW interpolation is provided in Figure 3. These results highlight the bulk of estimates to be between 2% and 4%, with a long right tail reflecting values approaching 6%.

Figure 2. Inverse distance weighted prevalence of the “gay porn” search term in Canada in 2015-2019. Yellow/green estimates higher prevalence, while darker shades of blue represent lower prevalence.

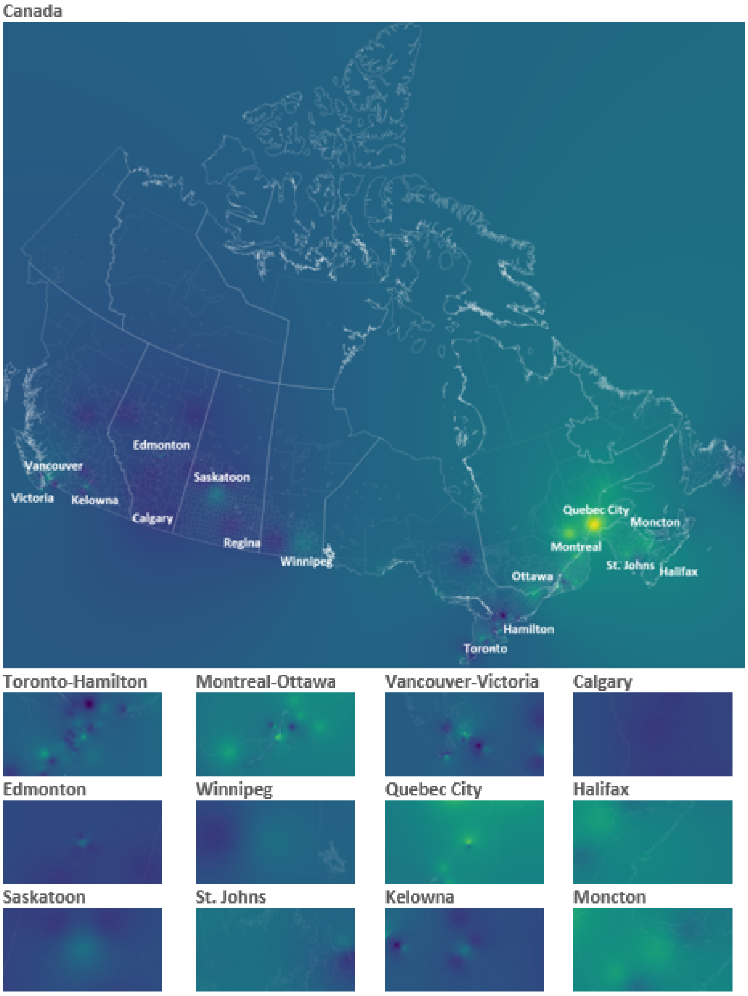
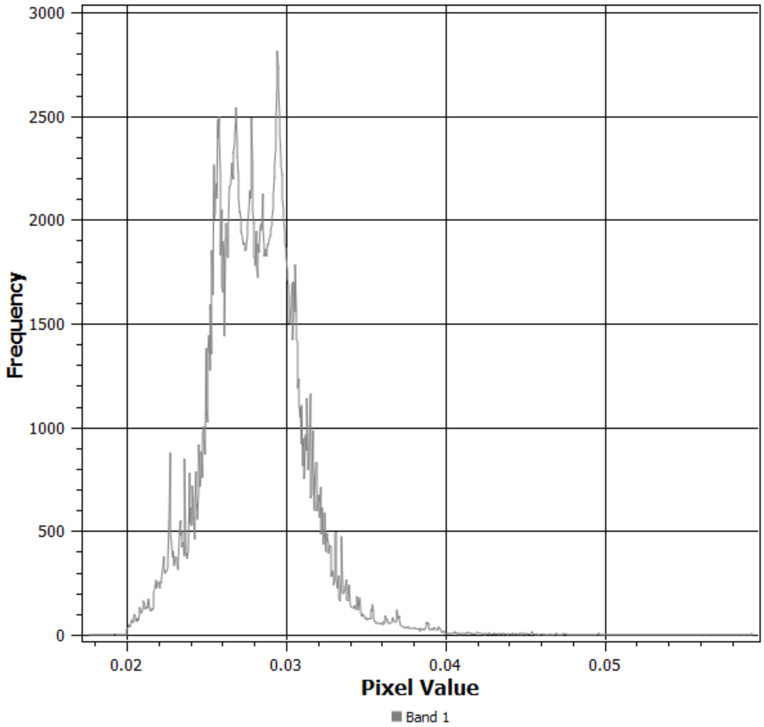


Figure 3. Raster histogram of interpolated prevalence of the “gay porn” search term in Canada in 2015-2019.



Discussion

Principal Findings

This proof-of-concept study explored the use of internet-porn search trends, tracked using the free, easy-to-use Google Trends platform, and approximated an estimate of the spatial heterogeneity of the spatial distribution of gbMSM. In doing so, we showed that a somewhat reasonable description of the spatial distribution and population size estimation could be achieved with further development and validation of this estimate. We hypothesized that Google Trends search volume for "porn" and "gay porn" would provide a *good enough* estimate for the distribution of gbMSM across Canada, with estimates available at the city level. Results from our analyses are largely consistent with other estimates of the population size of gbMSM in Canada—falling in the 1%-5% range (with the most probable estimates being somewhere in the 2%-4% range) [6,7]. Our results also highlight the gradient in the prevalence of "gay porn" searches: estimates in the 2% range for more rural locations and the 4%-5% range for large urban population centers such as Vancouver, Toronto, and Montreal. This again is consistent with what is generally understood about the spatial distribution for gbMSM. For example, using much more time-intensive approaches to examine the spatial distribution of gbMSM, Algarin and colleagues [4] and Card and colleagues [5] used geosocial sexual networking apps to find that the higher density of users is strongly correlated with population density. Card and colleagues [5] reported a 3% increase in the number of users for each 100-person increase in population density; Algarin and colleagues [4] reported a 1%-2% increase in the number of users for each 100-person increase in population density (depending on the time of day). These estimates are close to, perhaps a bit higher, compared with our estimate found here, showing a 0.7% increase per 100-person increase in population density. Our underestimation of this relationship relative to previous studies may reflect the ability of Google Trends data to surveil pornography consumption patterns of individuals who might not be identified using alternative methods (eg, hard-to-identify gbMSM). As such, based on passive surveillance approaches—such as those utilized in these examples—it is strongly suggested that denser population centers have a greater proportion of gbMSM relative to the overall population. It remains unclear whether the increase in population density is closer to 3% per 100 persons or 0.7% per 100 persons. Clearly, uncertainty remains in these estimates and population size estimation studies should at least recognize these regional differences and attempt to correct for them in their estimates when the target geography covers a mix of urban and rural areas. Sensitivity analyses using estimates identified in this study and others could provide a range of plausible values for public health professionals to work with.

The strength of using internet search data to estimate the spatial distribution of gbMSM is that it takes less than a minute to obtain a potentially reasonable estimate for a given city, provided of course that the data are available for a given city via Google Trends. However, the feasibility of using internet search data to estimate the spatial distribution of gbMSM is based on several primary assumptions, which are at least partially violated in reality. First, we assume that there is not a confounding effect arising from differences in the prevalence of porn consumption between gbMSM and other internet users. In reality, we know that sexual minority men use pornography earlier and with greater frequency compared to heterosexual people, and men use it more than women [19,20]. For example, a study of Danish adults aged 18-30 years showed that 26.2% of men watched porn in the last 24 hours compared to 3.1% of women and that only 6.9% of women watched porn 3 times per week or more compared to 38.8% of men [14]. Similarly, by sexual orientation, heterosexual men (29.5%) in the United States are less likely to view pornography online once a day or more compared to both gay (51.3%) and bisexual (52.6%) men [15]. Given these statistics, it is possible that our estimates may as much as double the population size estimates. Adjusting for these differences would bring our estimates in line with those of others, which suggest that between 2% and 4% of the males (rather than total population) are nonheterosexuals [6,7]. Second, we assume that searching for gay porn or porn is a sufficient representation of sexual orientation. It should be obvious that in reality, we do not know the gender or sexual orientation of individuals searching for "porn" or "gay porn." This is underscored by the reality that gay porn use is not limited to gbMSM, and the relationship between these various constructs is dependent on recall period and how sexual orientation is defined [21]. Indeed, sexual orientation can be defined by behavior, attraction, or identity—all three of which can vary over time. Conversely, not all gay men would necessarily use the prefix "gay" when searching for porn. Third, we assume that the prevalence of porn search among gbMSM and non-gbMSM internet users does not vary geographically. In reality, we know that factors such as financial stress (which does vary geographically) impact the prevalence and frequency of pornography use [22]. Another limitation of this study is that Google Trends data only report the prevalence of search terms to the nearest whole percentage. The lack of a decimal point challenges the use of Google Trends search data for generating precise estimates. Of course, the need for precise estimates (as opposed to generating estimates that are "good enough") varies depending on the purpose and intent of the professionals using these estimates. For example, the method could be used to help policy makers determine whether there is a sufficiently large gbMSM population to justify the creation of subcommunity-specific health services but may not be sufficient to assess year-to-year variation in the rates of sexually transmitted and blood-borne infections. In instances where precise estimates are needed, sensitivity tests and comparisons between multiple methods will also be required [1]. We also note that the location data available in Google Trends might be obscured by the use of virtual private network software, which can be used to change a user's location. It is possible that servers located in urban centers might increase the prevalence of search terms. Although little is known about virtual private network usage or about its relationship to sexually explicit media consumption, we anticipate that this error would be small. As this pilot study aims to provide a proof of concept, a simple indicator was used. However, future research could seek to develop better and more precise indicators that leverage one or more platforms (eg, combining weighted estimates from Google

Trends with other platforms or by considering open public health data or medical prescription data; identifying multiple keywords with strong discriminate validity). For example, it is necessary to validate how accurately the search term “gay porn” correlates with sexual orientation. Although the added complexity of these future approaches may again move this work beyond its utility, the additional research could be used to validate simple measures such as the one we have used. These challenges reflect the broader issues inherent in utilizing platforms such as Google Trends. However, in situations in which imprecise estimations provide sufficient evidence for informing public health efforts, these tools appear to offer some utility. At the very least, these data provide a point by which data can be triangulated from different sources through the use of scan statistic techniques that could compare patterns arising from different methods.

Future Research

Although this proof-of-concept study showed that Google Trends data can be feasibly and quickly used to derive an estimate of the spatial and population density of gbMSM, it is our opinion that further experiments and analyses for this metric are required to demonstrate that it provides a reasonably accurate and precise proxy for the true spatial distribution of the gbMSM population. To achieve this validation, we suggest that future research should assess the spatial correlation between the estimates reported using this methodology and those from other surveys or data sources. As we have discussed, studies of the gbMSM population distribution can be difficult for myriad reasons. However, by looking at correlations in patterns of response rates for gbMSM-specific surveys or looking at the prevalence of gbMSM populations within key population centers as found in government surveys, it is likely possible that the validation of this proposed approach could readily be completed.

Conclusion

The Google Trends prevalence of “gay porn” internet searches relative to “porn” internet searches is a passive surveillance indicator that may approximate existing population size estimates of the gbMSM population down to the municipal level. Although lacking precision, it is a “good enough” estimate, especially considering its relatively minimal demands on financial and human resources for regions with high levels of internet access. Matched with existing methods (which are vulnerable to a different assortment of biases), internet porn searches can help triangulate the validity of subregional population size estimates. If keywords can be identified that allow for comparisons between other marginalized populations or communities, it is possible that search terms on Google Trends could allow for other population sizes to be estimated.

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Authors' Contributions

All authors contributed to the conceptualization of the study. KGC collected the data, conducted the analyses, and drafted the results. All authors contributed to the writing, revision, and editing of the manuscript.

Conflicts of Interest

None declared.

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Abbreviations

gbMSM: gay, bisexual, and other men who have sex with men
IDW: inverse distance weighting

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Original Paper

Algorithm for Individual Prediction of COVID-19–Related Hospitalization Based on Symptoms: Development and Implementation Study

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Abstract

Background: The COVID-19 pandemic has placed a huge strain on the health care system globally. The metropolitan area of Milan, Italy, was one of the regions most impacted by the COVID-19 pandemic worldwide. Risk prediction models developed by combining administrative databases and basic clinical data are needed to stratify individual patient risk for public health purposes.

Objective: This study aims to develop a stratification tool aimed at improving COVID-19 patient management and health care organization.

Methods: A predictive algorithm was developed and applied to 36,834 patients with COVID-19 in Italy between March 8 and the October 9, 2020, in order to foresee their risk of hospitalization. Exposures considered were age, sex, comorbidities, and symptoms associated with COVID-19 (eg, vomiting, cough, fever, diarrhea, myalgia, asthenia, headache, anosmia, ageusia, and dyspnea). The outcome was hospitalizations and emergency department admissions for COVID-19. Discrimination and calibration of the model were also assessed.

Results: The predictive model showed a good fit for predicting COVID-19 hospitalization (C-index 0.79) and a good overall prediction accuracy (Brier score 0.14). The model was well calibrated (intercept –0.0028, slope 0.9970). Based on these results, 118,804 patients diagnosed with COVID-19 from October 25 to December 11, 2020, were stratified into low, medium, and high risk for COVID-19 severity. Among the overall study population, 67,030 (56.42%) were classified as low-risk patients; 43,886 (36.94%), as medium-risk patients; and 7888 (6.64%), as high-risk patients. In all, 89.37% (106,179/118,804) of the overall study population was being assisted at home, 9% (10,695/118,804) was hospitalized, and 1.62% (1930/118,804) died. Among those assisted at home, most people (63,983/106,179, 60.26%) were classified as low risk, whereas only 3.63% (3858/106,179) were classified at high risk. According to ordinal logistic regression, the odds ratio (OR) of being hospitalized or dead was 5.0 (95% CI 4.6-5.4) among high-risk patients and 2.7 (95% CI 2.6-2.9) among medium-risk patients, as compared to low-risk patients.

Conclusions: A simple monitoring system, based on primary care data sets linked to COVID-19 testing results, hospital admissions data, and death records may assist in the proper planning and allocation of patients and resources during the ongoing COVID-19 pandemic.

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KEYWORDS

COVID-19; severe outcome; prediction; monitoring system; symptoms; risk prediction; risk; algorithms; prediction models; pandemic; digital data; health records

Introduction

With 85,783,178 infections and 1,855,872 deaths as of January 5, 2021 [1], the ongoing COVID-19 pandemic has put an unprecedented strain on the health care system worldwide. Three different priorities can be envisaged in order to limit the impact of virus spread: (1) social and occupational health measures to decrease the risk of an airborne spread; (2) population screening using mass testing to identify sources of infection, with subsequent isolation of those who test positive for COVID-19; and (3) more selective testing of symptomatic patients to identify those with a confirmed diagnosis of COVID-19 (as opposed to influenza-like illness), as well as those patients who will most likely need hospital admission. Although the first and second tasks pertain to health care authorities, the third is typical of primary care, provided that validated predictive algorithms are available.

General practitioners (GPs) are in the forefront of this process and should be provided with tools that have inherent clinical sense and are easy to use to facilitate quick decision-making given the overwhelming numbers of patients they are engaged with in daily clinical practice. Even though several prediction models have been developed, their predictive performance has been questioned because of their ability to be representative of the general population [2,3]. A real-world approach, using primary care data sets linked to the testing results, hospital admissions data, and death records, has been extensively developed in the British population in order to assist risk prediction of hospital admission and mortality due to COVID-19 [4]. This methodology might be informative in order to detect patients with COVID-19 and, among them, those with higher risk of requiring early hospital admission. Our working group has previously released a consensus document drawn up by hospital consultant physicians and GPs in order to stratify patients with symptoms suspected of SARS-CoV-2 infection and improve their management in appropriate “hot spot” facilities [5].

However, a comprehensive analysis in Lombardy region, Italy, that uses all data available in the administrative data set is currently lacking. This could potentially be highly useful to inform and guide treatment and vaccination campaigns. In the initial weeks of March, when the COVID-19 epidemic was growing exponentially, a predictive model was developed to stratify patient risk of dying at the individual level, according to age and the presence of comorbidities [6].

Here, we aimed to evaluate potential risk factors for hospitalization. Therefore, with the start of the second wave of COVID-19, we further implemented an algorithm to estimate, among patients with COVID-19, the risk of being admitted to the hospital with SARS-CoV-2 infection based on sex, age, COVID-19 symptoms, and comorbidities. Second, by combining the algorithms for the risk of overall mortality and that for the risk of hospitalization, we propose a stratification method (ie, low, medium, and high risk) that has been successfully implemented for patients with COVID-19.

Methods

Ethics Approval and Consent to Participate

This study was conducted in accordance with ethical principles based on the Declaration of Helsinki [7] and current ethical guidelines. No individual-level data were used for this study, and patients cannot be identified from aggregated data that do not contain low counts. For this reason, and in accordance with the Italian legislation, this study was not submitted for ethics approval [8].

Study Setting

From March 8, 2020, onward, a surveillance system of the Agency for Health Protection of Metropolitan Area of Milan (ATS Milan) collected data on all residents of the territory who had either a positive or negative COVID-19 test result. A confirmed case is defined as a person with a real-time reverse-transcription polymerase chain reaction (RT-PCR) positive test result for SARS-CoV-2, irrespective of clinical signs and symptoms. In addition, GPs inputted individual patient data on the presence or absence of specific symptoms associated with COVID [9-15], namely, vomiting, cough, fever, diarrhea, myalgia, asthenia, headache, anosmia, ageusia, and dyspnea.

Predictive Algorithm for Risk of Hospitalization Due to COVID-19

From the surveillance system developed by the ATS of Milan, we collected data on all patients with a positive test result for SARS-CoV-2 between March 8 and October 9, 2020, along with additional information reported by GPs about the presence or absence of COVID-19 symptoms.

Using the administrative discharge records from ATS Milan, all hospitalizations and emergency department admissions occurring in the 31 days before or after the date of inclusion in the cohort were also collected. Date of inclusion in the cohort was defined as the date of symptom onset for symptomatic patients, and date of first positive swab in asymptomatic patients. We decided to include asymptomatic patients because their status of having no symptoms contributed to nonhospitalization data. Hospital admissions data for COVID-19 cases were shortlisted from total hospital admissions data based on the cases with International Classification of Diseases-9 (ICD-9) [16] codes V01.82, 079.82, 480.3, V07.0, and 078.89. Individual-level comorbidity data were derived using the chronic disease administrative database of ATS Milan, according to the algorithms specified in the Regional Act X/6164 [17] and X/7655 [18] of 2017. These algorithms are based on the following databases: hospital discharge, outpatient visits and exams, exempt from copayment, and drug prescriptions.

To assess the association between COVID-19–related hospitalization and the presence of symptoms in COVID-19–positive patients, we implemented a logistic regression model adjusted for age (as a continuous variable, where each value represented an increase in age of 5 years compared to the preceding value); sex (reference category: female); and comorbidities, such as cardiovascular disease (eg, peripheral artery disease, chronic heart failure, venous disease, ischemic heart disease, valvular heart disease, and cardiomyopathy with and without arrhythmia), hypercholesterolemia, hypertension, diabetes, chronic gastrointestinal (GI) disease (eg, chronic pancreatitis, chronic hepatitis and cirrhosis, and inflammatory bowel disease), and chronic pulmonary disease (eg, respiratory failure or oxygen therapy, chronic obstructive pulmonary disease, and asthma). Results are presented as odds ratios (ORs) with 95% CIs, and estimated model parameters are reported in in the Results section. Individual predicted probabilities were calculated by reversing the logit transformation. The algorithm for the risk of being hospitalized due to COVID-19 was developed following the TRIPOD (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis) guidelines [19].

A priori clinical knowledge on the associations between symptoms and hospitalization due to COVID-19 was limited. However, given the high number of events and the minimal cost represented by the collection of this information, and to maximize the expected discrimination ability based on administrative data only, it was decided to develop a full model without performing model selection using automated statistical techniques.

The validation of the algorithm was assessed internally using bootstrap resampling (1000 repetitions) to evaluate the discrimination and calibration of the model [20]. Discrimination was assessed using the C-index/area under the curve (AUC) value [21], which produces a value of 1 for ideal discrimination and a value of 0.5 for discrimination that is no better than chance. A value between 0.7 and 0.8 is considered *fair* and that between 0.8 and 0.9 is considered *good* [22]. Model calibration was evaluated by estimating calibration intercept and slope, where an intercept close to 0 and a slope close to 1 indicate *good* calibration and provided a calibration plot [23]. In addition, Brier score was evaluated to estimate overall prediction accuracy, which ranges from 0 (*perfect*) to 0.25 (*worthless*) for sensible models [20].

Validation and calibration of the model were performed using R software (version 4.0.5; R Core Team) and R package rms (version 6.2-0; F. Harrel).

Risk Stratification Model for Patients With COVID-19

Beginning on October 25, 2020, with the start of the second wave of COVID-19 in Lombardy, we developed a surveillance and monitoring system for patients with COVID-19. Each patient was stratified as a high-, medium-, or low-risk patient for the combined outcome of hospitalization and death, according to the clinical and demographic characteristics highlighted by 2 predictive models developed by ATS Milan—the aforementioned predictive model for hospitalization and the predictive model for the overall mortality risk [6].

We thus defined the risk of a patient as follows:

- High risk: if the patient was older than 70 years and had one of the comorbidities identified by the prediction algorithm for overall mortality risk (ie, presence of neurological disorders, chronic heart failure, ischemic heart disease, valvular disease, renal failure, and neoplasm diagnosed in the last 2 years). In addition, a patient was considered at high risk if they had pneumonia within 15 days before or after the date of swabbing.
- Medium risk: if the patient was not at high risk and if the predicted probability of hospitalization was greater than or equal to 40%, as determined based on the predictive model for hospitalization. In addition, a patient was considered at medium risk if no information about their symptoms was present in the database (either because they had not registered in the portal or because although their GPs registered, they did not enter any symptoms).
- Low risk: if the patient was not at high or medium risk, was asymptomatic, or had a predicted probability of hospitalization lesser than 40%.

Considering potential misclassification, we decided to use 40% as a probability cutoff for prediction, instead of the usual 50% used in logistic models [24]; this allowed us to include a larger number of patients in the medium-risk category. We thus used the prediction algorithm for overall mortality risk [6] to define high-risk patients and the aforementioned predictive model for hospitalization for the definition of medium- and low-risk patients. Individual predicted probabilities for hospitalization were calculated for each patient according to the estimated model parameters (Table 1), as well as demographic and clinical characteristics. Clinical characteristics (ie, comorbidities) were derived, as described above, using the chronic disease administrative database of ATS Milan, according to the algorithms specified in the Regional Act X/6164 [17] and X/7655 [18] of 2017, which are based on the following databases: hospital discharge, outpatient visits and exams, exempt from copayment, and drug prescriptions. Symptom data were obtained, as described above, from the information inputted by GPs.

Table 1. Demographic and clinical characteristics of training and validation sets and risk factors for COVID-19–related hospitalization. Data sourced from the surveillance system developed by the Agency for Health Protection of Metropolitan Area of Milan, which covers the provinces of Lodi and Milan in Italy, comprising swab-positive SARS-CoV-2 cases between March 8 and October 9, 2020, for which general practitioners reported the presence or absence of COVID-19 symptoms.

Characteristic	Predictive algorithm for COVID-19 hospitalization, n (%)			OR[a] (95% CI)[b]
	Overall (N=36,834)	Training (n=29,563)	Validation (n=7271)	
Sex, male	16,591 (45.04)	13,361 (45.20)	3230 (44.42)	2.46 (2.33-2.61)
Age in years				1.12 (1.11-1.13)
<18	3186 (8.65)	2582 (8.73)	604 (8.31)	
18-40	6402 (17.38)	5107 (17.27)	1295 (17.81)	—[c]
40-70	13,943 (37.85)	11,252 (38.06)	2691 (37.01)	—
≥70	13,303 (36.12)	10,622 (35.93)	2681 (36.87)	—
Outcome = yes	8069 (21.91)	6468 (21.88)	1601 (22.02)	—
Asymptomatic	4475 (12.15)	3589 (12.14)	886 (12.19)	—
Symptoms = yes				
Vomiting	791 (2.15)	639 (2.16)	152 (2.09)	1.43 (1.16-1.75)
Cough	9889 (26.85)	7954 (26.91)	1935 (26.61)	1.23 (1.15-1.32)
Fever	18,747 (50.9)	15,092 (51.05)	3655 (50.27)	1.84 (1.73-1.96)
Diarrhea	2416 (6.56)	1939 (6.56)	477 (6.56)	0.85 (0.74-0.97)
Myalgia	3634 (9.87)	2922 (9.88)	712 (9.79)	0.50 (0.44-0.57)
Asthenia	6383 (17.33)	5101 (17.25)	1282 (17.63)	0.57 (0.52-0.63)
Headache	3201 (8.69)	2566 (8.68)	635 (8.73)	0.59 (0.51-0.68)
Anosmia	1874 (5.09)	1494 (5.05)	380 (5.23)	0.18 (0.13-0.24)
Ageusia	708 (1.92)	573 (1.94)	135 (1.86)	1.04 (0.69-1.57)
Dyspnea	7487 (20.33)	6013 (20.34)	1474 (20.27)	3.95 (3.72-4.21)
Comorbidities = yes				
Cardiovascular disease	7140 (19.38)	5676 (19.20)	1464 (20.13)	0.86 (0.79-0.92)
Hypercholesterolemia	4183 (11.36)	3345 (11.31)	838 (11.53)	1.32 (1.21-1.43)
Hypertension	12,167 (33.03)	9773 (33.06)	2394 (32.93)	1.40 (1.31-1.51)
Diabetes	3742 (10.16)	3036 (10.27)	706 (9.71)	1.39 (1.28-1.51)
GI[d] disease	1085 (2.95)	869 (2.94)	216 (2.97)	1.34 (1.16-1.54)
Pulmonary disease	2745 (7.45)	2179 (7.37)	566 (7.78)	1.28 (1.17-1.41)

[a]OR: odds ratio.

[b]OR and corresponding 95% CI values were calculated from a multivariate logistic model, including age (5-year age classes), sex (reference category: female), COVID-19 symptoms (eg, vomiting, cough, fever, diarrhea, myalgia, asthenia, headache, anosmia, ageusia, and dyspnea), and comorbidities (eg, cardiovascular disease, hypercholesterolemia, hypertension, diabetes, gastrointestinal disease, and pulmonary disease).

[c]Not available.

[d]GI: gastrointestinal.

The system granted a telephone call by a trained operator who assessed the patient's state of health and, if necessary, gave advice to the patient to visit the hospital or emergency department. For this purpose, ATS Milan trained an internal call center as well as external operators, who received a set of patients to be contacted on a daily basis. Each call center received a number of patients in line with its capacity (based on the number of operators, staff roasters, etc). This number was decided by each call center during the implementation of the system, and eventually updated during the epidemic according to staff modifications. Given the huge number of positive cases and the limited capacity of the call centers, we decided to send patients to surveillance in order of priority: first high-risk patients, followed by medium- and low-risk patients.

The second part of this study intends to present the results of this monitoring system from October 25 to December 11, 2020. To measure the association between patient stratification as high, medium, and low risk and actual severity of COVID-19, we used ordinal (cumulative) logistic models. Severity of COVID-19 was defined as an ordinal outcome equal to 0 if treated at home (home-treated), equal to 1 if hospitalized, and equal to 2 if deceased. The models were adjusted for sex, age, and comorbidities (cardiovascular disease, hypercholesterolemia, hypertension, diabetes, chronic gastrointestinal disease, and chronic pulmonary disease). Results are presented as odds ratios (ORs) with 95% CI values. ORs for the ordinal logistic model are interpreted in their cumulative formulation, that is, the odds of deceased versus the combined categories of hospitalized and home-treated patients, as well as of the combined categories of deceased and hospitalized versus home-treated patients. The analyses were performed using SAS software (version 9.4; SAS Institute Inc).

Availability of Data and Materials

Data are not publicly available because they are owned by ATS Milan and cannot be distributed to third parties.

Results

Study Cohort Used for the Predictive Algorithm for Risk of COVID-19–Related Hospitalization

From March 8, 2020, to October 9, 2020, we collected data of 36,834 patients with a positive test result for COVID-19 (demographic and clinical characteristics are reported in Table 1), for which the patients' GPs reported the presence or absence of COVID-19 symptoms. Among these patients, 8069 (22%) were hospitalized or admitted to an emergency department with a COVID-19 diagnosis. Fever, cough, and dyspnea were the most common symptoms, reported by more than 20% of the cohort, whereas 12.15% (4475/36,834) of the cohort comprised asymptomatic COVID-19 cases. In this cohort (N=36,834), 19.38% (n=7140) had cardiovascular diseases, 11.36% (n=4183) had hypercholesterolemia, 33.03% (n=12,167) had hypertension, 10.16% (n=3742) had diabetes, 2.95% (n=1085) had GI disease, and 7% (n=2745) had pulmonary disease.

Table 1 presents the OR and corresponding 95% CI values from the logistic regression model estimating the risk of COVID-19 hospitalization. The likelihood of being hospitalized for COVID-19 was higher among older patients, with increasing odds of 12% for an increase in age-class (OR 1.12, 95% CI 1.11-1.13), male patients with OR 2.46 (95% CI 2.33-2.61 vs female patients). Vomit, cough, fever, and dyspnea were statistically significant risk factors for COVID-19 hospitalization, whereas no association was found for ageusia. On the other hand, diarrhea, myalgia, asthenia, headache, and anosmia showed a negative association with the risk of COVID-19–related hospitalization.

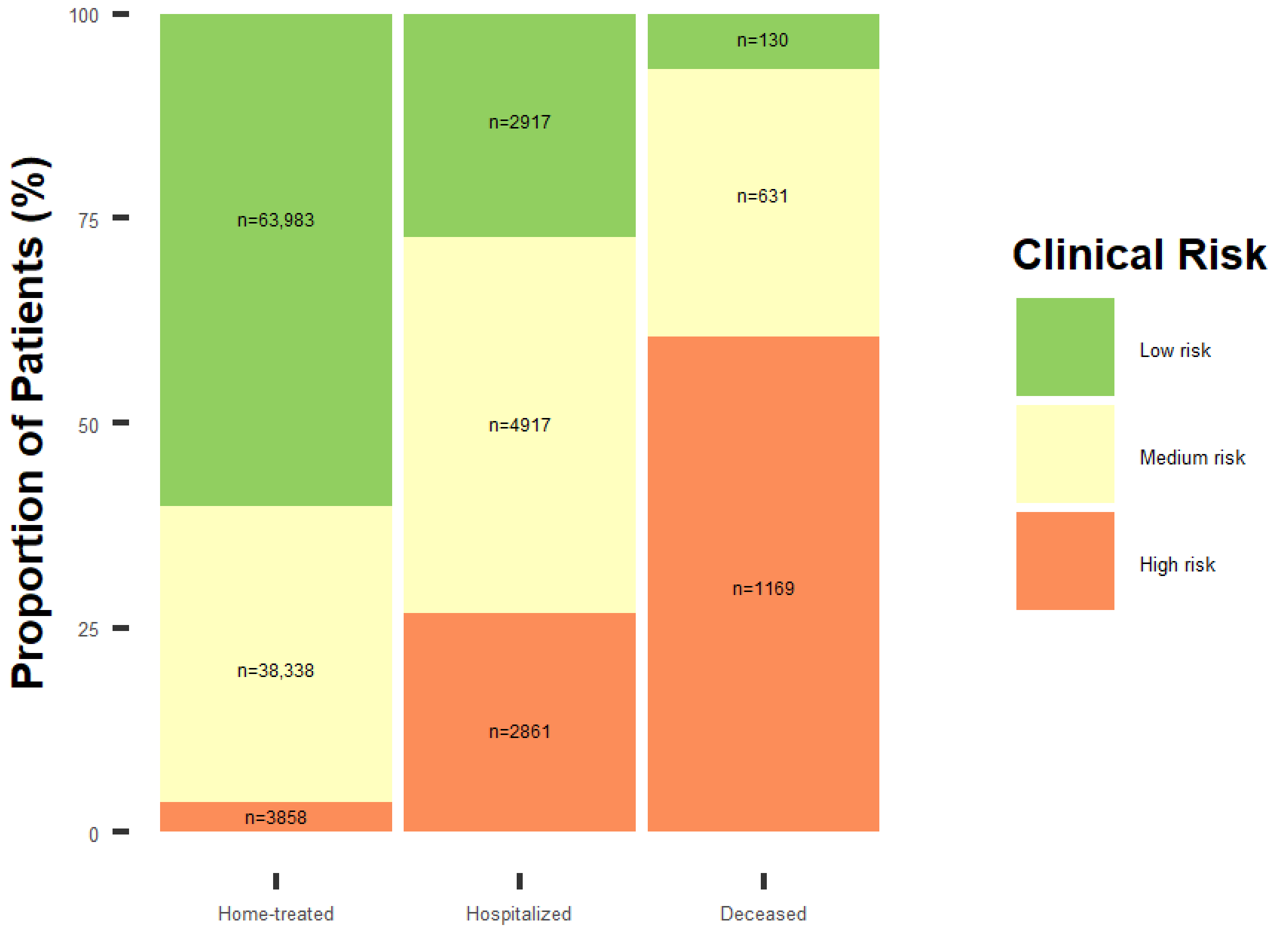
This algorithm produced a C-index of 0.79, which suggest a *fair* and *almost good* discriminator ability to predict COVID-19 hospitalization. This model had good overall prediction accuracy (Brier score 0.14) and was well calibrated (intercept –0.0028, slope 0.9970; see Multimedia Appendix 1 for calibration plot).

We acquired BMI information at diagnosis for a subset of the general cohort (4586/36,834, 12.45%): 9.62% (441/4586) were underweight (BMI<18.5), 53.1% (2435/4586) were normal weight (BMI 18.5-24.9), 26.65% (1222/4586) were overweight (BMI 25-29.9), and 10.64% (488/4586) were obese (BMI ≥30). According to a logistic regression model adjusted for age and sex, BMI (continuous variable) was associated with a higher risk of being hospitalized (OR 1.05, 95% CI 1.03-1.08), and overweight and obese were associated with a high risk of being hospitalized compared to normal weight (OR 1.4, 95% CI 1.04-1.8, and OR 1.9, 95% CI 1.3-2.6, respectively). In the subset with nonmissing BMI information, we evaluated the discrimination ability of the same model described previously, including BMI (continuous variable), which produced a c-index of 0.89.

Results of the Epidemiological Monitoring System

Beginning on October 25, 2020, with the start of the second wave of COVID-19 in Lombardy, we developed a surveillance and monitoring system for COVID-19 patients, stratifying (up to December 11, 2020) 118,804 COVID-19 cases into high-, medium-, and low-risk patients. Among these, 63,816 (53.72%) were actually included in the surveillance system and 39,167 (32.97%) were contacted by trained call center operators. Of the overall population, 67,030 (56.42%) were defined as low risk; 43,886 (36.94%), at medium risk; and 7888 (6.64%), as high risk. As of December 11, 2020, 89.37% (106,179/118,804) of the overall population was assisted at home, 9% (10,695/118,804) was hospitalized, and 1.62% (1930/118,804) had died. Among those assisted at home, the majority of patients (67030/118,804, 56.42%) were classified as low risk, whereas only 6.64% (7888/118,804) were classified as high risk (Figure 1). Among those hospitalized, 45.97% (4917/10,695) were classified to be at medium risk, and 26.75% (2861/10,695) were classified to be at high risk. Among the deceased, 60.57% (1169/1930) were classified to be at high risk and 6.74% (130/1930), at low risk.

Figure 1. Stratification of study patients by clinical risk and health status, based on results from the monitoring system developed during the second wave of COVID-19 by the Agency for Health Protection of Metropolitan Area of Milan (data updated on December 11, 2020).



According to the ordinal logistic model adjusted for age, sex, and comorbidities, we found statistically significant associations between having a severe outcome (ie, hospitalized or deceased) and the proposed stratification. Patients classified at high risk had an OR of 5.0 (95% CI 4.6-5.4) of having a worse outcome compared to low-risk patients. Patients classified at medium risk had an OR of 2.7 (95% CI 2.6-2.9) of having a worse outcome compared to low-risk patients.

Discussion

Principal Findings

In this study, we developed a risk prediction model for COVID-19 hospitalization using age, sex, symptoms, and comorbidities. The model showed a good discriminator ability that could be sensibly improved by including BMI information in the model prediction. However, this model had a good discriminative capability, especially considering that predictors were derived from administrative data [25]. The model highlighted vomit, cough, fever, and dyspnea as statistically significant risk factors for COVID-19 hospitalization. However, we found no association for ageusia, which was probably underestimated in the first wave of the epidemic. The main result of our research, performed using a population-based approach, is the development of a simple and robust stratification tool aimed at improving COVID-19 patient management and health care organization. This tool was constructed combining 2 predictive models developed by ATS Milan: the predictive model for hospitalization and the predictive model for overall mortality risk [6]. Using these predictive models, a stratification tool was easily generated with a close relationship between patient stratification and the health status. Among patients who were managed at home, only 3.63% (3858/106,179) were at high risk. In contrast, among those who died, 60.57% (1169/1930) were at high risk, and only 6.74% (130/1930) were at low risk. Results suggest that patients classified to be at high and medium risk were at higher risk of having a worse outcome than those classified to be as low risk. Most importantly, these data confirm the relevance of an integrated approach in patient management and the leading role of GPs surveillance in improving outcomes.

Since the first COVID-19 outbreak, there was a need to obtain risk stratification tools to assist clinicians in their decision-making, considering the limited resources available. With the spread of the pandemic, the strategy of focusing on an integrated approach of care became increasingly important in order to avoid the collapse of the hospital system and to preserve a high level of care for most critical COVID-19 cases, as well as for cardiovascular or oncological cases. The Metropolitan area of Milan was one of the most impacted areas worldwide, with coronary care units and surgical operating rooms converted to general intensive care units for patients with COVID-19 requiring high-dependency care, and noninvasive ventilation made available in converted internal medicine and infectious disease units. However, the high rate of patients who were mildly symptomatic or asymptomatic fosters the idea that, in most cases, the disease could be controlled by closely monitoring its course.

Since then, an approach based on record linkage between different health registries of COVID-19 testing results along with the implementation of a surveillance system has emerged as a practical and powerful option to balance the health resources and targeting interventions. In this study, we suggest an algorithm to predict the risk of COVID-19–related hospitalization that would be fundamental to the early implementation of measures of prevention and containment in the upcoming months.

Interventions that prevent COVID-19 progression can be expected to reduce the morbidity and mortality of infection, frequency of hospitalization, and current unbearable strain on health system. Monoclonal antibodies and hyperimmune plasma used early in outpatients have shown efficacy in reducing viral load and nasopharyngeal shedding, respectively [26,27], which are related to disease severity and hospitalization rate [28]. Moreover, such treatments are expensive and logistically challenging, but they may encourage early and rapid testing of persons at high risk for SARS-CoV-2 infection and use of algorithms to identify at diagnosis those who are at risk of hospitalization and death. By using the proposed algorithm, it was possible to identify 7.888 high-risk patients out of a total of 118.804 patients with a COVID-19 diagnosis (6.63%) during the second wave. In all, 1169 (15%) patients died, and 2861 (36%) were hospitalized. Therefore, the use of this algorithm could also be applied in order to improve the cost benefit of early antiviral treatments in patients with COVID-19.

Strengths and Limitations

Our work has several strengths, including the prospective recording of data and outcome, with minimal risk of ascertainment and performance bias, appropriate record linkage, along with validation in larger and different temporal frames. Finally, the model was based on variables readily available for each GP, who are the leading figures in providing care to the patients and primarily driving their clinical course. Thus, the described epidemiological surveillance system could launch a workflow for improving patient management well in the context of the COVID-19 pandemic, thereby informing the management of chronic conditions.

A major limitation of this study is the absence of a granular assessment of other prognostically important variables (eg, chronic kidney disease, tobacco use, and BMI), which have been implemented in other algorithms [4,29]. However, the variables included are the most easily available and collected in an administrative data set. Accordingly, recent systematic and critical reviews of modelling techniques have reported that predictions obtained using more complex models may not provide better information or be more reliable than those obtained using a simpler model [30]. Another limitation is the lack on BMI information that, in a subset of the overall population, sensitively improved the discrimination ability of the model. In addition, we investigated the effect of age on the risk of hospitalization for COVID-19 as a mere confounder in the exposure-outcome relationship. Further work has to be done in order to consider the possible differences in age-related symptoms observed after SARS-CoV-2 infection [31].

Conclusions

In conclusion, the predictive algorithms implemented and the ensuing stratification of patients with COVID-19 provided an accurate assessment of patients' prognosis, with a good calibration of the predicted risk and an inherent clinical sense of the stratification tool. If systematically implemented, it will allow for a prompt identification of the most appropriate pathway of care for each patient affected by COVID-19.

Authors' Contributions

RM and AGR conceptualized the study, defined the methodology, and accessed and verified the data. RM analyzed the data set. NM contributed to the literature search, data interpretation, and writing of the manuscript. SS supervised the methodologies and revised the manuscript. CC, MP, BO, WB, AV, PQR, GS, MGM, MTZ, AM, CB, MB, MC, FC, and MT have made substantial contributions to the revision of the manuscript. AGR supervised and administered the project. All authors have read and approve the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Calibration plot of the multivariable logistic regression model predicting hospitalization risk due to COVID-19.

[PNG File , 62 KB - publichealth_v7i11e29504_app1.png]

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Abbreviations

ATS Milan: Agency for Health Protection of Metropolitan Area of Milan
AUC: area under the curve
GI: gastrointestinal
GP: general practitioner
ICD: International Classification of Diseases
OR: odds ratio
RT-PCR: reverse-transcription polymerase chain reaction
SARS-CoV-2: severe acute respiratory syndrome–coronavirus-2
TRIPOD: Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis

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Original Paper

Central COVID-19 Coordination Centers in Germany: Description, Economic Evaluation, and Systematic Review

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Abstract

Background: During the COVID-19 pandemic, Central COVID-19 Coordination Centers (CCCCs) have been established at several hospitals across Germany with the intention to assist local health care professionals in efficiently referring patients with suspected or confirmed SARS-CoV-2 infection to regional hospitals and therefore to prevent the collapse of local health system structures. In addition, these centers coordinate interhospital transfers of patients with COVID-19 and provide or arrange specialized telemedical consultations.

Objective: This study describes the establishment and management of a CCCC at a German university hospital.

Methods: We performed economic analyses (cost, cost-effectiveness, use, and utility) according to the CHEERS (Consolidated Health Economic Evaluation Reporting Standards) criteria. Additionally, we conducted a systematic review to identify publications on similar institutions worldwide. The 2 months with the highest local incidence of COVID-19 cases (December 2020 and January 2021) were considered.

Results: During this time, 17.3 requests per day were made to the CCCC regarding admission or transfer of patients with COVID-19. The majority of requests were made by emergency medical services (601/1068, 56.3%), patients with an average age of 71.8 (SD 17.2) years were involved, and for 737 of 1068 cases (69%), SARS-CoV-2 had already been detected by a positive polymerase chain reaction test. In 59.8% (639/1068) of the concerned patients, further treatment by a general practitioner or outpatient presentation in a hospital could be initiated after appropriate advice, 27.2% (291/1068) of patients were admitted to normal wards, and 12.9% (138/1068) were directly transmitted to an intensive care unit. The operating costs of the CCCC amounted to more than €52,000 (US $60,031) per month. Of the 334 patients with detected SARS-CoV-2 who were referred via EMS or outpatient physicians, 302 (90.4%) were triaged and announced in advance by the CCCC. No other published economic analysis of COVID-19 coordination or management institutions at hospitals could be found.

Conclusions: Despite the high cost of the CCCC, we were able to show that it is a beneficial concept to both the providing hospital and the public health system. However, the most important benefits of the CCCC are that it prevents hospitals from being overrun by patients and that it avoids situations in which physicians must weigh one patient's life against another's.

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KEYWORDS

telemedical consultation; patient allocation; algorithm-based treatment; telemedicine; telehealth; consultation; allocation; algorithm; treatment; COVID-19; coordination; Germany; economic; review; establishment; management

Introduction

COVID-19 has infected more than 230 million people, including over 4 million people in Germany (as of September 2021) [1], since it was declared a global pandemic by the World Health Organization on March 11, 2020 [2]. Due to large numbers of hospital admissions of patients with COVID-19 within a very short time, catastrophic overloads of hospitals have repeatedly occurred worldwide, as observed in Bergamo [3] and New York City [4].

