Viewpoint

Tackling the Burden of Electronic Health Record Use Among Physicians in a Mental Health Setting: Physician Engagement Strategy

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Abstract

The burden associated with using the electronic health record system continues to be a critical issue for physicians and is potentially contributing to physician burnout. At a large academic mental health hospital in Canada, we recently implemented a Physician Engagement Strategy focused on reducing the burden of electronic health record use through close collaboration with clinical leadership, information technology leadership, and physicians. Built on extensive stakeholder consultation, this strategy highlights initiatives that we have implemented (or will be implementing in the near future) under four components: engage, inspire, change, and measure. In this viewpoint paper, we share our process of developing and implementing the Physician Engagement Strategy and discuss the lessons learned and implications of this work.

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KEYWORDS

burnout; organizational strategy; electronic health record use; clinical informatics; medical informatics

Introduction

Background

With growing levels of clinician burnout both before and during the COVID-19 pandemic, the burden associated with the use of electronic health record (EHR) systems has emerged as a paramount challenge [1]. In particular, with an increase in reporting and clinical research needs required by consumers of health data (ie, administrators and researchers) during the spread of the pandemic, there have been additional burden for data generators (ie, providers who document care in the EHR) [2]. This has resulted in clinicians spending more time using the EHR system to complete documentation than actual patient care. The recent call to action by Shanafelt [3] highlighted the importance of thinking about how digital technologies are being introduced as another component into the clinical environment. In particular, there is a greater demand to think about better designed solutions that fit the needs of clinicians [3]. In addition to reports by physicians on the impact of EHR burden on burnout [4,5], this has resulted in numerous recommendations from organizations such as the Ontario Medical Association [6] on reconsidering the impact and use of technology in clinical practice. Therefore, it is likely that EHR-related burden, in addition to the efforts and challenges involved in managing the pandemic, have collectively led clinician burnout to an all-time high [7,8].

As EHR systems are increasingly enhanced with advanced features to improve patient care, such as clinical decision support and predictive analytics, the impact of these capabilities on clinicians' ability to effectively and meaningfully deliver care must not be forgotten. As highlighted in many commentaries on this topic and most recently, in a chapter on EHR burden by the National Academies of Sciences, Engineering, and Medicine [9], the use of the EHR must not detract from the core aspects of medicine, such as the therapeutic relationship, nor cause unnecessary frustration, complexity, and burden on clinicians [10]. In this context, many initiatives in this field have recently emerged. For example, the *Clickbusters* initiative, developed by the Vanderbilt Clinical Informatics Centre [11], aims to reduce the number of unnecessary alerts delivered to end users, thereby reducing EHR burden and burnout.

Of note, most efforts to date that address EHR-related burden for clinicians have focused on the US context, with scant evidence emerging from other countries. Given that each country has varying practice and clinical requirements, the factors and bottlenecks that influence EHR burden in various settings are likely different. For example, in a recent survey on EHR burnout conducted as part of the 25×5 Symposium [12] in the United States, documentation requirements for reimbursement were cited as a main factor leading to EHR burden for physicians. These challenges are specific to the US context and do not apply to many other countries, including Canada, where health care is publicly funded. However, even without such reimbursement-driven documentation requirements in Canada, we face substantial EHR-related burnout rates [13] comparable with those in other countries. In addition, it is expected that the challenges associated with EHR burden differ across disciplines. For example, given that mental health relies heavily on narrative documentation, the pain points in using the EHR would likely differ from those experienced by specialties that rely on the use of forms or structured templates. Without sufficient discussion and evidence in the literature on how mental health care organizations in Canada are managing these challenges, there is a lack of guidance for these organizations to build relevant and effective initiatives in their own settings. Moreover, it is unclear how existing best practices for system development and implementation (eg, super users) should be best leveraged to address EHR burden. Given these evidence gaps, we seek to contribute to the emerging body of evidence and support the collective effort of reducing EHR burden for all disciplines across countries.

In this viewpoint paper, we describe our efforts to reduce EHR burden for physicians at a large academic mental health hospital in Canada. Building on our previously published studies focused on needs assessment, implementation, and evaluation of individual initiatives [4,14,15], this viewpoint shares the development and implementation of our overarching strategy. We discuss our Physician Engagement Strategy, which aims at identifying and addressing opportunities for EHR improvements at our site. On the basis of our experience to date, we conclude with key success factors and lessons learned in developing and implementing the initiatives included in this strategy.

The Organization

The Physician Engagement Strategy was implemented in a large academic mental health hospital that provides care to >34,000 patients experiencing mental illness in Toronto, Ontario, Canada. In an effort to improve the quality and continuity of patient care, the organization implemented an integrated EHR system (Cerner Millennium) in 2014. Now, the organization offers a paperless care environment, where all processes, from orders to medication administration, are conducted through and with the EHR system. With a *single source of truth*, the organization has since been able to improve key quality of care outcomes by enhancing medication safety [16] and embedding psychiatric risk flags in the system [17]. This has resulted in obtaining the highest rating (stage 7) on the Electronic Medical Record Adoption Model [18] and level 6 on the Adoption Model for Analytics Maturity [19] from the Healthcare Information and Management Systems Society. Most notably, the organization was awarded the prestigious Davies Enterprise Award in 2018 [20]. On average, the EHR system is used by >400 physicians to deliver care at the organization.

Despite these achievements and the organization's focus on improving the safety and quality of patient care, physicians have had mounting concerns regarding the usability of the EHR in their daily workflows, highlighting it as a major source of burnout in our 2017 physician wellness survey (conducted with all physicians across the hospital) [15]. Our organization's wider Physician Engagement, Wellness, and Excellence Strategy included several interventions to improve physician support at the individual, team, and organizational levels. One of the six proposed initiatives under this strategy included *efforts to optimize use of EHRs to enhance the efficiency of practice* [15]. In alignment with departmental leadership (VS) needs to optimize the use of EHR and reduce the associated burden for clinicians, leadership (DJ) from information management prioritized clinician-driven innovation, including efforts to address EHR-related clinician burnout. Consequently, in 2018, the inaugural Chief Medical Information Officer (CMIO) was tasked with improving physicians' experiences with the EHR to reduce EHR-related burden. Given the importance of leadership buy-in and prioritization of strategies, the CMIO developed and implemented a multipronged strategy to address the ongoing and emerging challenges for physicians related to the use of the EHR.

Building Our Physician Engagement Strategy

As part of the formative work toward developing and implementing a tailored Physician Engagement Strategy, we undertook a needs assessment in 2019 to understand the main challenges experienced by and EHR-related goals of each academic division within our organization and reviewed the literature to identify strategies and initiatives that could help to address these challenges and aspirations. This effort and the resulting strategy are further described below.

Needs Assessment

Overview

As part of preparatory work to inform and align initiatives targeting EHR burden on physicians to the needs of the organization, it was essential to achieve a holistic understanding of the frustrations and challenges that hinder the effective and meaningful use of the EHR across our organization. A tour of the academic divisions was undertaken and a benchmark survey was launched in 2019 to collect direct feedback and insights on burnout and the current state of EHR use by physicians at our organization. The divisional tour focused on obtaining feedback mostly from physician leadership across the organization, whereas the benchmark survey more broadly and anonymously captured the voice of frontline physicians. This ensured that a balanced *bottom-up* leadership approach was embedded in the development of the strategy. It should be noted that this divisional tour was conducted when several foundational articles (eg, *Why doctors hate their computer* by Gawande [21]) appeared in the published literature highlighting the issues for the medical community, including within the Canadian context [22]. As such, there was great interest from both the organization and frontline physicians to participate in these activities.

Divisional Tour

Through the divisional tour, our hospital's CMIO visited each of the 7 academic physician divisions' monthly meetings and gathered feedback on their top 3 priorities for EHR optimization. There were 2 main purposes for the divisional tour. First, given that the benchmark survey focused on collecting individual feedback from frontline physicians, the divisional tour helped to contextualize the results through an in-depth discussion with the team. Second, it was also used to obtain buy-in from frontline and clinician leaders. Buy-in was a critical part of the success of these initiatives, and this opportunity provided another forum for physicians to contribute their ideas and perspectives.

In addition to discussions with clinical leadership during these meetings, frontline physicians were also consulted through the existing team huddles for each academic division to obtain their perspective on these issues. It should be noted that this divisional tour was conducted 5 years after the introduction of the hospital's EHR system. From these consultations, the identified improvement priorities included documentation, orders, and chart navigation through the EHR. More specifically, within *documentation*, there were requests to improve standardized templates and auto-population, increase access to speech recognition technology, and reduce clicks. Second, regarding *orders*, physicians identified the need to increase practice-specific order sets, reduce clicks within workflows, and simplify order measures. Third, in *chart navigation*, there were requests to make the EHR more user-friendly and intuitive with respect to finding relevant information. The automatic inclusion of all laboratory test results and previous medications through the EHR has led to an increase in note sizes that contain multiple pages of nonessential information, which is a phenomenon termed as *note bloat* [23,24], and is frequently identified as a concern for patient safety. Other priorities were also identified, such as the desire to integrate physician billings within the EHR and to simplify the process of discharge medication reconciliation.

Benchmark Survey

Following this tour, we conducted a benchmark survey to identify the extent of burnout among our physicians and identify the significant EHR-related contributors to physician burnout [4]. The methods and approach are detailed in a separate paper [4]. We achieved a high survey response rate among full-time physicians (156/208, 75%), with 25.6% (45/176) of physicians reporting having one or more symptoms of burnout. Furthermore, 74.5% (155/208) of respondents who reported burnout symptoms identified the EHR as a contributor. Safety concerns with the EHR and efficient communication were 2 factors that differentiated the groups that were burned out from those that were not. Respondents who had high satisfaction with the EHR used work-arounds to complete tasks (eg, copy and paste from word processing software) or were super users with knowledge of documentation *shortcuts*. Those with low EHR-satisfaction reported excessive clicks and time sinks with using the EHR [4].

Overall, our survey demonstrated that there was a critical need to mitigate EHR-related burden and the associated burnout by optimizing the EHR to fit within physicians' workflows and by improving awareness of EHR best practices.

Literature Review

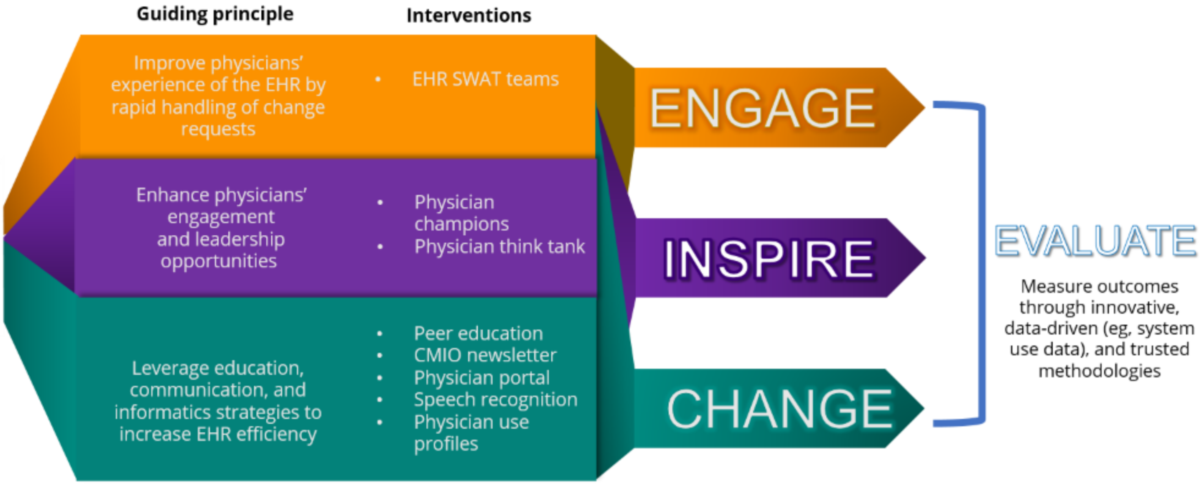
Consistent with academic practices, we sought to inform our Physician Engagement Strategy with the latest evidence. Given the number of interventions aimed at combating EHR-related burnout in the published literature, our team conducted a rapid literature review on this topic [25]. From a review of 50 related articles published between 2014 and 2019, we found that the measurement of EHR burden needs to be performed both subjectively (eg, via surveys) and objectively (eg, using use data) [26]. We also identified that interventions to reduce EHR burnout were focused on four main aspects: enhancing and redesigning the interface of EHR screens, delivering tailored education and training to end users, improving communication, and providing additional support for administrative tasks [25]. To implement many of these interventions, approaches similar to a Plan-Do-Study-Act cycle for quality improvement [27] were used, which was in alignment with our needs assessment process (ie, measuring *pain points*). Through our literature review, we also learned that following the implementation of interventions, it is essential to continue enhancing and optimizing these through further evaluation using analytics data, surveys, and other methods. Although findings from our literature review have laid the foundational building blocks of our strategy, it was important to adapt and align these strategies and interventions to the specific challenges present within our organization.