In the event that intensive care units (ICUs) are overcrowded, patients must be transferred to more distant hospitals by intensive care transport. However, interhospital transport of critically ill patients always involves a high risk for the patient (eg, dislocation of intravascular catheters or airway devices) and should therefore be avoided if possible.

Emergency medical services (EMS) in Germany are usually dispatched by a regional rescue directing center, where emergency calls are handled by specially trained firefighters or paramedics. During the pandemic, however, a special coordination center with an up-to-date overview of the highly dynamic capacities of the surrounding hospitals became necessary. Main tasks have included triage of suspected and confirmed patients with COVID-19, coordination of secondary patient transfers of critically ill patients requiring intensive care based on current hospital capacity, and the arrangement of specialist telemedical consultations for peripheral hospitals in need of expertise in the treatment of patients with COVID-19. The staff deployed thus need to be able to use the information given via telephone to advise outpatients on further medical care and, if an inpatient admission is necessary, to estimate the correct level of care now and in advance at the hospital. This would significantly exceed the capacities of the rescue control center, which is why the CCCCs as separate coordination centers with permanent medical staffing were introduced.

The main goals of the CCCCs were to implement an efficient distribution of patients with COVID-19 to provide the best medical care to all and to reduce interhospital transfers of patients with COVID-19 to a minimum.

Therefore, on behalf of the state government, three CCCCs were established in Saxony, Germany, located at Dresden University Hospital for eastern Saxony, Chemnitz Hospital for southwestern Saxony, and Leipzig University Hospital (LUH) for northern Saxony. The CCCC at LUH is responsible for the coordination of 18 hospitals, 112 EMS vehicles, and over 700 primary care physicians [5].

The following article aims to describe the structure of the CCCC at LUH and to perform an economic evaluation of the two months with the highest incidence in the second COVID-19 wave (December 2020 to January 2021, local incidences >500/100,000/week) [6]. In addition, we conducted a systematic literature review on economic data for similar coordination units.

Methods

The study was approved by the Local Ethics Committee (158/21-ek). The literature review was conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines [7], and the economical evaluation was performed according to the CHEERS (Consolidated Health Economic Evaluation Reporting Standards) guidelines [8].

Systematic Review

A search of published records was conducted using the following equations: (COVID* OR SARS*) AND (Coordination* OR Management*) AND Cost*, in the PubMed (n=555) and Web of Science (n=767) databases (last update 07/15/2021). The search was not restricted to any field. First, all publications before 2020 (n=144) were removed, followed by all duplicates (n=295). For this review, full-text availability articles published in peer-reviewed journals and written in English or German were considered. Abstracts and conference proceedings were excluded (n=109). In addition, we investigated the reference lists of the articles. The articles were required to meet the quality standards of CHEERS.

Setup of the Central COVID-19 Coordination Center

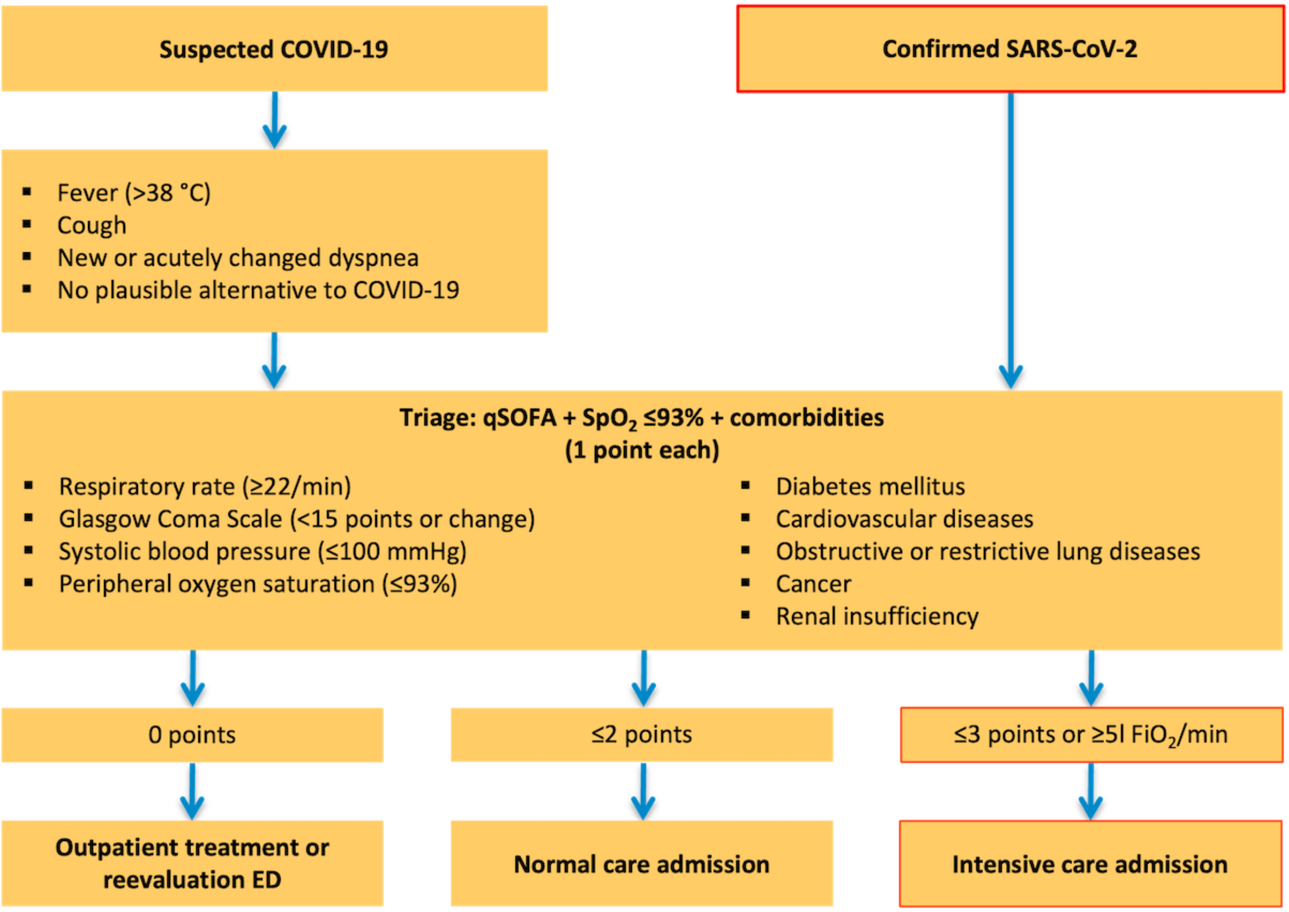
The CCCC at LUH is staffed 24 hours per day, 7 days per week in a 4-shift system by physicians (early duty, 2 physicians; mid-duty, 1 physician; late duty, 1 physician; and night duty, 1 physician). Medical students and nurses are also assigned to the overlapping mid-shift duty. A 51 m^2 conference room equipped with three workstations was chosen (Figure 1).

When requests were received, patient history and triage were performed according to a predetermined algorithm (Figure 2). The allocation was made based on the current bed capacity, which was displayed on a specially developed dashboard, and after telephone consultation with the target hospital. The queried information and the derived decision were documented in a database.

Either the specialized telemedical consultation was performed by the CCCC staff themselves, or the request was forwarded to appropriate specialists of the LUH (eg, inquiries regarding extracorporeal membrane oxygenation treatment due to severe lung failure, hemostasiological issues).

Figure 1. Setup of the Central COVID-19 Coordination Center at Leipzig University Hospital, including a conference room (51 square meters), a central widescreen display (dashboard), three computer workstations with telephones, two whiteboards, and a multifunction printer (not shown). The center is staffed in the early shift by two physicians (right and left), and the Deputy Chief of hospital emergency management is shown in front of the dashboard (center).

Figure 2. Algorithm of the Central COVID-19 Coordination Center at Leipzig University Hospital for handling requests from emergency medical services or outpatient physicians for suspected COVID-19 or SARS-CoV-2 confirmation. Based on the algorithm of Central COVID-19 Coordination Center Dresden (simplified presentation). ED: emergency department; FiO_2: fraction of inspired oxygen; qSOFA: quick sepsis-related organ failure assessment score; SpO_2: peripheral oxygen saturation.



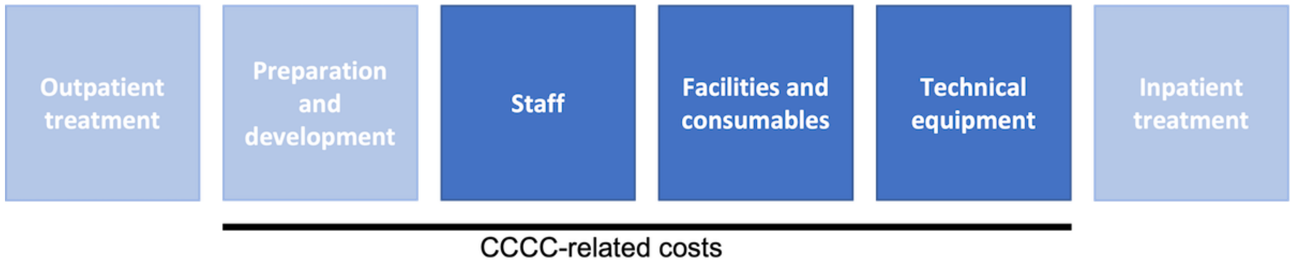
Requests and Patients

All received requests at the CCCC at LUH in December 2020 and January 2021 were included and analyzed in this evaluation. The time of each request, information about the requesters (contact person, function), the epidemiological data of the patients, and derived decisions were documented in a specially developed database and analyzed for this study.

Cost Analysis

To calculate the total ongoing costs of the CCCC at LUH, we chose a modular model (Figure 3). We did not consider the organizational costs previously incurred at LUH; development costs of the dashboard, database, and associated forms; out- and inpatient care costs; or construction-related costs (these were omitted due to dual hospital financing in the German health care system from the hospitals' perspective). We also did not consider indirect or intangible costs (eg, loss of personnel and resulting reduction in treatment capacity in the providing hospitals).

Figure 3. Calculation model of the costs of the Central COVID-19 Coordination Center at Leipzig University Hospital.



Staff

The staff costs correspond to the payroll of the human resources department for December 2020 and January 2021. The costs are listed separately according to grade (physicians, nurses, and medical students) and include all ancillary staff costs as well as working hours and holiday bonuses. Also considered separately are costs of the CCCC front-office services, back-office services (telemedicine consulting), and administrative activities (management and scheduling).

Facilities and Consumables

The selected conference room had a size of 51 m^2. The costs consist of operating costs (cleaning, energy, etc), consumables, and rent. The consumables (printer paper, whiteboard, etc) were calculated at a flat rate of 10€ (US $11.54) per day. The furnishings (chairs, desks, etc) were borrowed from the existing inventory; thus, no costs were incurred. The costs recorded correspond to the costs in 2020. For the calculation of the costs in 2021, they were increased by 4.1%, in accordance with the average development of material costs in German hospitals [9].

Technical Equipment

The technical equipment of the CCCC at LUH was newly purchased; the equipment will be used further after the end of the pandemic, and the costs will be depreciated over 4 years. We assume that the CCCC setup will exist for a total of 24 months, although not continuously in active operation; therefore, the running costs in each of the 2 months correspond to 1/12 of the annual depreciation. The cost of the multifunction printer is a blended monthly bill of lease, rental, and cost per printed page.

Cost-effectiveness Analysis

The internal economic evaluation of the CCCC includes a comparison of costs, requests, and workload. For this purpose, separate documentation was conducted by the CCCC front office staff in April 2021 (with a similar number of requests as in December 2020 and January 2021). In this process, the length of time spent processing requests was recorded (from the ringing of the telephone until completion of documentation) as well as the amount of work spent on other tasks. The results were compared with the employees' working hours.

Use and Utility Analysis

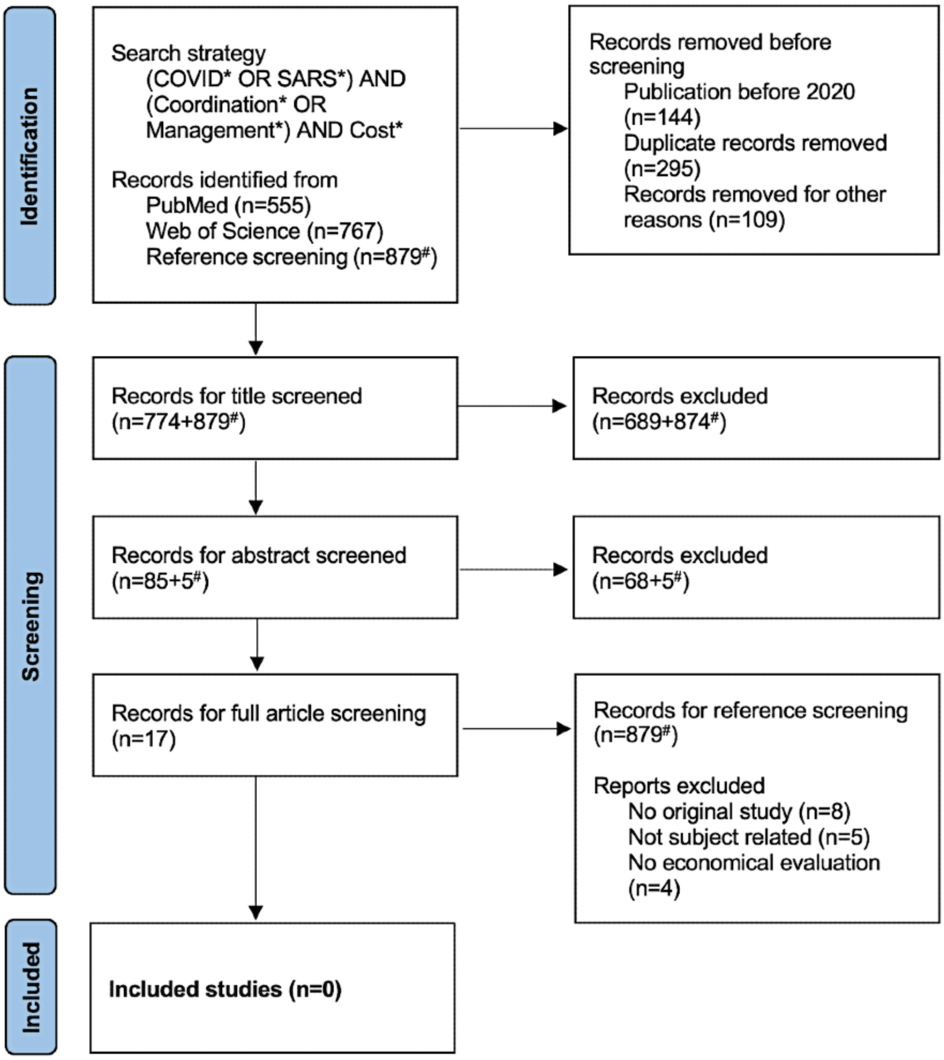
This investigation examined how many patients with SARS-CoV-2 infection were treated in the ED of the LUH (self-, EMS-, or physician-initiated presentations) or admitted via this department (transfers from other hospitals). For this purpose, an evaluation was performed in the investigated period and in an analogous period from December 2019 to January 2020 via the hospital information system. The results were compared with the decisions of the CCCC. In addition, the attending physicians of the ED were interviewed.

Results

Systematic Review

The PRISMA flow diagram for the literature analysis is shown in Figure 4. A total of 2201 publications were reviewed. No studies were found that addressed the costs of coordination or management tasks in the COVID-19 pandemic in regional or national health care systems. Moreover, the reference lists of full-text screened articles were screened and did not reveal any relevant publication (marked by # in Figure 4).

Figure 4. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of the systematic review. Last update July 15, 2021. Numbers marked with # are based on the reference screening and are not included in the records removed before screening.



Requests and Patients

Between December 01, 2020, and January 31, 2021, 1068 telephone inquiries were accepted by the CCCC at LUH (Figure 5), with a mean value of 18.9 requests (SD 6.7) per day in December 2020, and 15.6 requests per day (SD 5.8) in January 2021 (Figure 5A). In the period under investigation, 56.3% (601/1068) of the requests were made by the EMS, 21.0% (224/1068) by hospitals, 14.1% (151/1068) by outpatient physicians (general practitioners), and 8.6% (92/1068) by others (Figure 5B).

Requests were made for patients aged 0 to 100 years, with an average age of 72 years, and 69% of cases that presented with SARS-CoV-2 infection (737/1068) were confirmed by polymerase chain reaction at the time of inquiry. Approximately one-fifth of the patients (200/1068, 18.7%) were suspected or detected SARS-CoV-2 positive by rapid test, and 12.3% (131/1068) had no detection or suspicion (Table 1).

At the time of the request, 97 of the 1068 patients (9.1%) had a respiratory rate >22/min, 576 (53.9%) showed peripheral oxygen saturation ≤93%, and 30 (2.8%) presented a systolic blood pressure <100 mmHg. Outpatient treatment or telephone consultation was sufficient for 59.8% (639/1068) of all requests, and inpatient treatment was needed for 40.2% (429/1068) of requests (Figure 5C).

Figure 5. Requests and decisions of the Central COVID-19 Coordination Center (CCCC) at Leipzig University Hospital between December 01, 2020, and January 31, 2021. (A) Quantities of requests per 24 hours. (B) Proportions of different requestors. (C) Decisions by the CCCC after questions and consultation. ED: emergency department; EMS: emergency medical service; ICU: intensive care unit; NA: no admission; NC: normal care unit.

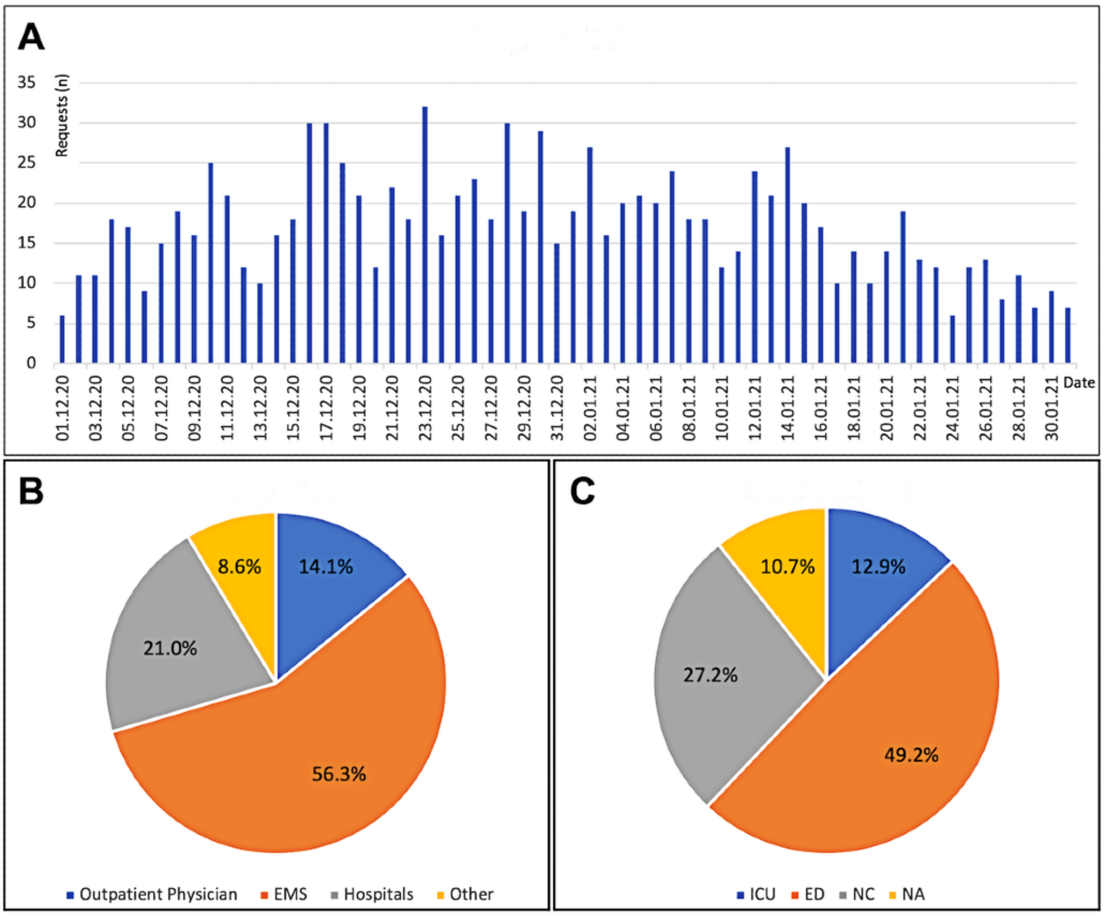


Table 1. Patient data of requests to the Central COVID-19 Coordination Center at the Leipzig University Hospital between December 01, 2020, and January 31, 2021 (N=1068).

Characteristic	Value
Epidemiological data	
Female, n (%)	475 (44.5)
Mean age, mean (SD)	71.8 (17.2)
SARS-CoV-2 status, n (%)	
Polymerase chain reaction test positive	737 (69)
Suspicion/rapid test positive	200 (18.7)
No suspicion	131 (12.3)
Previous diseases, n (%)	
Diabetes mellitus	142 (13.3)
Cardiovascular diseases	292 (27.3)
COPD[a]/bronchial asthma	106 (9.9)
Malignant neoplasia	47 (4.4)
Renal insufficiency	109 (10.2)
No relevant comorbidity	551 (51.6)
Current symptoms, n (%)	
Respiratory rate (≥22/min)	97 (9.1)
GCS[b] (<15 or change) staff cost (€)[c]	33 (3.1)
Systolic blood pressure (≤100 mmHg)	30 (2.8)
SpO_2[d] (≤93%)	576 (53.9)
Points in triage, n (%)	
0 points	281 (26.3)
1-2 points	624 (58.4)
≥3 points	163 (15.3)

[a]COPD: chronic obstructive pulmonary disease.
[b]GCS: Glasgow Coma Scale.
[c]1€=US $1.15.
[d]SpO_2: peripheral oxygen saturation.

Cost Analysis

Detailed costs and total costs are presented in Table 2, separately for December 2020 and January 2021 and in total.

Table 2. Detailed cost report of the Central COVID-19 Coordination Center at the Leipzig University Hospital between December 01, 2020, and January 31, 2021.

Characteristic	Staff cost (€)[a]		
	12/2020	01/2021	Total
Front office	41,067.99	43,849.02	84,917.01
Physician	34,816.57	40,294.38	75,110.95
Nurse	5998.61	3554.64	9553.25
Student assistant	252.81	N/A[b]	252.81
Back office	6355.26	N/A	6355.26
Administration	6207.12	6207.12	12,414.24
Facilities and consumables			
Rent	305.64	318.17	623.81
Operating costs	472.72	492.10	964.83
Consumables	310.00	322.71	632.71
Technical equipment			
Wide screen display (n=1)	666.67	694.00	1360.67
Computers (n=4)	243.77	253.76	497.53
Monitors (n=6)	66.15	68.86	135.01
Desktop telephones (n=3)	50.00	52.05	102.05
DECT[c] telephones (n=3)	75.0	78.08	153.08
Multifunction printer (n=1)	74.41	64.04	138.45
Total	55,894.73	52,399.92	108,294.65

[a]1€=US $1.15.

[b]N/A: not applicable.

[c]DECT: digital enhanced cordless telecommunications.

Cost-effectiveness Analysis

During 10 shifts in early and late duty, 74 calls were documented. Out of these, 23 calls were of informative or consulting character, and 51 concerned admission or transfer of patients. The average duration of work per request was 15.7 minutes (range 2-110 minutes, consultation: 10.2 minutes, admission: 18.1 minutes). This resulted in a workload of 24.1% of the working time at the front office.

Use and Utility Analysis

At LUH, 4873 patients were treated or admitted via the ED during the investigated period. A total of 736 of these 4873 patients required isolation (15.1%, compared to 9.5% [577/6049] from December 2019 to January 2020); 7.2% (352/4873) because of SARS-CoV-2 (compared to 0% [0/6049]), 6.5% (318/4873) because of multidrug-resistant bacteria (compared to 8.2% [493/6049]), and 1.4% (66/4873) for other causes, such as immune-suppressed or other viral diseases (compared to 1.4% [84/6049]).

SARS-CoV-2 was detected in 352 patients, of whom 334 (94.8%) were referred via EMS or outpatient physicians. Among these 334 patients, 302 admissions or transfers were referred to LUH by the CCCC during the same period (90.4%). During the whole period that the CCCC was in operation, the ED was never overcrowded with patients with COVID-19.

Discussion

Principal Findings

For regional management of prehospital and in-hospital patients with COVID-19, a supportive unit was created at a tertiary hospital in Germany. The use and utility analysis underlines the benefit of the CCCC, whereas the health economic analysis shows potential for improvement in cost-effectiveness. In the additionally conducted systematic review, no studies of similar units could be found. Analyses addressing the coordination of other pandemics were also not found, although the establishment of similar regional, national, and international facilities was repeatedly requested in relevant literature [10-12].

Public health studies on coordination units for managing mass casualty incidents caused by accidents or natural disasters have been performed. So-called Disaster Medical Assistant Teams are used in various countries and can also support the logistical organization, but economic analyses are lacking [13-16].

Successful telemedical approaches already exist in the preclinical care of severely injured people [17,18]. A national program for telemedicine consultation after neurotrauma could eliminate the need for 68% of patient transfers [19].

A reduction in mortality of patients requiring intensive care after telemedicine consultation was also recently shown in a meta-analysis of 13 studies [20]. The successful implementation in other countries of supportive coordination units in disaster medicine and the good results of prehospital telemedicine consultation in the ED and ICU underline the joint approach of CCCCs in Germany.

Dealing with disasters and pandemics requires collaboration, coordination, and management [21,22]. Before the SARS-CoV-2 pandemic, major viral outbreaks such as severe acute respiratory syndrome in 2002, H1N1 in 2009, Middle East respiratory syndrome in 2012, H7N9 in 2013, Ebola virus in 2014, Zika virus in 2015, and dengue virus in 2020 have demonstrated that emergency management is essential to minimize damage to populations and economies [23-29]. Even developed countries with otherwise highly functional health care systems, such as the United States, United Kingdom, and Italy, observed a (time-limited) regional collapse of their health care systems.

To prevent similar situations in Germany, CCCCs have been set up in several regions across the country. These centers provide advice and support for the admission and transfer of patients. Here, we describe the structure, economic considerations, and benefits of a coordination center in one of the most severely affected regions of Germany.

In our systematic review, we could not find any similar previous studies on this topic.

By centralizing coordination, it was possible to establish a standardized procedure very early and thus make transparent decisions for all coordinated hospitals, which supported outpatient physicians and the EMS. At the beginning of the pandemic, when the CCCCs were formed, established decision-supporting algorithms were only available for other diseases. Therefore, the algorithm (Figure 2) is based on a combination of the quick sepsis-related organ failure assessment (qSOFA) score, which was actually developed for early sepsis detection [30] (the normal SOFA score does not seem to be optimal for risk stratification in patients with COVID-19, so adjustments may be necessary [31]); oxygen saturation to estimate oxygenation disturbance; and pre-existing conditions that predispose patients to severe COVID-19 progression [32].

To increase the acceptance of the CCCCs' recommendations, we decided that they should be staffed primarily by physicians. The cost analysis shows that the majority of the costs of the CCCCs are contributed by human resources. Administrative activities (mainly planning and organization) and back-office activities (specialty physician consultation) together represent less than 20% of the total costs. We do not see any possibility of saving administrative costs due to the dynamic situation and constantly necessary adjustments. The costs for specialist consulting could decrease in the future as the experience of external colleagues increases and the requests become fewer. The front office personnel costs are responsible for 78.4% of the total costs. In three areas, there is considerable potential for savings. First, more nonphysician staff could be employed in CCCCs; this is already being implemented at LUH as a consequence of this analysis. Second, the cost-efficiency analysis shows potential for optimization in the utilization of the manpower of the personnel deployed. Third, artificial intelligence solutions are becoming increasingly more relevant in the COVID-19 pandemic for diagnosis, public health, clinical decision-making, and therapeutics, and they could possibly replace human-based decisions in the future [33].

In the months considered here, with substantially higher incidence of COVID-19, hospitals needed to implement a noticeably lower reduction in surgery and treatment capacity than in the first pandemic wave (compare Dercks et al [34]). This also results from the improved distribution of patients with COVID-19 and more predictable planning by the CCCC, among others. In view of the expenses for the CCCC, which are partly compensated by the state government of Saxony, an efficient allocation of patients with COVID-19 by the CCCC will result in real cost savings. These savings can be seen not only for the LUH but for all hospitals under the CCCC's coordination as local overload.

Nonfinancial benefits of the CCCC are particularly evident in two areas. First, unmanageable situations in the ED (and ICU) as well as insufficient human and material resources were prevented at all times. In 11% of the requests, a presentation at the hospital was not necessary and could be anticipated. In addition, it was possible to allocate the patient presentations based on the current capacity of the ED, normal wards, and ICU, as well as the expected necessary medical resources. By giving advance notice prior to admission, necessary preparations could be made to minimize the risk of infection to staff and other patients. Second, the CCCC has a relevant effect in binding the EMS and referring physicians to the CCCC hospital (>90% involvement of the CCCC). We frequently received feedback from referring physicians on how satisfied they were with the fast and competent consultation that was provided (so that we will also consider offering the telemedical consultation in other areas in the future).

Limitations

Concerning the systematic review, relevant publications may not have been detected due to the search algorithm and screening. As no further relevant publications were found during the reference screening, we consider this limitation to be minor.

The costs of the CCCC are based on real costs (eg, human resources) or general calculation parameters (eg, operating costs/m^2) of the LUH. In the cost-effectiveness analysis, the workload was calculated using data from a similar but different period. The 2 months that have been taken into consideration in this study correspond to the peak of the pandemic in Saxony to date; therefore, the effectiveness for the total duration of the CCCC could be overestimated. In the use and utility analysis, we cannot directly attribute the requests to patients in the ED due to privacy concerns. We consider the limitations of the economic evaluation mentioned to be minor. A substantial limitation can be seen in that a complete and valid cost-benefit analysis could not be performed since the business year is still ongoing. This should be further investigated in future studies.

Conclusions

In summary, the establishment and operation of the CCCC has proved worthwhile. Despite the additional costs for the providing hospital, one can assume a significant reduction of financial risks for the hospital itself as well as for the public health system. Potential savings points and future development opportunities could be identified. The most important benefit of the CCCC, however, is that there was no time when hospitals were overrun and no lives had to be triaged as a result.

Data Availability

The data provided in this study can be obtained in the *Methods* section of this manuscript.

Acknowledgments

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Authors' Contributions

NS, SS, HP conceived and designed the study. SN, ND, and FG collected and assembled the data. NS, GO, ND, FG, CJ, HP analyzed and interpreted the data. NS, GO, and FG wrote and revised the manuscript. Final approval of manuscript was provided by all authors. All authors are accountable for all aspects of the work.

Conflicts of Interest

None declared.

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Abbreviations

CCCC: Central COVID-19 Coordination Center
CHEERS: Consolidated Health Economic Evaluation Reporting Standards
ECMO: extracorporeal membrane oxygenation
ED: emergency department
EMS: emergency medical services
GCS: Glasgow Coma Scale
ICU: intensive care unit
LUH: Leipzig University Hospital

PCR: polymerase chain reaction
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
qSOFA: quick sequential organ failure assessment score

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Review

Online Newspaper Reports on Ambulance Accidents in Austria, Germany, and Switzerland: Retrospective Cross-sectional Review

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Abstract

Background: Ambulance accidents are an unfortunate indirect result of ambulance emergency calls, which create hazardous environments for personnel, patients, and bystanders. However, in European German-speaking countries, factors contributing to ambulance accidents have not been optimally researched and analyzed.

Objective: The objective of this study was to extract, analyze, and compare data from online newspaper articles on ambulance accidents for Austria, Germany, and Switzerland. We hope to highlight future strategies to offset the deficit in research data and official registers for prevention of ambulance and emergency vehicle accidents.

Methods: Ambulance accident data were collected from Austrian, German, and Swiss free web-based daily newspapers, as listed in Wikipedia, for the period between January 2014 and January 2019. All included newspapers were searched for articles reporting ambulance accidents using German terms representing "ambulance" and "ambulance accident." Characteristics of the accidents were compiled and analyzed. Only ground ambulance accidents were covered.

Results: In Germany, a total of 597 ambulance accidents were recorded, corresponding to 0.719 (95% CI 0.663-0.779) per 100,000 inhabitants; 453 of these accidents left 1170 people injured, corresponding to 1.409 (95% CI 1.330-1.492) per 100,000 inhabitants, and 28 of these accidents caused 31 fatalities, corresponding to 0.037 (95% CI 0.025-0.053) per 100,000 inhabitants. In Austria, a total of 62 ambulance accidents were recorded, corresponding to 0.698 (95% CI 0.535-0.894) per 100,000 inhabitants; 47 of these accidents left 115 people injured, corresponding to 1.294 (95% CI 1.068-1.553) per 100,000 inhabitants, and 6 of these accidents caused 7 fatalities, corresponding to 0.079 (95% CI 0.032-0.162) per 100,000 inhabitants. In Switzerland, a total of 25 ambulance accidents were recorded, corresponding to 0.293 (95% CI 0.189-0.432) per 100,000 inhabitants; 11 of these accidents left 18 people injured, corresponding to 0.211(95% CI 0.113-0.308) per 100,000 inhabitants. There were no fatalities. In each of the three countries, the majority of the accidents involved another car (77%-81%). In Germany and Switzerland, most accidents occurred at an intersection. In Germany, Austria, and Switzerland, 38.7%, 26%, and 4%, respectively, of ambulance accidents occurred at intersections for which the ambulance had a red light ($P<.001$). In all three countries, most of the casualties were staff and not uncommonly a third party. Most accidents took place on weekdays and during the daytime. Ambulance accidents were evenly distributed across the four seasons. The direction of travel was reported in 28%-37% of the accidents and the patient was in the ambulance approximately 50% of the time in all countries. The cause of the ambulance accidents was reported to be the ambulance itself in 125 (48.1% of accidents where the cause was reported), 22 (42%), and 8 (40%) accidents in Germany, Austria, and Switzerland, respectively ($P=.02$), and another vehicle in 118 (45.4%), 29 (56%), and 9 (45%) accidents, respectively ($P<.001$). A total of 292 accidents occurred while blue lights and sirens were used, which caused 3 deaths and 577 injuries.

Conclusions: This study draws attention to much needed auxiliary sources of data that may allow for creation of a contemporary registry of all ambulance accidents in Austria, Germany, and Switzerland. To improve risk management and set European standards, it should be mandatory to collect standardized goal-directed and representative information using various sources (including the wide range presented by the press and social media), which should then be made available for audit, analysis, and research.

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KEYWORDS

ambulance accidents; ambulance collisions; ambulance crashes; media-based; media-based review; newspaper review; Austria; Germany; Switzerland; German-speaking European countries; retrospective; cross-sectional; review; ambulance; accident; data; media; newspaper

Introduction

Ambulances respond to medical emergencies worldwide. Such emergencies often include hazardous processes and environments for the personnel, patients, and bystanders [1,2]. Unfortunately, ambulances can also be involved in accidents, leading to additional injured people and even fatalities. A representative example is an accident in Thun, Switzerland, where a delivery van collided with an ambulance using blue lights and sirens on the way to a patient. This must have been a high-impact collision at the intersection, because the ambulance overturned and skidded to a standstill. Two ambulance staff members and the delivery van driver were injured. Another two ambulances brought the three injured individuals to hospital for evaluation. The police reported considerable disruption due to the central location of the accident site. The surrounding roads were temporarily closed and traffic was diverted. Many police patrols, the fire brigade, the military, the Federal Roads Office, and a tow truck were present at the scene of the accident (Figure 1) [3].

Figure 1. Collision of a delivery van with an ambulance using blue lights and sirens on the way to a patient in Thun, Switzerland. Photo: Michael Gurtner.

Austria, Germany, and Switzerland have comparable organizational structures and response systems for ambulance services, which are provided by multiple emergency service providers in each city, municipality, or region. Austrian Ambulance Emergency Services (AAES) are organized individually by each of the nine federal states and by some cities (Vienna and Graz). The AAES is efficiently coordinated between private organizations and other providers in each area. Germany also organizes emergency ambulance and health services internally in each of the 16 federal states via more than one public and/or private provider of emergency services.

In Switzerland, the responsibility and organization of emergency ambulance response services rest with each canton and some individual municipalities. Switzerland stores the information on all emergency service accidents (police, fire brigade, and other) in central databases, which makes it difficult to analyze the data for ambulances alone, thereby hindering data analysis to improve the safety of patients, passengers, and the public. The lack of appropriate data from the responsible institutions is not a unique problem. For example, Chester et al [4] experienced similar difficulties when trying to obtain helicopter accident data from 1987 to 2014 for the United Kingdom, Germany, and the United States. Certain states in the United States and other parts of the world have systems in place for data collection and analysis of ambulance accidents/crashes [5-8]. Nevertheless, Sanddal et al [9] found that these data are often not accessible for further research. In Austria, Germany, and Switzerland, published research on ambulance accidents is very limited. Given that so little has been published for each individual country, an alternative information source needs to be explored. This study was therefore based on analysis of media reports, which positions itself as the most accessible and relevant source.

For many years, various media types have become a major source of information for the vast majority of the population. The media provide significant news coverage that is of public interest. The first weekly newspaper in the world was printed in 1604 in Strasbourg, which was then part of the Holy Roman Empire. In the early 1900s, a retired mechanical engineer, Hugh DeHaven, collected data from newspapers, magazines, and journals on the mechanisms of death and injuries due to airplanes, as well as human and vehicular accidents. This was a remarkable accomplishment, since he had received no institutional support. DeHaven is thus considered to be the "father of crashworthiness research." Together with medical institutions, he encouraged and lobbied for crash injury studies aiming to increase the safety of aircrafts and cars by providing relevant information to production engineers and manufacturers [10]. Media-based research is increasingly used as an information source, including selfie-related deaths, which would only be reported in the media [11-13]. Woodcock [14] further studied the contributing factors to amusement park ride accidents, as reported by the media. Sandal et al [9] extended their initial peer-reviewed publication to identify the factors involved in rural ambulance accidents by including the popular press for more descriptive data. Since 1997, medical internet research as an entity has been represented and published electronically in a dedicated peer-review online journal [15]. Reporters such as Herrnkind have indicated that ambulance collisions may not be so uncommon; for example, in 2017, the Stern newspaper commented "Every few days it crashes" [16,17].

We failed to find published reviews on the outcome and factors involved in ambulance accidents in Austria, Germany, and Switzerland. To our knowledge, no research has compared ambulance accidents in Austria, Germany, and Switzerland, nor have the media been used as a data source to investigate these incidents. Information in daily web-based free newspapers is easily accessible and is of interest to researchers, the public, and the local press. This review is therefore a retrospective study of web-based newspaper articles reporting ambulance accidents in the main three German-speaking European countries for the period between January 2014 and January 2019. The objective was to extract, analyze, and compare data from online newspaper articles on ambulance accidents for these countries. We hope to highlight the deficit in research data and official registers relevant for the prevention of future accidents with ambulance and emergency vehicles. Extractable and comparable data would go a long way toward identifying the cause of ambulance accidents. In turn, this may allow additional protocols to be implemented for the prevention of future ambulance and emergency vehicle accidents.

Methods

Data were collected from articles in web-based daily free newspapers, as listed in Wikipedia for Germany, Austria, and Switzerland [18-20]. All included newspapers were searched for articles reporting ambulance accidents in the three countries between January 2014 and January 2019, using the following German search terms: "Ambulanz," "Rettungswagen," "Rettungsauto," "Krankenwagen," "Unfall Ambulanz," "Unfall Rettungswagen," "Unfall Rettungsauto," and "Unfall Krankenwagen." These terms represent "ambulance" and "ambulance accident" in the English language. In Switzerland, the search of French, Italian, and Rhaeto-Romansh newspapers was performed in the relevant languages. If accidents were reported in multiple newspapers, the article that provided the most data was used or data were extracted from more than one article when the data were cumulative. Some accidents involving ambulances were reported in newspapers requiring a subscription fee to access the relevant article; these were excluded unless such incidents were published in free online newspapers. A considerable number of listed newspapers are managed by the same publisher and rerouted to identical websites. The research data were obtained from a total of 203 daily online newspapers. Only ground ambulance accidents were covered in this study.

Data compiled included the number of accidents reported, number of people transported by the ambulance, number of people involved in the accident (including other vehicles and/or pedestrians), outcome of the people involved in the accident (injury or death), environmental demographics, destination of the ambulance, possible use of blue light and/or siren, people involved in the ambulance accident (staff, patients, or bystanders), date, day of the week, time of day, place/type of road/type of intersection, traffic signals, and the cause of the accident. Data that were not available in a newspaper article are described as "unknown."

The above characteristics were analyzed using Microsoft Excel for Mac (Version 16.47, Microsoft Corporation) and Stata 16.1 (StataCorp). Associations of categorical variables and countries were evaluated using the χ^2 test. Continuous variables between countries were compared using the Kruskal-Wallis test.

Results

Extensive data were gathered from online newspapers between January 2014 and January 2019 (Table 1).

Table 1. Ambulance accidents in Germany, Austria, and Switzerland.

State/canton	Ambulance accidents, n (%)[a]	Inhabitants in 2018, n	Accidents/100,000 inhabitants (95% CI)
Germany			
Baden Wurttemberg	105 (17.6)	11,069,533	0.949 (0.767 to 1.130)
Bavaria	144 (24.1)	13,076,721	1.101 (0.921 to 1.281)
Berlin	38 (6.4)	3,644,826	1.043 (0.711 to 1.374)
Brandenburg	9 (1.5)	2,511,917	0.358 (0.124 to 0.592)
Bremen	7 (1.2)	682,986	1.025 (0.266 to 1.784)
Hamburg	11 (1.8)	1,841,179	0.597 (0.244 to 0.555)
Hesse	25 (4.2)	6,265,809	0.399 (0.243 to 0.555)
Lower Saxony	45 (7.5)	7,982,448	0.564 (0.399 to 0.728)
Mecklenburg-Western Pomerania	10 (1.7)	1,609,675	0.621 (0.236 to 1.006)
North Rhine-Westphalia	120 (20.1)	17,932,651	0.669 (0.549 to 0.789)
Rhineland-Palatinate	16 (2.7)	4,084,844	0.392 (0.200 to 0.584)
Saarland	10 (1.7)	990,509	1.010 (0.384 to 1.635)
Saxony	18 (3.0)	4,077,937	0.441 (0.237 to 0.645)
Saxony-Anhalt	22 (3.7)	2,208,321	0.996 (0.580 to 1.413)
Schleswig-Holstein	14 (2.4)	2,896,712	0.483 (0.230 to 0.736)
Thuringia	3 (0.5)	2,143,145	0.140 (0.000 to 0.298)
Total	597 (100.0)	83,019,213 [21][b]	0.719 (0.661 to 0.777)
Total accidents causing injury	453 (75.9)	83,019,213	0.546 (0.495 to 0.596)
Total accidents causing death	28 (4.7)	83,019,213	0.034 (0.021 to 0.046)
Austria			
Burgenland	2 (3)	292,675	0.683 (0.000 to 1.630)
Carinthia	8 (13)	560,898	1.426 (0.438 to 2.415)
Lower Austria	5 (8)	1,670,668	0.299 (0.037 to 0.562)
Salzburg	3 (5)	552,579	0.543 (0.000 to 1.157)
Styria	14 (23)	1,240,214	1.129 (0.538 to 1.720)
Tyrol	5 (8)	75,114	6.657 (0.822 to 12.491)
Upper Austria	15 (24)	1,473,576	1.018 (0.503 to 1.533)
Vienna	4 (6)	1,888,776	0.212 (0.004 to 2.757)
Vorarlberg	6 (10)	391,741	1.532 (0.306 to 2.757)
Total	62 (100)	8,888,775 [22][b]	0.698 (0.524 to 0.871)
Total accidents causing injury	47 (76)	8,888,775	0.529 (0.378 to 0.680)
Total accidents causing death	6 (10)	8,888,775	0.068 (0.013 to 0.122)
Switzerland			
Appenzell Outer-Rhodes	2 (8)	55,234	3.621 (0.000 to 8.639)
Basel-Country	1 (4)	287,032	0.348 (0.000 to 1.031)
Berne	5 (20)	1,034,977	0.483 (0.060 to 0.907)
Grisons	1 (4)	198,379	0.504 (0.000 to 1.492)
Lucerne	1 (4)	409,557	0.244 (0.000 to 0.723)
Solothurn	1 (4)	273,194	0.366 (0.000 to 1.083)
St Gallen	7 (28)	507,697	1.379 (0.357 to 2.400)

State/canton	Ambulance accidents, n (%)[a]	Inhabitants in 2018, n	Accidents/100,000 inhabitants (95% CI)
Ticino	1 (4)	353,343	0.283 (0.000 to 0.838)
Zug	3 (12)	126,837	2.365 (0.000 to 5.042)
Zurich	3 (12)	1,520,968	0.197 (–0.026 to 0.420)
Total	25 (100)	8,544,527 [23][b]	0.293 (0.178 to 0.407)
Total accidents causing injury	11 (44)	8,544,527	0.129 (0.053 to 0.205)
Total accidents causing death	0 (0)	8,544,527	0.000 (0.000 to 0.000)

[a]Due to rounding, percentages may not add up to 100.

[b]References [21-23] represent the population of each country in 2018.

German newspapers reported a total of 597 ambulance accidents, corresponding to 0.719/100,000 inhabitants. In total, 453 of these accidents left 1170 people injured, corresponding to 1.409/100,000 inhabitants; 28 of these accidents caused 31 fatalities, corresponding to 0.037/100,000 inhabitants. Austrian newspapers reported a total of 62 ambulance accidents, corresponding to 0.698 /100,000 inhabitants. In total, 47 of these accidents left 115 people injured, corresponding to 1.294/100,000 inhabitants; 6 of these accidents caused 7 fatalities, corresponding to 0.079/100,000 inhabitants. Swiss newspapers reported a total of 25 ambulance accidents, corresponding to 0.293/100,000 inhabitants. A total of 11 of these accidents left 18 people injured, corresponding to 0.211/100,000 inhabitants. There were no fatalities (Table 1 and Table 2).

For each accident with an ambulance, on average two people were injured, except in Switzerland reporting a lower rate of 0.72 injured per accident. In all three countries, most of the casualties were staff and, not uncommonly, a third party. In Austria and Germany, ambulance accidents caused the death of a third party, patient, and staff in over 50%, 30%, and 13% of cases, respectively. Two children succumbed in these accidents in Germany. According to our data, the fatal ambulance accident incidence per 100,000 inhabitants was 0.034 for Germany, 0.068 for Austria, and zero for Switzerland (Table 2).

The newspaper articles also reported whether only blue light, sirens alone, or both blue light and sirens were used by the ambulance. The highest number of accidents with both blue light and sirens was reported in Germany, followed by Switzerland and Austria ($P<.001$). Blue light alone was reported to be used in 71 (12% of total accidents), 7 (11%), and 3 (12%) accidents in Germany, Austria, and Switzerland, respectively ($P=.01$). Sirens alone were recorded during one transport by ambulance in Germany and one in Austria; 291 ambulance accidents during which blue light and sirens were used caused 3 deaths and 573 injuries in total (Table 2). The absence of sirens or blue light was also mentioned in some newspaper accounts.

Table 2. Injuries and fatalities reported in Germany, Austria, and Switzerland.[a]

Accidents reported	Germany (n=597)	Austria (n=62)	Switzerland (n=25)	*P* value
Accidents causing injury				
Total, n (%)	453 (75.9)	47 (76)	11 (44)	<.001
Injured (cumulative), n	1170	115	18	
Staff, n (%)	537 (45.9)	47 (41)	8 (44)	
Third party, n (%)	217 (18.6)	8 (7)	8 (44)	
Patient, n (%)	113 (9.7)	12 (10)	2 (11)	
Children, n (%)	7 (0.6)	3 (3)	0 (0)	
Not reported	296 (25.3)	45 (39)	0 (0)	
Injured persons per accident, mean (95% CI)	1.96 (1.76-2.15)	1.85 (1.49-2.22)	0.72 (0.28-1.16)	<.001
Injured/100,000 inhabitants (95% CI)	1.409 (1.329-1.49)	1.294 (1.057-1.53)	0.211 (0.113-0.308)	<.001
Accidents causing death				
Total, n (%)	28 (4.7)	6 (10)	0 (0)	<.001
Fatalities (cumulative), n	31	7	0	
Third party, n (%)	16 (51.6)	4 (67)	0 (0)	
Patient in the ambulance, n (%)	9 (29.0)	1 (17)	0 (0)	
Staff, n (%)	4 (12.9)	1 (17)	0 (0)	
Children, n (%)	2 (6.5)	0 (0)	0 (0)	
Fatalities per accident, mean (95% CI)	0.052 (0.032-0.072)	0.113 (0.020-0.201)	0	.74
Fatalities/100,000 citizens (95% CI)	0.037 (0.024-0.05)	0.079 (0.02-0.137)	0	<.001
Accidents causing death or injury (/100,000 inhabitants)				
Total, n (%)	461 (77.2)	49 (79.03)	11 (44.99)	<.001
Injured or death/100,000 inhabitants (95% CI)	0.555 (0.505-0.606)	0.551 (0.397-0.706)	0.129 (0.053-0.205)	
Blue light and sirens, n (%)	272 (45.6)	8 (13)	10 (40)	<.001
Blue light and sirens causing death and injury, n (% of all blue light and sirens)	213 (77.6)	8 (100)	7 (70)	.27

[a]Due to rounding, percentages may not add up to 100.

During the investigation period, the number of published ambulance accidents per year remained stable in all countries (*P*=.41)

The majority (77%-81%) of the accidents involved another car (Table 3). In Germany, most accidents occurred at an intersection, junction, or simply on a stretch of road in the city (street). In Austria, accidents most commonly occurred on the street, on a regional road, or at an intersection. For Switzerland, the highest accident incidence was on the street, followed by intersections and highways (Table 3).

Ambulance accidents on the street were further classified (Table 3). Most frequently, street accidents involved turning off or overtaking. For 143 of the 296 ambulance accidents that occurred at an intersection and one at a zebra crossing, the report included whether the traffic light was red or not. In Germany, Austria, and Switzerland, 38.8%, 27%, and 4% of ambulance accidents occurred at intersections for which the ambulance had the red light (*P*<.001). The red traffic light was disobeyed twice by other vehicles and once at a zebra crossing by a child, resulting in a fatality.

Table 3. Collision object, location, and location on the city street of ambulance accidents (N=684).

Accident details	Proportion of reported, n (%)[a]	Proportion of total accidents reported, %[a]
Object the ambulance collided with (n=611)		
Passenger car	489 (80.0)	71.5
Lorry	38 (6.2)	5.5
Person	24 (3.9)	3.5
Two-wheeler	18 (3.0)	2.6
Service car	10 (1.5)	1.5
Tram/train	9 (1.5)	1.3
Object	8 (1.3)	1.2
Bus	7 (1.2)	1.0
Animal	6 (1.0)	0.9
Tractor	2 (0.3)	0.3
Location of the accident (n=649)		
Intersection	296 (45.6)	43.3
Street	192 (29.6)	28.1
City	49 (7.6)	7.2
Regional road	38 (5.9)	5.6
Highway	33 (5.1)	4.8
Bend	25 (3.9)	3.7
Accident site	6 (0.9)	0.9
Other	5 (0.8)	0.7
Railway	3 (0.5)	0.4
Rescue lane	2 (0.3)	0.3
Location on a street in the city (n=80)		
Turning off	45 (56)	6.58
Overtaking	10 (13)	1.46
Driveway	4 (5)	0.58
Exit	4 (5)	0.58
Lane change	4 (5)	0.58
U-turn	2 (3)	0.29
Rescue lane	2 (3)	0.29
Road traffic light	2 (3)	0.29
Zebra crossing	1 (1)	0.15
Roadworks	1 (1)	0.15
While crossing	1 (1)	0.15
Congestion	1 (1)	0.15
Turning in	1 (1)	0.15
Narrowing	1 (1)	0.15
Accident site	1 (1)	0.15

[a]Due to rounding, percentages do not add up to 100.

Ambulance accidents were evenly distributed over the four seasons. Most accidents took place on weekdays, with few accidents occurring at night (between 6:00 pm and 6:00 am).

There was no significant difference between the incidence of ambulance accidents in the three countries with respect to seasons (*P*=.28), weekends (*P*=.56), or time of day (*P*=.64) (Table 4).

The direction of travel of the ambulance at the time of the accident was documented for 268/597 (44.9%), 29/62 (47%), and 9/25 (36%) accidents in Germany, Austria, and Switzerland, respectively (*P*=.64). Whether or not the patient was in the ambulance at the time of the accident was indicated in 54.8%, 74%, and 64% of reports for Germany, Austria, and Switzerland, respectively. Third-party violence caused injury to staff members in four cases in Germany and once for Austria and Switzerland each. In Switzerland, there was a report of one patient causing injury to a staff member (Table 4).

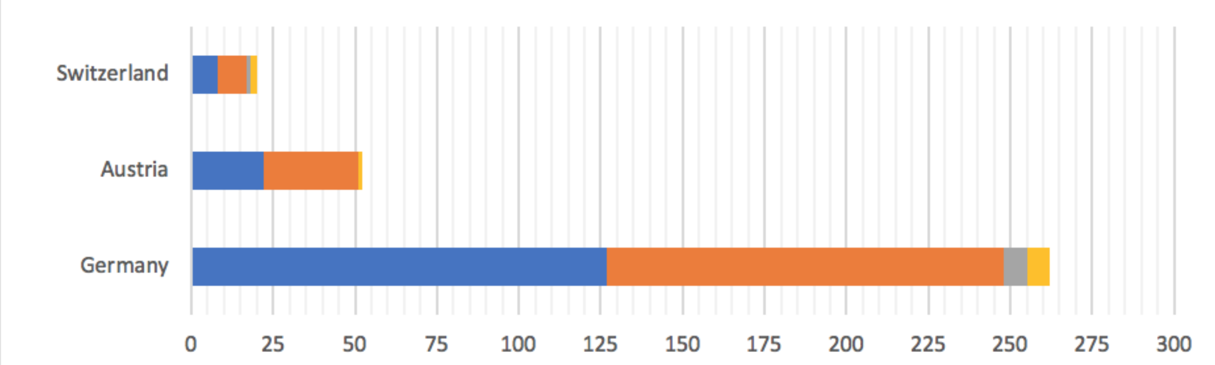
Table 4. Direction of travel, patient in ambulance, violence reported, day of the week, and time of day of the ambulance accidents in Germany, Austria, and Switzerland.

Characteristic of the accident	Germany, n (%)[a]	Austria, n (%)[a]	Switzerland, n (%)[a]	*P* value
Direction of travel				<.001
Total reported cases, n	268	29	9	
To the patient	154 (57.5)	18 (62)	6 (67)	
To the hospital	114 (42.5)	9 (31)	3 (33)	
Other	0 (0.0)	2 (7)	0 (0)	
Patient in ambulance				.79
Total of reported cases, n	327	39	16	
Yes	167 (51.1)	21 (54)	7 (44)	
No	160 (48.9)	18 (46)	9 (56)	
Violence toward staff				<.001
Total of reported cases, n	4	1	2	
Third party	4 (1)	1 (2)	1 (4)	
Patient	0 (0)	0 (0)	1 (4)	
Part of the week				.56
Total of reported cases, n	597	62	25	
Weekdays	458 (76.7)	50 (81)	21 (84)	
Weekend	139 (23.3)	12 (19)	4 (16)	
Time of day				.64
Total of reported cases, n	502	54	21	
Day	369 (72.1)	38 (70)	17 (81)	
Night	143 (27.9)	16 (30)	4 (19)	

[a]Due to rounding, percentages do not add up to 100.

The newspaper reports provided information to determine the cause of ambulance accidents in 43.5%, 83%, and 80% of total cases in Germany, Austria, and Switzerland, respectively (*P*<.001). The cause of the ambulance accidents was reported to be the ambulance itself in 125 accidents in Germany (representing 48.1% of accidents for which the cause was reported), 22 (42%) in Austria, and 8 (40%) in Switzerland (*P*=.52), and by another vehicle in 118 collisions (45.4%) in Germany, 29 (56%) in Austria, and 9 (45%) in Switzerland (*P*=.04) (Figure 2).

Figure 2. Cause of ambulance accidents in Austria, Germany, and Switzerland (*P*=.48).



	Germany	Austria	Switzerland
Ambulance	127	22	8
Other vehicle	121	29	9
Two wheeler	7	0	1
Person	7	1	2

Discussion

Principal Findings

Currently, most countries provide emergency services for their citizens, such as police, fire, rescue, and medical services. Ambulances are equipped to transport patients to and from hospitals and provide initial care for medical and trauma emergencies. An ambulance is not designed for high-speed driving nor are most drivers trained for complicated decision-making during high-speed driving. Unfortunately, ambulance accidents are an element of these emergency services. Auerbach [24] reported that an ambulance accident delays the patient's arrival in hospital by a mean of 9.4 minutes. Notwithstanding an overall decrease in road traffic accidents (RTAs) in the last 10 years, a slight rise has been observed since 2016. This downward trend may be explained (at least partially) by improvements in car safety design and increased use of bicycles. The recent rise may be associated with distractions such as the use of smartphones.

Switzerland exhibited a significantly lower rate of ambulance accidents than Germany and Austria (Table 1). Our data suggest that certain cantons in Switzerland were spared from ambulance accidents. This may be explained by the very low accident rate in Switzerland, the limitations of this study (see below), and the 5-year research window. We are unable to add or draw conclusions nor improve standards because of the limited information available at our relevant institutions. To the best of our knowledge, this study is the first to provide information on ambulance accidents in Austria, Germany, and Switzerland, the three largest German-speaking countries in Europe [25]. This is also the first media-based study to collect information about ambulance crashes in these three countries.

Comparison Between Ambulance Accidents and Overall Road Traffic Fatalities

The International Road Safety Annual Report 2019 reported that the fatality rate from RTAs was 2.7 per 100,000 inhabitants in Switzerland, 3.8 in Germany, and 4.7 in Austria [26,27]. Switzerland represents one of the best outcomes, with under 0.4 deaths per 10,000 cars owned.

According to our data, the incidence of fatal ambulance accidents per 100,000 inhabitants was 0.034 for Germany, 0.068 for Austria, but zero for Switzerland (Table 2). These values correspond to 0.97%, 1.68%, and 0% of total RTAs for Germany, Austria, and Switzerland, respectively. Since our search was restricted to free-access newspapers, the true ambulance accident death rate is probably higher. In each of these three countries, the incidence of ambulance accidents and total RTAs have both tended to decrease in recent years.

The International Road Traffic and Accident Database established that pedestrians and cyclists are most likely to suffer the fatal consequences of an RTA [26]. This is concurrent with ambulance accident injuries and fatalities in the three countries analyzed in this study (Table 2).

Injuries From Ambulance Accidents

For each accident with an ambulance, a mean of nearly two people were injured (Germany, 1.96; Austria, 1.85), except in Switzerland where a rate of 0.72 injured per accident was reported (Table 2). In 1987, Auerbach [24] established that 2.24 injuries occurred per accident in Tennessee. Despite modernization of ambulances, more than 30 years later, these statistics remain very similar. This could also be because minor accidents with ambulances were not reported in the newspapers accessed for this study. Additionally, ambulance design and safety measures for passengers have perhaps not been sufficiently adapted for high-speed driving.

Circumstances of Ambulance Accidents

The data suggest that in Germany and Austria, respectively 39% and 27% of ambulance accidents at intersections happened when a traffic light signaled red for the ambulance. In Switzerland, one accident (4%) took place at a red traffic light. This could be explained by available traffic signal preemption installed in emergency vehicles, which is in force in Switzerland at major intersections to allow ambulances the right of way.

In Austria and Switzerland, the media reported the cause of the accident in over 80% of the ambulance accidents, which then allowed us to categorize the cause of the accidents. The ambulance was implicated in more than half of the reported accidents in all three countries. This validates the need for further research to mitigate ambulance accident rates and the sequelae thereof. Studies have often focused on the analysis of accident prevention by the emergency service provider and institutions through ambulance engineering, driver experience/training, and environmental factors [6-9,28,29].

Blue Lights and Sirens

Both blue lights and sirens were used in approximately 45% of the ambulance crashes in Germany and Switzerland and in 13% of these accidents in Austria. The reason for the lower use in Austria was not quite clear. In other European countries such as the Netherlands, the use of blue lights and sirens is restricted. In Switzerland, injuries occurred in 70% of ambulance accidents where blue lights and sirens were used, which is similar to the values for Germany (77%) and Austria (100%). In Germany, three people died when blue lights and sirens were used. Blue lights and sirens also can be used intermittently, and these signals are typically turned on when priority is needed in difficult traffic scenarios or when high-speed driving is deemed necessary. Sanddal et al [9] reported a 100% injury rate when an ambulance accident occurred while the blue lights and sirens were being used. Lights and sirens often cause a distraction and decrease the auditory awareness of all those who hear the signal, as people then search for the location of the emergency vehicle. An example was an incident when a police car and ambulance were coming from opposite directions and then collided at an intersection; neither vehicle heard the other, because both were driving with their blue light and sirens to the same accident. In 2017, Alexander Stevens, a German lawyer and paramedic, used "Ambulance Accidents–when speeding life savers become a risk" as the theme of his thesis. Stevens concluded that with blue light and sirens, emergency service vehicles were 4 times more likely to cause fatalities, 8 times more likely to cause serious injury, and resulted in a 17 times higher incidence of third-party trauma. Stevens' opinion was that neither the police nor the government recorded how often ambulances were associated with an accident. He also added that the regulations for the activation of blue light and/or sirens were nebulous [30]. However, other studies have found that the higher incidence of ambulance collisions with blue lights and sirens was not statistically significant [31-33]. Missikpode et al [5] did not find an increased risk of accidents when blue lights and sirens were used. Ho and Casey [34] reported that the 3 minutes saved with blue lights and sirens was statistically significant. Additionally, Petzäll et al [35] illustrated that ambulance response time with blue lights and sirens was only 2.9 minutes shorter on urban roads and 8.9 minutes shorter in rural areas. Marques et al [36] established a mean time saved of 2.62 minutes (ranging from 26 minutes faster to 24 minutes slower) and suggested that blue lights and sirens should only be implemented where hospital intervention is required. Saunders and Heye [33] did find that the incidence of injury was higher when blue lights and sirens were used, which then vitiated the time saved. Sandal et al [9] advised the nonuse of blue lights and sirens and policies including use of these signals. It therefore appears that using blue lights and sirens significantly increases the likelihood of ambulance-related trauma, with no discernible or measurable benefit to patient outcome.

Comparison With Other Studies

Reporter Kerstin Herrnkind quoted the only study by the German State Traffic Department reporting on ambulance accidents at the time (2017), which suggested that one fatality had occurred every 5 days due to ambulance accidents [16,17]. The 31 fatalities in Germany over the 5-year period of this study certainly represents a dramatic decrease from the study performed 10 years previously (Table 2). Herrnkind also mentioned the financial impact of these collisions.

A review of the literature for the United States showed that 19% of the fatalities involved patients being transported by ambulance at the time of the accident, 14% were staff, and 67% involved a third party [9]. In this study, we found that in Germany and Austria, 28% of the fatalities were patients, 14% were staff, and 56% a third party. In Austria, one of the two patients was accidentally run over as the ambulance reversed at the accident site.

We collected a wide range of web-based information, which allowed us to allocate accidents to each federal state in Austria and Germany, as well as to specific cantons in Switzerland, and these details could be compared with published international research. As in other countries, the time of the year and the weather did not clearly influence the incidence or occurrence of an ambulance accident [6-8,31,37,38]. However, in contrast to some other studies, we were able to distinguish the day of the week when the accidents occurred. Accidents were less frequent over weekends and at night, which can be explained by the reduced traffic over weekends and no rush hour congestion. By contrast, Ray and Kupas [37] found that ambulances were involved in more accidents than similar nonemergency vehicles over the weekends and at night. Kahn et al [6] also found that bystanders not in the ambulance were more likely to be injured or killed when an ambulance accident occurred. Intersections were the most dangerous place for pedestrians, cars, two-wheelers, children, and ambulances with or without blue lights and sirens (sometimes disobeying a red light) [24,31,33,37,38]. Our study reproduced these findings for Austria (but not for Germany) where mostly staff members were injured. This suggests that standard national procedures have not put sufficient focus on the safety of the staff. Reichard et al [39] noticed that injury events for emergency medical service workers were vehicle accidents in 8% of cases and assault and violence in 7% of cases.

Custalow [38] found that the risk of injury was higher at intersections. She advocated a safe slow approach, ensuring that other parties have stopped and maintaining eye contact at intersections where visibility may be relatively reduced in cities. Seatbelt use in the rear of the ambulance and insecurely fastened equipment were implicated in injuries to staff [23,27].

A psychiatric patient created a hazardous situation on the way to the hospital that resulted in two staff members being injured and the public endangered. The patient was unaccompanied and their behavior was unexpected. Media representation of events is not always a factually unbiased representation of true events. Cuijpers and Brown [40] have analyzed the representation of systemic and symbolic violence toward ambulance personnel.

Data Collection and the Internet

Real-time use of Google News and other news platforms may increase the accuracy and validity of data collected. Google News and some online newspapers offer an archive of the preceding year only. Consequently, we were not able to enhance our data collection by using Google News. For Switzerland, Google News was limited to the French and German regions. Google Trends provided search-trend information for Germany only and the German word "krankenwagen" (ambulance), because too few searches were conducted on this subject in Austria and Switzerland. Peaks were observed in November 2015, 2016, and 2018, which presented no correlation to the incidence of ambulance accidents as reported in the daily online newspapers.

Social media (Twitter feeds, chatrooms, LinkedIn, WhatsApp groups, blogs) may broaden data sources on ambulance accidents and increase awareness [41]. Recruitment of participants for medical research is omnipresent and some research groups have found social media to be helpful in recruitment for their studies [42]. The use of platform strategies (homebases, embassies, and listening posts) can assist knowledge translation and dissemination. An important aspect is that Twitter hashtags (words or phrases prefixed with "#"), word clouds, and visual abstracts particular to each topic may be created to engage and connect similar-minded researchers, experts, and coaches to enhance the quality of the research and analysis performed [41,43]. A word cloud is a visual representation of the word frequency in a given text. Word cloud creation may also help find and validate the search terms and results. Before standard traditional content analysis is used, word clouds may help researchers achieve a quick and basic understanding of the resulting data [44]. Realistic caution and suspicion about the quality of online resources is necessary if professional standards are to be maintained within conducted research [43].

Limitations

The first and probably most obvious limitation of this study is that not all newspapers were searched, as we accessed free web-based newspapers only. Notwithstanding the unknown proportion of missed ambulance accidents, we assume that this is low, as the daily regional free newspapers would report these newsworthy (sometimes sensational) ambulance accidents. Conversely, and yet for the same reason, minor ambulance accidents could be underreported.

Additionally, information is not very specific or uniform, and incidents are often reported by nonclinical, nonresearch personnel. Therefore, we cannot accurately reflect the true incidence, causes of these accidents, nor the cause of injury or death in Austria, Germany, and Switzerland. No causal, contributing, or interrelated factors could be isolated or interpreted from the newspaper articles. Several factors that have been shown to increase the risk of death and injury, such as whether the injured person was in the front or back of the ambulance, ambulance speed, human factors, and use of a seatbelt in the front and back of the ambulance (less relevant today), could not be assigned to each injured person, fatality, or even the ambulance accident itself [2,6,45]. Taken together, this limits the thoroughness and quality of the information for policy creation, changes, or their implementation.

The location of the accident was not subdivided into rural and urban ambulance accidents, since this distinction is not clearly defined in the literature at present [7,37].

The World Press Freedom Index 2020 ranks Switzerland, Germany, and Austria in 8th, 11th, and 18th position in the world, respectively, regarding the liberty of expression in the press. However, research still needs to be undertaken to study how representative the media is of the true population for ambulance accidents in these countries.

Furthermore, we were unable to compare the ambulance accident data collected from this media-based review with the information collected by local, regional, or national institutions in these countries. Such information is not freely available and special permission would be necessary to access and analyze such data. In this light, we could not calculate the incidence of ambulance accidents per total number of ambulance callouts, since the information is not easily obtainable from the relevant institutions. Nonetheless, we did not actively seek access to national protocols, safety directives, or the rights of emergency vehicles with or without blue lights and sirens to effectively interpret and compare with the media-based information obtained for Austria, Germany, and Switzerland.

Illustrations often accompany an article covering an ambulance accident. We only used the written article and annotations to the image for data collection. Photographs can provide additional data (eg, time of day, weather, location, whether blue lights and sirens were used). Despite this, the timing, size, and field covered by the photograph can be misleading and the extrapolated data may be incorrect.

Long-term sequelae and costs related to the ambulance accident reports were not investigated, because this information may not be available or easy to find in the media.

Conclusion

An ambulance accident delays the definitive treatment of a patient, can exacerbate or cause further injury, and proves to be an expensive outcome. Additionally, such accidents compromise trust in public safety. However, despite the reports of such incidents in the media, public trust appears to remain intact. This raises the question as to whether the public has a choice. Neither the public nor law enforcement insists on further investigation or improvement in the safety of all parties involved. The numbers are relatively small and perhaps not of consequence among other causes of deaths and injuries; nevertheless, the incidence can certainly be decreased. Contributing factors have not been optimally researched and analyzed in German-speaking countries. Goal-directed controls and protocols to decrease or even avoid accidents and their costly repercussions are desperately needed.

The internet, the media, and social media together present medical research with many possibilities such as data collection, telemedicine, open-access peer-reviewed journals, and online education, along with the rapid evolution of artificial intelligence. Many accidents are already prevented by advanced driver-assistance systems, traffic signal preemption by emergency vehicles, protocols, driver training, and traffic rules signposted to guide motorists when emergency vehicles with blue lights and sirens are in proximity. Intelligent vehicle signal communication is implemented in Austria, Germany, and Switzerland. In the future, artificial intelligence may be able to predict and, alongside simulation training, help to decrease the incidence of ambulance accidents. In Europe, since 2018, eCall112 is a mandatory vehicle sensor installation, which activates an automatic call initiating an audio channel between the vehicle and the most appropriate emergency center. Perhaps eCall112 should be installed in all ambulances and the details stored in a specific database only for ambulance accidents. Smartphone apps may now be used to collect information from people present at the time of an ambulance accident and educate the general public with updated real-time use of basic life support.

Further information available in the media through apps and telemedicine can also be used to decrease the urgent nature of an ambulance call, thus decreasing the morbidity and mortality associated with ambulance accidents. However, this can only be achieved through governance of the vastly increasing online information and platforms.

In Germany, Austria, and Switzerland, ambulance drivers are accountable for damages, injury, or death caused by nonadherence to traffic regulations when responding to an emergency call. This is not always equitable. The data collection and analysis in this study may seem insufficient, but nevertheless directs us to auxiliary data sources that may allow for the creation of up-to-date registers of all ambulance accidents in Austria, Germany, and Switzerland. To improve risk management and establish European standards, it must be mandatory to collect standardized and accurate representative information using a variety of sources (press and modern strategies such as social media platforms, blogs, and targeted news groups). The control of the information concerning the accuracy of the data needs to be further researched before such analyses are performed and subsequent strategies are applied in practice. As a next step, this information should be made available for audit, analysis, and research purposes. Future research should analyze the array of human, engineering, environmental, organizational, and political factors that impact the balance between the outcome and safety of the patient, the staff, and the people present at the perimeter of an ambulance call.

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Conflicts of Interest

None declared.

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Abbreviations

AAES: Austrian Ambulance Emergency Services
RTA: road traffic accident

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Original Paper

Investigating Unhealthy Alcohol Use As an Independent Risk Factor for Increased COVID-19 Disease Severity: Observational Cross-sectional Study

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Abstract

Background: Unhealthy alcohol use (UAU) is known to disrupt pulmonary immune mechanisms and increase the risk of acute respiratory distress syndrome in patients with pneumonia; however, little is known about the effects of UAU on outcomes in patients with COVID-19 pneumonia. To our knowledge, this is the first observational cross-sectional study that aims to understand the effect of UAU on the severity of COVID-19.

Objective: We aim to determine if UAU is associated with more severe clinical presentation and worse health outcomes related to COVID-19 and if socioeconomic status, smoking, age, BMI, race/ethnicity, and pattern of alcohol use modify the risk.

Methods: In this observational cross-sectional study that took place between January 1, 2020, and December 31, 2020, we ran a digital machine learning classifier on the electronic health record of patients who tested positive for SARS-CoV-2 via nasopharyngeal swab or had two COVID-19 International Classification of Disease, 10th Revision (ICD-10) codes to identify patients with UAU. After controlling for age, sex, ethnicity, BMI, smoking status, insurance status, and presence of ICD-10 codes for cancer, cardiovascular disease, and diabetes, we then performed a multivariable regression to examine the relationship between UAU and COVID-19 severity as measured by hospital care level (ie, emergency department admission, emergency department admission with ventilator, or death). We used a predefined cutoff with optimal sensitivity and specificity on the digital classifier to compare disease severity in patients with and without UAU. Models were adjusted for age, sex, race/ethnicity, BMI, smoking status, and insurance status.

Results: Each incremental increase in the predicted probability from the digital alcohol classifier was associated with a greater odds risk for more severe COVID-19 disease (odds ratio 1.15, 95% CI 1.10-1.20). We found that patients in the unhealthy alcohol group had a greater odds risk to develop more severe disease (odds ratio 1.89, 95% CI 1.17-3.06), suggesting that UAU was associated with an 89% increase in the odds of being in a higher severity category.

Conclusions: In patients infected with SARS-CoV-2, UAU is an independent risk factor associated with greater disease severity and/or death.

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KEYWORDS

unhealthy alcohol use; COVID-19; SARS-CoV-2; acute respiratory distress syndrome; substance misuse; mechanical ventilation; substance use

Introduction

In patients with COVID-19, age, obesity, smoking, and chronic comorbidities are risk factors that impact the rate of contracting COVID-19 and severity of infection; however, a significant number of patients without these comorbidities also develop severe disease [1,2]. This suggests that additional risk factors may promote an exaggerated immune response to the virus. Alcohol is the most common drug used in the United States and its use has increased during the COVID-19 pandemic [3,4]. Unhealthy alcohol use (UAU) is known to interrupt pulmonary immune mechanisms and can lead to increased rates of viral pneumonia and progression into acute respiratory distress syndrome (ARDS) [5]. Chronic alcohol consumption also causes severe oxidative stress that may lead to an increased susceptibility for sepsis-mediated ARDS [6]. Despite the known deleterious effect of alcohol use on the pulmonary immune system, many of the early large studies performed on patients with COVID-19 did not include alcohol use history [7]. Furthermore, a meta-analysis of six studies found that alcohol use did not impact the severity of COVID-19 infection [8]. The studies described in this meta-analysis all originate from China, and among the major limitations is a purely clinical assessment of UAU (without validated measures). Another prospective cohort study in the United Kingdom examined the relationship between lifestyle risk factors (physical inactivity, smoking, obesity, and UAU) and COVID-19 infection and found that UAU was not related to COVID-19 disease [9]. A more recent study in the United States suggested that the alcohol lung represents a very likely comorbidity for the negative consequences of both COVID-19 susceptibility and severity [10]. Generally, research on alcohol and substance use has been limited by small samples with the use of validated measures or large samples reliant on International Classification of Disease, 10th Revision (ICD-10) codes. The latter is believed to severely underreport UAU and substance misuse. Due to the sparse evidence and conflicting theories, we aim to further study the interaction between UAU and COVID-19 disease severity using a novel approach to identify UAU and we believe that these results will better inform treatment management of at-risk patients.

Methods

Recruitment

Males and females aged ≥18 years who tested positive for SARS-CoV-2 via a nasopharyngeal swab or had two COVID-19 ICD-10 codes at Rush University Medical Center between January 1, 2020, and December 31, 2020, were included in this observational cross-sectional study. Patients younger than 18 years of age were excluded from the study. This study was approved by the Rush University Medical Center Institutional Review Board (17090601-IRB02) and informed consent was waived. Demographic data were extracted from the electronic health record (EHR) including sex, age, BMI, and race/ethnicity (Table 1). Each patient's COVID-19 severity was determined by the maximal level of care they received. COVID-19 severity categories were defined as the following: (1) emergency department admission without need for a ventilator; (2) emergency department admission requiring use of a ventilator; and (3) death.

To identify cases of UAU, we used a digital machine learning classifier that was applied to all clinical notes in the EHR [11]. Free-text clinical notes containing details about a patient's behavioral conditions were used to feed the alcohol misuse digital classifier with methods of natural language processing with supervised machine learning to predict a patient's probability of UAU. The classifier has demonstrated excellent ability to predict alcohol misuse based on validation against ICD-10 codes as well as manual annotation of charts. A study that is presently under review has also found that the classifier is accurate, using the Alcohol Use Disorders Identification Test (AUDIT) as the reference standard. A higher predictive probability was previously shown to indicate a greater likelihood of UAU and had a dose-dependent correlation with severity of UAU [11]. For analysis, the predicted probabilities were log-transformed to account for their non-normal distribution. The probability of having UAU as determined by the classifier was entered into the model examining the association with the primary outcome.

Statistical Analysis

To account for patients with repeat hospital encounters, we performed mixed effects ordinal logistic regression analysis with random intercepts to predict a patient's COVID-19 severity group. Additionally, we performed two sensitivity analyses to assess the robustness of the classifier in predicting outcome severity across different parameterizations. In the first analysis, patients were categorized into alcohol/nonalcohol groups and the mixed effects ordinal logistic regression was used to predict COVID-19 severity. In the second analysis, severity outcome was dichotomized into two categories to represent severity of disease by hospital disposition: (1) emergency department admission without requiring a ventilator and (2) emergency department admission requiring the use of a ventilator or death. All analyses controlled for age, sex, ethnicity, BMI, smoking status, insurance status, and presence of ICD-10 codes for cancer, cardiovascular disease, and diabetes. We further explored interactions between the classifier and these demographic characteristics to assess potential moderation by these variables. All analyses were conducted using a significance level of .05 in Python (version 3.9.0; Python Software Foundation) and Stata (version 17; StataCorp LLC).

Results

In total, 3480 patients, who accounted for 4134 hospital encounters, were included for analysis. Overall patient characteristics are depicted in Table 1. We found that as the probability of predicting UAU increases, so does the risk for poor health outcomes (odds ratio 1.24, 95% CI 1.14-1.37; Figure 1). Age, sex, and BMI were also associated with COVID-19 severity status, but smoking status, ethnicity, insurance status, or presence of other health condition codes were not (Table 2). No interactions between classifier status and demographic variables were significant (*P*>.40). When we dichotomized patients' classifier status into those with UAU and those without, we found that this dichotomous classification was also associated with COVID-19 severity (odds ratio 1.85, 95% CI 1.11-3.09; see Table S1 in Multimedia Appendix 1). The distribution of hospital admission type stratified by patients' alcohol misuse status is depicted in Figure 2. Of the patients with alcohol misuse, 67.8% (61/90) were inpatient admissions from the emergency department (ED), 22.2% (20/90) were admitted through the ED and required a ventilator during their hospitalization, and 10.0% (9/90) died (Figure 2). Of the patients with no alcohol misuse, 81.4% (3292/4042) were inpatient ED admissions, 10.8% (437/4042) were admitted through the ED and required a ventilator during their hospitalization, and 7.8% (313/4042) died (Figure 2). The ability for alcohol classifier status to predict COVID-19 severity was also robust to reparameterization of severity into two severity categories, as the alcohol classifier estimate was associated with increased odds of ventilation or death in the dichotomous outcome model (odds ratio 1.15, 95% CI 1.09-1.22; see Table S2 in Multimedia Appendix 1).

Table 1. Patient characteristics from an observational cross-sectional study of patients diagnosed with COVID-19 conducted in Chicago, Illinois, between January 1, 2020, and December 31, 2020, investigating the relationship between alcohol use and COVID-19 disease severity.

Demographics	Values
Age (years), mean (SD)	59.15 (17.52)
Sex, n (%)	
Male	1793 (51.52)
Female	1687 (48.48)
Race/ethnicity, n (%)	
Non-Hispanic White	713 (20.49)
Non-Hispanic Black	1447 (41.58)
Hispanic	1010 (29.02)
Other	310 (8.91)
BMI, mean (SD)	31.62 (10.18)
Smoking status, n (%)	
Never smoker	1631 (61.22)
Quit	815 (30.59)
Current smoker (some days)	61 (2.29)
Current smoker (every day)	157 (5.89)
Length of hospital stay (days), mean (SD)	8.39 (9.28)
Minimum oxygen saturation (%), mean (SD)	81.04 (18.34)
Insurance status, n (%)	
Medicaid	1268 (36.44)
Medicare	1099 (31.58)
Private	817 (23.48)
Other	296 (8.51)
International Classification of Disease, n (%)	
Cancer	117 (3.36)
Cardiovascular	393 (11.29)
Diabetes	215 (6.18)

Figure 1. Increased likelihood of unhealthy alcohol use (determined by a digital machine learning classifier) in patients diagnosed with COVID-19 at a large academic hospital in Chicago, Illinois, between January 1, 2020, and December 31, 2020, was associated with more severe disease outcomes as measured by hospital admission status (odds ratio 1.24, 95% CI 1.14-1.37; *P*<.001). ED: emergency department.

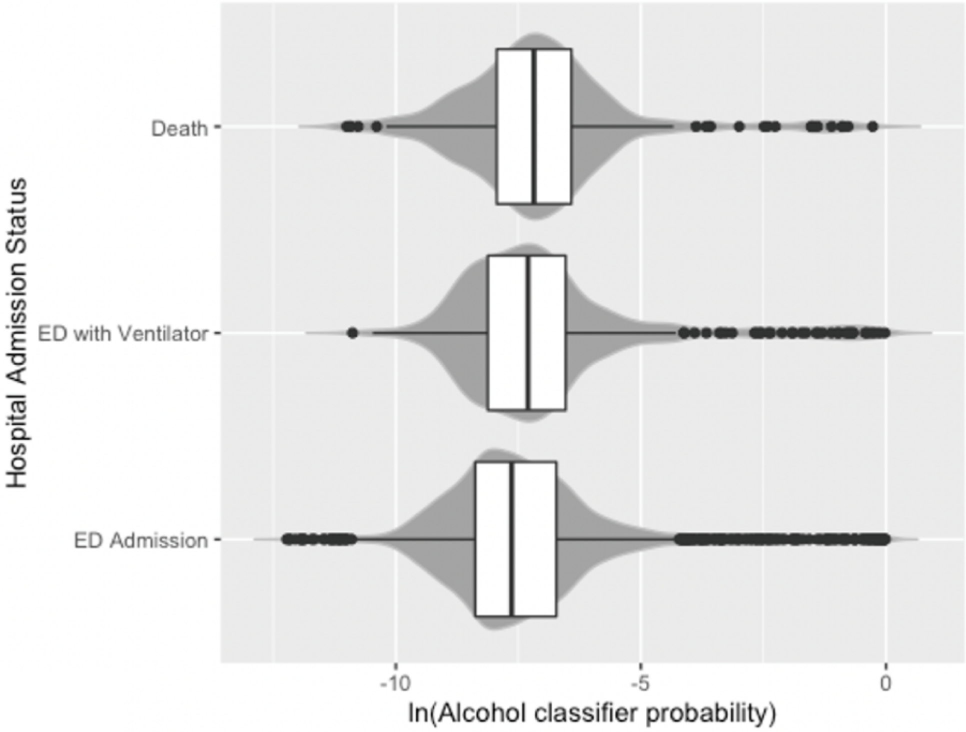
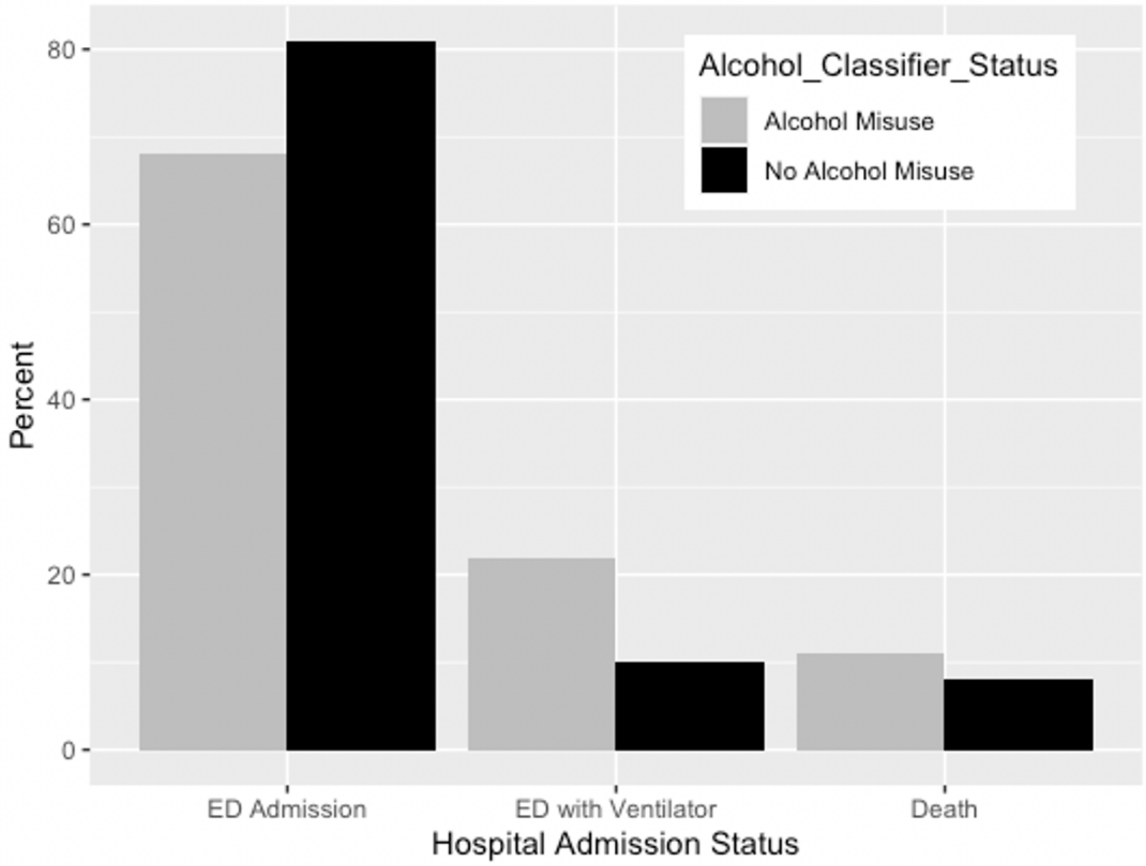


Table 2. Adjusted associations between risk factors and severity of COVID-19 in patients diagnosed with COVID-19 at a large academic hospital in Chicago, Illinois, between January 1, 2020, and December 31, 2020 (N=4134).

Predictor	Unhealthy alcohol use	No unhealthy alcohol use	Odds ratio	95% CI	*P* value
Alcohol classifier, n	90	4044	1.24	1.14-1.37	<.001
Age	N/A[a]	N/A	1.02	1.01-1.03	<.001
Mean age (SD), years	59.58 (17.29)	50.12 (18.07)	N/A	N/A	
Sex, n			0.64	0.49-0.85	.002
Male	66	2050	N/A	N/A	
Female	24	1994	N/A	N/A	
Race/ethnicity, n					
Non-Hispanic White	18	823	Reference		
Non-Hispanic Black	42	1715	0.95	0.68-1.35	.79
Hispanic	24	1171	1.17	0.81-1.70	.41
Other	6	335	1.46	0.88-2.41	.14
BMI, mean (SD)	31.71 (10.20)	26.93 (7.73)	1.02	1.01-1.04	.001
Smoking status, n					
Never smoker	22	1885	Reference		
Quit	18	1001	0.85	0.67-1.08	.25
Current smoker (some days)	6	68	0.59	0.27-1.27	.07
Current smoker (every day)	17	161	1.14	0.75-1.75	.13
Insurance status, n					
Medicaid	51	1429	Reference		
Medicare	11	1387	0.83	0.60-1.15	.25
Private	10	909	0.73	0.52-1.03	.07
Other	18	319	0.68	0.41-1.11	.13
International Classification of Disease, n					
Cancer	0	142	0.49	0.22-1.08	.08
Cardiovascular	3	476	0.76	0.51-1.13	.17
Diabetes	1	265	1.1	0.68-1.77	.70

[a]N/A: not applicable.

Figure 2. Hospital admission status for 3480 patients in Chicago, Illinois, who were diagnosed with COVID-19 at a large academic hospital between January 1, 2020, and December 31, 2020, stratified by their alcohol misuse status determined by a digital machine learning classifier for alcohol misuse. ED: emergency department.