The Physician Engagement Strategy

Overview

On the basis of our in-depth needs assessment and review of the literature, we developed our first iteration of the Physician Engagement Strategy in 2020. In the development of this physician-centric multipronged approach, we had in-depth discussions with our information technology (IT) and clinical leadership teams to ensure feasibility and availability of resources. An overview of the strategy is depicted in Figure 1. The strategy comprises four main goals: (1) improving the handling and resolution of EHR issues; (2) enhancing physician engagement and leadership opportunities on EHR-related decisions; (3) leveraging communication, education, and informatics strategies to increase efficient and meaningful use of the EHR; and (4) measuring the impact of these strategies to achieve data-driven insights.

Figure 1. Physician Engagement Strategy. CMIO: Chief Medical Information Officer; EHR: electronic health record.



Throughout the implementation of initiatives to support these goals, 3 main guiding principles (pillars) were considered essential for success. Foremost, it was critical to *engage* all relevant stakeholders and frontline physicians to ensure that their perspectives are heard and any challenges are brought up for examination. We also considered it important to provide physicians an opportunity to be *inspired* to participate in leadership roles and be involved in the decision-making process of EHR changes that impact patient care and physicians' use of the EHR. Finally, we detailed a multitude of initiatives aimed at collectively supporting the ability to *change* the use of the EHR system such that it improves efficiency and end user experience. Throughout these pillars, we also ensured that there was a focus on measuring outcomes to *evaluate* whether the specific initiatives have worked as intended. The initiatives outlined in the strategy are described in detail below.

Engage: Improve Physician's Experience With the EHR by Rapid Handling of Change Requests (SWAT Teams)

To engage physicians across our organization, we developed an EHR *SWAT* team initiative through adaptation of initiatives [28] identified from our literature review. Traditional governance models have focused on identifying and implementing requirements solely by the IT team [3]. However, from the IT perspective, there is often a lack of understanding of the actual requirements needed for the change to be impactful. Moreover, many of the changes often affect other clinical areas (eg, pharmacy and laboratory). Thus, implementing in isolation can lead to more downstream challenges. As such, the SWAT team model, which mirrors other initiatives at the University of Colorado School of Medicine [28,29], overcomes this challenge by bringing together a collaborative team to discuss and identify a commonly agreed set of requirements for each issue. Our team-based intervention (*SWAT*) included assembling an interdisciplinary team of specialists including our CMIO; clinical informatics nurses and educators; and representatives from pharmacy informatics, health information management, clinical applications, and project management [14]. Through this intervention, we met with physicians from each of the seven academic divisions across our organization, collected EHR change requests, and prioritized them into four categories: (1) additional education, (2) quick fixes (<6 weeks), (3) future fixes (≥1 year), and (4) unable to address owing to technical or regulatory restraints. In total, we gathered 118 requests (eg, including adding keyword search functionality, minimizing freezing, and auto-faxing) [14].

Inspire: Enhance Physician's Engagement and Leadership Opportunities

Physician Champions

As part of our focus on inspiring and fostering physicians' voices in the decision-making process, we designated physician EHR champions (*liaisons*) tasked with liaising with all physicians in their division and bringing forward pain points and recommended changes on an ongoing basis. Divisional liaisons were nominated annually by both their peers and divisional leadership and became the link between different stakeholders, helping us make meaningful EHR changes. These individuals were key players within our EHR SWAT initiative. Liaisons' responsibilities continued to evolve with the changing needs of the initiatives, and they became the pilot user group for future technology and informatics applications.

Physician Think Tanks

Discussions with physician champions highlighted the need for a cross-divisional lens to identify the applicability of EHR changes. As such, a venue to address this gap and facilitate discussion between physician divisional liaisons and other relevant stakeholders was needed. We implemented monthly

Physician Think Tanks in 2019, which focused on the successful use of the EHR to improve patient safety and quality of care. These meetings are chaired by our CMIO and are attended by physician champions from each academic division and relevant clinical (eg, pharmacy, laboratory, and diagnostics informatics and professional practice) and IT leaders (eg, clinical applications), with composition similar to that of our SWAT team. Before each of these meetings, stakeholders are encouraged to bring forward challenges and questions for discussion at these meetings.

Appropriate engagement with stakeholders is critical for implementing digital tools in a meaningful manner that aligns with the needs of end users, and therefore, we used this forum before the implementation of any new initiatives. As these meetings evolved since their inception in 2019, the venue became a versatile space for EHR optimization. New ideas and features (eg, optimizing order set and reducing auto-population content) are demonstrated at these meetings to collect initial feedback from clinicians. Updates on initiatives (eg, SWAT) and implementations are also presented at these meetings to help support brainstorming of the feasibility and availability of resources. From a quality improvement perspective, evaluation results are presented to solicit feedback from the group for contextualizing the results and identifying next steps for optimization of the EHR.

Change: Leverage Communication, Education, and Informatics Initiatives to Increase EHR Efficiency

Communication: CMIO Monthly Newsletter

One of the main challenges identified from our benchmark survey was the lack of appropriate communication channels for EHR-related updates (eg, policy and technical changes). Although the organization provided EHR updates to all users on a regular basis, these email updates were incomplete and not tailored to physicians. Given that these EHR changes usually coincide with broader organizational policy changes and mandates, physicians reported a lack of a single source of truth for any EHR-related updates. These issues can cause confusion and inconsistency in EHR use across the organization, leading to concerns regarding patient safety and quality of care.

To address this issue, the CMIO monthly newsletter was developed. These newsletters are developed with in-depth consultation with clinical (eg, clinical informatics nurse educators) and IT stakeholders to ensure that the content is relevant and useful. The content of the newsletter varies each month and depends on the changes and discussions at that time (Figure 2). Examples of content include initiative updates, interviews with digital health leaders, EHR tips and tricks, related literature, IT changes and EHR changes for health records, pharmacy and therapeutics, and laboratory and diagnostics related EHR updates and clarifications. The newsletter was also a critical method to close the loop of communication on all changes requested through our SWAT initiative. The monthly read rates of these newsletters continue to increase, with our last newsletter (ie, April 2021) being opened by >208 physicians (approximately 50% open rate).

Figure 2. Chief Medical Information Officer monthly newsletter (table of contents). FAQ: frequently asked questions.

TANIA'S CORNER		**NEW** Peer Education – Discharge Summary & How To Autofax	1
NEWSFLASH		**NEW** Clinician Recruitment (Mental Health Notes)	2
		NEW NEW I-CARE Login Process	3
		NEW Additional Drive for "Clinical Access" Users	4
		UPDATE Revised Instructions for Prescription Faxing	5
		Q&A A Quick FAQ for Physicians	6
		UPDATE How To Obtain Secure Mail on Your Phone	7
		TIP OF THE MONTH Manage Proposed Orders and Order Sets (Supervisors)	8
I-CARE UPDATES	LAB	**CHANGE** Sending a Private Lab Requisition	9
	HEALTH RECORDS	**REMINDER** How to find COVID Vaccine Information	10

Communication: Physician Portal

In addition to the issues related to communication, another intervention was developed to support navigation and rapid finding of EHR-related information. The *Physician Portal* is a collaborative initiative with the physician-in-chief to provide physicians with a one-stop web-based location for all information relevant to physicians, such as wellness initiative updates, policies, and educational presentations. Within the portal's EHR tips and tricks section, all EHR-related information can be found. Previous CMIO monthly newsletters are made available through this portal, and physicians are able to use a search functionality to find relevant information across the site. Our peer education videos are also hosted on this portal. Recently, tip sheets for EHR use have been added to the site, and physicians are encouraged to visit the site to access these resources. The centralized location for EHR-related information is expected to reduce the navigation burden for EHR-related information.

Education: Peer Education Videos

Electronic learning modules have become a staple for providing training and support for a wide range of practice- and policy-related topics. However, their uptake and effectiveness for EHR training and best practices for physicians remain very limited. Given that this user group is inundated with information daily, it was essential to develop targeted messaging that aligns with their needs and questions [30]. As such, peer education was identified to be a useful approach for addressing these issues. Peer education through super users can support end users in mastering the use of the EHR, and previous peer-led EHR training initiatives in Southern California Permanente Medical Group have found that it can save physicians 4 to 5 minutes per hour, equating to approximately 40 minutes a day [31].

Although peer EHR education is typically done in real time and in person, social distancing restrictions of the COVID-19 pandemic have made this difficult to achieve. As a result, we piloted the development of peer education videos. These peer education videos are short in length (3-5 minutes) and focus on specific knowledge gaps found across the organization. During these videos, super users are invited to provide education and guidance (eg, demonstration of a workflow) to the audience based on their experiences and best practices. These videos are posted on our *Physician Portal*, and communication to increase awareness of these tools are done through the monthly CMIO newsletter and the weekly departmental physician newsletter. Physicians are invited to watch the videos in their own time and pace. Currently, two modules have been developed (medication reconciliation and discharge summaries) and a few other videos are in development.

Informatics: Speech Recognition Technology

Documentation burden was identified as an important issue for physicians in both the benchmark survey and the divisional tour. In particular, given that psychiatric documentation is fairly narrative in nature, physicians spend significant amount of time typing directly into their EHR system. As a result, documentation methods remain a significant pain point for the organization.

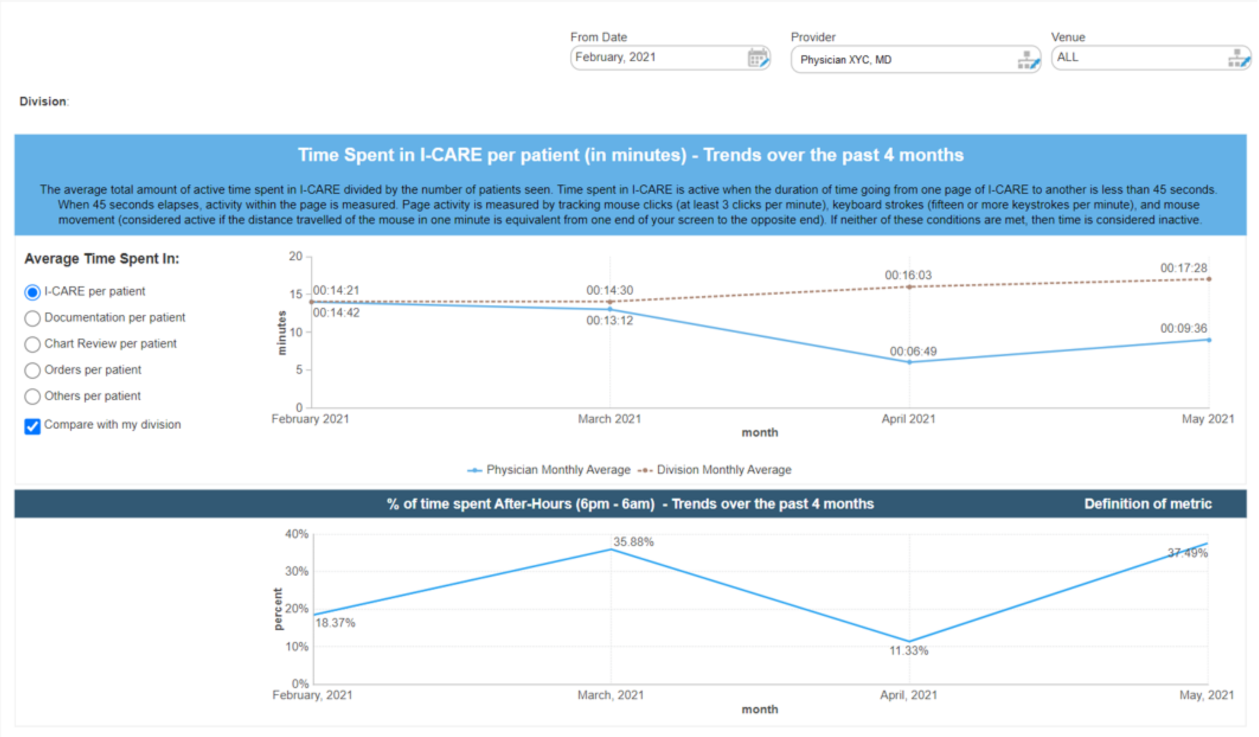
Speech recognition technology has been identified as a suitable solution for mitigating documentation burden in the EHR. Evaluations conducted in other settings have found that physicians report satisfaction with speech recognition technology and its utility in reducing the burden. At our organization, an older version of speech recognition software was procured and deployed to a small number of physicians [32]. However, the limited licenses and lack of a concerted support strategy led to its suboptimal adoption across the organization. Given the renewed focus on this issue, we endeavored to roll out an improved version of speech recognition technology that features improved accuracy, a mobile app microphone, and cloud-based dictation engine. As part of this rollout, all physicians and residents will have access to speech recognition technology for documentation in the EHR system [30].