Discussion

Principal Results

Alcohol interferes with pulmonary adaptive and innate immunity, increases susceptibility to viral infections, and increases the risk for developing ARDS [5,12]. Furthermore, alcohol is exhaled by the lungs, and a patient with impaired lung function due to COVID-19 pneumonia could have increased levels of toxic alcohol metabolites in addition to compromised defense mechanisms. To test our hypothesis that alcohol use increases the risk for severe COVID-19 infection, we used a previously proven digital machine learning classifier to predict patients' alcohol use and severity and found an association between the predicted probability of alcohol use and COVID-19 disease severity. The results also suggest that UAU classification was associated with a nearly two-fold odds risk of being in a higher COVID-19 disease severity category.

Comparison With Prior Work

There is limited data regarding risks, disparity, and outcomes for COVID-19 in individuals with substance use disorders. Prior research demonstrated that patients diagnosed with substance misuse disorder in the 12 months before contracting COVID-19 had increased rates of hospitalization, ventilator use, and mortality [13,14]. Only one of these studies differentiated based on type of substance misuse and found the risk for those with opioid misuse to be the highest, followed by those with tobacco use disorder, then alcohol use disorder [14]. Our study further explores the effect UAU has on COVID-19 disease outcomes. Our findings are supported by prior studies that suggest that alcohol exposure may augment the activity of proinflammatory cytokines (interleukin 1β, interleukin 6, and tumor necrosis factor) in SARS-CoV-2 infection and cause pulmonary, gastrointestinal, hepatic, and neurologic organ dysfunction [15,16]. Another study demonstrated that alcohol causes severe oxidative stress due to the depletion of glutathione in the alveolar space, which leads to increased susceptibility to sepsis-mediated ARDS [17]. Our study contradicts the meta-analysis of 6 Chinese studies that found alcohol consumption did not affect COVID-19 disease severity [8]. This is likely due to our larger sample size and heterogenous population, but could also be explained by differing cultural definitions of UAU. Nonetheless, further studies must be conducted to understand the exact mechanisms linking alcohol consumption and COVID-19 disease severity.

Limitations

Our study is not without limitations. The machine learning classifier is not a diagnostic tool; rather, it is a probability predictor of UAU. More information on quantity and frequency of alcohol use would be helpful in parsing out a dose-dependent effect of alcohol on COVID-19 disease severity. However, our classifier provides a practical tool to screen for UAU using the first 24 hours of EHR notes collected during usual care. We previously showed good screening characteristics and anticipate that as natural language processing becomes more commonplace, these tools can be deployed to help physicians intervene on a modifiable risk factor like UAU. Another limitation is that there may also be other factors that contributed to the severity of COVID-19 disease that are not adequately captured in the EHR data. This study was meant to be a preliminary examination; therefore, we only examined three comorbid conditions. There are several others identified by the Centers for Disease Control and Prevention that could be included in future studies regarding COVID-19 disease severity. Our data also does not take into account the effect vaccines have on COVID-19 disease severity in those who have UAU. Future research that examines disease severity in vaccinated adults with UAU may be of interest.

Conclusions

Using a previously tested machine learning classifier for UAU, we studied the effect alcohol may have on COVID-19 disease severity. We found that those who were more likely to practice UAU were significantly more likely to require a ventilator and die if they contracted COVID-19. Therefore, we concluded that UAU is an independent risk factor for more severe COVID-19 disease. As the risk for COVID-19 infection persists, providers should be mindful of vulnerable patient populations that may be more likely to experience severe disease, and attempt to encourage patients to get vaccinated and reduce their alcohol use.

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Authors' Contributions

SB contributed to writing of the original draft, to review and editing of the manuscript, and resources. BS contributed to data curation, formal analysis, and software creation. DS contributed to formal analysis and validation. R Boley and CM contributed to project administration and manuscript review and editing. YI contributed to data curation and manuscript review and editing. MA contributed to project conceptualization, funding acquisition, project supervision, methodology, data validation, and manuscript review and editing. R Balk contributed to conceptualization, project supervision, data validation, and manuscript review and editing. NK and AK contributed to conceptualization, funding acquisition, project supervision, and manuscript review and editing.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplemental data.
[DOCX File , 26 KB - publichealth_v7i11e33022_app1.docx]

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Abbreviations

ARDS: acute respiratory distress syndrome
AUDIT: Alcohol Use Disorders Identification Test
ED: emergency department
EHR: electronic health record
ICD-10: International Classification of Disease, 10th Revision
UAU: unhealthy alcohol use

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Original Paper

The Influence of Normative Perceptions on the Uptake of the COVID-19 TraceTogether Digital Contact Tracing System: Cross-sectional Study

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Abstract

Background: In 2020, the Singapore government rolled out the TraceTogether program, a digital system to facilitate contact tracing efforts in response to the COVID-19 pandemic. This system is available as a smartphone app and Bluetooth-enabled token to help identify close contacts. As of February 1, 2021, more than 80% of the population has either downloaded the mobile app or received the token in Singapore. Despite the high adoption rate of the TraceTogether mobile app and token (ie, device), it is crucial to understand the role of social and normative perceptions in uptake and usage by the public, given the collective efforts for contact tracing.

Objective: This study aimed to examine normative influences (descriptive and injunctive norms) on TraceTogether device use for contact tracing purposes, informed by the theory of normative social behavior, a theoretical framework to explain how perceived social norms are related to behaviors.

Methods: From January to February 2021, cross-sectional data were collected by a local research company through emailing their panel members who were (1) Singapore citizens or permanent residents aged 21 years or above; (2) able to read English; and (3) internet users with access to a personal email account. The study sample (n=1137) was restricted to those who had either downloaded the TraceTogether mobile app or received the token.

Results: Multivariate (linear and ordinal logistic) regression analyses were carried out to assess the relationships of the behavioral outcome variables (TraceTogether device usage and intention of TraceTogether device usage) with potential correlates, including perceived social norms, perceived community, and interpersonal communication. Multivariate regression analyses indicated that descriptive norms (unstandardized regression coefficient β=0.31, SE=0.05; *P*<.001) and injunctive norms (unstandardized regression coefficient β=0.16, SE=0.04; *P*<.001) were significantly positively associated with the intention to use the TraceTogether device. It was also found that descriptive norms were a significant correlate of TraceTogether device use frequency (adjusted odds ratio [aOR] 2.08, 95% CI 1.66-2.61; *P*<.001). Though not significantly related to TraceTogether device use frequency, injunctive norms moderated the relationship between descriptive norms and the outcome variable (aOR 1.12, 95% CI 1.03-1.21; *P*=.005).

Conclusions: This study provides useful implications for the design of effective intervention strategies to promote the uptake and usage of digital methods for contact tracing in a multiethnic Asian population. Our findings highlight that influence from social networks plays an important role in developing normative perceptions in relation to TraceTogether device use for contact tracing. To promote the uptake of the TraceTogether device and other preventive behaviors for COVID-19, it would be useful to devise norm-based interventions that address these normative perceptions by presenting high prevalence and approval of important social referents, such as family and close friends.

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KEYWORDS
COVID-19; social norms; TraceTogether; Singapore; contact tracing; mobile app; token

Introduction

After more than a year since the World Health Organization declared COVID-19 a global pandemic, the world's cumulative confirmed cases and deaths have reached approximately 152 million and 3.2 million, respectively [1]. In Singapore, the total number of confirmed cases has grown to 61,378, while the fatality count remains low, with 31 deaths as of May 11, 2021 [2]. Since the start of the COVID-19 outbreak, Singapore has adopted a 3-pronged approach to contain the virus by (1) reducing importation of cases through various travel restrictions and measures; (2) detecting and isolating cases early; and (3) emphasizing social responsibility and good personal hygiene practices [3].

To prevent further spread of the infectious disease, contact tracing is an evidence-based strategy for breaking the chain of transmission through the identification of close contacts who may have been exposed to the virus [4]. In Singapore, the contact tracing operation is overseen by the Ministry of Health and involves other key players including hospital staff, police, and volunteers. When a COVID-19 case is identified, the hospital staff interview the patient to map out their activity over the 14 days prior to the onset of symptoms, until diagnosis and isolation. This activity map is then submitted to the Ministry of Health, filling information gaps and identifying the patient's close contacts. Close contacts presenting with coronavirus symptoms are hospitalized and tested for the virus, and those with no symptoms or those with low risks are placed under quarantine and phone surveillance [3]. The contact tracing operation entails extensive processes, because it requires excessive time and resources, and may involve significant errors due to recall biases, when it is done manually [5].

In an effort to augment comprehensive manual contact tracing, Singapore has launched the TraceTogether program to help identify close contacts, employing a mobile app and Bluetooth-enabled token (ie, device). Using Bluetooth technology, TraceTogether facilitates contact tracing by recording and exchanging anonymized proximity data with nearby TraceTogether devices. These Bluetooth data are encrypted, securely stored on the user's device, and automatically deleted after 25 days. Only if the user tests positive for COVID-19 or is identified as a close contact of a positive case, the Ministry of Health asks the user to upload the data for contact tracing [6]. Although using the TraceTogether device is not compulsory, Singaporeans are encouraged to adopt the device for efficient identification and tracking of virus infection [7].

As of February 1, 2021, more than 80% of the population has either downloaded the TraceTogether app or received the token [7]. The introduction of TraceTogether, along with other digital devices, has reduced the average time required for contact tracing from 4 days to less than 1.5 days [7]. Despite the high adoption of the TraceTogether device, there is limited clarity about the uptake and usage by Singaporeans to optimize current contract tracing efforts. There is an urgent need to identify important social factors/determinants that influence TraceTogether device uptake and usage in the local context, so that health agencies and other stakeholders can develop effective campaigns and intervention strategies to increase the participation in the program.

Behavioral decisions for COVID-19 prevention, such as safe distancing and face mask wearing, are made with uncertainty. These behaviors are mainly shaped by the prominence of normative influences through direct experience or symbolically through mediated mechanisms [8]. Given that collective efforts for contact tracing are essential to contain COVID-19 transmission in the community, normative perceptions would play a significant role in the acceptance and continued use of contact tracing devices.

Since the launch of the TraceTogether program, the Singapore government has continuously emphasized to the general public the importance of contact tracing and their social responsibility to protect their community from COVID-19 [6]. For instance, the public is encouraged to check in with their TraceTogether device when visiting public venues, such as workplaces, malls, and health care facilities. There are currently several other options for checking in, which include scanning the *SafeEntry* QR code with a phone camera or a barcode on the official ID. However, these options only provide a timestamp of the date and location, without tracking the proximity with other individuals [7]. Although use of the TraceTogether device is not compulsory, the mandatory check-in at all public venues makes the public more vulnerable to normative influences [9,10]. In this regard, the theory of normative social behavior (TNSB) [11] may serve as a guiding framework to uncover mechanisms explaining the effects of perceived social norms on the uptake and usage of TraceTogether devices in Singapore.

The TNSB [10-13] is a theoretical framework to explain how and why normative influences occur. It makes a distinction between 2 closely related concepts (ie, descriptive norms and injunctive norms) and describes how these perceived norms are related to behaviors. According to the theory conceptualized by Rimal and Real, descriptive norms refer to beliefs about the prevalence of a behavior in the reference group [13]. Descriptive norms are formed largely through observations of how important referents are behaving in the group. Injunctive norms, on the other hand, refer to perceived social approval or social sanction regarding a behavior [13]. Injunctive norms help individuals to assess whether a behavior is acceptable or approved in a specific situation [12,14]. These 2 normative perceptions are considered important facilitators for the uptake of preventive measures, including the use of digital contact tracing methods.

The TNSB theorizes underlying mechanisms that explain the influence of descriptive norms on behavior by testing potential moderators, including injunctive norms, group identity, and interpersonal communication [13,15]. Individuals' propensities to enact a behavior are significantly determined by the perception that the behavior is prevalent (eg, witnessing a group of people using the TraceTogether device for check-in at a public venue) [9,13]. The TNSB posits that perceived social pressure or approval (injunctive norms) would magnify the positive relationship between perceived prevalence and behavior [13,16]. A great deal of research has assessed the moderating role of injunctive norms in the associations between descriptive norms and various health-related behaviors, including alcohol consumption [16,17], disease screening [18], and vaccination [19,20]. Yet, the theoretical proposition has barely been tested on COVID-19–related preventive behaviors.

In addition to injunctive norms, the theory posits that the impact of descriptive norms on behavior is modified by group identity [13]. While previous studies have assessed the moderating role of group identity in the norm-behavior relationship [10,21], little is known about the role of an individual's group identity or membership in the uptake of COVID-19–related preventive behaviors and measures. According to the theory, group identity has been conceptualized as perceived similarity with one's reference group and aspirations to emulate members of the group [13]. Although this study focused on the psychological sense of community that is conceptually distinct from group identity, it is fruitful to examine the role of perceived community in the norm-behavior relationship for 2 reasons.

First, the TraceTogether program adopted a community-driven approach for facilitating contact tracing by exchanging anonymized proximity data with nearby TraceTogether devices [7]. Due to the importance of collective participation in the prevention of COVID-19 in the community, the TraceTogether program has been largely centered on imbuing the sense of "togetherness" or "community" among Singaporeans to promote active participation in the program. Additionally, the TraceTogether mobile app was designed to trigger feelings of closeness and connectedness to other users. For example, the app interface indicates the number of activated devices nearby and shows how many daily exchanges have been performed. As sense of community has varying definitions [22,23], in this paper, we construed it as group membership (or belonging) and emotional attachment by referencing those who are using TraceTogether devices [24]. Considering the nature of the program and the collective action for contact tracing in Singapore, strong perceptions of community would amplify the influence of normative perceptions on TraceTogether device usage for contact tracing.

Deriving from the diffusion of innovations theory [25] and social cognitive theory [26], interpersonal communication plays a crucial role in the formation of normative influences. As normative information is transmitted in a community through various forms of communication, including conversations with important social referents [15,27-29], the influence of descriptive norms on behavior would be modified by interpersonal communication. Given that the optimization of contact tracing efforts is facilitated by the collective action of the general public, normative perceptions strengthened by conversations with significant others would be a strong force motivating active participation in the TraceTogether program for contact tracing. Thus, we sought to understand the underlying process by testing the proposition that the interaction between descriptive norms and interpersonal communication is associated with TraceTogether device use. Specifically, conversing about the benefits of TraceTogether devices with important referents will magnify the norm-behavior relationship.

Studies have suggested that social norms are significant factors associated with the acceptance and intention to use contact tracing apps. However, little is known about whether and how social and normative factors influence the actual usage of a digital contact tracing device in a multiethnic population. Based on the theoretical background and abovementioned evidence, this study aimed to (1) examine whether perceived social norms (descriptive and injunctive), perceived community, and interpersonal communication influence the use of TraceTogether devices and (2) assess whether perceived injunctive norms, perceived community, and interpersonal communication moderate the relationship between perceived descriptive norms and the use of TraceTogether devices among Singapore adults who have either downloaded the TraceTogether mobile app or received the token.

Methods

Recruitment

From January to February 2021, cross-sectional data (N=1198) were collected by a local research company through emailing their panel members about participation in an online survey. The research company has established a panel of individuals willing to be polled on research-related topics drawn from across Singapore. The panel members are paid a sign-up fee on recruitment, and those who participate in surveys/polls are compensated with credit points by the research company in line with research industry standards. The inclusion criteria for this study were as follows: (1) Singapore citizen or permanent resident aged 21 years or above; (2) ability to read English; and (3) internet user with access to a personal email account. During the time of study recruitment, the COVID-19 situation in Singapore stabilized with only 3 clusters in the community [30,31] and a weekly moving average of less than two daily locally transmitted cases over a 2-month period [32].

Given that Singapore is a multiethnic country with 3 major Asian ethnic groups (Chinese, Malay, and Indian), the quota sampling procedure was applied to ensure that the study sample was in proportion to the demographic and ethnic structures of the national population [33]. Our study sample (n=1137) was restricted to those who had either downloaded the TraceTogether mobile app or received the token, as this study focused on the actual practice/usage of the contact tracing device (ie, use frequency or intensity) rather than the adoption of the device. All research participants were required to complete an electronic consent form prior to the online survey. Participation in this research was completely voluntary, and participants had the option to withdraw from the research at any time. To ensure the anonymity and privacy of the participants, unique study identification numbers were assigned at the beginning of the survey. Additionally, personal data (eg, identity card numbers) were not collected. The study protocol was approved by the institutional review board of Nanyang Technological University, Singapore in December 2020.

Measures

The primary focus of the study was to examine the usage of the TraceTogether device (app/token) and its determinants. Hence, the survey questionnaire included measures for the frequency/intensity of TraceTogether device use, the intention to use the TraceTogether device, perceived social norms (descriptive and injunctive norms), perceived community, interpersonal communication, and sociodemographic characteristics. Prior to creating composite score variables for the multi-item measures derived from the TNSB (ie, perceived social norms, perceived community, and behavioral intentions), exploratory factor analyses were performed to assess the validity of the TNSB measures. Cronbach alpha was also estimated to evaluate the internal consistency (reliability) of the composite score variables.

Frequency/Intensity of TraceTogether Device Use

The primary outcome was assessed by the following 2 items: "In the last 7 days, how often did you use the TraceTogether app (keeping the app open in the background) when going out?" and "In the last 7 days, how often did you bring the TraceTogether token (keeping Bluetooth on) when going out?" As people tend to use either one option for the digital check-in when visiting a public venue, the intensity of TraceTogether device use was determined by the higher value of TraceTogether app use or TraceTogether token use frequency. The response options of the variable were on a 7-point scale (1, never; 2, almost never; 3, rarely; 4, sometimes; 5, quite a bit; 6, almost always; and 7, always), and they were collapsed into 3 ordinal levels (seldom [1+2+3], frequently [4+5+6], and always [7]) due to skewed distribution of the categories.

Intention to Use the TraceTogether Device

The secondary outcome was measured by asking how much participants agreed with 3 statements concerning their intention to use the TraceTogether device in the following week, and the responses were on a 7-point scale ranging from "strongly disagree" (1) to "strongly agree" (7). The statements were as follows: "I will use TraceTogether in the following week," "I expect to use TraceTogether in the following week," and "I plan to use TraceTogether in the following week." The intention measure was adapted from the scale by Fishbein and Ajzen (Cronbach α=.96) [34].

Perceived Social Norms

Descriptive norms were assessed as perceived prevalence of the uptake of the TraceTogether device on a 7-point scale ranging from "not at all" (1) to "very great extent" (7). The common stem, "To what extent do you think the following groups use TraceTogether…" was completed with the following 3 items: "People like me in Singapore," "My family," and "My friends." The mean of these 3 items was used as a measure of descriptive norms (Cronbach α=.93). Injunctive norms were assessed as perceived social approval on a 7-point scale ranging from "strongly disagree" (1) to "strongly agree" (7), with the statements "People like me in Singapore think that I should use TraceTogether," "My family thinks that I should use TraceTogether," and "My friends think that I should use TraceTogether." The mean of the 3 items was reported (Cronbach α=.95).

Perceived Community

Participants' sense of community was measured using a 5-item measure on a 7-point scale ranging from "strongly disagree" (1) to "strongly agree" (7). Adapted from the Brief Sense of Community Scale [23,35] and other community perception measures [24], the perceived community measure primarily assessed the following 2 elements of the sense of community: group membership/belonging and emotional ties with TraceTogether users. The community perception items were designed to reference TraceTogether users participating in the program. The items were "It makes me feel like I am part of a community," "I feel a sense of attachment with other users," "I feel emotional connection with other users," "It reminds me of the people around me," and "It makes me feel a sense of belonging" (Cronbach α=.95).

Interpersonal Communication

Interpersonal communication about the benefits of contact tracing was assessed by the average of the following 2 dichotomous items: "In the last 30 days, have you talked with your family members about the benefits of contact tracing?" and "In the last 30 days, have you talked with your friends about the benefits of contact tracing?"

In addition, data were collected on participants' COVID-19–related worries (5 items), knowledge about contact tracing (6 items), and length of time using the TraceTogether device (1 item).

Sociodemographic characteristics, including age (last birthday immediately preceding the fieldwork), gender, ethnicity, housing type, and educational attainment, were used as control variables. Data on monthly household income were excluded from the analyses due to a missing rate of 15%. Housing type and education were then used as proxies to assess the socioeconomic status. In Singapore, public housing covers over 80% of the resident population. The government has provided a public-subsidized housing scheme in which income is used to determine eligibility for subsidies for rent or purchase of an apartment unit and the size of the unit. Hence, housing type is often positively correlated with household income [36]. In addition to the demographic characteristics, participants were asked about their health status using the following item: "Would you say that in general your health is (1) poor, (2) fair, (3) good, (4) very good, or (5) excellent?" [37].

Statistical Analysis

Numbers and percentages were used to describe participants' characteristics that were represented by categorical variables, while means and SDs were used to describe composite score variables. Multivariate linear and ordinal logistic regression analyses were carried out to address the research aims. A multicollinearity test was performed to check if the variables were mutually correlated. Results showed that the tolerance values were greater than 0.30 and the variance inflation factors were less than 3.30, indicating that all correlates were acceptable for regression analyses. The validity of the proportional odds assumption was also assessed by the test of parallel regression assumption. The proportions of missing data were minimal, ranging from 0% to 0.01% across variables, and were handled by the listwise deletion method. All statistical analyses were performed using Stata version 17 (StataCorp).

We first performed a linear regression analysis to investigate the relationships of the intention to use the TraceTogether device with potential correlates. The analysis yielded unstandardized regression coefficients, standard errors of the unstandardized coefficients (SE), and standardized regression coefficients to indicate the strengths and directions of the associations. Next, an ordinal logistic regression analysis was carried out to identify determinants of the frequency of TraceTogether device use comprising 3 ordinal categories. The ordinal logistic regression model estimated adjusted proportional odds ratios (aORs) and 95% CIs. In these multivariate regression models, the outcome variables (ie, intention to use the TraceTogether device and use of the TraceTogether device) were regressed on the dimensions of perceived social norms (descriptive and injunctive norms), perceived community, interpersonal communication, COVID-19–related worry, and knowledge on contact tracing. Sociodemographic variables, self-assessed health status, and length of time using the TraceTogether device were modeled as control variables.

Three interaction terms were created to test the moderation effects as follows: descriptive norms × injunctive norms, descriptive norms × perceived community, and descriptive norms × interpersonal communication. The interaction terms were then added to the regression models to assess whether the relationship between the descriptive norms and outcome variables (intentions and use frequency) varied by potential moderators (ie, injunctive norms, perceived community, and interpersonal communication). This study did not adopt any procedure for model selection (eg, forward selection approach), because the study variables, including the interaction terms, were selected and entered into the regression models as guided by the theoretical framework [13].

Results

Sociodemographic Characteristics

Table 1 presents the sociodemographic characteristics of the study sample. Our study sample constituted 1137 participants, with a mean age of 42.9 years (SD 11.6 years). Among the participants, 583 (51.3%) were male and 584 (51.4%) had obtained a bachelor's degree or above. The distribution of ethnicity in our study sample was as follows: 74.5% (n=847) Chinese, 15.6% (n=178) Malay, and 9.9% (n=112) Indian, which was similar to the national statistics on ethnic proportions but with a slight overrepresentation of the Indian group [33]. The majority of the participants (n=944, 83.5%) resided in public housing, while 16.5% (n=186) lived in a private property. Close to 75% (n=858) of the participants indicated their health status as "excellent," "very good," or "good." Table 1 also shows the descriptive statistics of the study variables. Majority of the participants had downloaded the mobile app (n=951, 83.6%) and received the token (n=819, 72.0%). Nearly half (n=526, 46.3%) reported that they used the TraceTogether device (mobile app or token) "always" when going out in the last 7 days (ie, keeping the mobile app open in the background or keeping Bluetooth on for the token). About 22.8% (n=259) of the participants used the TraceTogether device for more than 6 months, while 16.4% (n=186) used it for less than a month.

Table 1. Descriptive statistics.

Variable	Value (N=1137)
Sociodemographics	
Gender, n (%)	
Male	583 (51.3)
Female	554 (48.7)
Age group (years), n (%)	
21-34	296 (26.0)
35-49	517 (45.5)
50-64	282 (24.8)
65 or above	42 (3.7)
Mean age (years), mean (SD)	42.9 (11.6)
Ethnicity, n (%)	
Chinese	847 (74.5)
Malay	178 (15.7)
Indian	112 (9.9)
Education level, n (%)	
Secondary education or below	33 (2.9)
"A" level/diploma/polytechnic/institute of technical education/national technical certificate	513 (45.4)
University degree or above	584 (51.7)
Housing type, n (%)	
1 to 3-room Housing & Development Board public housing flat	233 (20.6)
4-room Housing & Development Board public housing flat	440 (38.9)
5-room Housing & Development Board public housing flat	271 (24.0)
Private condo or landed house	186 (16.5)
Self-assessed health status, n (%)	
Poor	23 (2.0)
Fair	256 (22.5)
Good	486 (42.7)
Very good	299 (26.3)
Excellent	73 (6.4)
TraceTogether use patterns and intentions	
Adoption of the TraceTogether device, n (%)	
Have downloaded TraceTogether app (Yes)	951 (83.6)
Have received TraceTogether token (Yes)	819 (72.0)
In the last 7 days, how often did you use the TraceTogether app, n (%)	
Never	66 (6.9)
Almost never	34 (3.6)
Rarely	56 (5.9)
Sometimes	136 (14.3)
Quite a bit	115 (12.1)
Almost always	159 (16.7)
Always	385 (40.5)
In the last 7 days, how often did you bring the TraceTogether token with you, n (%)	

Variable	Value (N=1137)
Never	89 (10.9)
Almost never	37 (4.5)
Rarely	58 (7.1)
Sometimes	119 (14.5)
Quite a bit	88 (10.7)
Almost always	150 (18.3)
Always	278 (33.9)
Collapsed TraceTogether device (app or token) frequency, n (%)	
Never	66 (5.8)
Almost never	32 (2.8)
Rarely	49 (4.3)
Sometimes	136 (12.0)
Quite a bit	122 (10.7)
Almost always	206 (18.1)
Always	526 (46.3)
How long have you used the TraceTogether app or token, n (%)	
Less than a month	186 (16.4)
1-2 months	213 (18.7)
2-3 months	187 (16.4)
3-4 months	127 (11.2)
4-5 months	104 (9.1)
5-6 months	61 (5.4)
More than 6 months	259 (22.8)
TraceTogether device use intention (mean of 3 items), mean (SD)	5.33 (1.49)
Correlates	
Descriptive norms (mean of 3 items), mean (SD)	5.17 (1.38)
Injunctive norms (mean of 3 items), mean (SD)	5.08 (1.48)
Perceived community (mean of 5 items), mean (SD)	4.65 (1.61)
Knowledge about contact tracing (mean of 6 items), mean (SD)	5.69 (1.16)
COVID-19–related worry (mean of 5 items), mean (SD)	5.23 (1.33)
Interpersonal communication about benefits with family members (Yes), n (%)	564 (49.6)
Interpersonal communication about benefits with friends (Yes), n (%)	531 (46.7)

Results of the Linear Regression Analysis

Table 2 displays the results of the linear regression model predicting the behavioral intention. Descriptive norms (unstandardized β=0.31, SE=0.05; *P*<.001) and injunctive norms (unstandardized β=0.16, SE=0.04; *P*<.001) were both significantly positively associated with the intention to use the TraceTogether device, such that participants who reported stronger perceptions of prevalence and social pressure were more likely to have a greater intention to use the TraceTogether device for contact tracing. As anticipated, perceived community was a significant correlate of the outcome variable, meaning that those who reported a stronger community perception had a greater intention to use the TraceTogether device (unstandardized β=0.08, SE=0.03; *P*=.001). However, the analysis did not support our anticipation of the moderating role in the relationship between descriptive norms and the intention to use the TraceTogether device. Additionally, ethnicity and length of time to adopt the TraceTogether device were significantly associated with the behavioral intention. Malay participants reported that they had a significantly lower behavioral intention than their Chinese counterparts (unstandardized β=−0.21, SE=0.09; *P*=.01). As compared with participants who used the device for less than a month, those who used the device for a longer period of time reported a higher level of intention (more than 6 months: unstandardized β=0.49, SE=0.10; *P*<.001; 3-5 months: unstandardized β=0.35, SE=0.10; *P*<.001; 1-3 months: unstandardized β=0.34, SE=0.09; *P*<.001).

Table 2. Linear regression analysis for correlates of TraceTogether use intention (N=1128).

Parameter	TraceTogether app/token use intention (adjusted R^2=0.62)			
	Unst β[a]	St β[b]	SE[c]	*P* value
Gender[d] (reference: male)				
Female	0.07	0.02	0.06	.20
Age[d] (years) (reference: 21-34)				
35-49	0.10	0.03	0.07	.15
50-64	0.12	0.03	0.08	.17
65 or above	0.16	0.02	0.16	.32
Ethnicity[d] (reference: Chinese)				
Malay	−0.21	−0.05	0.09	.01
Indian	0.03	0.005	0.09	.79
Education level[d] (reference: secondary education or below)				
"A" level/diploma/polytechnic/institute of technical education/national technical certificate	0.09	0.01	0.17	.60
University degree or above	0.08	0.03	0.06	.19
Housing type[d] (reference: private condo or landed house)				
1 to 3-room Housing & Development Board public housing flat	0.08	0.02	0.01	.39
4-room Housing & Development Board public housing flat	0.05	0.02	0.08	.53
5-room Housing & Development Board public housing flat	0.14	0.04	0.09	.12
Descriptive norms	0.31	0.29	0.05	<.001
Injunctive norms	0.16	0.16	0.04	<.001
Perceived community	0.08	0.09	0.03	.001
Knowledge about contact tracing	0.46	0.33	0.03	<.001
COVID-19–related worry	0.02	0.01	0.02	.48
Interpersonal communication[d] (reference: no)				
Yes	0.03	0.01	0.06	.70
Health status	−0.05	−0.03	0.03	.11
Length of time using the TraceTogether app token[d] (reference: less than a month)				
1-3 months	0.34	0.11	0.09	<.001
3-6 months	0.35	0.10	0.10	<.001
More than 6 months	0.49	0.14	0.10	<.001
Descriptive norms × injunctive norms	0.001	0.002	0.02	.94
Descriptive norms × perceived community	−0.03	−0.05	0.02	.08
Descriptive norms × interpersonal communication	−0.06	−0.04	0.05	.19

[a]Unst β: adjusted unstandardized regression coefficient.

[b]St β: adjusted standardized regression coefficient.

[c]SE: standard error of unstandardized regression coefficient.

[d]Gender, age, ethnicity, education, housing type, interpersonal communication, and length of time using the TraceTogether app/token were dummy-coded variables.

Results of the Ordinal Logistic Regression Analysis

Table 3 presents the results of the ordinal logistic regression model focusing on the frequency of TraceTogether device use as an outcome. It was found that stronger perception of descriptive norms was significantly associated with elevated TraceTogether use frequency (aOR 2.08, 95% CI 1.66-2.61, *P*<.001). Contrary to our anticipation, perceived injunctive norms were not a significant correlate of the outcome variable. We also investigated the relationships of the TraceTogether device use frequency with perceived community and interpersonal communication (about benefits); however, no significant relationships were observed.

Table 3. Ordinal logistic regression analysis for correlates of TraceTogether use frequency (N=1128).

Parameter	TraceTogether app/token use frequency (pseudo R^2=0.18)		
	Adjusted odds ratio	95% CI	*P* value
Gender[a] (reference: male)			
Female	1.05	0.82-1.35	.69
Age[a] (years) (reference: 21-34)			
35-49	1.17	0.86-1.58	.32
50-64	1.08	0.74-1.58	.68
65 or above	1.43	0.71-2.89	.32
Ethnicity[a] (reference: Chinese)			
Malay	0.24	0.17-0.35	<.001
Indian	0.66	0.43-1.02	.06
Education level[a] (reference: secondary education or below)			
"A" level/diploma/polytechnic/institute of technical education/national technical certificate	1.48	0.70-3.18	.31
University degree or above	1.12	0.86-1.47	.40
Housing type[a] (reference: private condo or landed house)			
1 to 3-room Housing & Development Board public housing flat	1.95	1.27-3.01	.002
4-room Housing & Development Board public housing flat	1.50	1.03-2.19	.04
5-room Housing & Development Board public housing flat	1.18	0.79-1.78	.42
Descriptive norms	2.08	1.66-2.61	<.001
Injunctive norms	1.12	0.96-1.31	.15
Perceived community	1.07	0.95-1.20	.27
Knowledge about contact tracing	0.93	0.81-1.08	.34
COVID-19–related worry	1.01	0.92-1.13	.72
Interpersonal communication[a] (reference: no)			
Yes	0.82	0.61-1.09	.18
Health status	1.02	0.88-1.19	.77
Length of time using the TraceTogether app/token[a] (reference: less than a month)			
1-3 months	3.49	2.38-5.12	<.001
3-6 months	4.05	2.65-6.18	<.001
More than 6 months	9.03	5.69-14.32	<.001
Descriptive norms × injunctive norms	1.12	1.03-1.21	.005
Descriptive norms × perceived community	0.95	0.88-1.03	.25
Descriptive norms × interpersonal communication	0.81	0.64-1.02	.08

[a]Gender, age, ethnicity, education, housing type, interpersonal communication, and length of time using the TraceTogether app/token were dummy-coded variables.

Based on the theoretical propositions, we assessed 3 potential moderators (perceived injunctive norms, perceived community, and interpersonal communication) in the relationship between descriptive norms and TraceTogether device use frequency. The regression analysis found a significant interaction between the 2 perceived social norms (descriptive and injunctive norms) as being associated with the frequency of TraceTogether device use. This result indicated that those who reported stronger descriptive norms (ie, perception of TraceTogether use prevalence) demonstrated a significantly higher frequency of TraceTogether device use when they had stronger perception of injunctive norms (ie, social pressure to use the TraceTogether device from the members of reference groups; aOR 1.12, 95% CI 1.03-1.21; *P*=.005). However, the interactions between descriptive norms and other variables were not significant, indicating that perceived community and interpersonal communication did not moderate the influence of descriptive norms on the outcome variable.

The analysis also showed that those who adopted the TraceTogether device for a longer period of time elevated their TraceTogether device use frequency. More specifically, the odds of TraceTogether use frequency were the highest among participants who had used the device for more than 6 months (aOR 9.03, 95% CI 5.69-14.32; *P*<.001), followed by 3 to 6 months (aOR 4.05, 95% CI 2.65-6.18; *P*<.001) and 1 to 3 months (aOR 3.49, 95% CI 2.38-5.12; *P*<.001), as compared with those who had used the device for less than a month (reference category). Among sociodemographic factors, ethnicity and housing type were significantly related to the outcome variable. When comparing by ethnicity, Malay participants exhibited a 0.24 decrease in the odds of TraceTogether device use frequency (aOR 0.24, 95% CI 0.17-0.35; *P*<.001) as compared with their Chinese counterparts. In terms of housing type, those who resided in public housing, specifically in a 1 to 3-room Housing & Development Board flat (aOR 1.95, 95% CI 1.27-3.01; *P*=.002) or 4-room Housing & Development Board flat (aOR 1.50, 95% CI 1.03-2.19; *P*=.04) were more likely to use the TraceTogether device than those who lived in private properties (eg, private condo or landed house). Gender, education, age, and health status were not significantly associated with TraceTogether device use frequency.

Discussion

Principal Findings

Our study findings provide evidence for the normative social influence on COVID-19–related preventive behaviors in the Singapore context. Despite the high adoption rate of the TraceTogether mobile app and token in the multiethnic island state [7], actual uptake and usage are paramount to contain the spread of COVID-19. Recent studies have assessed the determinants of acceptance and behavioral intentions of mobile apps for contact tracing [38-41], and social norms have been suggested as significant factors associated with the acceptance and intention to use contact tracing apps [42]. In this study, we found direct and moderation effects of social and normative factors on the usage of a digital contact tracing device in Singapore, a multiethnic Asian city-state.

In this study, we conceptualized and assessed the following 2 distinct constructs of perceived social norms: descriptive norms (what is normal) and injunctive norms (what ought to be done) [12]. Consistent with our anticipation, use of the contact tracing device by Singaporeans was significantly influenced by descriptive norms, such that stronger perceptions of TraceTogether device use prevalence increased the intention to use the TraceTogether device and the likelihood of frequent TraceTogether device use. As discussed earlier, observable behaviors make people more vulnerable to others' influences [43]. Use of the TraceTogether device is readily visible in Singapore as everyone is required to check-in at all public venues using the device or through other check-in methods. Our findings suggest that influence from social networks plays an important role in forming beliefs about the prevalence of TraceTogether device uptake and usage. To promote preventive behaviors, including the use of digital contact tracing methods, it would be useful to devise social norm interventions that address the target audience's perceived descriptive norms by presenting the high prevalence of TraceTogether device use for contact tracing (or other preventive behaviors) among influential social referents, such as family and close friends [13].

To further understand the mechanisms explaining the normative influences on behavior, we assessed the influence of descriptive norms on TraceTogether device use by incorporating potential moderators, including injunctive norms, perceived community, and interpersonal communication. The study results identified that injunctive norms moderated the relationship between descriptive norms and TraceTogether device use frequency, while there were no moderation effects of perceived community and interpersonal communication. The investigation of these normative influences suggested that individual uptake of contact tracing devices is not solely governed by the perception of prevalence among referent others (eg, family and close friends). In order to boost the influence of descriptive norms, intervention messages should highlight important reference groups' expectations and support for enacting these preventive behaviors. In this manner, the norms and expectations of the reference groups can be presented as social cues in public communications, motivating people to adopt and continuously use digital devices for contact tracing.

In this study, we also examined the role of individuals' perceptions of community in the relationship between descriptive norms and TraceTogether device use. While the results did not support the theoretical proposition on the moderating role of perceived community, it was significantly positively associated with the behavioral intention. Although perceived community in the mobile app environment may differ from a sense of place-based community, digital contact tracing devices/apps may adopt some features to evoke feelings of belonging or emotional connection, as well as to develop affinity toward the device. The notion of community has been explored in the context of virtual communities [24,44], yet less is known about the effects and functions of perceived community in mobile and digital apps for disease prevention and health promotion. Future studies need to explore underlying mechanisms by explaining the role of perceived community in the adoption of healthy choices through the incorporation of various forms of community-induced features and functions in the apps.

Limitations

Our study is not without limitations. First, the cross-sectional data could not be used to infer causality between perceived social norms and TraceTogether device use. Second, self-reported data used in the study may be prone to social desirability and recall biases. In addition, the data have limited generalizability to the Singapore adult population as our study sample was overrepresented with those having higher education attainment. Nevertheless, the study sample had a similar distribution of ethnicity as the national population. Despite the study limitations, this is one of the first studies to present valid evidence exploring social and normative influences on the uptake and usage of a contact tracing device for COVID-19 in a multiethnic Asian population. This study in turn contributes to the literature by serving as a baseline for future studies aimed at assessing the usage of digital devices in the COVID-19 pandemic.

Future Research

As of June 1, 2021, the use of the TraceTogether device will become mandatory at malls, workplaces, and schools [45]. Future research may collect longitudinal data through prospective cohort studies to assess changes in social norms/social pressures and actual usage of digital contact tracing devices before and after the implementation of the new regulation. Additionally, given that Western countries have technical protocols and legal systems that differ from those in Singapore [46], population-based cross-national research may be fruitful to further understand the differences in social and environmental influences on the uptake and usage of digital contact tracing apps.

Conclusions

To our knowledge, this is one of the first studies to explore social and normative influences on the usage of contact tracing devices for COVID-19 (TraceTogether app and token) as part of the nationwide contact tracing program in Singapore. This study provides useful information for the design of effective intervention strategies to promote the uptake of digital methods for contact tracing in the multiethnic Asian population. Our results also demonstrate that the differential functions of the 2 distinct social norm factors (descriptive and injunctive norms) are important and beneficial to curb the spread of an infectious disease in the community. The study findings suggest that influence from social networks plays an important role in forming normative perceptions (ie, perceived prevalence and social pressure) regarding TraceTogether device use for contact tracing. Therefore, it would be useful to devise norm-based interventions that harness the influence of important social referents, such as family and close friends, to promote the uptake of digital contact tracing devices and other preventive behaviors for COVID-19.

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Conflicts of Interest

None declared.

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Abbreviations

aOR: adjusted odds ratio
TNSB: theory of normative social behavior

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Original Paper

Characterization of Unlinked Cases of COVID-19 and Implications for Contact Tracing Measures: Retrospective Analysis of Surveillance Data

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Abstract

Background: Contact tracing and intensive testing programs are essential for controlling the spread of COVID-19. However, conventional contact tracing is resource intensive and may not result in the tracing of all cases due to recall bias and cases not knowing the identity of some close contacts. Few studies have reported the epidemiological features of cases not identified by contact tracing (“unlinked cases”) or described their potential roles in seeding community outbreaks.

Objective: For this study, we characterized the role of unlinked cases in the epidemic by comparing their epidemiological profile with the linked cases; we also estimated their transmission potential across different settings.

Methods: We obtained rapid surveillance data from the government, which contained the line listing of COVID-19 confirmed cases during the first three waves in Hong Kong. We compared the demographics, history of chronic illnesses, epidemiological characteristics, clinical characteristics, and outcomes of linked and unlinked cases. Transmission potentials in different settings were assessed by fitting a negative binomial distribution to the observed offspring distribution.

Results: Time interval from illness onset to hospital admission was longer among unlinked cases than linked cases (median 5.00 days versus 3.78 days; P<.001), with a higher proportion of cases whose condition was critical or serious (13.0% versus 8.2%; P<.001). The proportion of unlinked cases was associated with an increase in the weekly number of local cases (P=.049). Cluster transmissions from the unlinked cases were most frequently identified in household settings, followed by eateries and workplaces, with the estimated probability of cluster transmissions being around 0.4 for households and 0.1-0.3 for the latter two settings.

Conclusions: The unlinked cases were positively associated with time to hospital admission, severity of infection, and epidemic size—implying a need to design and implement digital tracing methods to complement current conventional testing and tracing. To minimize the risk of cluster transmissions from unlinked cases, digital tracing approaches should be effectively applied in high-risk socioeconomic settings, and risk assessments should be conducted to review and adjust the policies.

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KEYWORDS

COVID-19; contact tracing; unlinked; superspreading; dispersion; surveillance; monitoring; digital health; testing; transmission; epidemiology; outbreak; spread

Introduction

As COVID-19 cases are still rising around the world and new variants are emerging, nonpharmaceutical interventions (NPIs) are essential for controlling the spread of COVID-19 [1,2] in many countries, especially when vaccination programs are impeded by factors such as vaccine hesitancy, reduced efficacy against some new variants, and vaccine shortage. NPIs such as personal protective equipment, social distancing, contact tracing followed by quarantine, border controls, travel restrictions, and enforced or recommended "stay-at-home" policies and "lockdowns" reduce transmission arising from individual contacts [3].

Hong Kong is a densely populated cosmopolitan city with extensive connections with mainland China and the rest of the world. The city experienced and successfully controlled three waves of COVID-19 in mid-January, March, and July 2020, respectively. Early in the first wave, the government closed its borders with the mainland and enforced a 14-day mandatory quarantine for all arrivals from mainland China and the close contacts of confirmed cases. Quarantine was then extended to arrivals from high-risk countries, and eventually to all arrivals, and entry was denied for all nonresidents during the second wave [1,2]. Unlike the first two waves, during which cases were predominantly imported cases and their close contacts, the third wave was characterized by community transmission in local clusters [3]. In response, the government stepped up public health measures, by implementing mandates for physical distancing, expanded community testing, enhanced case detection, contact tracing, and quarantine [4].

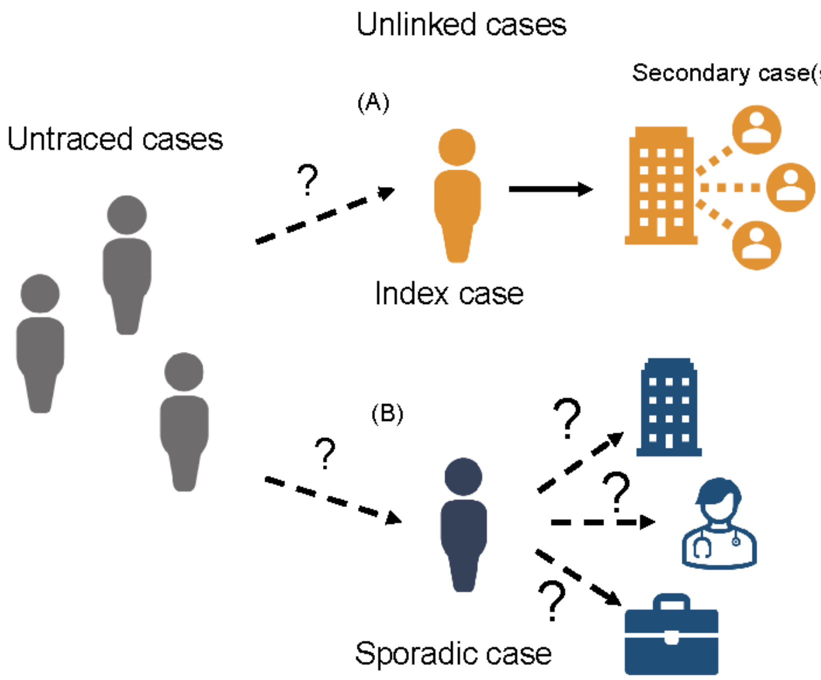
Active identification and isolation of infected persons and quarantine of close contacts reduced subsequent transmissions and brought the third wave under control within two months [3]. The importance and effectiveness of contact tracing have been documented elsewhere [5-8]. According to Aleta et al [5], aggressive social distancing measures, robust testing, contact tracing, and quarantine kept the disease within the capacity of the health care system in the absence of herd immunity.

Ideally, all local cases can be epidemiologically linked, forming a meta-cluster of a closed transmission network in the absence of imported cases. However, in reality, resources for contact tracing are limited, and cases are not able to recollect (ie, recall bias) or choose not to disclose all their close contacts. Close contacts may also not be known to the index case and therefore cannot be traced by conventional methods. As a consequence, some of the cases in a cluster outbreak or in unrecognized chains of transmissions could eventually emerge as "unlinked cases," either as the index case in a new cluster outbreak or as a sporadic case without known involvement in any identified cluster (Figure 1). As shown by a modelling study [7], unlinked secondary cases can markedly impede outbreak control due to delayed isolation. Another simulation study predicted that at least 71% of close contacts of infectors needed to be traced to control the epidemic (ie, reproduction number reduced to <1) [8].

Hong Kong has implemented stringent containment measures since January 2020 [9,10]. Individuals who contacted a confirmed case up to two days before the initial case's symptom onset would be put under mandatory quarantine and be tested [11]. Contact tracing became even more important during the third wave, which was characterized by more local transmissions, the impact of which should be evaluated.

It is critical to obtain empirical evidence on the effect of contact tracing on the containment of the epidemic in jurisdictions with control strategies (eg, Singapore, South Korea, and Hong Kong), where intensive contact tracing systems are applied to suppress transmission, to try to avoid the need for extensive restrictions to socioeconomic life (eg, lockdowns). Such data will also be invaluable for informing policies regarding the development of digital tracing technologies that have the potential to minimize the proportion of epidemiologically unlinked cases as well as the perpetuation of outbreaks. In this study, we investigated the clinical and epidemiological characteristics of the unlinked COVID-19 cases in Hong Kong, and estimated the transmission potential of the unlinked cases in different socioeconomic settings. Our study period covers the first three waves of the COVID-19 pandemic in Hong Kong. The findings provide empirical evidence on the value of contact tracing by comparing the epidemiological characteristics of the linked and unlinked cases, and estimating the probability of unlinked cases seeding community outbreaks. We also identified "hot spots" of outbreaks that were triggered by unlinked cases, which can inform risk assessments for designing future public health interventions to control transmission and prevent the health care system from being overwhelmed.

Figure 1. A schematic of the types of unlinked cases in a community. All local cases are supposed to be epidemiologically linked. Untraced cases (in grey) have silent transmissions (dashed arrows), which are the unlinked cases with no information about prior transmission chains. An unlinked case can either be (A) the index case of another cluster or (B) a sporadic case with no identified secondary transmissions. The transmission potential of the unlinked cases can be inferred by the size of the secondary transmission cluster triggered by one case (in orange). For sporadic unlinked cases (in blue), there is no information on whether they caused secondary transmissions or their location history. For each setting u, we estimated the transmission potential of the unlinked cases in that setting by considering a range of probabilities pu (5%-95%) that the sporadic unlinked cases may have visited that setting before.



Methods

Data Sources

Rapid surveillance data containing the line listing of SARS-CoV-2 infections was obtained from the Centre of Health Protection of the Government of the Hong Kong Special Administrative Region. Individual-level data from January 23 to September 18, 2020, were extracted, including demographics (age, gender, residency), presence of chronic diseases (eg, hypertension, diabetes, and stroke), epidemiological characteristics (imported/local transmission, epidemiological linkages, hospital admission/detection date, mode of detection, types of exposure settings for clusters, any secondary generations linked, and cross-border travel history), clinical characteristics, and outcomes (symptomatic or asymptomatic status, illness onset date, clinical condition, death event). The polymerase chain reaction (PCR) cycle threshold (Ct) value collected on the date closest to the admission date after a 7-day window period was obtained. A lower Ct value suggests a higher viral load.

Asymptomatic cases were those diagnosed without any symptoms of COVID-19 at the time of detection. Modes of detection included the following: (1) medical surveillance, (2) general outpatient clinics (GOPC) or Accident & Emergency (A&E) departments, (3) enhanced surveillance in the private sector, and (4) others (eg, testing for inbound travelers or high-risk groups, and community screening programs). Close contacts of an infected case were quarantined in designated locations and medical surveillance was arranged for other contacts. Time from illness onset to hospital admission was defined as the time interval (days) from illness onset date to hospital admission date.

Ethics approval was obtained from the Joint Chinese University of Hong Kong – New Territories East Cluster Clinical Research Ethics Committee.

Clusters and Epidemiological Linkages

In accordance with definitions from our previous study, transmission clusters identified by contact tracing may belong to one of the following settings: household, dormitory, workplace, eatery, party, shopping, health care, entertainment, and education. Detailed descriptions of settings can be found in [12]. Household refers to the residential setting where individuals live together most of the time. A dormitory is a room or apartment where a group of unrelated residents reside. A workplace is any working space for and shared by staff. An eatery refers to places where customers stay for meals (eg, cafeterias and restaurants). A party refers to a private social gathering, while a place of entertainment refers to social activities at premises including bars and karaoke bars. A shopping venue can be a market or a department store. A health care setting is where health care services are provided (long-term care facilities are included in this category). In an education setting, teaching and learning activities are carried out—this category includes primary and secondary schools.

Case Definitions

A linked case is defined as a local secondary case (infectee) epidemiologically linked to a confirmed case (local/imported), either via personal contact or exposure to the same setting at the same time. An unlinked case refers to a local case without any source of infection identified by epidemiological linkage. An unlinked case could be detected either as an index case that has led to further secondary transmission(s) in different socioeconomic settings, or as a sporadic unlinked case without any secondary cases identified (Figure 1).

Statistical Analysis

As the third wave was predominated by local cases, we divided the data into two epochs: epoch one (from January 23 to June 18, 2020), covering the first and second waves, and epoch two (from June 19 to September 18, 2020), covering the third wave. For each epoch, we compared the categorical variables (ie, age group, sex, symptomatic/asymptomatic, presence of chronic conditions, mode of case detection, ever consulted private clinics prior to admission, critical/serious condition, and death event) of linked and unlinked cases by using chi-square tests, whereas we compared the PCR Ct values of linked and unlinked cases as a continuous variable by using independent *t* tests.

We examined the correlation between the weekly proportion of unlinked cases among all local infections and the weekly number of new local cases using the Spearman correlation coefficient (*r*). For the time interval from illness onset to hospital admission, we compared the survival functions between the linked and unlinked cases on their time to admission using the Kaplan-Meier method. The time to admission was further compared between the two groups when adjusted for age and gender in a Cox proportional hazard model.

The probability that an unlinked case would generate one or more secondary case(s) in a particular setting is estimated by assuming that the offspring distribution (Z) follows a negative binomial distribution [13,14]. Compared with other distributions, such as Poisson distribution, the dispersed distributional assumption can account for transmission heterogeneity via specification of the dispersion parameter (k) and effective reproductive number (R), which have been found to be more rigorous for modeling the offspring distribution when epidemics are characterized by superspreading events [15,16]. Following Lloyd-Smith et al [15], we assumed Z_u, the number of secondary cases generated by a case in a setting u (eg, household), follows a negative binomial distribution with mean=R and dispersion=k. Z_u=0 if a local case did not have any identified secondary cases and thus contributed to a cluster of size j=1. For Z_u≥1, j would be ≥2 (Figure 1).

By employing a branching process, we formulated the likelihood function (L_u) as follows:

where $N_{z_u}=z_u$ is the number of clusters of size j_u. $N_{z_u}=z_u$ can only be observed when j_u≥2 (ie, when the case was an index case with traced secondary cases that form a cluster at a specific setting u; Figure 1A). Conversely, $N_{z_u}=0$ is unobserved, as there is no information indicating whether the sporadic unlinked case had been in the particular setting, but only that no further secondary cases were known to be traced or linked to the sporadic case (Figure 1B). Therefore, for each setting u, we computed the number of sporadic unlinked cases that have been in or associated with that particular setting by multiplying the total number of sporadic unlinked cases with a percentage p_u (which varied from 5%-95% to account for uncertainty). Since places visited were not mutually exclusive, we assumed p_u to be independent of each other and considered each setting separately. We determined the probability of secondary transmission per unlinked case for each setting u, , by solving for the likelihood using the Markov chain Monte Carlo method.

Results

Characteristics of Unlinked Cases

There were 438 and 3345 confirmed local cases during epoch one (first and second wave) and epoch two (third wave), respectively. In each epoch, around one-third of the local cases were unlinked cases (ie, not epidemiologically linked with any clusters). Table 1 shows the comparison of the epidemiological characteristics of the linked and unlinked cases. A higher proportion of the unlinked cases were ≥18 years old (*P*<.001) when data from the two epochs were combined. More unlinked cases were male in epoch one (*P*=.02), but this association was not observed in epoch two.

In both epochs, the proportion of asymptomatic cases was lower among the unlinked cases than among the linked cases (9.2% versus 21.2%; *P*<.001). The unlinked cases also had higher Ct values (median 24.8 versus 23.3; *P*<.001), indicating a lower viral load at presentation. Linked cases were more likely to be detected through medical surveillance, whereas unlinked cases were more likely to be detected in GOPCs, A&E departments, and private clinics (*P*<.001). The unlinked cases were also more likely to have consulted private doctors prior to an admission (10.4% versus 4.9%; *P*<.001). For disease outcomes, the mortality rate did not differ significantly between linked and unlinked cases, but unlinked cases were more likely to progress to a critical or serious clinical condition (13.0% versus 8.2%; *P*<.001).

Table 1. Comparison of epidemiological characteristics between the linked and unlinked cases in epoch 1 (wave 1 and 2) and epoch 2 (wave 3).

Variables	Epoch 1[a] (N=438)			Epoch 2[b] (N=3345)			Overall (N=3783)		
	Linked cases (N=267)	Unlinked cases (N=171)	*P* value[c]	Linked cases (N=2058)	Unlinked cases (N=1287)	*P* value	Linked cases (N=2325)	Unlinked cases (N=1458)	*P* value
Age group (in years), n (%)			.07			<.001			<.001
<18	12 (4.5)	1 (0.6)		203 (9.9)	24 (1.9)		215 (9.2)	25 (1.7)	
18-49	161 (60.3)	114 (66.7)		855 (41.5)	552 (42.9)		1016 (43.7)	666 (45.7)	
50-64	62 (23.2)	41 (24.0)		565 (27.5)	419 (32.6)		627 (27.0)	460 (31.6)	
≥65	32 (12.0)	15 (8.8)		435 (21.1)	292 (22.7)		467 (20.1)	307 (21.1)	
Male, n (%)	128 (47.9)	101 (59.1)	.02	988 (48.0)	616 (47.9)	.94	1116 (48.0)	717 (49.2)	.48
Asymptomatic, n (%)	39 (14.6)	9 (5.3)	.002	450 (22.1)	124 (9.7)	<.001	489 (21.2)	133 (9.2)	<.001
Presence of chronic conditions, n (%)	88 (33.0)	54 (31.6)	.76	241 (11.7)	172 (13.4)	.16	329 (14.2)	226 (15.5)	.25
Mode of case detection, n (%)			<.001			<.001			<.001
Medical surveillance	145 (54.3)	9 (5.3)		828 (40.2)	65 (5.1)		973 (41.8)	74 (5.1)	
GOPC[d] and A&E	66 (24.7)	71 (41.5)		1004 (48.8)	764 (59.4)		1070 (46)	835 (57.3)	
Private clinics	7 (2.6)	35 (20.5)		196 (9.5)	375 (29.1)		203 (8.7)	410 (28.1)	
Others[e]	49 (18.4)	56 (32.7)		30 (1.5)	83 (6.4)		79 (3.4)	139 (9.5)	
Ever consulted private clinics prior to admission, n (%)	47 (17.6)	41 (24)	.10	67 (3.3)	111 (8.6)	<.001	114 (4.9)	152 (10.4)	<.001
PCR Ct[f] value, median (25th percentile to 75th percentile)	24.4 (19.1-31.1)	29.3 (22.3-33.8)	<.001	23.2 (18.8-28.8)	24.5 (19.8-29.7)	<.001	23.3 (18.8-29.0)	24.8 (19.9-30.1)	<.001
Critical/serious condition, n (%)	17 (6.4)	17 (9.9)	.17	173 (8.5)	171 (13.4)	<.001	190 (8.2)	188 (13.0)	<.001
Death, n (%)	3 (1.1)	2 (1.2)	.96	61 (3.0)	34 (2.6)	.59	64 (2.8)	36 (2.5)	.60

[a]January 23 to June 18, 2020, covering the first and second wave.

[b]June 19 to September 23, 2020, covering the third wave.

[c]*P* values were from chi-square tests and independent two-sample *t* tests for categorical and continuous variables, respectively.

[d]GOPC: general outpatient clinic; A&E: Accident & Emergency department.

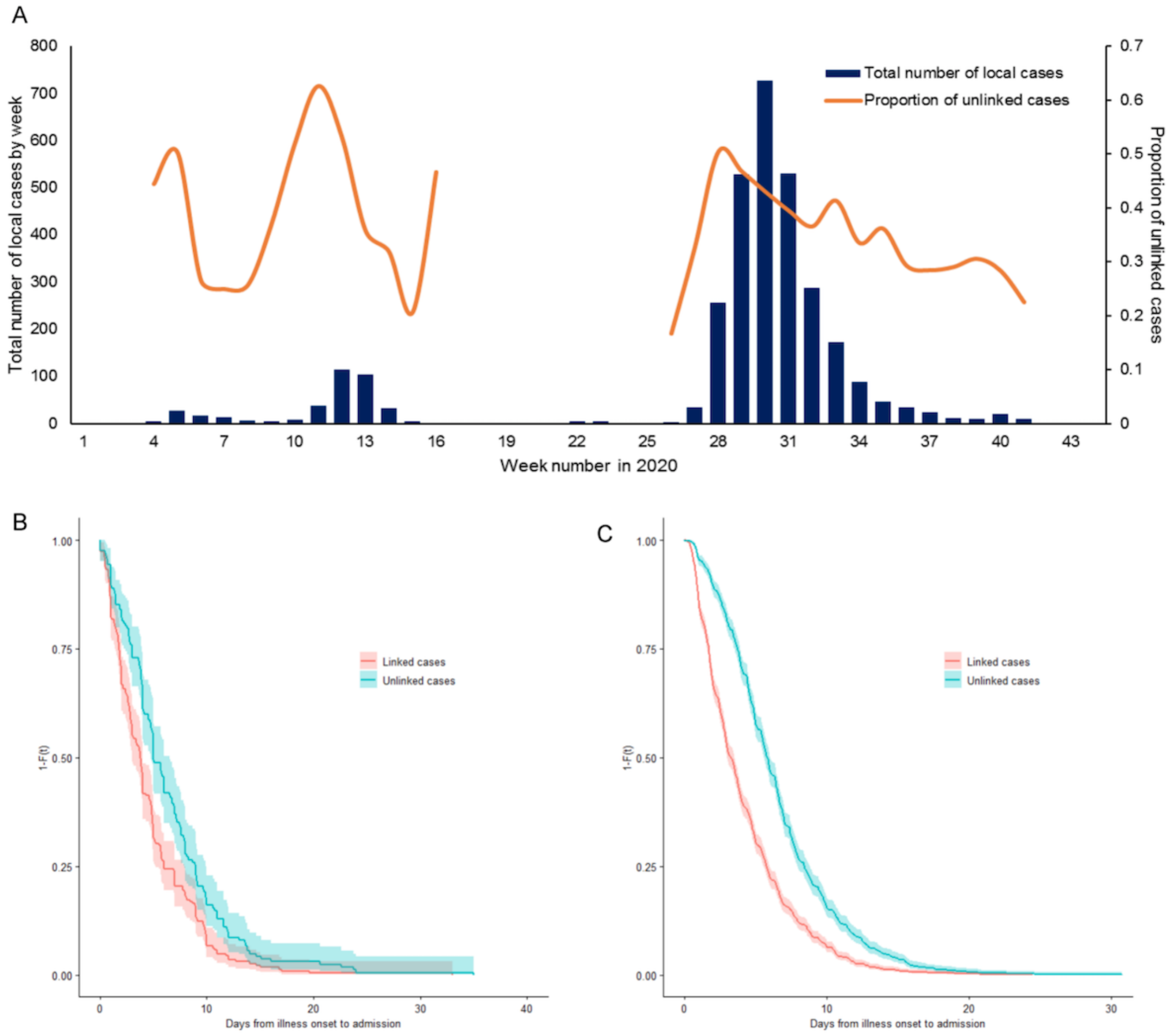
[e]Others includes testing for inbound travelers, testing for high-risk groups, and community screening programs.

[f]PCR Ct: polymerase chain reaction cycle threshold.

Relationship of Linked Cases With Epidemic Size and Time to Hospital Admission

The proportion of unlinked cases was significantly associated with the number of new local cases by week (r=0.39; P=.049; Figure 2A). In both epochs, the unlinked cases had significantly longer time to hospital admission than the linked cases (P<.001, sex and age adjusted; Figure 2B and Figure 2C). The median time to admission was 3.78 days for the linked cases (95% CI 3.30-4.27) and 5.00 days (95% CI 4.37-5.63) for the unlinked cases in epoch one, and 3.26 days (95% CI 3.06-3.47) and 4.46 days (95% CI 4.28-4.64) in epoch two, respectively.

Figure 2. (A) Relationship between the proportion of unlinked cases and weekly number of new local cases (in the week of illness onset). A survival analysis of the time to admission in epoch 1 (B) and epoch 2 (C). The proportion of unlinked cases was smoothed using a 1-week window period.

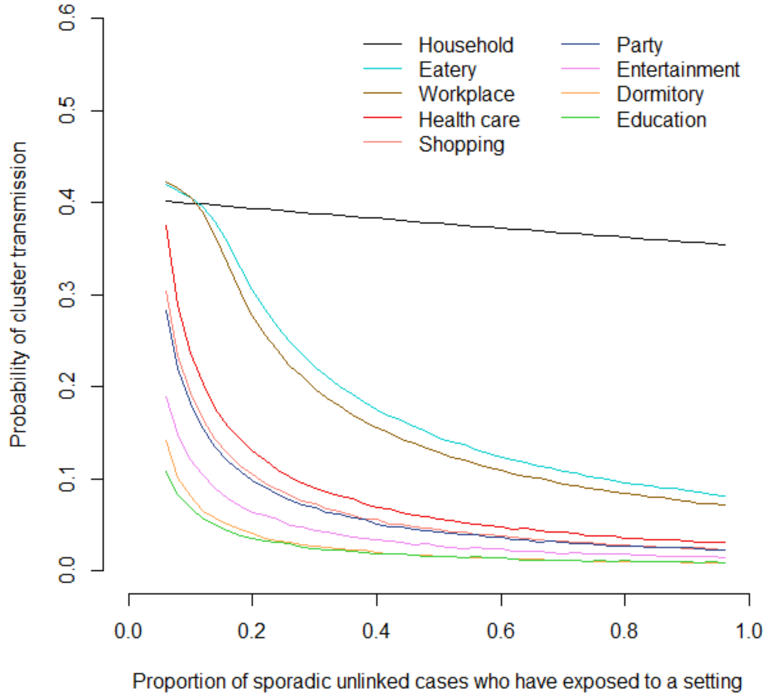


Transmission Potential of Unlinked Cases in Different Settings

Of the unlinked cases, 678 (46.5%) were identified as index cases with further secondary transmission. Settings where these cluster transmissions were most likely to be observed were households (493/678, 72.7%), eateries (54/678, 8.0%), and workplaces (48/678, 7.1%).

Households had the highest probability of outbreaks—each unlinked case had around 0.4 probability of causing a cluster of size $j \geq 2$ in household settings (Figure 3). In general, outbreak potential was sensitive to the values of p_u in all settings except households, where the probability of secondary transmission was insensitive to p_u, consistent with a previous study showing a comparatively low potential for dissemination from a household to other settings [12]. Eateries and workplaces also had high outbreak potentials compared to other settings, with probabilities ranging from around 0.1-0.4 under different values of p_u. Health care, shopping, and party settings were particularly sensitive to p_u and could have a secondary transmission probability of >0.3 if a small proportion of sporadic unlinked cases had been involved in these settings (ie, low p_u). An outbreak potential probability as high as 0.3 (or any threshold defining a "high" probability) informs decisions regarding the public health measures needed to mitigate the risk of transmission in those settings.

Figure 3. Probabilities of cluster transmissions in different settings across the proportions of unlinked sporadic cases assumed to have visited each setting. The probability of cluster transmissions is defined as the probability of having caused a cluster size >1 for each unlinked case, based on the offspring distribution that follows a negative binomial distribution given the estimated dispersion parameter and effective reproductive number. Since there is no location history for the sporadic unlinked cases, the number of these cases at a particular setting u was simulated by multiplying the total number of sporadic unlinked cases with a factor pu that varied from 5%-95%.



Discussion

In this study, we characterized the epidemiological profile of local unlinked cases in the first three epidemic waves of COVID-19 in Hong Kong, a Special Administrative Region with a well-established case detection and contact tracing system used as a key containment strategy. Nevertheless, conventional contact tracing is unable to identify all close contacts at risk of infection, resulting in a significant number of unlinked cases, detected either as sporadic cases or as index cases of clusters of infections. We showed that unlinked cases were positively correlated with time to hospital admission, serious/critical clinical condition, and epidemic size. The higher proportion of patients progressing to a serious/critical condition among the unlinked cases was particularly pronounced in the third wave when cases were mostly due to local transmission.

Compared with the linked cases that were quickly identified through contact tracing and could be diagnosed before symptom onset, unlinked cases—for which no information regarding epidemiological linkage had been obtained through conventional contact tracing methods—could only be ascertained when they sought medical consultation upon becoming symptomatic. This could result in a longer delay in receiving appropriate care and treatment, which could result in an increased likelihood of progressing to a serious/critical clinical condition, which is consistent with reports regarding other respiratory infectious diseases [17,18]. However, the overall mortality rate was not found to be significantly different between linked and unlinked cases. One possible reason is that the health care system provides effective clinical management of patients with COVID-19. In Hong Kong, the mortality rate has been relatively low [19] and the health care system still had the capacity to provide optimal care for patients with COVID-19 as the epidemic was brought under control rapidly with physical distancing measures during both epochs of the epidemic.

Another important finding was the association between the unlinked infections and the local epidemic situation. As indicated by Kretzschmar et al [6], the delay in detection and isolation would reduce the effectiveness of contact tracing measures for COVID-19 control. Across the different settings, the probability of an outbreak was highest in households, a phenomenon reported by studies in mainland China [20] and Korea [21]. However, it should be noted that household members are usually less subject to recall bias than others, leading to an overrepresentation of household secondary cases in our data set and an upward bias in the transmission potential for household settings. As shown by Adam et al [13], frequencies of secondary transmission were highest in households, while clusters were largest in social settings like restaurants, where superspreading events occurred. In line with our finding, a previous study showed that eateries and workplaces were the settings more likely to generate transmission cascades across more than a single setting in the second wave of the epidemic [12]. Such enclosed settings where large numbers of people were in close contact were a risk factor for transmission, while the congregation of people not known to each other was a risk factor for not being able to identify close contacts, allowing the dispersion of infections in a wide range of the settings.

Globally, it was estimated that 10% of cases outside China had caused 80% of secondary cases at the start of the pandemic [22]. Superspreading events have driven the pandemic significantly and could quickly overwhelm the contact tracing system; for example, for a single large cluster, the epidemic investigation team traced up to 1000 people in Hong Kong [23]. Although venues like gymnasiums and sport venues were closed in Hong Kong and the government encouraged people to work from home during the pandemic, most businesses were operational. Dining in in restaurants was permitted with restrictions in numbers, operational hours, and capacity. Unsurprisingly, we found a higher probability of cluster transmissions in eateries and workplaces compared to other settings. However, considering the scenario in which sporadic unlinked cases are not likely to have been involved in clusters in health care, shopping, and party settings, these settings would also have high potentials for cluster transmission. Our analysis thus provides a retrospective risk assessment for optimizing the relaxation of social/physical distancing restrictions in different settings; in these settings, risk can be managed with a robust and strictly enforced digital tracing system. Resurgences of infections could be prevented, obviating the need for a complete lockdown and the associated social and economic costs.

Many studies have focused on identifying hot spots for superspreading events. Although indoor environments with poor ventilation are generally riskier, human activities and behaviors (whether people have taken precautions) are even more crucial [12,24]. Therefore, health care, shopping, and party settings should have strictly implemented precautions for preventing cluster transmission, because of the risk and large number of contacts associated with such settings. Our findings offer empirical evidence for the differential influence of unlinked cases on epidemic control, which could help prioritize mitigation strategies.

Many jurisdictions in the Western Pacific Region heavily relied on stringent case detection, contact tracing, isolation, quarantine, and intensive testing programs together with border restrictions for COVID-19 control [19]. However, the conventional contact tracing approach is labor-intensive and feasible for low-incidence settings only [7], capturing only known contacts and being subject to cases' recall bias. Mobile phone data are a promising complementary tool. First, mobility data can inform incidence forecasts—for example, modeling combined with local mobility data showed that restaurants, bars, and gyms were hot spots for transmission [25]. Second, apps can be used to alert users instantaneously if their contacts are confirmed positive and recorded in the system [26,27]. This would prompt the alerted users to seek testing, especially for presymptomatic or asymptomatic transmissions [28-31]. In this study, we found that the percentage of asymptomatic infections was significantly lower in the unlinked cases than in the linked cases, primarily due to the fact that the unlinked cases would only be identified when they became symptomatic and sought medical consultation. However, even though contact tracing can identify some asymptomatic cases, others are missed by the system. App-based tools could prove useful for tracing these infections by providing improved coverage and timeliness and have the potential to address the challenge of anonymous close contacts that the index patients do not know. Digital contact tracing has been deployed in many countries [32], including India [33], Switzerland [26], and the United Kingdom [27]. Nevertheless, we acknowledge that the effectiveness of app-based monitoring tools on outbreak control remains controversial when variations in exposure relative to the infectiveness period, testing accuracy, isolation adherence, and coverage of the app-based technology are taken into account [34,35]. Most importantly, the use of smartphone data for digital contact tracing in such contexts raises a number of ethical and privacy concerns [36]. In Hong Kong, for example, residents were skeptical of the LeaveHomeSafe app implemented after the third wave of the epidemic, despite the government's reassurance that user registration was not required and the check-in data would not be uploaded to the government's system or any other systems [37,38]. The critical role of digital technology in complementing conventional contact tracing needs to be evaluated, and ethical and privacy concerns must be addressed.

One major limitation of this study is that the location history for the sporadic unlinked cases was unavailable. We estimated the transmission probability of the unlinked cases by considering a range of scenarios that varied by the proportion of sporadic unlinked cases. In addition, we did not quantify the frequency of outbreaks (eg, the number of clusters per 1000 unlinked cases), which would be of interest for decision-making due to the unknown number of sporadic unlinked cases in each setting. Instead, we provided the probability that an unlinked case could result in secondary transmission to convey the outbreak potential in that setting. This indicates a need for an exposure tracking system that automatically computes the risk level for different settings. Second, cases were linked epidemiologically without validation through other approaches such as the routine use of phylogenetic analysis due to a lack of viral sequencing data [39]. Fingerprinting of SARS-CoV-2 via phylogenetic information can assist in the identification of chains of transmission; therefore, such analyses should be performed in future investigations. Third, the retrospective data cannot infer transmission potential for some settings that were already closed during the study period (eg, kindergartens that were closed since the early phase of the first wave). Fourth, some of the unlinked cases may have been infected by the imported cases exempted from quarantine and testing [40], limiting the generalizability of our results to other places with different border control measures.

In conclusion, our findings suggest a need to promote the use of digital tracing methods on top of current conventional testing and tracing. Contact tracing measures can potentially shorten the time to admission, reduce serious cases, and prevent further spread. With the considerable probability of secondary transmission from the unlinked cases, digital tracing measures should be strictly enforced in high-risk social settings and the local epidemic should be closely monitored such that the measures can be adjusted in a timely manner.

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Authors' Contributions

KCC and EKY were responsible for the study concept and design. FTTL, NNSC, CHKY, and TYC were responsible for the literature search. FTTL, NNSC, CHKY, and TYC were responsible for acquisition of data. KCC and KMJ were responsible for statistical analysis and produced the output. KCC was responsible for figures. KCC, KMJ, SSL, CTH, NSW, and EKY were responsible for analysis and interpretation of data. KCC, KMJ, and EKY were responsible for drafting of the manuscript. SSL, CTH, NSW, FTTL, and YW were responsible for critical revision of the manuscript for important intellectual content. All authors contributed to revision of the manuscript and approved the final version for submission. All authors had full access to all the data in the study and were responsible for the decision to submit the manuscript for publication.

Conflicts of Interest

None declared.

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Abbreviations

A&E: Accident & Emergency
Ct: cycle threshold
GOPC: general outpatient clinic
NPI: nonpharmaceutical intervention
PCR: polymerase chain reaction

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Original Paper

Public Health Surveillance Systems in the Eastern Mediterranean Region: Bibliometric Analysis of Scientific Literature

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Abstract

Background: The Eastern Mediterranean Region (EMR) hosts some of the world's worst humanitarian and health crises. The implementation of health surveillance in this region has faced multiple constraints. New and novel approaches in surveillance are in a constant state of high and immediate demand. Identifying the existing literature on surveillance helps foster an understanding of scientific development and thus potentially supports future development directions.

Objective: This study aims to illustrate the scientific production, quantify the scholarly impact, and highlight the characteristics of publications on public health surveillance in the EMR over the past decade.

Methods: We performed a Scopus search using keywords related to public health surveillance or its disciplines, cross-referenced with EMR countries, from 2011 to July 2021. Data were exported and analyzed using Microsoft Excel and Visualization of Similarities Viewer. Quality of journals was determined using SCImago Journal Rank and CiteScore.

Results: We retrieved 1987 documents, of which 1927 (96.98%) were articles or reviews. There has been an incremental increase in the number of publications (exponential growth, R^2=0.80) over the past decade. Publications were mostly affiliated with Iran (501/1987, 25.21%), the United States (468/1987, 23.55%), Pakistan (243/1987, 12.23%), Egypt (224/1987, 11.27%), and Saudi Arabia (209/1987, 10.52%). However, Iran only had links with 40 other countries (total link strength 164), and the biggest collaborator from the EMR was Egypt, with 67 links (total link strength 402). Within the other EMR countries, only Morocco, Lebanon, and Jordan produced ≥79 publications in the 10-year period. Most publications (1551/1987, 78.06%) were affiliated with EMR universities. Most journals were categorized as medical journals, and the highest number of articles were published in the Eastern Mediterranean Health Journal (SCImago Journal Rank 0.442; CiteScore 1.5). Retrieved documents had an average of 18.4 (SD 125.5) citations per document and an h-index of 66. The top-3 most cited documents were from the Global Burden of Diseases study. We found 70 high-frequency terms, occurring ≥10 times in author keywords, connected in 3 clusters. *COVID-19*, *SARS-CoV-2*, and *pandemic* represented the most recent 2020 cluster.

Conclusions: This is the first research study to quantify the published literature on public health surveillance and its disciplines in the EMR. Research productivity has steadily increased over the past decade, and Iran has been the leading country publishing relevant research. Recurrent recent surveillance themes included COVID-19 and SARS-CoV-2. This study also sheds light on the gaps in surveillance research in the EMR, including inadequate publications on noncommunicable diseases and injury-related surveillance.

(JMIR Public Health Surveill 2021;7(11):e32639) doi:10.2196/32639

KEYWORDS

public health; surveillance; Eastern Mediterranean Region; bibliometric analysis; literature; research; review

Introduction

Background

Throughout history, the concepts of population surveillance and public health surveillance (PHS) have been in a continuous state of evolution [1]. In 1968, the 21st World Health Assembly embraced surveillance as a concept and acknowledged its 3 core functions: a systematic collection of data, methodical analysis and evaluation of the data, and timely dissemination of the results, especially to those who can take action [2]. Today, PHS is considered a fundamental function of public health practice and is defined by the World Health Organization (WHO) as the "continuous and systematic collection, orderly consolidation and evaluation of pertinent data with prompt dissemination of results to those who need to know, particularly those who are in a position to take action" [3].

Global commitment to surveillance was recognized in 2005 by the WHO when it revised and adopted the International Health Regulation treaty, defining specific events that require reporting to the WHO within 24 hours of their occurrence [4]. These regulations necessitate that countries have the capacity to detect, assess, report, and respond to public health events; however, only approximately one-third of the world has the capacity to implement this [5]. Technical, political, and economic challenges pose barriers to the implementation of disease surveillance in low- and middle-income countries (LMICs) [6], such as the Eastern Mediterranean Region (EMR) countries.

The EMR comprises 22 member countries, encompassing a total of approximately 679 million individuals [7]. It is host to some of the world's worst humanitarian and health crises, and >58% of the world's refugees and internally displaced people come from the EMR [8]. Indeed, the implementation of health surveillance in this region have faced multiple constraints [9], and recent initiatives by the WHO and the US Centers for Disease Control and Prevention (CDC) in collaboration with regional and local networks and governments have been put in place to try to mitigate these constraints and challenges [10,11].

The two main general categories of surveillance include indicator-based surveillance and event-based surveillance [12]. However, new and novel approaches in surveillance are in a constant state of high and immediate demand to directly tackle unexpected health challenges in a timely manner and address community health concerns [13]. A driver of the dynamics of PHS is the broad and diverse cultural, behavioral, economic, and societal differences that affect public health issues in the various countries of the world differently and thus influence the process and implementation of surveillance differently [13]. Four strategies of population surveillance and PHS thus emerge and include passive surveillance, active surveillance, sentinel surveillance, and syndromic surveillance [14]. Other concepts in surveillance have also surfaced, including biosurveillance, which monitors specific data to identify epidemic outbreaks resulting from accidents or bioterrorism [15].

Objective

Identifying existing literature on a topic helps foster an understanding of the topic's academic development and thus potentially supports future development directions. This study aims to illustrate the scientific evolution, quantify the scholarly impact, and highlight the characteristics of publications on PHS in the EMR over the last decade. This will provide useful information for the advancement of surveillance strategies to address health issues in the region and will shed light on possible future collaborations and potential joint research engagements.

Methods

Search Strategy

We performed our search on June 26, 2021, using the Scopus database, which contains specific useful functions for data mining and bibliometric analysis. Scopus is the largest indexing database; it combines the characteristics of both PubMed and Web of Science, allowing for enhanced utility, both for the literature research and academic needs, including citation analysis [16]. Subject headings as Medical Subject Heading terms or Emtree terms are not directly searchable on Scopus, and instead, Scopus manually assigns index terms (controlled vocabulary) that have a direct relation with the topic [17]. Therefore, in addition to searching abstracts and titles, our search query included the field code KEY, which combines author keywords and indexed terms [17]. To build the query, we used keywords relevant to surveillance and the WHO list of countries in the EMR (Multimedia Appendix 1) [7]. Keywords for surveillance included *population surveillance*, *health surveillance*, *surveillance system*, *biosurveillance*, *passive surveillance*, *active surveillance*, *event-based surveillance*, *indicator-based surveillance*,*case-based surveillance*, *sentinel surveillance*, *syndromic surveillance*, *disease surveillance*, *environmental surveillance*, and *epidemiological surveillance*. We used truncations and wild cards, as appropriate, to maximize the capture of relevant citations. To analyze the most recent publications in the field, which may have implications for future trends in research, we targeted the search to the period from 2010 to 2021. We included papers, reviews, letters, conference papers, and book chapters, as these citations usually report original scientific outputs. No language restrictions were applied, and we included both published papers and papers in the press.

Scientific Literature Bibliometric Indicators

Data from the retrieved documents were exported to Microsoft Excel. The exported data were used to calculate the following indicators: number of documents published by document type; number of documents published per language; number of documents published per year, and we excluded documents published in 2021 from the analysis of annual trends as this study was conducted in June 2021; number of documents published per journal; number of documents published per country; number of documents published per organizational affiliation, and we combined affiliations into 5 categories—universities in the EMR, universities outside the EMR, Ministries of Health in the EMR, research institutes in the EMR, research institutes outside, and global health institutes; number of documents per funding source; and number of documents published by subject category. We used the subject categories as indexed by Scopus.

Citations and Quality Assessment

We used the citation overview function on Scopus to determine the mean, median, and range of citations of all retrieved documents, including their h-index. We scrutinized the topmost cited documents, as well as the authors who published >20 papers on the topic.

We assessed the quality of the most productive 20 journals in the field of surveillance in the EMR using the SCImago Journal Rank (SJR) and CiteScore (CS). SJR is a metric that is based on centrality concepts and data from Scopus, and we chose it as it limits self-citations and thus limits falsely inflated quality ranks [18]. We additionally used CS, as it has become the new standard that gives a more comprehensive, transparent, and current view of a journal's impact [18]. To determine the subject area of journals, we used the subject area and category provided by the SCImago ranking website in addition to reviewing the official scope of each journal on its respective website.

Visualization of Similarities

Citation information, bibliographical information, abstracts and keywords, and included references were also imported to the Visualization of Similarities Viewer (VOSviewer) software v.1.6.16 (Centre for Science and Technology Studies, Leiden University) to analyze and visualize relationships among authors, countries, and the terms used in the papers [19]. This mapping method was used to estimate the association strength between items, which is indicative of the similarity between terms. The co-occurrence of 2 items in a larger number of documents indicates that the items are very similar to one another. Graphically, each cluster of items (eg, a group of linked keywords) is identified by a different color [20]. We used a resolution of clustering of 2 and a minimum cluster size of 12 to eliminate small clusters. Visualization maps were based on document weights, unless otherwise stated, and the diameter or the label size of an item denotes the number of occurrences in the documents, and the distance between 2 items represents the degree to which they are associated [20]. Network coauthorship analysis was first performed based on the full counting method on VOSviewer, with the unit of analysis being the author. Papers including >25 authors were excluded from this analysis, and both the minimum number of papers published by an author and the minimum number of citations of an author was set at 5 to identify prominent authors who have published on the topic. We also performed the same coauthorship analysis, with the unit being countries. Papers including >25 countries were excluded, and only countries with ≥5 published papers were included. No restriction was placed on the number of citations. Within the coauthorship network, the links attribute indicates the number of coauthorship links of a given country with other countries, whereas the total link strength attribute indicates the total strength of the coauthorship links of a given country with other countries. These numbers are readily provided by VOSviewer in the visualized network.

We used co-occurrence analysis to identify hot topics and time trends of the themes. We used author keywords, occurring >10 times, to identify network associations in underlying research themes among documents on surveillance in the EMR. To maintain the focus on scientific themes and keywords, we omitted the names of countries and regions from the resultant list. We also applied normalization to the analysis based on the association strength to eliminate redundancy in similar keywords that define the same concept. We further constructed an overlay visualization of this relationship to determine the evolution of themes with time during our study period.

Results

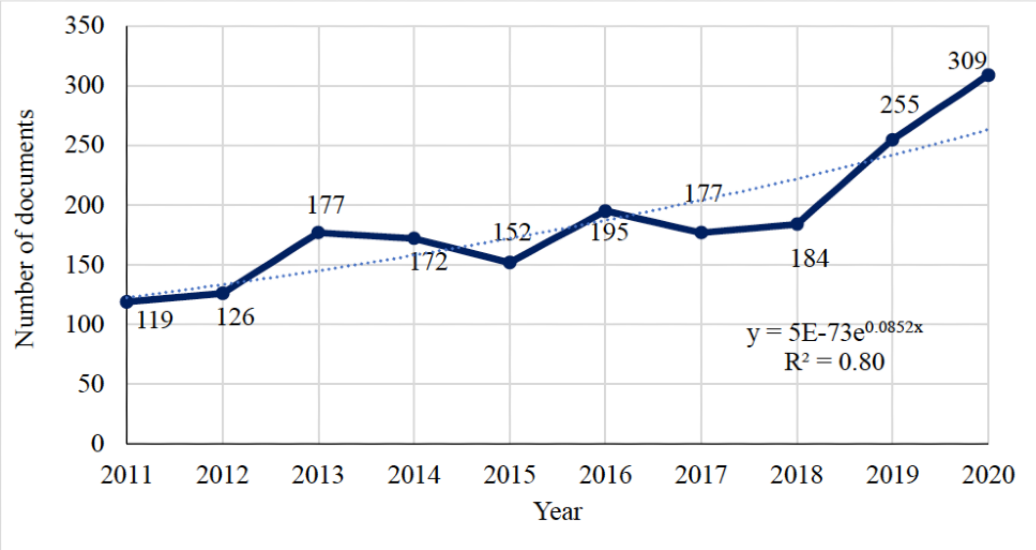
Volume and Type of Publications

We retrieved 1987 documents, of which 1239 (62.36%) were open access, and only 8 (0.4%) were still in press, whereas all others were in the final published stage. Most (1927/1987, 96.98%) of the retrieved documents were articles or reviews. Conference proceedings and book chapters constituted only 0.65% (13/1987) and 2.37% (47/1987), respectively. Documents were mostly published in English (1930/1987, 97.13%), whereas a minority were published in Persian, French, Arabic, Turkish, Spanish, Italian, or Chinese.

Annual Trend of Publications

Between 2011 and 2020, there was an incremental increase in the number of scientific publications, corresponding to an exponential growth model (R^2=0.80; Figure 1). Publications in 2020 were 2.6 times greater in number than those published in 2011. During the entire 10-year period, there was a surge of publications seen in 2013-2014, 2016, 2019, and 2020. A review of papers published during these periods showed a high percentage (>10%) of publications on the following: novel Middle East respiratory syndrome coronavirus in 2013-2014 (44/1987, 2.21% of documents; 46/349, 13.2% of the documents published in 2013-2014), influenza in 2016 (32/1987, 1.61% of documents; 32/195, 16.4% of the documents published in 2016) and 2019 (29/1987, 1.46% of documents; 28/255, 10.9% of the documents published in 2019), and COVID-19 in 2020 (59/1987, 2.97% of documents; 60/314, 19.1% of the documents published in 2020).

Figure 1. Number of published documents on surveillance in the Eastern Mediterranean region between 2011 and 2020. Dotted line represents exponential growth with R^2=0.8.



Publication Distribution by Country

Most publications on surveillance in the EMR were publications affiliated with Iran (501/1987, 25.21%) and the United States (468/1987, 23.55%), followed by Pakistan (243/1987, 12.23%), Egypt (224/1987, 11.27%), and Saudi Arabia (209/1987, 10.52%; Figure S1A in Multimedia Appendix 2). Among the other EMR countries, only Morocco, Lebanon, and Jordan produced ≥79 publications (≥4%) in the 10-year period, whereas 11 countries produced ≤50 publications, particularly Somalia, Syria, Bahrain, and Libya, each contributing <1% (n=4-17) to the publication output (Figure S1B in Multimedia Appendix 2).