The speech recognition service will be delivered collaboratively with the other initiatives of the strategy in several ways. The EHR SWAT team intervention will be used to collect technical issues and feature improvements with regard to the platform. The Physician Portal and CMIO newsletters will be used to communicate improvements to the platform and encourage physicians to receive optimization training and education using the platform.

Informatics: Physician EHR Use Profiles

Another complementary intervention to improve physicians' awareness of their EHR practice and deliver feedback was the use of dashboards. Direct feedback dashboards have been used widely across medicine for outcomes such as improving compliance for venous thromboembolism prophylaxis [33], reducing imaging use [34], and improving pediatric emergency care [35]. Dashboards convey information through the use of visual representation of data to help amplify cognition and capitalize on human perceptual capabilities [36]. Our *physician use profiles* (Figure 3) are dashboards that display information on an individual physician level, allowing physicians to view their own EHR system use including metrics such as time spent within the EHR per patient, time spent in documentation, percentage of after-hours use, number of clicks per order, and other measures of efficiency. Through these dashboards, physicians can also compare their EHR use with their divisional average and identify whether they need to lean into the various initiatives of the Physician Engagement Strategy, such as additional training through EHR SWAT meetings, peer education videos, or speech recognition technology. We also anticipate physicians to self-identify as super users through the use of these dashboards (as only the individual physician can look at their own data) and contribute to peer education within their division. Physicians can view their metrics for a specific period (eg, before and after using speech recognition), with provided context as to how each of the metrics is being calculated. Our team is currently in the process of finalizing the design and content of these *physician EHR use profiles* through extensive consultation with the physician divisional liaisons, academic chiefs, and Physician-In-Chief to make it a meaningful and useful intervention.

Figure 3. Physician electronic health record use profiles.



From Date: February, 2021
Provider: Physician XYC, MD
Venue: ALL
Division:

Time Spent in I-CARE per patient (in minutes) - Trends over the past 4 months

The average total amount of active time spent in I-CARE divided by the number of patients seen. Time spent in I-CARE is active when the duration of time going from one page of I-CARE to another is less than 45 seconds. When 45 seconds elapses, activity within the page is measured. Page activity is measured by tracking mouse clicks (at least 3 clicks per minute), keyboard strokes (fifteen or more keystrokes per minute), and mouse movement (considered active if the distance travelled of the mouse in one minute is equivalent from one end of your screen to the opposite end). If neither of these conditions are met, then time is considered inactive.

Average Time Spent In:
● I-CARE per patient
○ Documentation per patient
○ Chart Review per patient
○ Orders per patient
○ Others per patient
☑ Compare with my division

% of time spent After-Hours (6pm - 6am) - Trends over the past 4 months

Definition of metric

Evaluate: Measure Outcomes Through Innovative and Trusted Methodologies

Overview

Through our many complementary and interconnected initiatives, we have ensured that time, effort, and resources were used to evaluate each of them. Throughout the development of each intervention, we embedded an evaluation approach to determine whether we have achieved the objectives of the intervention and to identify approaches to streamline or optimize the intervention. This aligns closely with best practices [37] and the Plan-Do-Study-Act cycle [38] of quality improvement. The sources and examples of evaluation initiatives are elaborated in greater detail below.

System Use Data

The role of back-end use data has become an important source of information for identifying user-specific challenges within the EHR system and for guiding tailored and customized training. Within our organization, the use of *EHR use metrics* allow us to objectively measure the impact of our initiatives. Our EHR vendor's back-end analytics platforms (ie, Cerner *Lights On* and Cerner Advance [39]) provide detailed analyses of EHR use for all users including physicians, nurses, and those in other disciplines. Leveraging key metrics such as total time spent per patient in documentation, chart review, ordering, and medication reconciliation of the electronic medical record has allowed us to identify whether a specific intervention (eg, speech recognition technology) has impacted the targeted metric (ie, documentation time). There are several other metrics that can be explored, such as contextual metrics (eg, number of patients that a physician has seen over the past month and the percentage of time physicians spend in the EHR after hours) and workflow metrics (eg, number of clicks used per order and use of order set). Following a thorough validation of how the data within this system compares with our physicians' actual use, we are slowly beginning to leverage this tool to help learn about our physicians' experience with the EHR, eventually working to reduce EHR burden.

Similarly, we are also leveraging the use of *system use metrics* from other technologies that we have implemented, such as our speech recognition solution. For example, personalized messages are periodically delivered to physicians who have access to speech recognition technology and are not using the platform, to identify if they require any technical support or additional training.

Surveys, Interviews, and Focus Groups

When system use data collection is not feasible or fit for evaluation, we conducted evaluations through surveys, interviews, and focus groups, leveraging specific channels of our strategy such as the physician divisional liaisons where possible. For our EHR SWAT initiative, we used short anonymous surveys (with 5-point Likert scales and free-text questions) following the divisional meeting to gather physicians' satisfaction with the initiative [14]. In all, 61% (28/46) of the physicians reported that the intervention increased their proficiency in using EHR functionalities [14]. Surveys and interviews were also leveraged to measure the implementation feasibility of speech recognition, complementary to documentation time outcomes measured from system use data.

Discussion

Overview

To our knowledge, the Physician Engagement Strategy is one-of-a-kind collaborative approach in a Canadian mental health setting that aims to engage both frontline physicians, physician leadership, and IT leaders in reducing EHR burden. Previous national strategies in the United States to reduce clinician burnout have included recommendations such as engaging clinicians in the design and deployment of health IT to ensure the effectiveness, efficiency, usability, and safety of the technology [9], which we have implemented thoroughly throughout our strategy, especially within the *engage* and *inspire* pillars. The Office of the National Coordinator for Health Information Technology in the United States has also released its Strategy on Reducing Regulatory and Administrative Burden Relating to the Use of Health IT and EHRs, which includes recommendations such as better alignment of the EHR system design with real-world clinical workflows, increase in end user training, and improvement of the clinical documentation functionality [40], which we implemented through our EHR SWAT teams, peer education, and speech recognition initiatives, respectively. Our development of a shared vision and approach enables a concerted strategy developed and implemented with feedback and alignment across all stakeholder groups. As the digital health ecosystem (eg, web-based care) continues to become integral to clinical care, the numerous venues for discussion across multiple departments allow for unbiased feedback and opportunities to align the road maps of the EHR and related technologies.