Publication Distribution by Affiliation

Each publication had one or more institutional affiliation. Most of the published documents (1562/1987, 78.61%) were affiliated with universities in the EMR, whereas some (745/1987, 37.49%) were affiliated with universities from outside the region. Ministries of health, including those of Egypt, Iraq, Sudan, Kuwait, Qatar, Oman, Lebanon, Saudi Arabia, and Iran, contributed to approximately 17.41% (346/1987) of the published literature, with the Iranian Ministry of Health and Medical Education being the major contributor. Similarly, global health institutes, including the CDC, WHO, National Health Institute, and the Global Health Development/Eastern Mediterranean Public Health Network (GHD/EMPHNET), European Centre for Disease Prevention and Control, National Center for Emerging and Zoonotic Infectious Diseases, Medecins Sans Frontieres, and Food and Agriculture Organization of the United Nations, contributed to approximately 17.41% (346/1987) of the published literature. The top 5 most productive universities in the region were all in Iran, and included: Tehran University of Medical Sciences, Shahid Beheshti University of Medical Sciences, Aga Khan University, Iran University of Medical Sciences, and Shiraz University of Medical Sciences. The top 5 most productive universities outside the region were Johns Hopkins University, Imperial College London, London School of Hygiene and Tropical Medicine, University of Oxford, and The University of Sydney. As for the most productive research institutes, the top 5 in the EMR were the Endocrinology and Metabolism Research Institute in Iran, Pasteur Institute of Iran, National Institute of Health Pakistan, National Research Centre in Egypt, and the Noncommunicable Diseases Research Center in Iran; and Public Health England, Paris Institut Pasteur, Karolinska Institutet, Institut national de la santé et de la recherche médicale, and the International Centre for Diarrhoeal Disease Research Bangladesh, were the top 5 outside the EMR (Multimedia Appendix 2 Figure S2).

Source of Funding

Most of the identified publications did not report a source of funding (1415/1987, 71.21%); however, for those that did, most were funded by the US Department of Health and Human Services (121/572, 21.2%) or by the National Institute of Health (83/572, 14.5%). Department of Health and Human Services and National Institute of Health–funded publications substantially peaked in 2015 and in 2019, with an obvious decline in 2020, and these funded studies were mainly published by the United States. The CDC, European Commission, Bill and Miranda Gates Foundation, and the WHO funded approximately 38 to 42 papers each.

Most Productive Citing Journals

Of the 1987 published literature, 1931 (97.18%) documents were published in 160 distinct scientific journals, whereas the rest were included in conference proceedings, books, or their sources were not defined. Table 1 lists the top 20 most productive journals publishing the greatest number of papers related to the field of surveillance in the EMR between 2011 and 2021. Their median 2020 SJR was 1.123 (range 0.182-3.44), and the Eastern Mediterranean Health Journal (SJR 0.442, CS 1.5) topped the list, publishing approximately 3.82% (76/1987) of the literature retrieved on the topic. Most journals were categorized as medical journals, and on reviewing the scope of each of the top 20 journals, only 2 journals, Eurosurveillance [21] and JMIR Public Health and Surveillance [22], specifically focused on surveillance.

Table 1. The SCImago Journal Rank (SJR), CiteScore (CS), and h-index of the 20 most productive journals in the field of public health surveillance in the Eastern Mediterranean Region between 2011 and 2021, arranged by productivity (N=1931).

Top 20 journals	2020 SJR	CS	h-index	Values, n (%)[a]	Journal subject area and category
Eastern Mediterranean Health Journal	0.442	1.5	47	76 (3.93)	Medicine (miscellaneous)
PLOS One	0.990	5.3	332	61 (3.16)	Multidisciplinary (sciences)
International Journal of Infectious Diseases	1.278	7.0	89	45 (2.33)	Medicine (miscellaneous, ID[b], and medical microbiology)
PLOS Neglected Tropical Diseases	1.990	7.1	135	42 (2.18)	Medicine (ID and PHEOH[c]), pharmacology, toxicology, and pharmaceutics
Emerging Infectious Diseases	2.540	9.8	226	37 (1.92)	Medicine (epidemiology, ID, and medical microbiology)
Journal of Infection and Public Health	0.983	4.9	35	35 (1.81)	Medicine (miscellaneous, ID and PHEOH)
Journal of Infection in Developing Countries	0.322	1.6	49	29 (1.5)	Medicine (miscellaneous and ID) and immunology and microbiology
Vaccine	1.585	5.6	184	28 (1.45)	Medicine (ID and PHEOH), immunology and microbiology, veterinary (miscellaneous), biochemistry, and genetics and molecular biology (molecular medicine)
Journal of Infectious Diseases	2.690	9.2	252	27 (1.4)	Medicine (immunology and allergy and ID)
Archives of Iranian Medicine	0.490	2.3	47	26 (1.35)	Medicine (miscellaneous)
Eurosurveillance	2.766	13.9	104	26 (1.35)	Medicine (epidemiology, ID, and PHEOH) and immunology and microbiology (virology)
Iranian Journal of Epidemiology	0.182	0.7	11	26 (1.35)	Medicine (epidemiology)
BMC[d] Infectious Diseases	1.278	4.4	104	22 (1.14)	Medicine (ID)
Iranian Journal of Public Health	0.452	2.1	39	22 (1.14)	Medicine (PHEOH)
Clinical Infectious Diseases	3.440	13.2	336	21 (1.09)	Medicine (ID and medical microbiology)
Acta Tropica	0.969	5.2	101	18 (0.93)	Medicine (ID), immunology and microbiology (parasitology), veterinary (miscellaneous), and agricultural and biological sciences (insect sciences)
Transboundary and Emerging Diseases	1.392	7.6	63	18 (0.93)	Medicine (miscellaneous), immunology and microbiology (miscellaneous), and veterinary (miscellaneous)
American Journal of Tropical Medicine and Hygiene	1.015	4.0	151	16 (0.83)	Medicine (miscellaneous and ID) and immunology and microbiology (parasitology and virology)
BMC Public Health	1.230	4.1	143	16 (0.83)	Medicine (PHEOH)
Epidemiology and Infection	0.992	5.0	109	16 (0.83)	Medicine (epidemiology and ID)
JMIR Public Health and Surveillance	1.446	5.8	146	15 (0.78)	Not available on SCImago, description from journal website [22]: public health and technology, public health informatics, mass media campaigns, surveillance, participatory epidemiology, and innovation in public health practice and research
Journal of Medical Virology	0.782	11.6	121	14 (0.73)	Medicine (ID) and immunology and microbiology (virology)

[a]The total number of documents retrieved that were published in journals was 1931. Percentages were calculated as the (number of documents published by each journal × 100) / 1931.

[b]ID: infectious diseases.

[c]PHEOH: Public Health, Environmental, and Occupational Health.

[d]BMC: BioMed Central.

Publications by Subject Category

Each published document was categorized under one or more subject categories in Scopus. Most of the retrieved literature (1622/1987, 81.63%) were categorized under medicine as a subject. Approximately 20.43% (406/1987) were categorized under immunology and microbiology. Of those categorized under medicine, 90.14% (1462/1622) were labeled with indexed keywords related to surveillance: disease surveillance, population surveillance, surveillance, PHS, or sentinel surveillance.

Citation Metrics

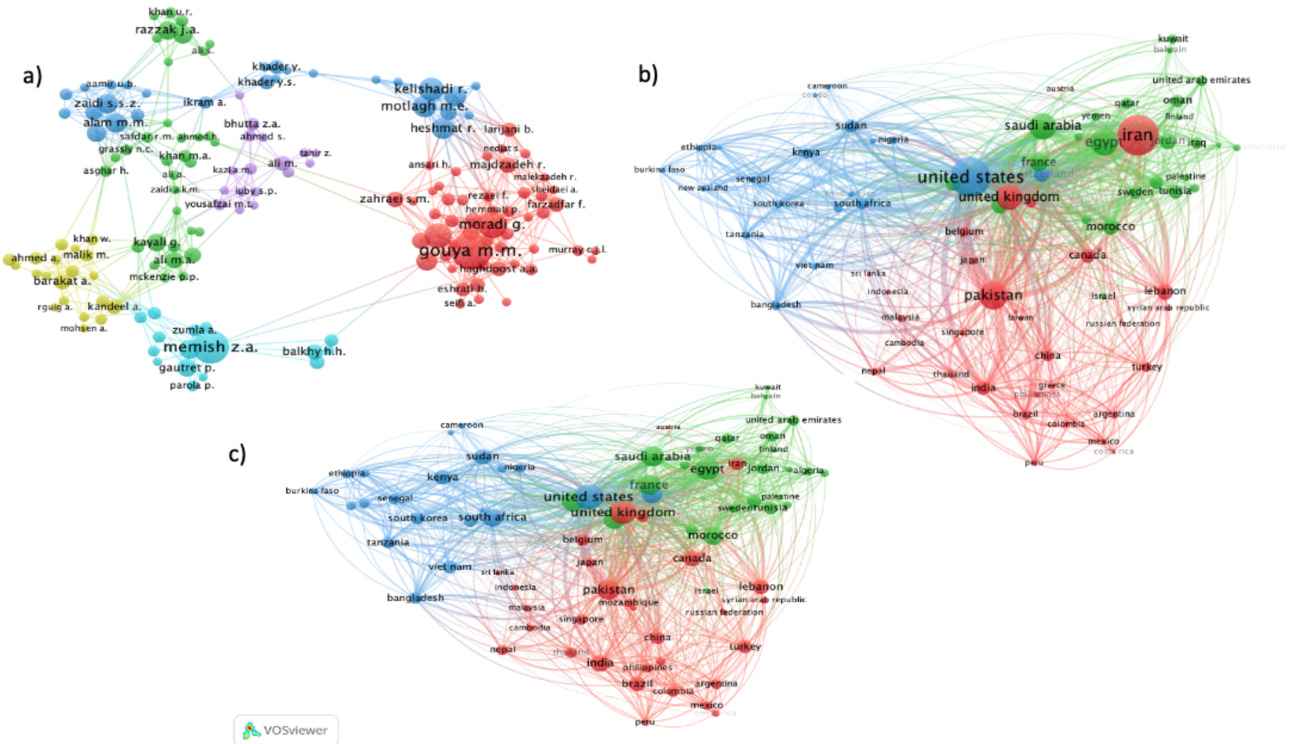
The retrieved documents received a total of 36,630 citations, with an average of 18.4 (SD 125.5) citations per document (median 5, range 0-4402) and an h-index of 66. The number of documents receiving ≥10, ≥50, or ≥100 citations was 679, 100, and 41 documents, respectively. The top-3 most cited documents were all from the ongoing Global Burden of Diseases (GBD) study and were open access papers published in The Lancet by the US Institute for Health Metrics and Evaluation, assessing global, national, and regional all-cause and specific-cause mortality [23-25]. These 3 global studies, which were published between 2015 and 2018, had >700-1000 collaborators or authors each and were cited 1729-4409 times [23-25]. Papers from the GBD study comprise 47% (7/15) of the most cited papers on the topic of surveillance in the EMR. The other most cited papers were also open-access global or multicounty studies, 2 of which were conducted by the CDC in collaboration with the WHO and assessed rotavirus infections or vaccines [26,27], and 2 were reviews assessing hepatocellular carcinoma [28] or hepatitis C virus [29], and all recommended the implementation of surveillance systems. The 6 authors, including 1 female author, who published >20 documents on the topic (range 20-42), were from Iran, Saudi Arabia, and Jordan. Their average h-index on Scopus was 55 (SD 32; median 51, range 18-98), and their median citation frequency was 17,236 (range 5198-85,491).

Visualization of Similarities and Associations

Coauthorship

In papers with <25 authors, 173 authors had at least 5 publications and were cited at least 5 times. Of these 173 authors, 165 (95.4%) authors were connected (have collaborated) in 6 distinct clusters (Figure 2A). Similarly, excluding papers coauthored by ≥25 countries, 78 countries had ≥5 papers published on the topic of surveillance in the EMR, and these countries were connected in 5 different coauthorship clusters (Figure 2B). In these figures, the size of circles represents the number of documents published by the author or country, and the thickness of the lines depicts the size of the collaboration between the authors or countries (Figures 2A and 2B, respectively). The EMR country publishing the most on the topic was Iran; however, it lags behind other countries in terms of collaboration and only has links with 40 other countries, with a total link strength of 164. The biggest collaborator from the EMR countries was Egypt, with 67 links and a total link strength of 402, followed by Pakistan, with 62 links and a total link strength of 390; Saudi Arabia, with 62 links and a total link strength of 307; Morocco, with 55 links and a total link strength of 206; and Lebanon, with 46 links and a total link strength of 177. The United States is the country outside the EMR with the most collaboration links (n=76), with a link strength of 890 (Figure 2C).

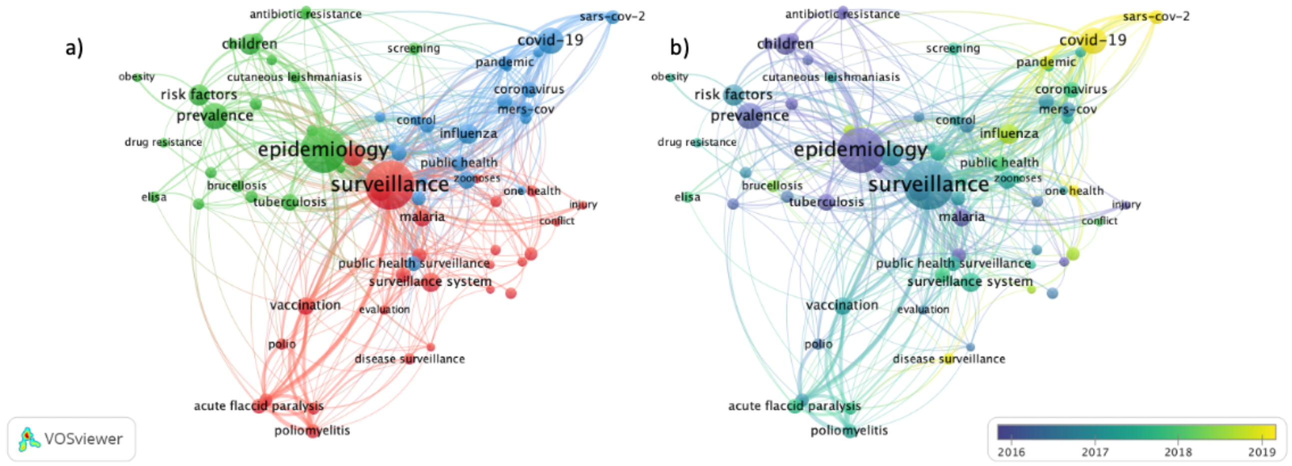
Figure 2. (A) Visualization of Similarities Viewer (VOSviewer) network of author coauthorship map representing 6 clusters of collaborations on surveillance research in the Eastern Mediterranean region, 2011-2021. Included authors (N=165) were those with at least 5 publications, with <25 authors per publication, and have been cited at least 5 times. (B) VOSviewer network of country coauthorship map weighted by the number of documents, representing 5 clusters of collaborations on surveillance research in the Eastern Mediterranean region, 2011-2021. Included countries (N=78) were those with at least 5 publications, with <25 countries collaborating per publication. (C) VOSviewer network of country coauthorship map, weighted by number of links, representing 5 clusters of collaborations on surveillance research in the Eastern Mediterranean region, 2011-2021. Included countries (N=78) were those with at least 5 publications, with <25 countries collaborating per publication. VOSviewer: Visualization of Similarities Viewer.



Co-occurrence

A knowledge map of author keyword co-occurrence is shown in Figure 3A. We found 70 high-frequency terms occurring at least 10 times in the author keywords. These keywords were connected in 3 distinct clusters. As expected, COVID-19, SARS-CoV-2, and pandemic represented the most recent 2020 cluster (Figure 3B).

Figure 3. (A) Visualization of Similarities Viewer (VOSviewer) network of author keyword co-occurrence map weighted by occurrence, representing three clusters of keywords relating to surveillance research in the Eastern Mediterranean Region, 2011-2021. Included keywords (N=70) were those occurring at least 10 times. (B) VOSviewer overlay visualization by time of author keyword relating to surveillance research in the Eastern Mediterranean Region, 2011-2021, weighted by occurrence and scored by the average publications per year. Included keywords (N=70) were those occurring at least 10 times. VOSviewer: Visualization of Similarities Viewer.



Discussion

Principal Findings

To the best of our knowledge, this is the first bibliometric study to assess publications on PHS and its disciplines during the last decade in the EMR. The information presented in this study shows the growth of publications between 2011 and 2021. It quantifies the contributions of countries, journals, organizations, and authors to this field and illustrates the collaborative behaviors between authors and countries. It also analyzes the documents by subject category and maps out the co-occurrence and time trends of relevant keywords and terms.

There was an exponential increase in publications on this topic in the EMR in the past decade, with a 2.6-fold increment in published papers in 2020 compared with 2011. This evolution of publications in the EMR mirrors the global trends of interest in health surveillance [30]. The peaks in the number of documents published in the 2013-2014 period and the years 2016 and 2020 might have been driven by certain disease outbreaks or the launch of pivotal surveillance networks in the region. Indeed, the first case of Middle East respiratory syndrome coronavirus was detected in 2012 in Saudi Arabia [31], and shortly after, multiple studies were published on the topic, contributing to approximately 13.2% (46/349) of publications seen in the following 2 years (2013-2014). Similarly, in 2016, there was a surge in influenza-related publications, which coincides with the official launch of the Eastern Mediterranean Flu Network, which is a web-based surveillance effort supervised by the WHO Regional Office for the Eastern Mediterranean to strengthen influenza surveillance systems in the region [32]. With the increasing burden of noncommunicable diseases (NCDs) both worldwide and in the region, there has also been an increasing interest in NCD research [33], which might explain the peak in publications in recent years. As for the year 2020, the explosion in publications echoes the scientific frenzy witnessed with the commence of the global COVID-19 pandemic, which took the lead and contributed massively to the literature at both the global and regional levels [34,35].

Papers cited >100 times are often referred to as citation *classics* [36]. Most *classic* papers identified during this search, based on citation counts, were open access papers of multicountry or global studies. The top-cited papers were mostly from the ongoing GBD study, which is the most descriptive worldwide epidemiological study examining the trends of 204 countries, dating back to 1990 [37]. It is a global collaborative initiative, with multiple resultant publications, following the guidelines for accurate and transparent health estimate reporting [37]. Some resultant papers were authored by EMR collaborators, specifically addressing health issues related to the EMR [38], including cardiovascular disease [39], neurodegenerative diseases [40], obesity [41], and child and adolescent injury [42].

Within countries in the region, research production was concentrated in Iran, Egypt, Pakistan, and Saudi Arabia. This is not surprising, as Iran, Egypt, and Pakistan are the most populated countries in the region, with a 2019 population estimate >82, >100, and >216 million individuals, respectively [43]. Similarly, although Saudi Arabia ranks eighth in terms of the total population compared with the other EMR countries, its gross domestic product exceeds 792 billion (2019 World Bank) [43]. For countries contributing to <1% of the retrieved literature, the long-standing devastating state of economic and political turmoil in Somalia [44], Libya [45], and Syria [46] might be the culprit behind these countries' lack of meaningful contribution to research production on the topic. Bahrain's low contribution to published research might reflect its small population, given that it is the least populated country in the EMR [43].

Research collaboration between countries does not necessarily mirror the volume of research produced by each country. Although Iran is the most productive country in terms of the volume of publications, its level of coauthorship collaboration lags behind that of Egypt, Pakistan, Saudi Arabia, Morocco, and Lebanon. This low level of scientific collaboration has been linked to the international political and economic sanctions placed on Iran [47,48]. International research collaboration is led by the United States, and the link strength of US collaboration on surveillance research with other countries reflects the concentration of funding agencies in the United States, as most funding, when provided, originated from US-based institutes.

As for organizational affiliations, in addition to connections with universities both inside and outside the region, there is considerable research affiliated with regional ministries of health as well as with global institutes, including the CDC and GHD/EMPHNET. In more than half of the world, health surveillance is carried out by competency-based field epidemiology training programs (FETPs) [49], which are key activities of the CDC in advancing health globally [50]. These programs, which mostly function within ministries of health, have conducted most of the surveillance of emerging infections worldwide and have trained most of the public health workers who manage surveillance systems at a country or regional level [49]. In a recent evaluation study, it was shown that approximately two-thirds of FETP graduates in the EMR are engaged in managing PHS systems or analyzing surveillance data [51]. During the COVID-19 outbreak, the efforts of FETP graduates in supporting the surveillance functions within their countries were witnessed firsthand within the EMR [11]. In this region, FETP programs have been launched and are maintained with the aid of GHD/EMPHNET, which works in close collaboration with the CDC and ministries of health across the region [52].

Very few journals focus on surveillance as a scholarly topic of its own. Instead, surveillance is embedded in medical or multidisciplinary journals, focusing on infectious diseases, immunology and microbiology, or medicine and public health in general. This is not specific to the EMR but is a phenomenon that is seen at the global level [30] and iterates how the current state of surveillance systems depends mostly on disease-specific approaches, limiting its generalizability and effectiveness as a multidisciplinary approach to public health [53].

Within the past few years, the topic of surveillance in the EMR has evolved from the concept of surveillance in general toward the concept of surveillance systems and disease surveillance. However, looking at the keyword co-occurrence map, one cannot help but notice the near lack of terms associated with injury surveillance and NCD surveillance, other than obesity. This is especially alarming given that two-thirds of injury-related deaths occur in LMICs [54], and in the EMR, injury-related mortality and disability are on the rise (both accident and war-related injury) [55]. Almost 19% of the global child-related injury deaths occur in the EMR; however, only a limited number of EMR countries have existing injury surveillance systems or trauma registries [42]. Similarly, the EMR carries a disproportionate burden of NCDs, and it is a region where the delivery of effective NCD interventions remains an overwhelming challenge to health systems [56,57]. The low number of publications on NCD surveillance has been partly attributed to the weak surveillance structure and capacity of these LMICs [58]. Several LMICs are still wrestling with the high prevalence of communicable diseases, and their overburdened health care systems have little capacity, if any, to focus on NCDs [58]. Unlike other NCDs and NCD risk factors, obesity does appear as a keyword on the co-occurrence map, although its co-occurrence is shy from being too significant. During the past 2 decades, with increasing obesity trends in the region, interest in obesity in the EMR has increased [41,59]. This is especially true, given that the rates of obesity among children in the EMR exceed those seen globally [41].

With regard to communicable diseases, several diseases are present within the surveillance cluster on the network map, including measles, malaria, typhoid, polio or poliomyelitis, dengue, and zoonoses. The prominence of the link between surveillance and polio, poliomyelitis, or acute flaccid paralysis, within this cluster, is not surprising, as although wild poliovirus has been mostly eradicated, it remains endemic to 2 countries in the EMR, Afghanistan and Pakistan [60]. Circulating vaccine-derived poliovirus outbreaks have also been reported in Syria and Somalia [61], and recently, new outbreaks have been reported in Yemen and Sudan [62]. Multiple surveillance capacity–building initiatives have been implemented by international health networks, such as the Global Polio Eradication Initiative, spearheaded by the WHO, CDC, the United Nations Children's Fund, in collaboration with other organizations [62], and by regional public health networks, including the Polio and Routine Immunization Program, spearheaded by GHD/EMPHNET, in collaboration with international agencies and ministries of health across the region [63].

Our study used mature analysis tools and validated methods using Scopus and VOSviewer to determine frequencies, construct trends, and determine associations. The limitations of this study are mostly those inherent to its bibliometric design, including the fact that the number of citations does not necessitate the quality of the publications, and citations in themselves may be misleading, especially when time is factored out of the equation, as citations continue to accumulate over time. Although most papers were retrieved from health-related disciplines, variations between subdisciplines might also artificially skew the results. Similarly, within the EMR, a number of papers are published in local journals; these are not indexed by Scopus and thus are not included in this analysis.

Conclusions

Our study is the first to quantify the published scholarly literature on health surveillance and its corresponding disciplines in the EMR. It provides an analysis of the scientific research on health surveillance in the EMR, with evidence-based descriptions and visualizations of research output. Research productivity, as measured by the number of publications on the topic, has steadily increased over the past decade. In addition to highlighting collaborations and recurrent surveillance themes, this study identifies leading countries and organizational affiliations publishing PHS-related research. It further describes the patterns of performance and impact of research and sheds light on the gaps in surveillance research in the EMR, including inadequate publications on NCDs and injury-related surveillance.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Scopus search strategy.

[DOCX File , 15 KB - publichealth_v7i11e32639_app1.docx]

Multimedia Appendix 2

Number of published documents in the field of public health surveillance in the Eastern Mediterranean Region (EMR), between 2011 and 2021, (a) by country worldwide and (b) by countries in the EMR. In addition to, affiliations of the published literature in the field of public health surveillance in the EMR 2011 and 2021.

[DOCX File , 139 KB - publichealth_v7i11e32639_app2.docx]

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Abbreviations

CDC: Centers for Disease Control and Prevention
CS: CiteScore
EMR: Eastern Mediterranean Region
FETP: field epidemiology training program
GBD: Global Burden of Diseases
GHD/EMPHNET: Global Health Development/Eastern Mediterranean Public Health Network
LMIC: low- and middle-income country
NCD: noncommunicable disease
PHS: public health surveillance
SJR: SCImago Journal Rank
VOSviewer: Visualization of Similarities Viewer
WHO: World Health Organization

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Original Paper

Examining the Utility of Social Media in COVID-19 Vaccination: Unsupervised Learning of 672,133 Twitter Posts

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Abstract

Background: Although COVID-19 vaccines have recently become available, efforts in global mass vaccination can be hampered by the widespread issue of vaccine hesitancy.

Objective: The aim of this study was to use social media data to capture close-to-real-time public perspectives and sentiments regarding COVID-19 vaccines, with the intention to understand the key issues that have captured public attention, as well as the barriers and facilitators to successful COVID-19 vaccination.

Methods: Twitter was searched for tweets related to “COVID-19” and “vaccine” over an 11-week period after November 18, 2020, following a press release regarding the first effective vaccine. An unsupervised machine learning approach (ie, structural topic modeling) was used to identify topics from tweets, with each topic further grouped into themes using manually conducted thematic analysis as well as guided by the theoretical framework of the COM-B (capability, opportunity, and motivation components of behavior) model. Sentiment analysis of the tweets was also performed using the rule-based machine learning model VADER (Valence Aware Dictionary and Sentiment Reasoner).

Results: Tweets related to COVID-19 vaccines were posted by individuals around the world (N=672,133). Six overarching themes were identified: (1) emotional reactions related to COVID-19 vaccines (19.3%), (2) public concerns related to COVID-19 vaccines (19.6%), (3) discussions about news items related to COVID-19 vaccines (13.3%), (4) public health communications about COVID-19 vaccines (10.3%), (5) discussions about approaches to COVID-19 vaccination drives (17.1%), and (6) discussions about the distribution of COVID-19 vaccines (20.3%). Tweets with negative sentiments largely fell within the themes of emotional reactions and public concerns related to COVID-19 vaccines. Tweets related to facilitators of vaccination showed temporal variations over time, while tweets related to barriers remained largely constant throughout the study period.

Conclusions: The findings from this study may facilitate the formulation of comprehensive strategies to improve COVID-19 vaccine uptake; they highlight the key processes that require attention in the planning of COVID-19 vaccination and provide feedback on evolving barriers and facilitators in ongoing vaccination drives to allow for further policy tweaks. The findings also illustrate three key roles of social media in COVID-19 vaccination, as follows: surveillance and monitoring, a communication platform, and evaluation of government responses.

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KEYWORDS

social media; COVID-19; vaccine hesitancy; natural language processing; machine learning; infodemiology

Introduction

COVID-19 first presented as an atypical pneumonia of unknown cause in Wuhan, China, in late December 2019. Within a short time frame, the virus spread to multiple countries despite international efforts to contain it, resulting in significant death, psychological impact, and economic disruption around the world [1]. This led the World Health Organization (WHO) to declare COVID-19 a Public Health Emergency of International Concern on January 30, 2020 [2], and a global pandemic on March 11, 2020 [3]. After more than one year of battling with the pandemic, vaccines for COVID-19 present as a promising and viable solution to end the pandemic, particularly through concerted efforts in global mass vaccination to achieve herd immunity from the COVID-19 virus [4]. On November 18, 2020, the hope of ending the COVID-19 pandemic became more conceivable when Pfizer-BioNTech announced in the press [5] the first available COVID-19 vaccine, which had 95% efficacy and a good safety profile [6].

Moving on, the next phase of the challenge was to ramp up public health efforts to increase vaccine uptake in the population, possibly through well-thought-out and coordinated vaccination drives. Yet, it is well known that vaccination drives are often hampered by the issue of "vaccine hesitancy," whereby a large majority of population may have conflicting motivation or opposition to receive vaccines [7-10]. Historically, the issue of vaccine hesitancy has resulted in low coverage rates in adult vaccination programs [9]. For example, in the United States, vaccination coverage of the 2019-2020 influenza vaccine ranged from 48.4% among the adult population [11] to 80.6% among health care workers [12]. Similarly, in the context of COVID-19 vaccination, recent nationally representative surveys demonstrated that only 61.4% of the US population [13] and 64.0% of the UK population [14] were willing to receive COVID-19 vaccines. In the literature, many reasons have been cited for individuals' conflicted motivation or opposition to receive vaccines [7-10]. Some of these reasons include concerns about vaccine safety, perceived low risk of contracting illness, perceived low severity of illness, fear of pain, perceived ineffectiveness of vaccines, and misinformation about vaccines [10]. Given the severity of the COVID-19 pandemic and the time pressure to accelerate COVID-19 vaccination, there is an urgent need to gain insight into the psychological proposition of how people think and feel—specific to the newly developed COVID-19 vaccines—so that effective recommendations or strategies may be proposed to improve vaccine uptake [7].

Traditionally, research on attitude, perception, and behavior has often relied on methodologies such as surveys, interviews, or focus group discussions. However, such traditional approaches can often be time-consuming in their data collection processes (ie, there can be a considerable time lag between the start of data collection and the eventual availability of data for further analysis), hence, findings from the traditional approaches may not sufficiently reflect real-time public sentiments on time-sensitive matters, such as those related to COVID-19 vaccination. An alternative would be using data from social media platforms such as Twitter, where researchers can collect near–real-time information that reflects prevailing perspectives and sentiments in the community [9,15,16]. Such an approach is in line with the growing field of infodemiology, which recognizes the utility of real-time information across the internet in informing public health and public policy [17,18]. The study of social media data is also particularly relevant in the context of COVID-19 vaccination, given recent findings that exposure to information, or misinformation, on social media can have a direct influence on individuals' intentions to receive COVID-19 vaccines [9,19].

In this infodemiology study, we sought to examine public conversations about COVID-19 vaccines as posted on Twitter—specifically after the press release about the first effective vaccine by Pfizer-BioNTech on November 18, 2020—with the intention to shed light on the potential utility of social media in the context of the COVID-19 vaccination drive, as well as to identify useful strategies that may address COVID-19 vaccine hesitancy and improve vaccine uptake. Specifically, we intended to address the following two research questions:

1. What are the key issues that have captured public attention following the press release of the first effective COVID-19 vaccine?
2. How may social media data inform the barriers and facilitators that can influence individuals' behaviors regarding receiving COVID-19 vaccines?

Methods

Data Source for the Infodemiology Study

Twitter was selected as the social media platform for data collection in this study, due to accessibility to researchers of its large quantity of global data [20]. Twitter is a popular social media platform worldwide [9], where members of the public may post their opinions and sentiments in short texts of up to 280 characters, also known as "tweets." On a monthly basis, Twitter has an estimated 329.5 million active users from around the world [9]. It is recognized as the third most popular social media platform in the United Kingdom [21] and is used by one-quarter of people in United States [9]. All data used in this study were collected according to Twitter's terms of use. The outline of the study was presented to the SingHealth Centralised Institutional Review Board of Singapore who concluded that the study did not meet the criteria for human subjects research requiring review by a research ethics committee.

A publicly available COVID-19 Twitter data set [20] was searched for original tweets (ie, not retweets or duplicate tweets) that were posted in English over an 11-week period from November 18, 2020 (ie, following the press release about the Pfizer-BioNTech vaccine) to February 3, 2021. The search terms were "COVID-19" (or similar terms, such as "coronavirus," "corona virus," "2019ncov," "COVID," "COVID19," "COVID_19," "COVID 19," "CoronavirusPandemic," "CoronaOutbreak," and "WuhanVirus") and "vaccine" (or similar terms, such as "vaccinat*," "immuniz*," "immunis*," "innoculat*," "anti-vaccin*," "antivaccin*," "anti_vaccin*," "anti-vaxxer," "antivaxxer," and "anti_vaxxer"). Following the same approach used by Koh and Liew [22], only tweets that were posted by individual users, and not organizations or news outlets, were included in this study so that we could focus on individuals' sentiments about COVID-19 vaccines and minimize the selection of objective reports about the vaccines, such as those in news articles, or tweets by nonhuman Twitter users (ie, bots). Individual Twitter users were identified by the use of actual human names on the Twitter account of each post; this process of identifying human names was conducted using the machine learning approach of natural language processing, based on the spacyr package [23] in R (version 4.0.2; The R Foundation).

Unsupervised Learning of Free-Text Data From Twitter

As the tweets comprised large volumes of free-text data, the unsupervised machine learning approach of topic modeling was used to analyze these data [24]. Topic modeling is a machine learning technique that identifies key topics within free-text data, based on statistical probability and correlations among words. It is akin to thematic analysis in traditional qualitative methodology. But unlike thematic analysis, topic modeling does not require manual labor to classify free-text data and, hence, is well suited for analyses of large volumes of free-text data [24] such as in this study.

Before conducting topic modeling, the following steps were performed to preprocess the free-text data based on currently recommended best practices [22,24]. First, sentences from each tweet were tokenized (ie, reduced to single words, punctuation and extra spaces removed, and words converted into lowercase). Then, frequently occurring words that add little to the meaning of sentences were removed (eg, "the" and "a"). Next, the remaining words were converted to their root form (eg, "went" was transformed to "go," and "friends" was transformed to "friend"). Lastly, words that occurred in less than 600 tweets (representing ~0.05% of tweets) were removed to reduce statistical noise and improve accuracy [24]. Preprocessing of free-text data was conducted using the spacyr package [23] in R.

In our topic modeling approach, the preprocessed words were presented to an unsupervised machine learning algorithm to identify clusters of words that tended to co-occur together. Words with a high probability of co-occurring in tweets were then considered to belong to the same "topic." Three covariates were included in topic modeling (ie, continent of tweets, date of tweets, and number of followers of the Twitter users) to improve the accuracy of the model in identifying topics. The optimal number of topics was identified using the algorithm proposed by Lee and Mimno [25]. Topic modeling was conducted using the stm package [26] in R.

Thematic Analyses to Further Refine the Output From Unsupervised Learning

Output from topic modeling was examined by the two authors (TML and CSL) to ensure coherence of the identified topics. A descriptive label for each topic was manually crafted by the two authors based on sample tweets of each topic. Thereafter, the topics were further grouped into themes by the two authors using the inductive and iterative processes of thematic analysis as introduced by Braun and Clarke [27].

In addition to the inductive thematic analysis, we also adopted the COM-B (capability, opportunity, and motivation components of behavior) model [28] to guide our analysis for the second research question: "How may social media data inform the barriers and facilitators that can influence individuals' behaviors in receiving COVID-19 vaccines?" The COM-B model was previously developed to provide a framework to understand and change human behaviors in the context of public health [28]. It has been widely used in the literature to understand human behavior in areas such as medication adherence [29], smoking cessation [30], diabetes [31], and obesity [32], and has recently been adopted by Public Health England as a key framework to guide its policy making [33]. Specific to the area of vaccine hesitancy, the COM-B model has been successfully applied in the literature to understand the barriers and facilitators related to childhood vaccination [34] and human papillomavirus vaccination [35]. In essence, the COM-B model proposes that an individual's behavior is the result of an interaction between three components: capability, opportunity, and motivation. Capability refers to an individual's psychological and physical capacity to make the behavior possible, such as having the necessary knowledge and skills to perform the target behavior. Opportunity refers to attributes that lie outside the individual physically or socially that make the behavior possible, such as environmental factors or social and cultural norms. Motivation refers to the automatic or reflective mental processes that energize and direct behavior, which can include the conscious thought process in deciding on a behavior or a less conscious thought process driven by desires or habits. By conceptualizing human behaviors using the three components (ie, capability, opportunity, and motivation), the COM-B model allows policy makers to design evidence-based interventions that specifically target each of the components [28]. Some examples are as follows:

- Issues related to capability can often be modified through education and training [28].
- Issues related to opportunity may possibly be modified through environmental restructuring (ie, shaping the physical or social environment to constrain or promote behavior), enablement (ie, providing the right support or tool to facilitate a desirable behavior), and restriction (ie, using rules to reduce the opportunity to engage in an undesirable behavior) [28].
- Issues related to motivation may potentially be modified, for example, through communication, modeling (ie, providing an example for people to aspire to or imitate), and incentivization (ie, creating an expectation of reward) [28].

Sentiment Analysis of Free-Text Data

To further enrich the main findings, we conducted an exploratory analysis to identify the underlying emotions of each tweet using the VADER (Valence Aware Dictionary and Sentiment Reasoner) package [36] in R. VADER is an established sentiment analysis tool that has been widely employed in recent studies of free-text data on Twitter [37-40] and online news [41]. For each tweet, VADER used a rule-based machine learning model to identify three key emotions (ie, positive, negative, and neutral), which were then combined into a composite sentiment score ranging from –1 (most negative sentiment) to +1 (most positive sentiment). The sentiment score for each topic was then computed by averaging the sentiment scores of all the tweets within the topic.

Although many sentiment analysis tools are currently available [36,42-45], VADER offers some advantages over existing tools. First, it is specifically attuned to sentiments expressed in social media [36] and has been extensively validated for Twitter content [36,42,44].

Second, it is based on a human-curated lexicon of 7500 emotion-related words as well as five human-interpretable rules that identify sentiment intensity (ie, exclamation point, capitalization, intensity adverbs, the contrastive conjunction "but," and negation flips preceding each emotion-related word). As such, unlike other sophisticated machine learning models, VADER's classification rules are interpretable by humans and not hidden within a machine-access-only black box [36,43].

Third, as VADER uses a simple rule-based machine learning model, it is computationally efficient and only takes a fraction of computational time to analyze free-text data compared to other sophisticated machine learning techniques. Using an example from a previous study [36], a set of free-text data that took less than a second to analyze with VADER could take hours when using more complex models, such as the support vector machine model.

Fourth, as VADER is based on a human-validated lexicon, it does not require any form of training data. This is in contrast to other sophisticated machine learning models that often require extensive sets of training data before they can produce accurate results in sentiment analysis [36,43].

Fifth, despite its simplicity, VADER has been shown in several comparative studies [36] to outperform many other highly regarded sentiment analysis tools. In one of the initial validation studies [36], VADER was found to have an overall accuracy of 96% in identifying correct sentiments in tweets. It was considerably better than seven other well-established sentiment analysis lexicons (ie, Linguistic Inquiry Word Count, General Inquirer, Affective Norms for English Words, SentiWordNet, SenticNet, Word-Sense Disambiguation using WordNet, and Hu & Liu Opinion Lexicon; overall accuracy of 56%-77%) and four other machine learning algorithms (ie, naïve Bayes, maximum entropy, support vector machine–classification, and support vector machine–regression; overall accuracy of 65%-84%). Notably, in the same validation study [36], VADER was also shown to outperform individual human raters which had an overall accuracy of 84%. Similar findings were replicated in more recent comparative studies [42,43], with VADER outperforming four sentiment analysis tools (ie, SentiWordNet, SentiStrength, Hu & Liu Opinion Lexicon, and AFINN-111) in one study [42] and two other tools (ie, TextBlob and Natural Language ToolKit) in another study [43].

Lastly, VADER is available as an open-source package that is easily accessible from widely used data science platforms, such as R and Python.

Results

Identification of Topics From Tweets

A total of 2,524,982 tweets were initially identified over the 11-week study from November 18, 2020, to February 3, 2021. After removing duplicate tweets and tweets from news media or organizations, a total of 672,133 tweets were eventually included. A flow diagram showing tweet selection is presented in Figure 1. The geographical distribution of tweets is shown in Figure 2, with 38.5% originating from North America, 14.3% from Europe, 5.7% from Asia, 2.1% from Africa, 1.4% from Australia, 1.1% from South America, and 37.0% from unknown locations.

Using the unsupervised machine learning algorithm of topic modeling, 60 topics could initially be identified from the tweets. Coherence of the 60 topics was manually examined by the two authors; during this process, one topic that had the lowest prevalence (~0.4%) was found to bear much similarity with another topic and, hence, the two topics were combined. As such, a total of 59 topics were eventually included. Following thematic analysis by the two authors, the 59 topics could be further grouped into six themes. Word clouds for the six themes are shown in Multimedia Appendix 1, while details related to each topic are presented in Table 1 as well as further described in the following paragraphs.

Figure 1. Flow diagram showing the selection of Twitter posts for this study.

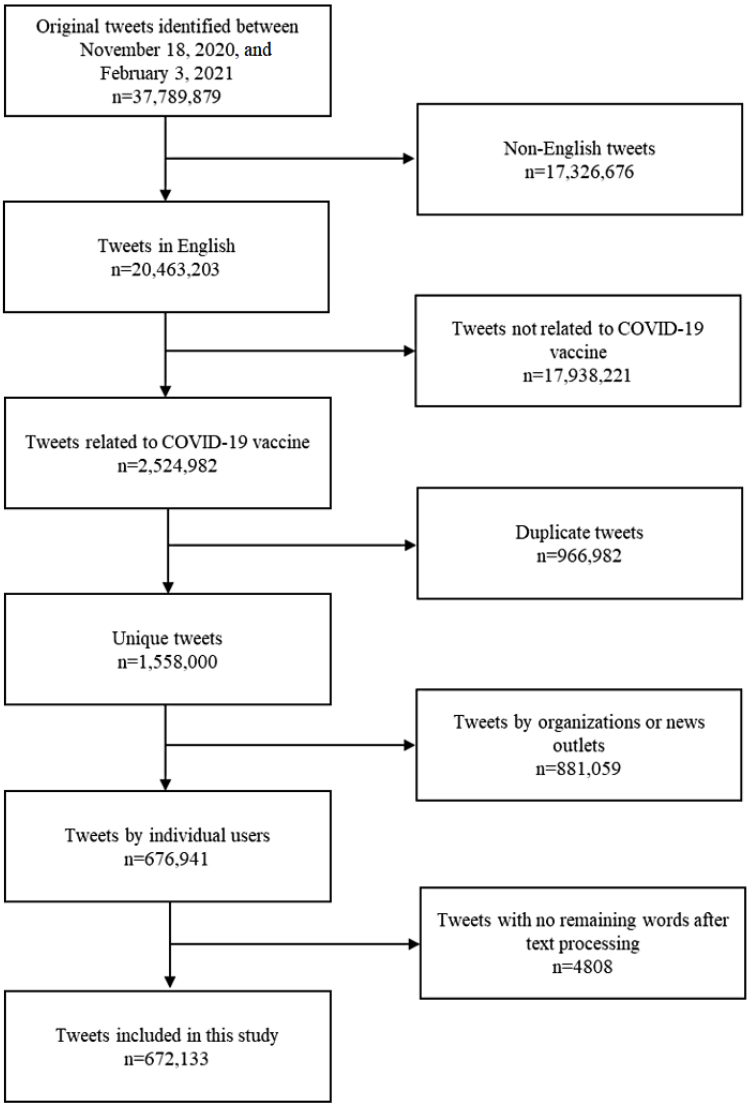


Figure 2. Geographical distribution of the Twitter posts. lat: latitude; long: longitude.

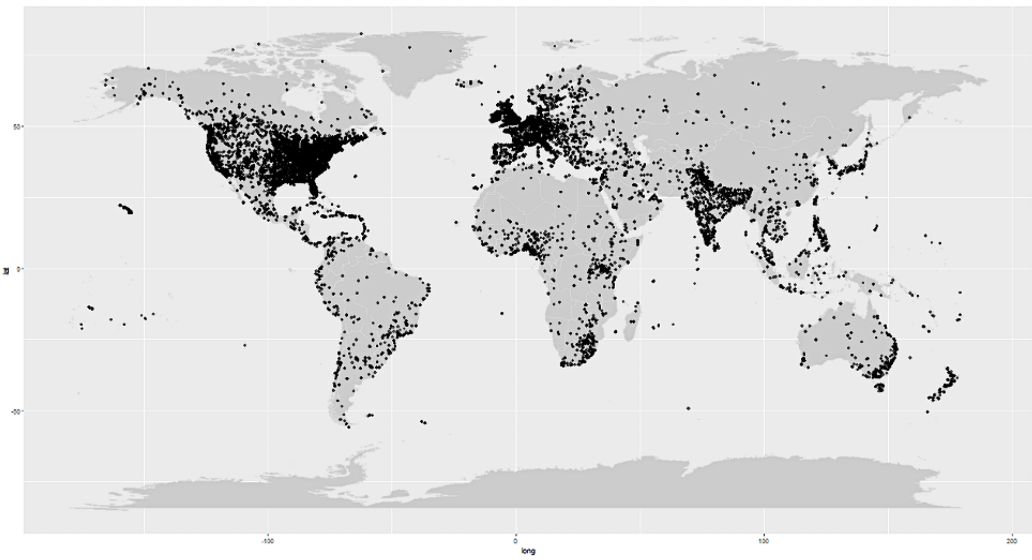


Table 1. Six themes related to COVID-19 vaccination, along with the respective topics and sample tweets (N=672,133).