Lessons Learned

As we enter the third year of implementing the EHR Physician Engagement Strategy, a few *lessons learned* that will guide future approaches to optimize the reach and impact of our strategy were identified. Foremost, it is essential that frontline physicians are recognized as the main stakeholders and decision makers in our strategy. Across all our initiatives, careful deliberation and stepwise iterative approaches were used to embed physicians' perspectives and feedback in the implementation and to roll out plans. These stepwise approaches ensured that any *red flags* can be considered and mitigated before the roll out of any initiatives. For example, for speech recognition technology, extensive consultation sessions were conducted before the development of the implementation plan. Understanding physicians' desires and needs helped curate the main components to consider in such an implementation plan. In addition, these discussions should be considered in multidisciplinary forums. Given that the organization has >70 clinics, each specializing in different diagnoses, treatment, or patient populations, it is expected that significant heterogeneity exists in terms of workflows and EHR use patterns. Ensuring that IT and clinical stakeholders from these clinics are engaged in the decision-making process reduces the possibility of unexpected roadblocks or unintended consequences during implementation. In addition, we realized that periodic review of the initiatives can yield synergistic opportunities to better align and reinforce initiatives within the strategy. In particular, interconnected initiatives can inform each other and maximize their success. For example, during the implementation of speech recognition, the Physician Think Tank was used to identify physicians' needs before the implementation. In addition, the CMIO newsletter was found to be a useful way to communicate updates and success outcomes to all physicians at the organization. Thus, the initiatives of this strategy enable a concerted effort to reduce EHR burden.

Future Directions

As we continue to implement and expand the Physician Engagement Strategy, it has become increasingly important to consider this work in the broader field of EHR burden and digital technologies. We expect that this road map will continue to expand as new features and technologies are becoming embedded within the organization. In this accord, we highlight a few important next steps that we hope to achieve in the coming years. First, many of the interventions available in the literature have not focused on evaluating their impact on EHR burden. With the advent of EHR back-end use data, there is a timely opportunity to evaluate the impact of these initiatives on efficiency and satisfaction with using the EHR. In the next year, we will focus on evaluating and determining the impact of these initiatives using our established evaluation methodologies. We will also explore the perceptions and experiences of clinicians in participating in these initiatives (eg, multidisciplinary groups and super users) to address EHR-related burden [37]. In addition, a number of emerging trends, such as measurement-based care [41,42] and web-based care [43], are becoming evident in our digital mental health infrastructure. As these models of care are streamlined, it would be useful to evaluate their impact on EHR burden. Future work should explore how these initiatives can be made useful prospectively in the planning and implementation of these digital models of care at the organizational level. Finally, we are currently exploring opportunities to embed these initiatives as part of creative professional activities for academic promotions. Doing so may help to support the development of *hybrid physicians* [44] who are equipped to enable the effective use of informatics by physicians to deliver better mental health care.

Conclusions

As EHR-related burden continues to be a critical challenge for many health care systems, we introduce our EHR Physician Engagement Strategy as an approach to reducing these unintended consequences. This strategy involves a multipronged approach that aims to engage clinicians in reimagining their future EHR experiences and empower them as central stakeholders and advocates for digital technologies to achieve the quadruple aim of health care. Future work should focus on evaluating the impact of these initiatives on EHR burden and expanding the impact of this work to other digital health tools at the organization.

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Conflicts of Interest

None declared.

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Abbreviations

CMIO: Chief Medical Information Officer
EHR: electronic health record
IT: information technology

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Review

Workarounds in Electronic Health Record Systems and the Revised Sociotechnical Electronic Health Record Workaround Analysis Framework: Scoping Review

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Abstract

Background: Electronic health record (EHR) system users devise workarounds to cope with mismatches between workflows designed in the EHR and preferred workflows in practice. Although workarounds appear beneficial at first sight, they frequently jeopardize patient safety, the quality of care, and the efficiency of care.

Objective: This review aims to aid in identifying, analyzing, and resolving EHR workarounds; the Sociotechnical EHR Workaround Analysis (SEWA) framework was published in 2019. Although the framework was based on a large case study, the framework still required theoretical validation, refinement, and enrichment.

Methods: A scoping literature review was performed on studies related to EHR workarounds published between 2010 and 2021 in the MEDLINE, Embase, CINAHL, Cochrane, or IEEE databases. A total of 737 studies were retrieved, of which 62 (8.4%) were included in the final analysis. Using an analytic framework, the included studies were investigated to uncover the rationales that EHR users have for workarounds, attributes characterizing workarounds, possible scopes, and types of perceived impacts of workarounds.

Results: The SEWA framework was theoretically validated and extended based on the scoping review. Extensive support for the pre-existing rationales, attributes, possible scopes, and types of impact was found in the included studies. Moreover, 7 new rationales, 4 new attributes, and 3 new types of impact were incorporated. Similarly, the descriptions of multiple pre-existing rationales for workarounds were refined to describe each rationale more accurately.

Conclusions: SEWA is now grounded in the existing body of peer-reviewed empirical evidence on EHR workarounds and, as such, provides a theoretically validated and more complete synthesis of EHR workaround rationales, attributes, possible scopes, and types of impact. The revised SEWA framework can aid researchers and practitioners in a wider range of health care settings to identify, analyze, and resolve workarounds. This will improve user-centered EHR design and redesign, ultimately leading to improved patient safety, quality of care, and efficiency of care.

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KEYWORDS

electronic health records; electronic medical records; framework; patient safety; unintended consequences; usability; workarounds; workflow

Introduction

Electronic health record (EHR) systems are the backbone of modern health care organizations. This is in pursuit of promising gains in patient safety, quality of care, efficiency, and control of spiraling costs by enabling value-based reimbursements. However, realizing these expected benefits is far from a given value. Over the years, an overwhelming number of studies have reported that EHRs have led to a multitude of unintended consequences. Examples include potential patient harm resulting from bad EHR usability [1,2]; increased odds of burnout of health care professionals [3,4]; physicians experiencing stress [5]; users spending an equal amount of time on *desktop medicine* as they spend on having face-to-face interaction with patients [6,7]; extensive *copy and paste* practices of patient notes leading to note bloating, internal inconsistencies, and errors [8]; and the unavailability of complete clinical information at the point of care [9].

Many causes of unintended consequences of EHR use can be traced back to discrepancies between the behavior, intentions, and expectations of EHR users and the workflows dictated by EHRs [10-15]. When EHR users experience workflow mismatches, they often create workarounds [16]. Workarounds are practices that handle exceptions to normal workflow [17] and do not follow the rules, assumptions, workflow regulations, or intentions of systems designers [18]. Although workarounds allow EHR users to proceed in accomplishing tasks in their preferred way (with or without the EHR), research shows that workarounds frequently jeopardize the safety, quality, and efficiency of care [19]. Given their common adverse effects, workarounds are valuable points of departure for improving the EHR design and redesign.

Blijleven et al [20] developed the Sociotechnical EHR Workaround Analysis (SEWA) framework for identifying, analyzing, and subsequently resolving EHR workarounds. The framework was inspired by the Systems Engineering Initiative for Patient Safety (SEIPS) framework [21]. The SEWA framework incorporates four angles: the different rationales EHR users have for creating workarounds (eg, memory aid and required data entry option missing), the stakeholders affected by a workaround (eg, patient and health care professional), the impact of a workaround (eg, on safety and efficiency), and inherent attributes of workarounds (eg, unavoidable, repetitive, and cascading).

The SEWA framework [20] was based on approximately 200 hours of audiovisual material of user–EHR interaction and semistructured follow-up interviews in a single large case study in an academic hospital setting [19,22]. However, the authors argued that the applicability of the framework in other contexts might be limited, such as in nonacademic hospitals or in hospitals where paper-based workarounds (eg, for ordering drugs) are still allowed. Therefore, they recommended validation, refinement, and enrichment of the framework by incorporating workarounds and related rationales, attributes, possible scopes, and types of consequences identified in other EHR workaround–related research and clinical contexts.

To address these shortcomings, a scoping literature review was performed to identify and map the available evidence on EHR workarounds [23]. This paper presents a revised version of the SEWA framework, with rationales, attributes, possible scopes, and types of impact described in workaround-related studies in the EHR, electronic medical record, and computerized physician order entry domains in primary, secondary, and tertiary care contexts published between 2010 and 2021.

Methods

Search Strategy

The MEDLINE, Embase, CINAHL, Cochrane, and IEEE databases were searched for relevant studies. We included original, full papers of research with empirical data and conference papers if there were no full papers published in the same study. *Gray literature*, such as books, was not considered. The search queries included the keywords *EHR*, *electronic health record*, and *workaround(s)* and their synonyms. As the aim was to identify new rationales, attributes, consequences, and scopes of EHR workarounds for the enrichment of the SEWA framework, we defined the searches as broad as possible. Pilot literature searches were conducted to check the appropriateness of the queries. During the pilot searches, the term *workflow* was used as a possible synonym for workarounds. The inclusion of this term led to a much larger pool of possible studies. However, most of these studies were focused on care processes that have no relation with EHR use and were thus, out of scope. Therefore, this term was excluded from search queries. Furthermore, to include the complete spectrum of possible EHRs, a combination of the terms *health/medical/patient/health care/clinical record* and *electronic/digital/online* was used. The results of this pilot evaluation were used to adjust the queries. The used queries are shown in Table 1.

Table 1. Search queries used for the scoping review.

Date of search	Database	Query
April 9, 2021	MEDLINE	([([([((((health record*) OR medical record*) OR patient record*) OR health care record*) OR clinical record*) AND electronic] OR digital) OR digitized] OR online) OR online] OR [([Electronic Health Records (MeSH Terms)] OR electronic health record*) OR EHR] OR [([Medical Records Systems, Computerized (MeSH Terms)] OR computerized patient record) OR computerised patient record]) AND ([(workaround*) OR work around*] OR workaround*)
April 9, 2021	Embase	(workaround OR workaround* OR workaround OR workaround*) AND ([(health record* OR medical record* OR patient record* OR health care record* OR clinical record*) AND (electronic OR digital OR online OR online OR digitized OR digitised)] OR [electronic health record* OR ehr OR electronic medical record* OR emr] OR [computerized patient record OR computerised patient record])
April 9, 2021	CINAHL	(workaround OR work around OR workarounds) AND ([(health record OR medical record OR patient record OR health care record OR clinical record) AND (electronic OR digital OR [online OR online] OR [digitized OR digitised])] OR [electronic health record* OR EHR OR electronic medical record* OR EMR] OR [computerized patient record OR computerised patient record])
April 9, 2021	IEEE	([([([(workaround*) OR work around*] OR workaround*)])] AND [([health record OR medical record OR patient record OR health care record OR clinical record] AND [electronic OR digital OR (online OR online) OR (digitized OR digitised)]) OR (electronic health record* OR EHR OR electronic medical record* OR EMR) OR (computerized patient record OR computerised patient record)])
April 9, 2021	Cochrane	(workaround*): ti, ab,kw OR (work-around*): ti, ab, kw OR (work around*): ti, ab, kw AND ([(electronic health record*): ti, ab, kw OR (health record*): ti, ab, kw OR (medical record*): ti, ab, kw OR (patient record*): ti, ab, kw OR (health care record): ti, ab, kw OR (EHR): ti, ab, kw OR (EMR):ti, ab, kw OR (clinical record):ti, ab, kw OR ([computerized patient record]: ti, ab, kw OR [computerized patient record]: ti, ab, kw)] AND [electronic]: ti, ab, kw OR [digital]: ti, ab, kw OR [online]: ti, ab, kw OR [online]: ti, ab, kw OR [digitized]: ti, ab, kw OR [digitised]: ti, ab, kw)

Selection Criteria

The inclusion and exclusion criteria were chosen through discussions among the reviewers (FH, VB, and MJ). As the focus of this scoping review was on workarounds in EHR use, it was decided to exclude studies focused on barcode medication administration systems as these systems serve only 1 purpose and cover only a small part of the medication process. Furthermore, the choice was made to exclude research focused on EHR functionalities other than those aimed at supporting the clinical process. To ensure data quality, a study was excluded if the research methods were not reported or in case the study had not been peer reviewed. Furthermore, research published before 2010 was excluded as EHRs have undergone significant changes and improvements over the years. Finally, the inclusion and exclusion criteria were chosen.

The study inclusion criteria were as follows:

1. The health care setting of the study must be either ≥1 of primary, secondary, or tertiary care.
2. Workarounds were studied or reported in the context of EHR use.
3. The article was published between 2010 and 2021.