Theme and topics (keywords)	Sample tweet	Prevalence, %	Sentiment score[a]
Theme 1: emotional reactions related to COVID-19 vaccines			
Topic 37: feeling hopeful after receiving COVID-19 vaccines (be, shot, get, feel, go, ready, see, happy, hope, and friend)	"Cried happy tears seeing family and friends abroad getting their COVID19 vaccines. Better days ahead"	3.2	+0.262
Topic 30: feeling excited after receiving COVID-19 vaccines (get, receive, give, do, administer, complete, delay, deliver, waste, and order)	"Perks of completing the COVID19 vaccine series... we got a sticker!!."	2.6	+0.097
Topic 18: feeling angry toward politicians for claiming COVID-19 as a hoax (think, people, anti, right, believe, know, hoax, should, thing, and politician)	"Wow, wow majority of Republican house and senate are vaccinated. They are the one who denied that coronavirus existed and is a hoax. My, my they are the first one in the queue. They should not be in the queue at all if they believe coronavirus is a hoax."	2.6	–0.109
Topic 17: feeling angry toward President Trump for claiming COVID-19 as a hoax (want, go, would, Trump, will, name, Americans, credit, let, and people)	"The scientists developed the vaccines not the Trump Administration. The Trump Administration is responsible for 300,000+ deaths of Americans due to their incompetency and lying about the Coronavirus for months. Trump called the virus a Democratic HOAX!"	2.3	–0.110
Topic 42: feeling thankful toward scientists who were involved in the development of COVID-19 vaccines (news, thank, end, day, science, Moderna, team, work, Pfizer, and job)	"Thank you thank you thank you for my covid-19 vaccine today. I feel extremely lucky and grateful. Thank you to the scientists and everyone behind rolling out the vaccine. In a world of darkness there is light at the end of the tunnel"	2.2	+0.482
Topic 59: plea to stay vigilant even with the rollout of COVID-19 vaccination (mask, keep, continue, stay, social, wear, hand, safe, distance, and wearamask)	"Please remember control of COVID is in our hands-hands that put on our masks, the hands we sanitize and hands to maintain our spacing. Vaccines are coming but we cannot let our collective guard down!"	2.2	+0.175
Topic 40: feeling proud to have contributed to the development of COVID-19 vaccines (part, share, late, thank, volunteer, experience, involve, learn, help, and successful)	"We're proud to have played a part in the successful development of COVID19 vaccine."	1.5	+0.409
Topic 33: feeling frustrated about the inequitable access of COVID-19 vaccines (should, person, last, member, chief, resident, mandatory, people, outbreak, and medical)	"'r there no workhouses?? r there no prisons??' Prisons are Covid-19 hotbeds. When should inmates get the vaccine?"	1.4	–0.028
Topic 55: feeling angry over the antivaccine movement and conspiracy claims (claim, conspiracy, misinformation, Twitter, dangerous, theory, medium, true, truth, and Bill_Gates)	"Sad that there even have to be articles like this to rebut the right-wing and anti-vaxer nonsense: No, COVID-19 vaccines don't contain Satan's microchips (and other scary conspiracy theories aren't true either)"	1.4	–0.188
Theme 2: public concerns related to COVID-19 vaccines			
Topic 19: concerns about death related to COVID-19 vaccines (people, die, many, more, kill, number, infect, most, death, and will)	"People are known to die from so many illnesses. Millions die each day, so many die suddenly. Imagine people who were supposed to die suddenly on a particular day having recieved Covid-19 vaccine on the preceding day, many of them will try to blame Covid-19 vaccine"	2.3	–0.241
Topic 11: concerns about the impact of COVID-19 vaccines on fertility (mRNA [messenger RNA], work, safety, efficacy, base, explain, research, datum, understand, and thread)	"It is UNKNOWN whether COVID-19 mRNA Vaccine BNT162b2 has an impact on fertility. Animal studies into potential toxicity to reproduction and development have not been completed"	2.1	+0.236
Topic 26: concerns about misinformation related to COVID-19 vaccines (good, great, news, big, bad, fake, break, welcome, sell, and wake)	"Fed up of: lies lockdown FAKE NEWS covid vaccine coronavirus"	1.8	+0.206
Topic 12: concerns about insufficient supply of COVID-19 vaccines (supply, have, run, hold, problem, try, demand, due, lack, and could)	"New York City could run out of COVID19 vaccines as early as next week. We need the federal government to act NOW."	1.6	–0.057

Theme and topics (keywords)	Sample tweet	Prevalence, %	Sentiment score[a]
Topic 31: concerns about delays in vaccine rollout amid rising deaths related to COVID-19 (death, case, story, record, rollout, top, more, rise, and us)	"The US set a new record for coronavirus deaths reported in 24 hours with more than 3,700 on Wednesday amid troubles with the vaccine rollout. The harrowing tally from Johns Hopkins University marked the fourth time daily deaths have exceeded 3,000 throughout the pandemic."	1.5	–0.027
Topic 54: concerns about vaccine scams that mine personal and financial details (important, information, warn, send, detail, info, scam, write, fall, and more)	"scam alert service has notified of a scam COVID-19 vaccine text linking to a bogus NHS website with a registration form for the vaccine in an attempt to mine personal and financial details."	1.5	+0.141
Topic 43: concerns about the safety of COVID-19 vaccines among pregnant women and children (should, woman, become, child, scientist, risk, man, decision, pregnant, and benefit)	"They have not experimented the COVID19 vaccine on pregnant women and young children."	1.4	+0.078
Topic 5: concerns about the reported statistics on adverse events of COVID-19 vaccine (report, reaction, cause, serious, severe, history, allergic, event, adverse, case)	"USA death rates: COVID-19 cases VS reported adverse events (CDC link) Specific rate: VACCINE MODERNA VACCINE FATALITY REPORT EVENT RATE: 5.82% COVID-19 CASE FATALITY RATE: 1.7%"	1.3	–0.243
Topic 6: concerns about fitness to receive COVID-19 vaccines among individuals with medical conditions or allergies (know, read, jab, issue, need, have, people, rush, should, and article)	"Info so far, COVID19 vaccine is NOT a danger for people with allergies to foods or medications"	1.3	–0.004
Topic 16: concerns about the short development phases of COVID-19 vaccines (flu, virus, cold, cure, common, different, cancer, sense, immunity, make)	"40 years research to find a cure for HIV AIDS.. still no vaccine. More than 100 years research to find a cure for cancer... still no vaccine. Ongoing research to find a cure for common cold and flu. Less than a year of Covid19 and you have a vaccine? No thanks! logicalthinking"	1.3	–0.060
Topic 53: concerns that the vaccines would not be effective against a new strain of the COVID-19 virus (new, strain, post, case, virus, variant, will, mutate, lockdown, and year)	"New Strains Of COVID Could Render Vaccines Completely Useless, And 2 Dangerous New Strains Are Already Spreading via COVID19"	1.3	–0.029
Topic 50: concerns about the short-term and long-term side effects of COVID-19 vaccines (effect, side, long, term, possible, potential, know, will, may, and short)	"COVID19 vaccines: What are the potential side effects? Doctors say most people will experience side effects such as fatigue, a sore arm for a day or two. Long-term effects are still unknow"	1.2	–0.023
Topic 41: concerns about COVID-19 vaccines causing false positive results on HIV tests (test, positive, antibody, HIV, virus, testing, rapid, quarantine, symptom, and negative)	"This is completely false and misrepresented. The vaccines didn't CAUSE people to get HIV, it caused them to have false-positive results. Totally different. Why an Australian COVID-19 vaccine caused false-positive HIV tests"	1.2	+0.147
Theme 3: discussions about news related to COVID-19 vaccines			
Topic 32: news about the launch of the COVID-19 vaccination drive in India (country, India, world, start, drive, will, nation, program, large, and poor)	"India is one of the world's largest vaccine manufacturers. India has started one of the world's largest mass vaccinations"	2.6	+0.133
Topic 1: news about Oxford-AstraZeneca COVID-19 vaccine approval (UK, EU, roll, approve, AstraZeneca, Pfizer_, Britain, Oxford, country, and Europe)	"Cheapest Coronavirus Vaccine: UK Approves Oxford-AstraZeneca Jab, Rollout to Begin from Jan 4. OxfordAstraZeneca By far the cheapest vaccine."	1.9	+0.139
Topic 52: news about the effectiveness of the vaccines against new strains of the COVID-19 virus (new, may, variant, mutation, current, virus, spread, appear, find, and suggest)	"CNN: A new study provides early evidence that a Covid-19 vaccine might be effective against two new coronavirus variants first identified in South Africa and the UK, despite a concerning mutation."	1.9	+0.074

Theme and topics (keywords)	Sample tweet	Prevalence, %	Sentiment score[a]
Topic 10: news about the approval of the Pfizer-BioNTech COVID-19 vaccine in the United States (use, Pfizer, approve, FDA, approval, authorization, Moderna, authorize, BioNTech, and seek)	"The FDA officially approves the Pfizer-Biontech coronavirus vaccine, the first approved in the U.S."	1.7	+0.135
Topic 13: news about progress in the development of various COVID-19 vaccines (trial, phase, show, result, datum, clinical, human, study, candidate, and efficacy)	"still in phase 3 clinical trials. There are now about 12 COVID-19 vaccines in phase-3, only Pfizer, Moderna and Gamaleya have released interim efficacy results. Even AstraZeneca which was one of the first to enter phase-3 have not released efficacy results."	1.7	+0.150
Topic 25: news about the approval of the Moderna COVID-19 vaccine in the United States (recommend, clear, US, FDA, vote, meet, panel, business, Moderna, and CEO)	"US clears second vaccine by Moderna for COVID-19: US clears Moderna vaccine for COVID-19"	1.2	+0.155
Topic 23: news about the approval of the Pfizer-BioNTech COVID-19 vaccine outside of the United States (emergency, BioNTech, Pfizer, approve, drug, UK, Moderna, could, worry, and the_United_States)	"Canada also approves COVID19Vaccine. Health Canada officially approves the Pfizer-BioNTech COVID-19 vaccine"	1.1	+0.126
Topic 56: news about the impact of COVID-19 around the world (doctor, NHS, policy, health, today, insurance, retweet, biotech, patients, and todaysmedicalupdate)	"As the virus resurges, mental health woes batter France"	0.8	+0.198
Topic 35: general news related to COVID-19 (medicine, pharmaceutical, medtech, politic, industry, breakingnews, FoxNews, health, giant, and science)	"California Reports First Case Of New COVID Variant"	0.5	+0.065
Theme 4: public health communications about COVID-19 vaccines			
Topic 8: involving an expert panel in public education on COVID-19 vaccines (expert, answer, join, discuss, Dr, concern, regard, key, check, and address)	"On this special episode, we talk with Dr. Steve Rockoff from Henry Ford West Bloomfield and Dr. Russell Faust from Oakland County Health as they answer FAQs about the COVID19 vaccine"	1.6	+0.258
Topic 9: using radio as a medium to clarify questions related to COVID-19 vaccines (question, ask, lot, wonder, talk, take, will, listen, hear, and come)	"Have a question about Covid or the vaccine? Send them my way and I'll ask as many as I can to our experts on-air!"	1.6	+0.139
Topic 22: using video to explain how COVID-19 vaccines work (patient, video, staff, watch, check, fact, live, link, email, message)	"Loved youtube videos on the Covid-19 vaccine! For those who are unsure and want to learn about how the covid-19 vaccine works please watch the video below!"	1.5	+0.213
Topic 34: summarizing the evidence on the efficacy of the Johnson & Johnson vaccine (effective, safe, prevent, disease, infection, show, single, Johnson, severe, and say)	"BREAKING: Johnson & Johnson says its single-shot covid-19 vaccine is: - 66% effective against moderate disease - 85% effective against severe disease"	1.5	+0.276
Topic 51: summarizing the evidence for the efficacy of the Sinovac vaccine (China, develop, produce, buy, Russia, Chinese, AstraZeneca, deal, Brazil, and purchase)	"An experimental COVID-19 vaccine developed by Chinese biopharmaceutical company Sinovac is 91.25% effective, a Turkish health official said on Thursday."	1.5	+0.094
Topic 7: providing simple explanations on how COVID-19 vaccines can help in achieving herd immunity (life, will, save, change, immunity, stop, end, cost, herd, and affect)	"The vast majority of vaccinated people will be protected from contracting Covid-19 at all. In turn, the virus will have far fewer opportunities to spread through the population (think a forest that's 90% firebreaks) and so transmission will be massively reduced."	1.3	+0.115
Topic 20: providing simple explanations about how mRNA vaccines work (system, immune, virus, body, make, future, will, DNA, cell, mind)	"The vaccine will not contain any virus. It will only contain the instructions (mRNA) on how to build those spike proteins. Your body then learns how to recognize those spikes so that your immune system can kill coronavirus."	1.3	+0.104
Theme 5: discussions about the approach to COVID-19 vaccination drives			
Topic 14: involving public figures to gain public trust regarding COVID-19 vaccines (take, say, public, available, trust, refuse, people, Americans, and would)	"I trust it and will take the vaccine when available! Obama, Bush and Clinton say they will take the COVID-19 vaccine publicly to gain public trust"	3.2	+0.154

Theme and topics (keywords)	Sample tweet	Prevalence, %	Sentiment score[a]
Topic 48: using an appointment system to register for COVID-19 vaccination (appointment, call, sign, make, old, schedule, clinic, eligible, senior, and register)	"Florida has launched a statewide pre-registration system for individuals who are eligible for the COVID-19 vaccine. You can pre-register for appointments and be notified when appointments are available in your area by visiting"	2.5	+0.100
Topic 24: involving employers to facilitate COVID-19 vaccination (can, wait, require, travel, make, employee, return, employer, mandate, and proof)	"Companies are considering compulsory COVID19 vaccination as a condition of employment. 'Under the law, an employer can force an employee to get vaccinated, and if they don't, fire them,' said Rogge Dunn, a Dallas labor and employment attorney."	2.1	+0.076
Topic 45: clarifying the subpopulations to prioritize for COVID-19 vaccines (care, health, school, home, teacher, worker, access, risk, include, and staff)	"When the vaccine is rolled out and the elderly especially in long term care and all health care workers are vaccinated, teachers should be soon after. If face to face brick and mortar schools are considered essential, teachers, education workers and school staff must be soon after."	1.8	+0.153
Topic 28: providing COVID-19 vaccines to frontline workers (worker, line, healthcare, frontline, front, next, essential, cut, stand, and place)	"COVID19 vaccine now for all frontline healthcare workers - patient care workers, no matter their title, deserve it before administrators."	1.7	+0.103
Topic 4: prioritizing COVID-19 vaccines for long-term care homes (health, care, home, facility, will, resident, roll, worker, official, and minister)	"The Province will begin COVID-19 vaccinations of health-care and long-term care workers at hospitals in Toronto and Ottawa starting Dec. 15"	1.6	+0.209
Topic 46: defining high-risk health conditions to prioritize for COVID-19 vaccines (group, free, priority, list, pay, should, people, citizen, general, and give)	"Should smoking be considered a high risk condition and smokers have priority for CovidVaccine?"	1.5	+0.109
Topic 36: addressing mistrust among minority communities with regard to COVID-19 vaccination (community, challenge, leader, fear, black, role, hesitancy, equity, approach, and market)	"As MDs, it is crucial that we discuss this sensitive issue among our vulnerable minority communities, esp because it has/is still annihilating Black/Latinx communities. We must first acknowledge the history of medical mistrust."	1.4	+0.210
Topic 58: showing COVID-19 vaccination of public figures on live television (president, live, receive, nurse, Dr, Biden, watch, elect, Joe_Biden, and former)	"US president-elect Joe Biden receives Pfizer's Covid-19 vaccine shot on live television"	1.4	+0.144
Theme 6: discussions about the distribution of COVID-19 vaccines			
Topic 27: updates on the number of people who have received COVID-19 vaccines (dose, say, receive, Pfizer, administer, people, arrive, accord, distribute, and first)	"To date, 7,761 doses of the COVID-19 vaccine have been administered in Connecticut. Last week, we received 31,200 doses of Pfizer's vaccine and anticipate receiving another 24,375 of that vaccine this week."	2.7	+0.096
Topic 15: call for equitable access to COVID-19 vaccines across different countries (need, help, protect, ensure, work, must, bring, can, let, and access)	"No one is safe until everyone is safe COVAX: Ensuring global equitable access to COVID-19 vaccines"	2.1	+0.297
Topic 38: discussions about the distribution plan of COVID-19 vaccines in the United States (Trump, company, administration, speed, development, delivery, promise, distribution, effort, and US)	"The federal 'Operation Warp Speed' calls on multiple organizations and companies in the logistics of distributing of millions of COVID-19 vaccines."	2.0	+0.062
Topic 57: call for a coordinated distribution plan of COVID-19 vaccines (plan, distribution, Biden, pandemic, strategy, rollout, national, release, relief, and economic)	"Decentralization of the distribution of vaccine has left a patchwork of madness. Vaccine distribution must be a National plan with the distribution centralized with the military. This is war - fight Covid like a war."	2.0	+0.096

Theme and topics (keywords)	Sample tweet	Prevalence, %	Sentiment score[a]
Topic 47: comparing the statistics related to COVID-19 and COVID-19 vaccination in the United States (state, number, rate, governor, track, California, slow, rollout, total, and case)	"Maryland coronavirus cases 1/18 328,214 0.5% higher than day before (+1769) Deaths 6423 0.45% higher than day before (+29) Hospitalizations day over day ICU +13 (421) Acute +14 (1429) Vaccines day over day +9569 (233,309)"	1.8	+0.023
Topic 49: updates on the shipment of COVID-19 vaccines (dose, hospital, expect, begin, shipment, Pfizer, will, arrive, breaking, and batch)	"UPS and FedEx trucks carrying the first U.S. shipment of coronavirus vaccine have left Pfizer's facility near Kalamazoo, Michigan."	1.7	+0.056
Topic 21: call for equitable access to COVID-19 vaccines across different income groups (would, could, Trump, like, god, time, election, American, money, and America)	"The Elite & Wealthy truly SUCK! The wealthy scramble for COVID-19 vaccines: 'If I donate $25,000 ... would that help me?' Vaccine Sad Wealthy covid CovidVaccine COVID19"	1.6	+0.153
Topic 44: updates on the rollout of the COVID-19 vaccination plan in Canada (Canada, government, will, force, minister, cdnpoli [Canadian politics], say, Ontario, head, and restriction)	"The Canadian military says it will be ready to distribute COVID-19 vaccines At noon, federal officials are providing an update on Canada's vaccination plan"	1.6	+0.039
Topic 39: call for equitable access to COVID-19 vaccines across different ethnic groups (population, world, lead, Israel, provide, race, corona, power)	"Human Rights Watch has called on 'Israel' to provide COVID-19 vaccines to more than 4.5 million Palestinians in the occupied West Bank and Gaza Strip. HRW urges 'Israel' to provide COVID vaccines to Palestinians"	1.5	+0.035
Topic 29: updates on the rollout of COVID-19 vaccination sites (site, open, mass, testing, close, centre, major, city, injection, and turn)	"Mass vaccination sites soon will be added to Chicago's mass testing sites COVID19"	1.4	+0.075
Topic 3: guidelines on the ethical considerations in the allocation of COVID-19 vaccines (follow, CDC [Centers for Disease Control and Prevention], meeting, director, guidance, guideline, recommendation, publichealth, allocation, and update)	"In addition to scientific data and implementation feasibility, four ethical principles will assist ACIP in formulating recommendations for the initial allocation of COVID-19 vaccine: 1) maximizing benefits and minimizing harms; 2) promoting justice;"	1.0	+0.107
Topic 2: comparing the statistics related to COVID-19 and COVID-19 vaccination outside of the United States (high, low, economy, reduce, contract, risk, price, mortality, and pandemic)	"Italy seems close to rise again in its COVID19 epidemic activity (R-eff=1.07), at high levels of activity, plateauing at very high levels of mortality, for 7 more days. 128,880 vaccinated as of Jan 04."	0.9	+0.042

[a]The sentiment scores range from –1 (most negative sentiment) to +1 (most positive sentiment).

Descriptions of Six Identified Themes

Theme 1 describes "emotional reactions related to COVID-19 vaccines," and involved 19.3% of the tweets. Tweets in this theme had a mixture of negative emotions, including those toward politicians, over inequitable access of vaccine, and over the antivaccine movement, as well as positive emotions, including those regarding receiving the vaccines and availability of the vaccines. Theme 2 describes "public concerns related to COVID-19 vaccines," and involved 19.6% of the tweets. Common concerns included vaccine-related death, impact of the vaccines on fertility, and widespread misinformation related to the vaccines. Meanwhile, concerns with a negative tone included those related to insufficient supply of vaccine, delays in vaccine rollout, reported statistics on adverse events related to the vaccines, fitness to receive the vaccines among individuals with medical conditions or allergies, short development phases regarding the vaccines, effectiveness of the vaccines against new strains of the COVID-19 virus, and short-term and long-term side effects of the vaccines.

Theme 3 describes "discussions about news related to COVID-19 vaccines," and involved 13.3% of the tweets. Commonly discussed news items included those related to vaccine development and approval as well as effectiveness of the vaccines against new strains of the COVID-19 virus. Theme 4 describes "public health communications about COVID-19 vaccines," and involved 10.3% of the tweets. Tweets in this theme included efforts to provide simple explanations on vaccine-related issues, such as those related to the vaccines' efficacies and mechanisms of action, as well as the use of various media in providing public education (eg, involving expert panels, radio, and video).

Theme 5 describes “discussions about the approach to COVID-19 vaccination drives,” and involved 17.1% of the tweets. Within this theme, several approaches to vaccination drives have commonly been highlighted, including engaging relevant stakeholders in vaccination drives (eg, public figures, employers, and minority communities) and defining priority groups for vaccination (eg, frontline workers, long-term care homes, and individuals with high-risk health conditions). Theme 6 describes “discussions about the distribution of COVID-19 vaccines,” and involved 20.3% of the tweets. Commonly described topics in this theme included discussions about equitable access to vaccines, such as ethical principles of vaccine allocation and equitable access across various subpopulations, as well as rollout efforts of COVID-19 vaccination (eg, shipment, distribution plan, vaccination sites, and vaccination statistics).

Barriers and Facilitators to COVID-19 Vaccination

We further examined the barriers and facilitators related to COVID-19 vaccination by matching our initial 59 topics to the three components in the COM-B model (ie, capability, opportunity, and motivation). Detailed results on the barriers and facilitators are presented in Table 2. Briefly, barriers to COVID-19 vaccination could be grouped into those related to capability (eg, vaccine misinformation), opportunity (eg, limited access to the vaccines and poorly planned vaccination drives), and motivation (eg, public concerns related to the vaccines). Similarly, facilitators of COVID-19 vaccination could be grouped into those related to capability (eg, access to accurate information related to the vaccines and having the right approach in delivering public education), opportunity (eg, sufficient access to the vaccines and well-planned vaccination drives), and motivation (eg, public perception about the threat of COVID-19 and public optimism about the vaccines).

Figure 3 shows the variations in the prevalence of barriers and facilitators related to each component in the COM-B model (ie, capability, opportunity, and motivation) over the 11-week study period. In general, tweets related to facilitators had a higher prevalence than those related to barriers. Facilitators related to capability were highly talked about in the initial weeks after the press release regarding the Pfizer-BioNTech vaccine, followed by a declining trend in the subsequent weeks. Facilitators related to opportunity rose drastically over the 11 weeks, while facilitators related to motivation peaked around the sixth week. In contrast, tweets related to barriers remained largely constant throughout the study period, with those related to motivation being more prevalent than those related to capability or opportunity.

Table 2. Barriers and facilitators of COVID-19 vaccination, grouped according to the three components of the COM-B model.

COM-B model[a] component	Barriers	Facilitators

Capability[b]	• Inaccurate information related to COVID-19 vaccines:
	  • Vaccine misinformation (Topic 26)
	  • Politicians' claims about COVID-19 as a hoax (Topics 17 and 18)
	  • The antivaccine movement and conspiracy claims (Topic 55)
		• Access to accurate information related to COVID-19 vaccines:
		  • Accurate news reporting related vaccine development and approval (Topics 1, 10, 13, 23, and 25)
		  • Accurate news reporting related to effectiveness of the vaccines against new strains of the COVID-19 virus (Topic 52)
		  • Accurate news reporting on the impact of COVID-19 (Topics 35 and 56)
		• Having the right approach to delivering public education on COVID-19 vaccines:
		  • Involving an expert panel in public education on COVID-19 vaccines (Topic 8)
		  • Using various media (eg, radio and video) in public education on COVID-19 vaccines (Topics 9 and 22)
		  • Providing simple explanations about vaccine-related issues (eg, efficacy of the vaccines, the mechanisms of how the vaccines may work, and how the vaccines can help in achieving herd immunity; Topics 7, 20, 34, and 51)

Opportunity[c]	• Limited access to COVID-19 vaccines:
	  • Insufficient supply of COVID-19 vaccines (Topic 12)
	  • Inequitable access to the vaccines (Topic 33)
	• Poorly planned vaccination drives:
	  • Delays in vaccination rollout (Topic 31)
		• Having sufficient access to COVID-19 vaccines:
		  • Ensuring equitable access to the vaccines (eg, ethical principles of vaccine allocation and equitable access across various populations; Topics 3, 15, 21, and 39)
		  • Ensuring timely shipment of the vaccines (Topic 49)
		  • Having a coordinated distribution plan for the vaccines (Topics 38 and 57)
		• Having a well-planned vaccination drive:
		  • Defining priority groups for vaccination, (eg, frontline workers, long-term care homes, and individuals with high-risk health conditions; Topics 4, 28, 45, and 46)
		  • Engaging employers in facilitating COVID-19 vaccination (Topic 24)
		  • Using appointment systems and multiple vaccination sites in vaccination rollouts (Topics 29 and 48)
		  • Having a coordinated national plan for vaccination drives (Topics 32 and 44)

Motivation[d]	• Public concerns related to COVID-19 vaccines:
	  • Public concerns about death related to COVID-19 vaccines (Topic 19)
	  • Public concerns about the impact of COVID-19 vaccines on fertility (Topic 11)
	  • Concerns about COVID-19 vaccine safety in pregnancy and the vaccines' use in children (Topic 43)
	  • Public concerns about adverse events related to COVID-19 vaccines (Topics 5 and 50)
	  • Public concerns about fitness for vaccination among individuals with medical conditions or allergies (Topic 6)
	  • Public concerns about short development phases of COVID-19 vaccines (Topic 16)
	  • Public concerns about the effectiveness of COVID-19 vaccines against new strains of COVID-19 (Topic 53)
	  • Public concerns about vaccine scams regarding mining of personal and financial information (Topic 54)
	  • Public concerns about COVID-19 causing false-positive results on HIV tests (Topic 41)
	  • Mistrust among minority communities with regard to COVID-19 vaccination (Topic 36)
		• Public perception about the threat of COVID-19:
		  • Voicing the importance of staying vigilant to keep control of COVID-19 (Topic 59)
		  • Comparing COVID-19 and COVID-19 vaccination statistics to drive vaccination efforts (Topics 2, 27, and 47)
		• Public optimism about COVID-19 vaccines:
		  • Hoping for COVID-19 vaccination in making the days ahead better (Topic 37)
		  • Sharing of positive emotions related to receiving COVID-19 vaccines (Topic 30)
		  • Feeling positivity regarding contributing to COVID-19 vaccination development (Topics 40 and 42)
		  • Influence of public figures in instilling public trust (Topics 14 and 58)

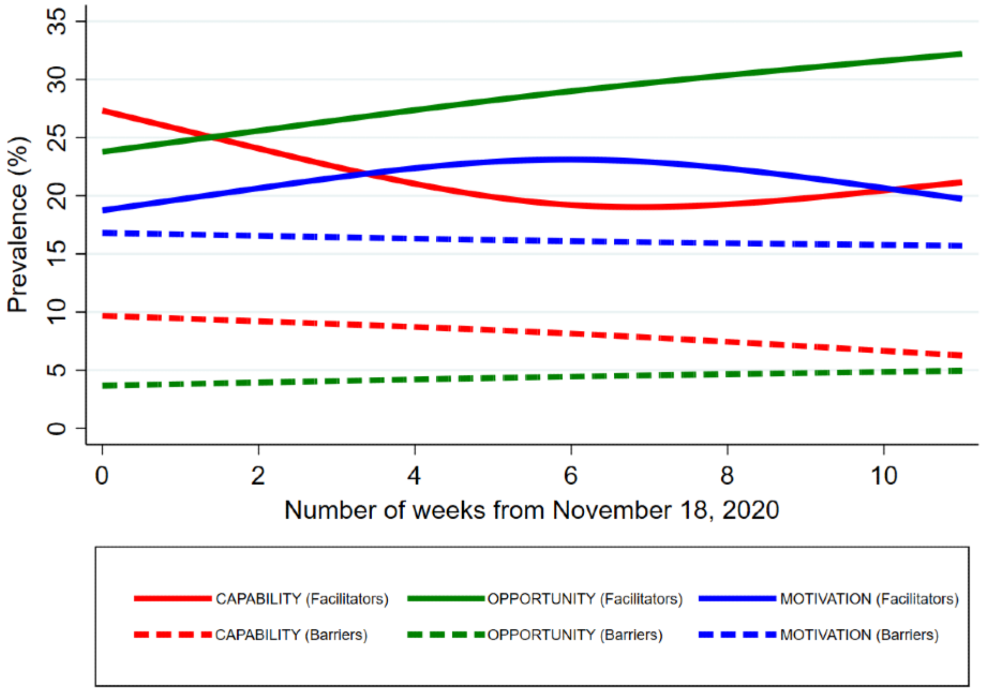
[a]The COM-B (capability, opportunity, and motivation components of behavior) model provides a framework to understand and change human behaviors in the context of public health.

[b]Capability refers to an individual's psychological and physical capacity to make a behavior possible, such as having the necessary knowledge and skills to perform a target behavior.

[c]Opportunity refers to attributes that lie outside an individual, physically and socially, that make a behavior possible, such as environmental factors or social and cultural norms.

[d]Motivation refers to the automatic or reflective mental processes that energize and direct behavior, which can include a conscious thought process in deciding on a behavior or a less conscious thought process driven by desires or habits.

Figure 3. Temporal variations in the prevalence of the barriers and facilitators related to each component in the COM-B model. The graph was plotted using restricted cubic spline smoothing.



Discussion

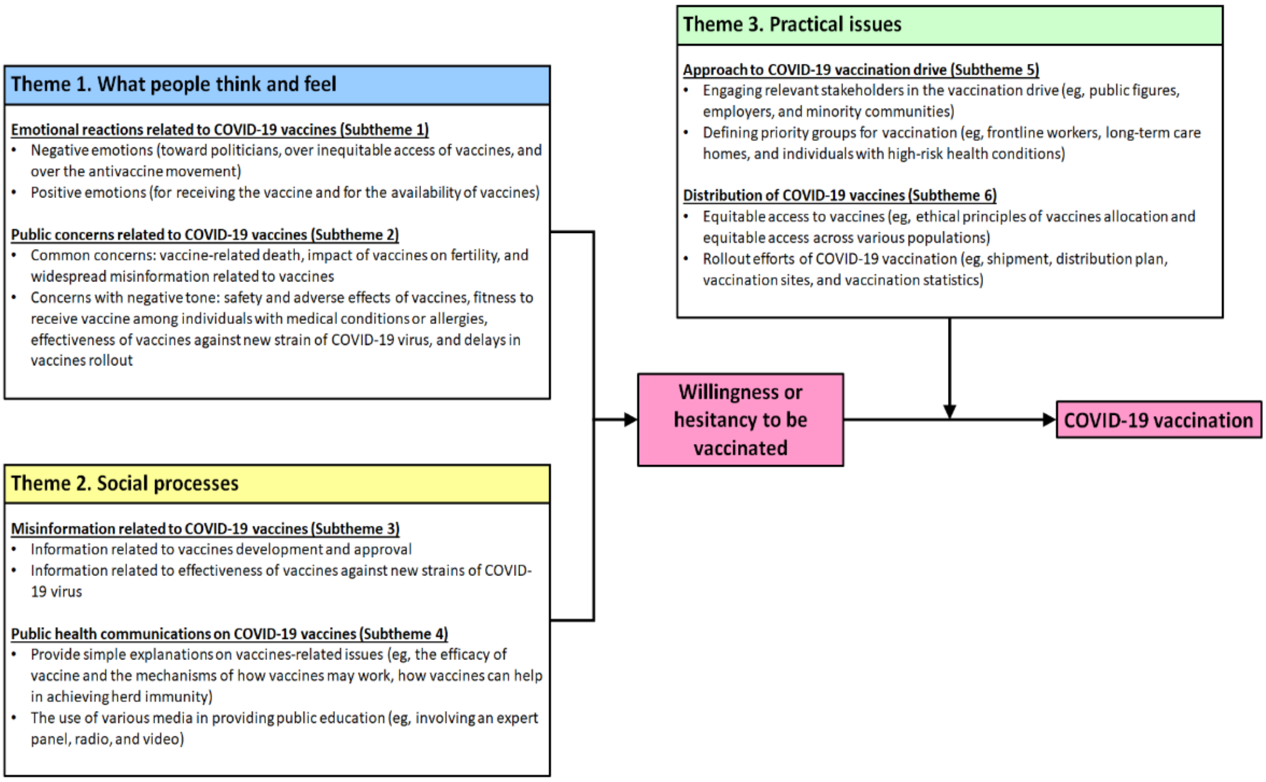
Principal Findings

This study used social media data to capture real-time public conversations about COVID-19 vaccines after November 18, 2020, following a press release regarding the first effective vaccine. Six main themes could be identified from the tweets: (1) emotional reactions related to COVID-19 vaccines, (2) public concerns related to COVID-19 vaccines, (3) discussions about news related to COVID-19 vaccines, (4) public health communications about COVID-19 vaccines, (5) discussions about the approach to COVID-19 vaccination drives, and (6) discussions about the distribution of COVID-19 vaccines. Tweets with negative sentiments largely fell within the themes of emotional reactions and public concerns related to COVID-19 vaccines. The tweets could be further classified using the COM-B model to examine the barriers and facilitators related to COVID-19 vaccines. Tweets that focused on barriers remained largely constant throughout the study period, with those related to motivation (eg, public concern) being more prevalent than those related to capability (eg, misinformation) or opportunity (eg, vaccine inaccessibility and poorly planned vaccination drive). In contrast, tweets that focused on facilitators showed temporal variations over the 11-week study period: those related to capability (eg, access to accurate information and public education) peaked initially, while those related to motivation (eg, perceived threats from COVID-19 and optimistic attitudes) peaked around the sixth week and those related to opportunity (eg, sufficient supply and well-planned vaccination drives) rose drastically over time.

Using Social Media Data to Inform Vaccination Strategies

Our findings on the six themes (Table 1) are consistent with recent literature related to individuals' motivations to receive vaccines and may potentially have policy implications for improving COVID-19 vaccine uptake. In 2018, the WHO convened an expert working group [8] to track and address the challenge of undervaccination that is often prevalent around the world. By adapting from prior literature [7], the working group published a theoretical Increasing Vaccination Model (IVM) [8] to clarify key processes that may affect whether an individual receives a vaccine. At the heart of this model, the WHO highlighted that individuals' motivations to be vaccinated are shaped by what they think and feel (eg, perceived risks and benefits of vaccination), as well as by social processes that play out in their environment (eg, strong recommendation from health care providers and misinformation that circulates within their social networks) [8]. Eventually, practical issues (eg, vaccine availability, accessibility, cost, and convenience) will further shift the individuals from being willing to be vaccinated to actually receiving the vaccines. It is notable that the six themes from this study possibly align well with the WHO's IVM and may potentially expand on the key processes that are specific to the context of COVID-19 vaccination. For instance, our first two themes provide real-time examples regarding what people think and feel toward COVID-19 vaccination, while the third and fourth themes highlight the social processes that are currently in play in the community (eg, circulating news items that have captured public attention and ongoing public health communications about COVID-19 vaccines). Similarly, the fifth and sixth themes possibly exemplify vaccine-related practical issues that have captured public attention, including those related to vaccine distribution and vaccination drives. Such mapping, between our six themes and the three key processes from the IVM, is further illustrated in Figure 4. Given the expected rollout of COVID-19 vaccination globally, this expanded model in Figure 4 may possibly provide richer contextual details on the key processes that are relevant to successful COVID-19 vaccination drives. For example, in the planning of COVID-19 vaccination, Figure 4 highlights the need for policy makers to be mindful of common emotions and concerns in the community, which may then be addressed through targeted public health communications as well as through cautious debunking of misinformation. In addition, Figure 4 also elaborates on practical issues that need to be addressed in vaccination drives, such as engagement of stakeholders, clarification of priority groups for vaccination, and equitable access to the vaccines.

Figure 4. An explanatory model regarding the key drivers of COVID-19 vaccination, expanding on the original Increasing Vaccination Model.

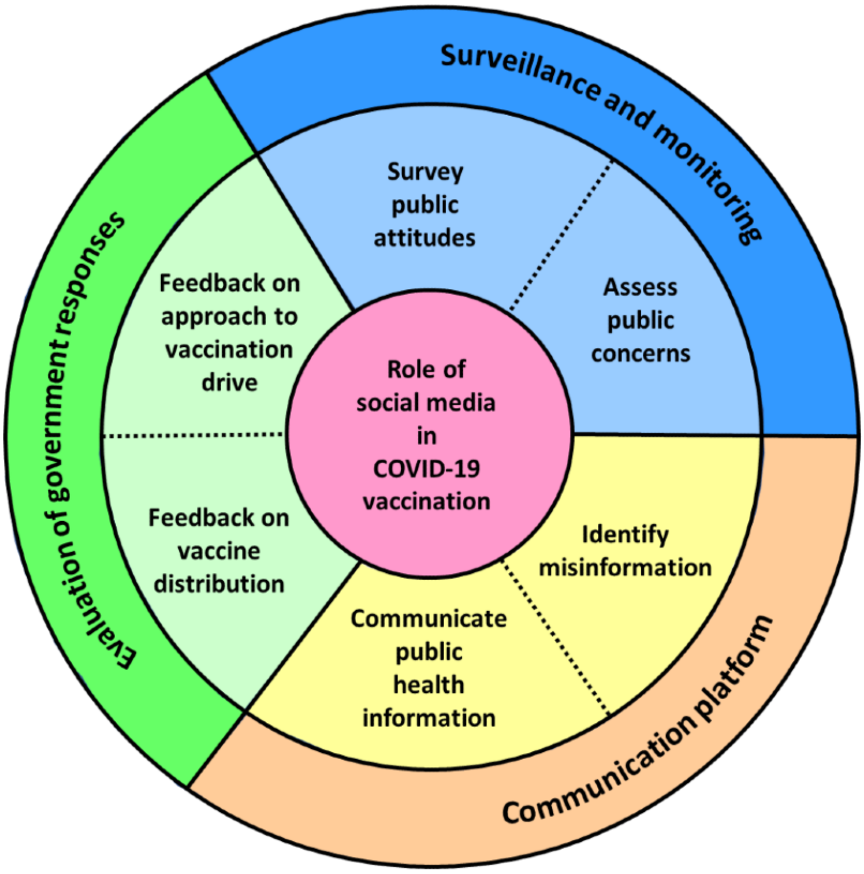


Our findings on the barriers and facilitators to COVID-19 vaccination (Table 2 and Figure 3) present a different, yet equally relevant, set of information to policy makers. Figure 3 provides feedback to policy makers on the evolving barriers and facilitators in ongoing COVID-19 vaccination and, hence, may allow policy makers to further tweak their policies given these close-to-real-time ground sentiments. For example, the findings from Figure 3 may possibly assure policy makers that the facilitators of COVID-19 vaccination have largely been put in place, with these facilitators outweighing the various barriers to vaccination in the community. Yet, at the same time, Figure 3 also highlights a disquieting trend: barriers related to individuals' motivations to receive COVID-19 vaccines have remained prominent and unchanging across time and may be an area that requires further interventions by policy makers. Given that the barriers related to motivation were largely driven by public concerns regarding COVID-19 vaccines, such as those related to vaccine safety as seen in Table 2, policy makers may potentially adopt some of the proposed interventions related to the COM-B model [28] to address these prevailing public concerns, which have been highlighted in Table 2. As an illustration, barriers related to motivation in the COM-B model can often be modified through persuasion (ie, using communication to stimulate action), modeling (ie, providing an example for people to aspire to or imitate), and incentivization (ie, creating an expectation of reward) [28]. Policy makers may possibly intensify the use of these three approaches in modifying barriers related to motivation, such as by convincing the public of the safety and effectiveness of COVID-19 vaccines (ie, persuasion) [46], broadcasting special events with public figures or celebrities receiving the vaccines (ie, modeling) [47,48], and lifting COVID-19 restrictions related to social gatherings among those who have received the vaccines (ie, incentivization) [49].

Broader Roles of Social Media in COVID-19 Vaccination

From a broader perspective, findings from this study demonstrated the potential roles of social media in ongoing COVID-19 vaccination drives. Social media has been increasingly recognized in recent literature as a useful source of data to inform issues of public health interest [50] given the nature of social media data, which reflect real-time ground sentiments, as well as the potential utility of social media platforms for mass dissemination of health-related information [9]. The relevance of social media data became more apparent during the COVID-19 pandemic, whereby many pandemic-related issues were fluid in nature, such as those related to infection rate, government policy, and vaccination plans; hence, there is a constant need to disseminate accurate information related to the pandemic in a timely manner [9]. The potential roles of social media during the COVID-19 pandemic were further highlighted in a recent scoping review [50], whereby six generic roles of social media could be identified, as follows: surveying public attitudes, assessing mental health, detecting COVID-19 cases, identifying misinformation, evaluating the quality of public health communications, and analyzing government responses to the pandemic [50]. Although not all of the generic roles are applicable to the specific context of COVID-19 vaccination, some of these roles are exemplified by findings from this study. For example, the role of social media in surveying public attitudes is epitomized by our first two themes, which further clarified the emotional reactions and public concerns related to COVID-19 vaccines. Meanwhile, the role of social media in identifying misinformation may possibly be seen in our third theme. News items related to COVID-19 vaccines are constantly discussed on social media, and during this process, inaccurate or false information may potentially be communicated. Consequently, social media may be used to identify real-time misinformation that has been widely circulated in public. Similarly, the role of social media in evaluating the quality of public health communications is illustrated by our fourth theme, whereby social media posts may be surveyed to examine the prevailing approach and content in public health communications related to COVID-19 vaccines. Likewise, the role of social media in analyzing government responses to the pandemic is seen in our fifth and sixth themes, whereby social media posts may be used to gain real-time public feedback on operational issues related to vaccination drives. By consolidating prior evidence [50] and findings from this study, the role of social media—specific to COVID-19 vaccination—may possibly be summarized in the framework in Figure 5. In essence, we propose that social media may play at least three key roles in ongoing COVID-19 vaccination drives, as follows: surveillance and monitoring of public concerns regarding COVID-19 vaccines, a platform for accurate communication of vaccine-related information, and evaluation of government responses in the vaccine rollout.

Figure 5. A framework for the role of social media in COVID-19 vaccination.



Limitations

Some limitations should be considered in this study. First, Twitter posts were used to exemplify social media data. Although Twitter is among the most widely used social media platforms [9,21], it may not fully represent users of other social media platforms. Second, we only included tweets that were posted in English due to challenges in analyzing posts in different languages together. Hence, our findings may be more representative of English-speaking populations.

Third, most of Twitter's users were from North America and Europe. Keeping this in mind, our findings may not be as generalizable to other countries. Fourth, the findings may not fully represent the perspectives of the wider population, given that social media is largely used by individuals who have internet access and are technology savvy [51].

Fifth, previous research has found that nonhuman Twitter users (ie, bots) may artificially manipulate public opinion on social media [52]. Most of such nonhuman tweets would have been excluded in this study, as we selected only tweets by users with actual human names and we excluded retweets and duplicate tweets. Notwithstanding these efforts, a small number of these nonhuman tweets could possibly still have remained in the study sample.

Sixth, insofar as unsupervised machine learning is well suited to analyses of large volumes of free-text data [24], such analyses may not be as in depth as manually conducted qualitative analyses. To address this limitation, the output from machine learning was further refined by manual analyses by the two authors using currently recommended best practices in qualitative studies [53].

Seventh, the sentiment analysis in this study was conducted to supplement the main findings from topic modeling. Although the results from our sentiment analysis have face validity (ie, consistently highlighting topics with negative sentiments, as seen in Table 1) and our approach to sentiment analysis, using the VADER package, has good supporting evidence from the literature [36,42,43], readers should be mindful that sentiment analysis remains an evolving area in the field of natural language processing and, hence, the findings from sentiment analysis should probably be treated as exploratory in nature. It is also possible that other newer techniques of sentiment analysis, especially those based on supervised deep learning, may achieve better accuracy in sentiment analysis. However, the development of new models for sentiment analysis is probably a separate area that may benefit from further research and may be beyond the scope of this study.

Conclusions

In conclusion, this study used unsupervised machine learning to identify six overarching themes related to COVID-19 vaccines on social media, of which some themes contained tweets with more negative sentiments. The findings may facilitate the formulation of comprehensive strategies to improve COVID-19 vaccine uptake in the community; they highlight the key processes that require attention by policy makers in the planning of COVID-19 vaccination and provide feedback on the evolving barriers and facilitators in ongoing vaccination drives to allow further policy tweaks. From a broader perspective, the findings may also be consolidated into a framework to illustrate three key roles of social media in COVID-19 vaccination, as follows: surveillance and monitoring, a communication platform, and evaluation of government responses.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Word clouds for the six themes related to COVID-19 vaccination. The word clouds have been weighted using term frequency–inverse document frequency to give more emphasis to words that are unique to each tweet.

[DOCX File , 1600 KB - publichealth_v7i11e29789_app1.docx]

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Abbreviations

COM-B: capability, opportunity, and motivation components of behavior
IVM: Increasing Vaccination Model
VADER: Valence Aware Dictionary and Sentiment Reasoner
WHO: World Health Organization

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Original Paper

Multilevel Determinants of COVID-19 Vaccine Uptake Among South Asian Ethnic Minorities in Hong Kong: Cross-sectional Web-Based Survey

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Abstract

Background: The COVID-19 pandemic continues to have a disproportionate effect on ethnic minorities. Across countries, greater vaccine hesitancy has been observed among ethnic minorities. After excluding foreign domestic helpers, South Asians make up the largest proportion of ethnic minorities in Hong Kong. It is necessary to plan for COVID-19 vaccination promotional strategies that cater to the unique needs of South Asians in Hong Kong.

Objective: This study investigated the prevalence of COVID-19 vaccine uptake among a sample of South Asians in Hong Kong. We examined the effects of sociodemographic data and factors at individual level (perceptions), interpersonal level (information exposure on social media), and sociostructural level (cultural) based on the socioecological model.

Methods: A cross-sectional web-based survey was conducted on May 1-31, 2021. Participants were South Asian people aged 18 years or older living in Hong Kong; able to comprehend English, Hindi, Nepali, or Urdu; and having access to a smartphone. Three community-based organizations providing services to South Asians in Hong Kong facilitated the data collection. The staff of the community-based organizations posted the study information in WhatsApp groups involving South Asian clients and invited them to participate in a web-based survey. Logistic regression models were fit for data analysis.

Results: Among 245 participants, 81 (33.1%) had taken at least one dose of the COVID-19 vaccine (one dose, 62/245, 25.2%; and both doses, 19/245, 7.9%). After adjusting for significant background characteristics, cultural and religious reasons for COVID-19 vaccine hesitancy were associated with lower COVID-19 vaccine uptake (adjusted odds ratio [AOR] 0.83, 95% CI 0.71-0.97; *P*=.02). At the individual level, having more positive attitudes toward COVID-19 vaccination (AOR 1.31, 95% CI 1.10-1.55; *P*=.002), perceived support from significant others (AOR 1.29, 95% CI 1.03-1.60; *P*=.03), and perceived higher behavioral control to receive COVID-19 vaccination (AOR 2.63, 95% CI 1.65-4.19; *P*<.001) were associated with higher COVID-19 vaccine uptake, while a negative association was found between negative attitudes and the dependent variable (AOR 0.73, 95% CI 0.62-0.85; *P*<.001). Knowing more peers who had taken the COVID-19 vaccine was also associated with higher uptake (AOR 1.39, 95% CI 1.11-1.74; *P*=.01). At the interpersonal level, higher exposure to information about deaths and other serious conditions caused by COVID-19 vaccination was associated with lower uptake (AOR 0.54, 95% CI 0.33-0.86; *P*=.01).

Conclusions: In this study, one-third (81/245) of our participants received at least one dose of the COVID-19 vaccine. Cultural or religious reasons, perceptions, information exposure on social media, and influence of peers were found to be the determinants of COVID-19 vaccine uptake among South Asians. Future programs should engage community groups, champions, and faith leaders, and develop culturally competent interventions.

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KEYWORDS

COVID-19; South Asian ethnic minorities; COVID-19 vaccination; uptake; cultural and religious reasons for vaccine hesitancy; perceptions; information exposure on social media; influence of peers; socioecological model; Hong Kong

Introduction

The COVID-19 pandemic is an ongoing threat [1]. COVID-19 vaccination and other behavioral preventive measures can help to eradicate this pandemic. The Hong Kong government procured 2 types of COVID-19 vaccines (Sinovac-Biotech and BioNTech-Fosun Pharma) and implemented a free-of-charge territory-wide vaccination program to all Hong Kong residents aged 16 years or older. The vaccination services were provided through community vaccination centers, designated public and private clinics, and outreach vaccination services at residential care homes or nursing homes [2]. The program aimed to cover the entire Hong Kong population. During the study period (May 1-31, 2021), priorities to receive COVID-19 vaccination were given to the following groups of Hong Kong residents: (1) individuals aged 30 years or older and caregivers of older adults aged more than 70 years; (2) personnel in health care settings and those participating in antiepidemic-related work; (3) residents and staff of residential care homes for the older adults/persons with disabilities; (4) personnel maintaining critical public services; (5) those providing cross-boundary transportation or working at control points/ports; (6) staff of food and beverage premises; (7) staff of local public transportation operators; (8) registered construction workers; (9) staff of property management; (10) teachers and school staff; (11) staff of tourism industry; (12) staff of scheduled premises under the Prevention and Control of Disease Regulation (eg, staff of fitness centers, beauty parlors); (13) students studying outside Hong Kong (aged 16 years or older); and (14) domestic helpers [2]. The latest estimate shows that at least 70% immune individuals would be necessary to achieve herd immunity for COVID-19 [3]. The number of people who received at least one dose of COVID-19 vaccine increased from 936,400 on May 1, 2021 to 1,379,400 on May 31, 2021, accounting for 12.3% and 18.2% of the entire population in Hong Kong, respectively [4]. However, it will take about 1 year for Hong Kong to achieve herd immunity based on the current progress.

Across countries, COVID-19 pandemic continues to have a disproportionate effect on ethnic minorities, with higher COVID-19 morbidity and mortality and greater adverse socioeconomic consequences [5]. With mass COVID-19 vaccination programs in progress, disparities in its uptake may aggravate the vulnerability of ethnic minorities. Across countries, greater vaccine hesitancy has been observed among people from some ethnic minorities [5-7]. In the United Kingdom, vaccine hesitancy was higher among Black, Bangladeshi, and Pakistani people compared with people from a White ethnic background [8]. Two other studies reported lower COVID-19 vaccine uptake rates among ethnic minorities who were older than 80 years (20.5% among Black people vs 42.5% among White people) and those who were health care workers (70.9% White people, 58.5% South Asians, and 36.8% Black people) [9,10]. It is hence important to understand and address the disparities in COVID-19 vaccination among ethnic minorities.

In Hong Kong, the ethnic minority population increased significantly by 70.8% from 2006 to 2016 and accounted for 8.0% (n=584,383) of the entire population (Census, 2016) [11]. After excluding foreign domestic helpers (most of them are Filipinos and Indonesians), South Asians, including Indians, Pakistanis, Nepalis, Bangladeshis, and Sri Lankans make up the largest proportion of the ethnic minorities in Hong Kong (n=85,875, accounting for 1.2% of the entire Hong Kong population) [11]. A recent study found that health system responsiveness reported by South Asians was lower than that reported by Chinese patients for both outpatient and inpatient services in Hong Kong [12]. The largest disparity in the responsiveness was shown in the communication barriers experienced by South Asians owing to cultural and language differences between South Asian patients and local health care service providers [12]. During hospitalization, South Asian inpatients perceived limited access to community support in comparison with the Chinese inpatients [12]. There is also a lack of autonomy in decision-making and choice of health care providers experienced by South Asians [12]. Health professionals in Hong Kong also indicated barriers in their delivery of services to the ethnic minorities, including inadequate dissemination of appropriate information, insufficient provision of cross-cultural care education and training, inadequate availability of public primary care services, and presence of bias and discrimination among hospital staff [12]. Cultural differences between ethnic minorities and health service providers affect patient-provider interactions and health care quality, resulting in mistrust of government and health authorities, which in turn becomes an obstacle for the COVID-19 vaccination program [5]. With an increasing population of South Asians in Hong Kong, it is necessary to plan for COVID-19 vaccination promotional strategies that cater to their unique needs.

This study applied the socioecological model as the conceptual framework, which considered determinants of a health behavior at the individual, interpersonal, and sociostructural levels [13]. An intervention addressing factors at multiple levels is more likely to be successful in changing behavior [13]. At the sociostructural level, previous studies have pointed out the association between cultural/religious belief and COVID-19 vaccine hesitancy. A Malaysian study showed that 20.8% and 6.8% of the ethnic minorities believed that their COVID-19 vaccine hesitancy was caused by concerns regarding religious and cultural factors, respectively [14]. News reports also suggested that there were concerns among Muslims over the halal status of the COVID-19 vaccine [15], and the beliefs that COVID-19 should be healed by God and the body is sacred were cited as reasons to refuse the COVID-19 vaccine [16]. Because a large percentage of the South Asians in Hong Kong are Muslims, there is a need to understand the effects of religious beliefs on COVID-19 vaccine uptake, so that policymakers can target this specific population for the relevant COVID-19 vaccine promotional strategy. Limited evidence is available to date to inform us on the cultural effect of COVID-19 vaccine uptake in Hong Kong.

At the interpersonal level, misinformation related to COVID-19 vaccination threatened vaccine uptake [17]. The government used to report deaths after COVID-19 vaccination, regardless of the existence of the direct causality evidence. Such information exposure might inhibit the motivation to receive COVID-19 vaccination among South Asians as they will associate COVID-19 vaccination directly with deaths. For example, public's concerns about vaccine safety increased substantially after media reported deaths after COVID-19 vaccination, which resulted in a drop in the proportion of people turning up for their vaccination appointment in Hong Kong (from >90% to 72%) [2]. However, communication with peers may be effective among South Asians owing to higher level of rapport between people of the same ethnicity [18]. The Social Learning Theory posits that observation of peers has a major influence on people's health behaviors. Therefore, vaccinated peers may play important roles as volunteers in future programs promoting COVID-19 vaccination among South Asians by sharing their positive experience. Peers' experiences related to COVID-19 vaccination might have a strong influence on South Asians' decision to receive such vaccinations. Based on these observations, socialization, in terms of receiving vaccine-related information or interpersonal interaction, is assumed to affect vaccine uptake.

At the individual level, the Theory of Planned Behavior (TPB) postulates that in order to perform a behavior, one would evaluate the pros and cons of the behavior (positive and negative attitudes), consider whether their significant others would support such behavior (perceived subjective norm), and appraise how much control one has over the behavior (perceived behavioral control) [19]. The TPB was commonly used to explain a health behavior and guide the behavioral intervention [20,21]; it has been used to explain willingness to receive COVID-19 vaccination among Chinese people [22]. Studies conducted among the Hong Kong general population identified the perceived pros and cons that were associated with the willingness to receive COVID-19 vaccination. Pros included perceived greater risk and severe consequences of infection, perceived higher effectiveness of COVID-19 vaccines, perceived greater impact of COVID-19 vaccination in pandemic control, perceived larger proportion of general public and acquaintance would take up such vaccination, being recommended by physicians and family members, and perceived higher behavioral control to take up the vaccination [23-26]. Concerns related to side effects and access issues as well as difficulties in choosing one out of the available COVID-19 vaccines were commonly mentioned as cons against vaccination [23-26]. These perceptions were considered by this study. To our knowledge, there is a dearth of studies investigating the determinants of COVID-19 vaccine uptake among ethnic minorities in the Asian region. To address the knowledge gaps, this study investigated the prevalence of COVID-19 vaccine uptake among a sample of South Asians in Hong Kong. We examined the effects of factors, including sociodemographic data, and all 3 levels of factors based on the socioecological model.

Methods

Study Design

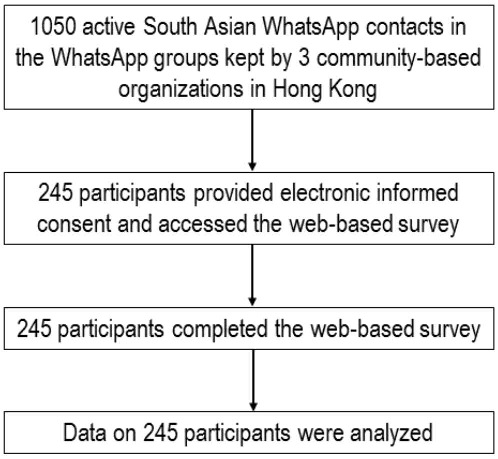
We conducted a cross-sectional web-based survey of 245 South Asian adults in Hong Kong, China on May 1-31, 2021.

Participants and Data Collection

Participants were South Asian people aged 18 years or older living in Hong Kong; able to comprehend English, Hindi, Nepali, or Urdu; and having access to a smartphone. Three community-based organizations (CBOs) in Hong Kong facilitated the data collection. These CBOs provide a wide range of services to ethnic minorities, including early childhood education, child rehabilitation, school social work, treatment and social rehabilitation for drug abusers, home care for older adults, employee assistance and development, health check-up, and health education. However, their services do not include provision of COVID-19 vaccination. The CBOs keep a list of South Asian people using their services and WhatsApp groups involving CBO staff, and these service users are established. There are around 1050 active South Asian people in the WhatsApp groups held by the CBOs. CBO staff posted the study information in the WhatsApp groups and invited South Asian people in these groups to participate in the web-based survey. A link to access a web-based self-administered survey was also posted in the WhatsApp groups. Through the link, participants first selected the language of the survey (English, Hindi, Nepali, or Urdu) and then accessed an electronic consent form. On the form, they read the study information and a statement indicating that the information collected by the survey was only used for scientific research purposes and would be kept strictly confidential. Participation was completely voluntary, and refusal would have no consequences. After clicking "I agree" on the electronic consent form, they could start the web-based survey. We developed the questionnaire by using Google forms, a commonly used web-based survey platform. Each WhatsApp account was only allowed to access the web-based questionnaire once to avoid duplicate responses. The survey had about 100 items, which took about 20 minutes to complete. The Google form performed a completeness check before each questionnaire was submitted. Participants were able to review and change their responses before submission. Participants were asked to leave an address at the end of the survey. The procedure of data collection is shown in Figure 1. A supermarket coupon of HK

$50 (US $6.5) was sent to the participants by mail upon completion. All data were stored in the web-based server of the Google form and protected by a password. Only the corresponding author had access to the database.

Figure 1. Flowchart of data collection.



Ethics Approval and Consent to Participate

Informed consent was obtained from all the participants involved in this study. Ethical approval was obtained from the Survey and Behavioral Research Committee of the Chinese University of Hong Kong (Reference SBRE-20-534).

Sample Size Planning

Our target sample size was 250. Given a statistical power of .80 and an α value of .05 and assuming the COVID-19 vaccine uptake in the reference group (without a facilitating condition) to be 10%-20%, the sample size could detect the smallest odds ratio of 2.23 between people with and without the facilitating conditions (PASS 11.0, NCSS LLC).

Measurements

Development of the Questionnaire

A panel consisting of public health researchers, social workers, health psychologists, representatives from South Asian communities, and CBO workers was formed to develop the questionnaire. Bilingual researchers with master's degrees translated the English version of the questionnaire into Hindi, Nepali, or Urdu. The agreed versions were back translated into English by independent bilingual researchers to ensure linguistic equivalence. The questionnaire was tested on the readability and length among 20 South Asians speaking English, Hindi, Nepali, or Urdu. All participants in the pilot testing agreed that the wordings of the questions were appropriate and easy to understand. However, 15 of them commented that the questionnaire was too long. The panel trimmed down the questionnaire from 130 items to 100 items. Thereafter, the participants were invited to comment on the length of the revised questionnaire, and they all agreed that the length was acceptable. The panel then finalized the questionnaire for the actual survey. The English version of the questionnaire is in Multimedia Appendix 1.

Background Characteristics

Participants were asked to report on sociodemographic data and living arrangements (eg, number of family members living with them, whether they were living with children younger than 18 years or older adults aged ≥60 years). Participants also reported compliance to personal preventive behaviors in the past month, including frequency of wearing facemasks when having close contact with others in workplaces and other public spaces and sanitizing hands after returning from public spaces or touching public installation (response categories: every time, often, sometimes, and never). Two physical distancing behaviors were also measured (whether they avoided social or meal gatherings with people who they do not live with and crowded places in the past month). Same measurements of personal preventive behaviors and physical distancing were used in published studies [19,22,27,28].

COVID-19 Vaccine Uptake

Participants reported whether they had taken any COVID-19 vaccine. Some supplementary information was collected from the vaccinated participants, including number of doses and types of COVID-19 vaccines received, presence of side effects, and severity of such side effects.

Individual-, Interpersonal-, and Sociostructural-Level Variables Related to COVID-19 Vaccination

At the individual level, positive attitudes toward COVID-19 vaccination were measured by the validated Chinese version of the Positive Attitude Scale [19]. The original scale has 5 items, and the Cronbach α was .84 [19]. The scale was adapted by replacing "China" in the original scale with "Hong Kong." Perceived subjective norm related to COVID-19 vaccination was measured by the validated Chinese version of the Subjective Norm Scale [19]. The Cronbach α of the original 2-item scale was .85. We added 1 more item "your friends from South Asia would support you to receive COVID-19 vaccination" to the original scale. Regarding perceived behavioral control related to COVID-19 vaccination, we added 1 more item "you are confident to receive COVID-19 vaccination in the next six months if you want to" to the validated single-item measurement [19]. One scale (6 items) was constructed for this study to measure negative attitudes toward COVID-19 vaccination (eg, the side effects of COVID-19 vaccines in the long run is unclear). The response categories to the aforementioned scale items were 1 (disagree), 2 (neutral), and 3 (agree). In addition, one single item was constructed to measure the descriptive norm related to COVID-19 vaccination "Among South Asians you know who are living in Hong Kong, how many of them have already taken up COVID-19 vaccines?" (response categories: 1=none/not sure, 2=1-2, 3=3-5, 4=6-10, and 5=more than 10). At the interpersonal level, the frequency of exposing to negative information related to COVID-19 vaccination on social media (eg, Facebook, Twitter, Flicker, TikTok) in the past were measured (response categories: 0=almost never, 1= seldom, 2=sometimes, and 3=always). Participants were also asked about whether they heard about any South Asians who experienced serious side effects after taking up COVID-19 vaccines. At the sociostructural level, 5 items measured cultural and religious reasons for COVID-19 vaccine hesitancy (eg, you are concerned about the halal status of the COVID-19 vaccines and the body is sacred; it should not receive certain chemicals or blood or tissues from animals). The Cultural and Religious Barrier Scale was constructed by summing up individual item scores. In addition, 2 items measured how much confidence they had in Hong Kong's health care system and how much they trusted the Hong Kong government regarding COVID-19 control (response categories: from 1=not at all to 10=extremely).

Statistical Analysis

Self-reported uptake of any COVID-19 vaccine was the dependent variable. Univariate logistic regression models first assessed the significance of the association between background characteristics and the dependent variable. We fitted a single logistic regression model to obtain adjusted odds ratios (AOR), which involved one of the independent variable of interest and all background characteristics with *P* values less than .05 in univariate analysis. The same approach to obtain AOR was commonly used in published studies [19,20,22,27,28]. There was no missing value for the participants who completed the survey. Therefore, missing value analysis was not performed. SPSS version 26.0 (IBM Corp) was used for data analysis, with $P<.05$ considered statistically significant.

Results

Background Characteristics

Among the 245 participants who completed the web-based survey, 83 (33.9%) were Indians, 89 (36.3%) were Pakistanis, 52 (21.2%) were Nepalis, and 21 (8.6%) were from other ethnicity groups. The majority of the participants were younger than 40 years, females, married or cohabited with a partner, and with tertiary education. About 29.4% (72/245) of the participants were Hong Kong permanent residents and had a full-time job. Participants reported good compliance with personal preventive behaviors and physical distancing behaviors in the past month (Table 1).

Table 1. Background characteristics of the South Asians who completed the web-based survey in Hong Kong on May 1-31, 2021 (N=245).

Characteristics	Values, n (%)
Sociodemographic characteristics	
Age group (years)	
18-29	83 (33.9)
30-39	100 (40.8)
40-49	55 (22.4)
≥50	7 (2.9)
Gender	
Male	83 (33.9)
Female	162 (66.1)
Relationship status	
Currently single	90 (36.7)
Married or cohabiting with a partner	155 (63.3)
Ethnicity	
Indian	83 (33.9)
Pakistani	89 (36.3)
Nepali	52 (21.2)
Other ethnicity groups	21 (8.6)
Permanent residents of Hong Kong	
Yes	72 (29.4)
No	173 (70.6)
Highest education level attained	
Junior high or below	35 (14.3)
Senior high or equivalent	64 (26.1)
College or university	103 (42.0)
Postgraduate	43 (17.6)
Employment status	
Full-time	85 (34.7)
Part-time/self-employed/housewife/unemployed/retired/students	160 (65.3)
Family members living with the participant	
0	15 (6.1)
1-2	44 (18.0)
3-4	124 (50.6)
≥5	62 (25.3)
Living with an older adult aged ≥60 years	
No	69 (28.2)
Yes	176 (71.8)
Living with a child aged <18 years	
No	181 (73.9)
Yes	64 (26.1)
Having at least one chronic condition	
No	221 (90.2)
Yes	24 (9.8)

Characteristics	Values, n (%)
Compliance to personal preventive behaviors and physical distancing	
Frequency of facemask wearing when in proximity with other people in workplace	
Never/sometimes/often	20 (8.2)
Every time	225 (91.8)
Frequency of facemask wearing in public spaces/transportations other than workplaces	
Never/sometimes/often	46 (18.8)
Every time	199 (81.2)
Sanitizing hands after returning from public spaces or touching public installation	
Never/sometimes/often	60 (24.5)
Every time	185 (75.5)
Avoiding social/meal gathering with other people who do not live together	
No	65 (26.5)
Yes	180 (73.5)
Avoiding crowded places	
No	59 (24.1)
Yes	186 (75.9)

COVID-19 Vaccine Uptake

Among the participants, 33.1% (81/245) had received at least one dose of COVID-19 vaccine (one dose, 62/245, 25.2%; both doses, 19/245, 7.9%). Among the vaccinated participants (81/245), most of them chose mRNA vaccines manufactured by the BioNTech-Fosun Pharma and received vaccination at community vaccination centers. The side effects of the COVID-19 vaccination were reported by 64 participants (79%), and most of the side effects were very mild/mild (Table 2).

Table 2. Perceptions and influences of social media and peers related to COVID-19 vaccination among South Asians who completed the web-based survey in Hong Kong on May 1-31, 2021 (N=245).

Characteristics	Values
Uptake of at least one dose of COVID-19 vaccine, n (%)	
No	164 (66.9)
Yes	81 (33.1)
Individual-level factors, n (%)	
Perceptions related to COVID-19 vaccination based on the Theory of Planned Behavior	
Positive attitudes toward COVID-19 vaccination (agree)	
COVID-19 vaccination is highly effective in protecting you from COVID-19	130 (53.1)
Taking up COVID-19 vaccination is highly effective in protecting your family members against COVID-19	136 (55.5)
Taking up COVID-19 vaccination can facilitate resumption of cross-boundary travelling	164 (66.9)
Taking up COVID-19 vaccination can contribute to the control of COVID-19 in Hong Kong	159 (64.9)
Hong Kong will have adequate supply of COVID-19 vaccination	178 (72.7)
Positive Attitude Scale[a], mean (SD)	12.7 (2.3)
Negative attitudes toward COVID-19 vaccination (agree)	
COVID-19 vaccines will have severe side effects	69 (28.2)
The side effects of COVID-19 vaccines in the long run is unclear	104 (42.4)
The protection of COVID-19 vaccines will only last for a short time	54 (22.0)
It is difficult for you to register for COVID-19 vaccination	21 (8.6)
There is a lack of information related to the COVID-19 vaccination program in my mother tongue	79 (32.2)
You do not know which type of COVID-19 vaccine is the most suitable for you	105 (42.9)
Negative Attitude Scale[b], mean (SD)	11.9 (2.3)
Perceived subjective norm related to COVID-19 vaccination (agree)	
Doctors and nurses would support you to receive COVID-19 vaccination	121 (49.4)
Your family members will support you to receive COVID-19 vaccination	168 (68.6)
Your friends from South Asia would support you to receive COVID-19 vaccination	148 (60.4)
Subjective Norm Scale[c], mean (SD)	7.4 (1.6)
Perceived behavioral control related to COVID-19 vaccination (agree)	
Receiving COVID-19 vaccination is easy for you if you want to	188 (76.7)
You are confident to receive COVID-19 vaccination in the next 6 months if you want to	149 (60.8)
Perceived Behavioral Control Scale[d], mean (SD)	5.2 (1.1)
Among South Asians you know who are living in Hong Kong, how many of them have already taken up COVID-19 vaccines?	
0/not sure	54 (22.0)
1-2	34 (13.9)
3-5	51 (20.8)
6-10	29 (11.8)
>10	77 (31.4)
Interpersonal-level factors, n (%)	
Frequency of exposure to the following information related to COVID-19 vaccination on social media (sometimes/always)	
Positive information related to COVID-19 vaccination (eg, promising efficacy of the vaccines, new vaccines will enter the market soon)	151 (61.6)
COVID-19 vaccination will cause deaths and other serious conditions	120 (49.0)

Characteristics	Values
Many people in Hong Kong did not turn up for their appointment to receive COVID-19 vaccination	109 (44.5)
Influence of peers	
Did you hear about any South Asians who experienced serious side effects after taking up COVID-19 vaccines?	
No	188 (76.7)
Yes	57 (23.3)
Sociostructural-level factors , n (%)	
Cultural and religious reasons for COVID-19 vaccination hesitancy (agree)	
You are concerned about the halal status of the COVID-19 vaccines	66 (26.9)
You are concerned that COVID-19 vaccines may not work well among South Asians, as they are developed by China and western countries	54 (22.0)
The body is sacred; it should not receive certain chemicals or blood or tissues from animals	61 (24.9)
COVID-19 should be healed by God or natural means	54 (22.0)
Taking up vaccination is violating God’s will	12 (4.9)
Cultural and Religious Barrier Scale[e], mean (SD)	8.3 (2.5)
Level of confidence in Hong Kong’s health system, mean (SD)	7.2 (2.1)
Level of trust of the Hong Kong government regarding COVID-19 control, mean (SD)	7.7 (2.1)

[a]Positive Attitude Scale, 5 items, Cronbach α=.77, one factor was identified by exploratory factor analysis, explaining for 52.3% of the total variance.

[b]Negative Attitude Scale, 6 items, Cronbach α=.61, one factor was identified by exploratory factor analysis, explaining for 47.8% of the total variance.

[c]Subjective Norm Scale, 3 items, Cronbach α=.60, one factor was identified by exploratory factor analysis, explaining for 56.9% of the total variance.

[d]Perceived Behavioral Control Scale, 2 items, Cronbach α=.63, one factor was identified by exploratory factor analysis, explaining for 73.0% of the total variance.

[e]Cultural and Religious Barrier Scale, 5 items, Cronbach α=.65, one factor was identified by exploratory factor analysis, explaining for 42.2% of the total variance.

Individual-, Interpersonal-, and Sociostructural-Level Variables Related to COVID-19 Vaccination

The Cronbach α of the scales based on the TPB ranged from .60 to .77; single factors were identified by exploratory factor analysis, explaining for 47.8%-73% of the total variance. Among the participants, 31.4% (77/245) had at least 10 peers who had received COVID-19 vaccination. About half of the participants were sometimes/always exposed to the following COVID-19 vaccination-related information on social media such as positive information (eg, promising efficacy of the vaccines, and new vaccines will enter the market soon) (151/245, 61.6%), COVID-19 vaccination will cause deaths and other serious conditions (120/245, 49.0%), and many people in Hong Kong did not turn up for their appointment to receive COVID-19 vaccination (109/245, 44.5%). Regarding the sociostructural-level variables, the Cronbach α of the Cultural and Religious Barrier Scale was .65; one factor was identified by exploratory factor analysis, explaining for 42.2% of the total variance (Table 2).

Factors Associated With COVID-19 Vaccine Uptake

In univariate analysis, age group, ethnicity, relationship status, status as Hong Kong permanent residents, facemask wearing in public spaces/transportations other than workplaces, sanitizing hands after returning from public spaces or touching public installation, and avoiding social/meal gatherings with other people who do not live together were associated with COVID-19 vaccine uptake (Table 3).

Table 3. Associations between background characteristics and COVID-19 vaccine uptake among the South Asians who completed the web-based survey in Hong Kong on May 1-31, 2021 (N=245).

	Participants who had taken the COVID-19 vaccine (n=81), n (%)	Participants who had not taken the COVID-19 vaccine (n=164), n (%)	Crude odds ratio (95% CI)	*P* value
Sociodemographic data				
Age group (years)				
18-29	10 (12.3)	73 (44.5)	1.0	N/A[a]
30-39	42 (51.9)	58 (35.4)	5.29 (2.45-11.43)	<.001
40-49	27 (33.3)	28 (17.1)	7.04 (3.02-16.41)	<.001
≥50	2 (2.5)	5 (3.0)	2.92 (0.50-17.11)	.24
Gender				
Male	24 (29.6)	59 (36.0)	1.0	N/A
Female	57 (70.4)	105 (64.0)	1.34 (0.75-2.37)	.32
Relationship status				
Currently single	20 (24.7)	70 (42.7)	1.0	N/A
Married or cohabited with a partner	61 (75.3)	94 (57.3)	2.27 (1.26-4.11)	.007
Ethnicity				
Indian	33 (40.7)	50 (30.5)	1.0	N/A
Pakistani	16 (19.8)	73 (44.5)	0.33 (0.17-0.67)	.002
Nepali	25 (30.9)	27 (16.5)	1.40 (0.70-2.82)	.34
Other ethnicity groups	7 (8.6)	14 (8.5)	0.76 (0.28-2.08)	.59
Permanent residents of Hong Kong				
Yes	36 (44.4)	36 (22.0)	1.0	N/A
No	45 (55.6)	128 (78.0)	0.35 (0.20-0.62)	<.001
Highest education level attained				
Junior high or below	11 (13.6)	24 (16.4)	1.0	N/A
Senior high or equivalent	15 (18.5)	49 (29.9)	0.67 (0.27-1.67)	.39
College or university	38 (46.9)	65 (39.6)	1.28 (0.56-2.89)	.56
Postgraduate	17 (21.0)	26 (15.9)	1.43 (0.56-3.65)	.46
Employment status				
Full-time	32 (39.5)	53 (32.3)	1.0	N/A
Others	49 (60.5)	111 (67.7)	0.73 (0.42-1.27)	.27
Family members living with the participant				
0	7 (8.6)	8 (4.9)	1.0	N/A
1-2	19 (23.5)	25 (15.2)	0.87 (0.27-2.82)	.81
3-4	39 (48.1)	85 (51.8)	0.52 (0.18-1.55)	.24
≥5	16 (19.8)	46 (28.0)	0.40 (0.12-1.27)	.12
Living with an older adult aged ≥60 years				
No	61 (75.3)	120 (73.2)	1.0	N/A
Yes	20 (24.7)	44 (26.8)	0.89 (0.49-1.65)	.72
Living with a child younger than 18 years				
No	17 (21.0)	52 (31.7)	1.0	N/A
Yes	64 (79.0)	112 (68.3)	1.75 (0.93-3.28)	.08
Having at least one chronic condition				

	Participants who had taken the COVID-19 vaccine (n=81), n (%)	Participants who had not taken the COVID-19 vaccine (n=164), n (%)	Crude odds ratio (95% CI)	*P* value
No	74 (91.4)	147 (89.6)	1.0	N/A
Yes	7 (8.6)	17 (10.4)	0.82 (0.33-2.06)	.62
Compliance to personal preventive behaviors and physical distancing				
Frequency of facemask wearing when in proximity with other people in workplace				N/A
Never/sometimes/often	10 (12.3)	36 (22.0)	1.0	
Every time	71 (87.7)	128 (78.0)	2.00 (0.94-4.26)	.07
Frequency of facemask wearing in public spaces/transportations other than workplaces				
Never/sometimes/often	1 (1.2)	19 (11.6)	1.0	N/A
Every time	80 (98.8)	145 (88.4)	10.48 (1.38-79.76)	.02
Sanitizing hands after returning from public spaces or touching public installation				
Never/sometimes/often	13 (16.0)	47 (28.7)	1.0	N/A
Every time	68 (84.0)	117 (71.3)	2.10 (1.06-4.16)	.03
Avoiding social/meal gathering with other people who do not live together				
No	15 (18.5)	50 (30.5)	1.0	N/A
Yes	66 (81.5)	114 (69.5)	1.93 (1.01-3.70)	.048
Avoiding crowded places				
No	14 (17.3)	45 (27.4)	1.0	N/A
Yes	67 (82.7)	119 (72.6)	1.81 (0.93-3.54)	.08

[a]N/A: not applicable.

After adjusting for significant background characteristics, perceived higher cultural and religious barriers to receive COVID-19 vaccination were associated with lower COVID-19 vaccine uptake (AOR 0.83, 95% CI 0.71-0.97; *P*=.02). At the individual level, having more positive attitudes toward COVID-19 vaccination (AOR 1.31, 95% CI 1.10-1.55; *P*=.002), perceived support from significant others (AOR 1.29, 95% CI 1.03-1.60; *P*=.03), and perceived higher behavioral control to receive COVID-19 vaccination (AOR 2.63, 95% CI 1.65-4.19; *P*<.001) were associated with higher COVID-19 vaccine uptake, while a negative association was found between negative attitudes and the dependent variable (AOR 0.73, 95% CI 0.62-0.85; *P*<.001). Knowing more peers who had received COVID-19 vaccination was also associated with higher uptake (AOR 1.39, 95% CI 1.11-1.74; *P*=.01). At the interpersonal level, higher exposure to information about deaths and other serious conditions caused by COVID-19 vaccination was associated with lower uptake (AOR 0.54, 95% CI 0.33-0.86; *P*=.01) (Table 4).

Table 4. Factors associated with COVID-19 vaccine uptake among the South Asians who completed the web-based survey in Hong Kong on May 1-31, 2021.

Factors	Participants who had taken the COVID-19 vaccine (n=81)	Participants who had not taken the COVID-19 vaccine (n=164)	Crude odds ratio (95% CI)	*P* value	Adjusted odds ratio[a] (95% CI)	*P* value
Individual-level factors, mean (SD)						
Positive Attitude Scale	13.6 (1.7)	12.2 (2.5)	1.31 (1.17-1.56)	<.001	1.31 (1.10-1.55)	.002
Negative Attitude Scale	10.9 (2.1)	12.4 (2.3)	0.74 (0.64-0.84)	<.001	0.73 (0.62-0.85)	<.001
Subjective Norm Scale	7.9 (1.3)	7.1 (1.7)	1.47 (1.21-1.69)	<.001	1.29 (1.03-1.60)	.03
Perceived Behavioral Control Scale	5.7 (0.7)	4.9 (1.2)	2.70 (1.82-4.00)	<.001	2.63 (1.65-4.19)	<.001
Among South Asians you know who are living in Hong Kong-how many of them have already taken up COVID-19 vaccines?	3.9 (1.5)	2.8 (1.5)	1.60 (1.32-1.95)	<.001	1.39 (1.11-1.74)	.01
Interpersonal-level factors						
Frequency of exposure to the following information related to COVID-19 vaccination on social media, mean (SD)						
Positive information related to COVID-19 vaccination	1.8 (0.8)	1.6 (0.9)	1.32 (0.95-1.82)	.10	1.16 (0.78-1.72)	.46
COVID-19 vaccination will cause deaths and other serious conditions	1.3 (0.6)	1.5 (0.8)	0.67 (0.46-0.98)	.04	0.54 (0.33-0.86)	.01
Many people in Hong Kong did not turn up for their appointment to receive COVID-19 vaccination	1.3 (0.8)	1.3 (0.8)	0.99 (0.71-1.37)	.94	0.98 (0.66-1.56)	.92
Influence of peers, n (%)						
Did you hear about any South Asians who experienced serious side effects after taking up COVID-19 vaccines?						
No	65 (80.2)	123 (75.0)	1.0	N/A[b]	1.0	N/A
Yes	16 (19.8)	41 (25.0)	0.74 (0.39-1.42)	.36	0.69 (0.31-1.52)	.35
Sociostructural-level factors, mean (SD)						
Cultural and Religious Barrier Scale	7.5 (2.1)	8.7 (2.6)	0.81 (0.72-0.91)	.001	0.83 (0.71-0.97)	.02
Level of confidence in Hong Kong's health system	7.4 (2.4)	7.2 (2.0)	1.06 (0.93-1.21)	.36	0.95 (0.82-1.11)	.53
Level of trust of the Hong Kong government regarding COVID-19 control	8.2 (1.9)	7.5 (2.2)	1.18 (1.03-1.36)	.02	1.09 (0.92-1.29)	.33

[a]Odds ratio adjusted for significant background characteristics (age group, relationship status, ethnicity, permanent residents of Hong Kong, frequency of facemask wearing in public spaces/transportation other than workplaces, sanitizing hands after returning form public spaces or touching public installation, and avoiding social/meal gathering with other people who do not live together).

[b]N/A: not applicable.

Discussion

To our knowledge, this is one of the first studies investigating the determinants of COVID-19 vaccine uptake by using the socioecological perspective among ethnic minorities. About one-third of the participants received at least one dose of COVID-19 vaccination. Factors at the individual level (perceptions related to COVID-19 vaccination), interpersonal level (influence of social media), and sociostructural level (cultural belief) were determinants of the COVID-19 vaccine uptake. Using the socioecological model allows us to understand COVID-19 vaccination behaviors from a comprehensive perspective.

Participants aged 30-49 years reported the highest COVID-19 vaccine uptake; this finding was different from that reported in the Chinese population [23-26]. Married or cohabitation with a partner was also associated with higher COVID-19 vaccine uptake. Future studies should confirm whether protecting one's partner is the motivation to receive COVID-19 vaccination. In addition, South Asians who were not Hong Kong permanent residents reported lower COVID-19 vaccine uptake. Nonpermanent residents might be less familiar with the health care system in Hong Kong and should receive more support in future programs. As for COVID-19 preventive behaviors, similar to that reported in previous studies [19,22], higher compliance to personal preventive behaviors (eg, consistent facemask wearing in public spaces and hand hygiene) and physical distancing behaviors (eg, avoiding social/meal gathering) was associated with higher uptake.

Culturally, our findings also showed that Pakistanis reported significantly lower COVID-19 vaccine uptake compared to Indians. Differences in the religious belief might partially explain this variation. Islam is the major religion for Pakistanis, and news reported concerns about the halal status of COVID-19 vaccines among Muslims [13]. Our findings suggested that some unique strategies should be tailored for South Asians to address cultural and religious reasons for COVID-19 vaccination hesitancy. The results confirmed that concerns about the halal status of COVID-19 vaccines was a barrier for South Asians to take up the vaccines [15]. The government should work with the vaccine manufacturers to clarify whether gelatin, which has been commonly used as a stabilizer for the safety and effectiveness of vaccines during storage and transportation, is a part of the available COVID-19 vaccines. In order to address other cultural or religious issues, future programs should engage community groups, champions and faith leaders, and develop culturally competent interventions.

At the individual level, South Asians shared some similar facilitators as the local Chinese population to receive COVID-19 vaccination, including perceived efficacy of COVID-19 vaccination in protecting themselves and their family members, perceived impacts of COVID-19 vaccination on pandemic control, perceived support from significant others, and perceived behavioral control of taking up COVID-19 vaccination [23-26]. Concerns about side effects and difficulties in choosing the most suitable COVID-19 vaccine were common barriers [23-26]. Therefore, the same health promotion strategies might be useful for both South Asians and Chinese in Hong Kong. In order to prevent the choice overload [21], efficacies and side effects of different COVID-19 vaccines available in Hong Kong can be compared on a table, which makes it easy for participants to compare features across products [21]. Laymen's terms in participants' native language should be used to emphasize that severe side effects of COVID-19 vaccination are rare, and the pros of vaccination outweigh its cons. Testimonials of people who received different types of COVID-19 vaccines regarding side effects should be presented. Health communication messages should also demonstrate that the procedures to receive vaccination are easy and convenient to reduce concerns regarding vaccination procedures. The recommendation made by health care providers is a strong facilitator of COVID-19 vaccine uptake [23-26]. Performing outreach vaccination services in South Asian communities is also useful for enhancing their perceived behavioral control. The results also supported a significant influence of peers on COVID-19 vaccine uptake among South Asians. Updated information about how many South Asians had received COVID-19 vaccination should be disseminated to this group. At the interpersonal level, exposure to negative information about COVID-19 negatively affects vaccine uptake. Health authorities in Hong Kong should identify and address common misinformation in a timely manner. It is encouraging that the government has started to clarify this misinformation on the vaccination program webpage.

The findings of this study should be interpreted in light of some limitations. First, a direct measure of perceived behavioral control should assess self-efficacy and perceived controllability [29,30]. Previous studies have suggested that these 2 constructs were differently associated with behavioral intention and actual behaviors [29,30]. In this study, the scale measuring perceived behavioral control was adapted from a validated tool [19]. Owing to the limited length of the questionnaire, the measurement only had 2 items and mainly covered self-efficacy. Failure to measure perceived controllability together with self-efficacy was one major limitation of this study. Second, in the absence of a sampling frame, participants were conveniently recruited online. Similar to other web-based surveys, the response rate was relatively low (about 25%). We were not able to obtain the characteristics of the active WhatsApp contacts who did not respond to our invitation or refused to complete the survey. Therefore, we were not able to compare the characteristics of the respondents and nonrespondents. There was a selection bias. Generalizations should be made cautiously to South Asians in Hong Kong. Yet, because ethnic minorities is a special population in Hong Kong, using the traditional randomly sampling method of telephone or mail survey was not feasible for administering the questionnaire to this targeted population. Third, some items and scales used in this study were single items, self-constructed, or modified from those used in published studies in the general population. We purposely decided not to use standardized western scale measurements to account for the cultural variations experienced by the ethnic minorities in Hong Kong. A self-constructed or modified scale that is designed to suit the local context of Hong Kong is more suitable. Furthermore, the use of a single-item scale will significantly decrease the burden of the respondents who need to take time to complete the survey. Moreover, this was a cross-sectional study and could not establish causal relationships.

Using the socioecological model, this study offered an overview for us to identify tapping points that can encourage COVID-19 vaccine uptake among South Asian populations in Hong Kong. Because they shared cultural and social orientations dissimilar from those of the local Chinese in Hong Kong, current empirical evidence offered a guide on how promotional strategies can be customized for this population. We recommend religion-targeted, outreach community, and peer-based programs to enhance COVID-19 vaccine uptake rate among South Asians in Hong Kong. To further customize the promotion, these programs can be co-designed, shared, and endorsed by South Asian communities such as nonprofit groups, champions, and faith leaders to develop culturally competent interventions.

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Authors' Contributions

AS, AHYL, ZW, and EKY conceptualized this study. AS, AHYL, JW, SA, PSFC, and ZW performed the methodology in this study. Data were curated by AS, AHYL, JW, and ZW. AS, AHYL, and ZW conducted the formal analysis and the project administration. AHYL, ZW, and EKY provided the resources and supervised the study. AS, AHYL, PSFC, and ZW wrote the original draft. AS, AHYL, JW, SA, PSFC, ZW, and EKY reviewed and edited the manuscript. Funds were acquired by AHYL, ZW, and EKY. AS and AHYL contributed equally as first authors. ZW and EKY contributed equally as corresponding authors. All authors have read and agreed to the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
English version of the questionnaire survey.
[DOCX File , 31 KB - publichealth_v7i11e31707_app1.docx]

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Abbreviations

AOR: adjusted odds ratio
CBO: community-based organization
TPB: Theory of Planned Behavior

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