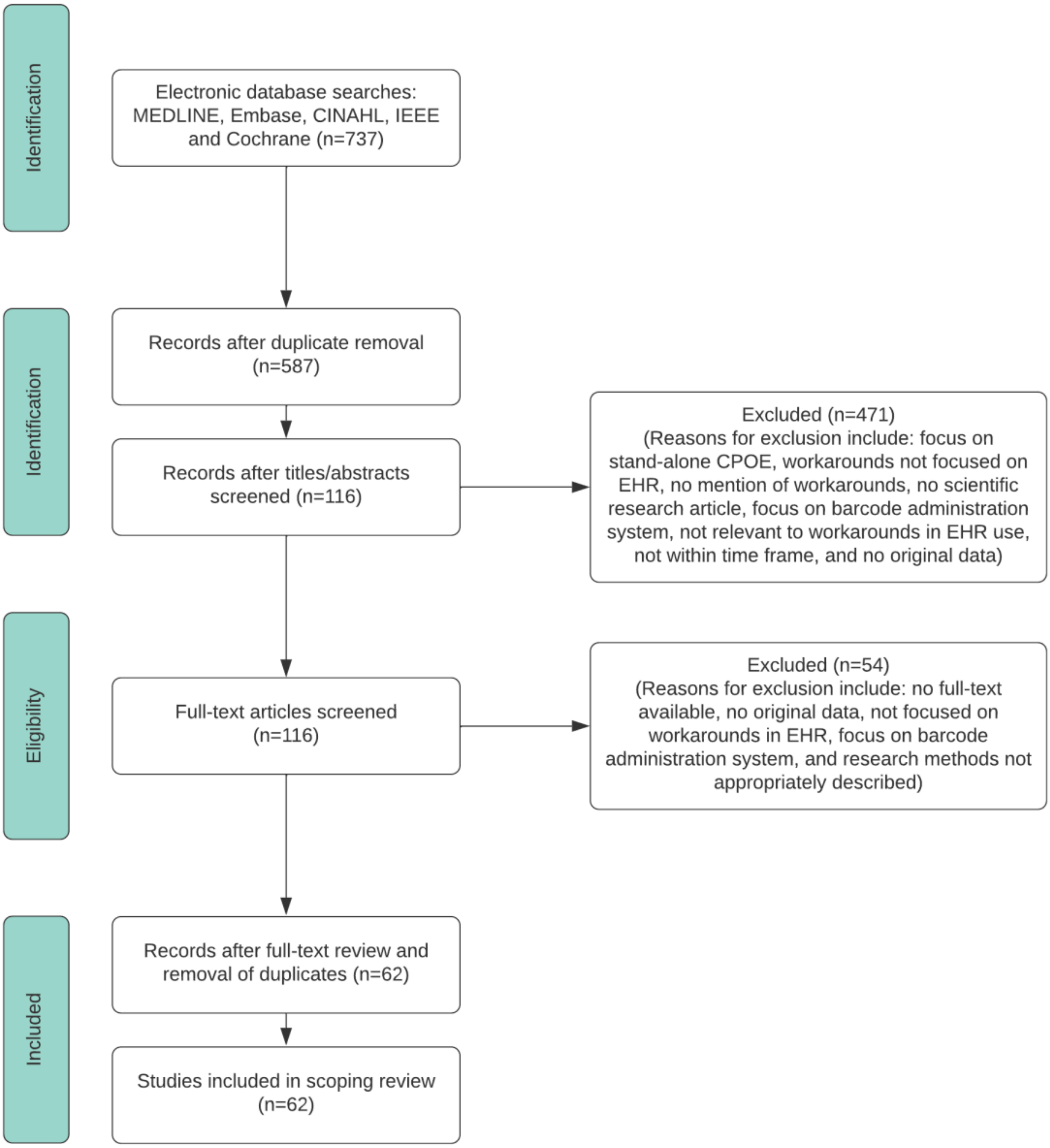
Studies were excluded if they met any of the following criteria:

1. The research focused on EHR functionalities other than those aimed at supporting within the clinical process.
2. The research focused on a barcode administration functionality.
3. The article was not written in English.
4. There was no access to the full-text article.
5. The article was not peer reviewed.
6. The research methods were not reported.

Article Selection

A literature search was conducted in April 2021. A total of 737 potentially relevant studies were retrieved from our initial search of electronic databases, more specifically MEDLINE (263/737, 35.7%), Embase (121/737, 16.4%), CINAHL (89/737, 12.1%), IEEE (58/737, 7.9%), and Cochrane (206/737, 27.9%). The results of the study selection process are shown in the PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analyses) flowchart in Figure 1.

Figure 1. PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analyses) flowchart of the study selection process. CPOE: computerized physician order entry; EHR: electronic health record.



The retrieved 737 studies were uploaded to EndNoteX9 (Clarivate), in which duplicates were first removed by both using EndNoteX9 and by performing a manual check (Figure 1). This led to 79.6% (587/737) of unique studies. These studies were reviewed by two independent reviewers (FH and VB). The 2 reviewers first independently screened the titles and abstracts of the eligible papers to evaluate whether they met the inclusion criteria. Of the 587 studies, 116 (19.8%) studies met the inclusion criteria, and 471 (60.2%) studies were excluded (because of, for example, workarounds not being focused on the EHR, not being a scientific research article, and no workarounds mentioned). Afterward, the reviewers independently screened the full texts of these 116 studies, leading to 62 (53.4%) included studies and 54 (46.6%) excluded studies (eg, no full-text available and methods inappropriately described). After each screening phase, the two reviewers (FH and VB) discussed their findings. The next screening phase was conducted only if a consensus was reached between the 2 independent reviewers. If a disagreement between the 2 reviewers could not be resolved by discussion, a third independent reviewer (MJ) was involved. After consensus was reached, interrater reliability was reported by calculating the Cohen κ. The interrater agreement was also calculated to show the extent to which the reviewers were able to reconcile through discussion [24]. For the first round (title and abstract screening), the Cohen κ value was 0.958, and the interrater agreement value was 0.985. For the second round (full-text screening), the Cohen κ value was 0.930, and the interrater agreement value was 0.966.

Data Analysis of Included Articles

Descriptive data from the included articles, such as title, authors, year of publication, study setting, functionalities of EHR studied, and research methods used, were captured in a generic overview per study (Multimedia Appendix 1). Workaround-related data from the included articles, such as workaround rationales, attributes, consequences, and scope, were captured in an analytic frame per study (Multimedia Appendix 2).

The data extracted from the included articles were compared with the SEWA framework on a study-by-study basis. In doing so, SEWA was supplemented with new rationales, attributes, possible scopes, and types of impact of EHR workarounds that were not previously included. After the analysis was completed, an updated (graphical) version of the SEWA framework was created.

Results

General Characteristics

The general characteristics of the 62 studies are shown in Table 2. There was an approximately even split in studies published between 2010 and 2015 and between 2016 and 2021. The study settings were almost equally distributed, with most (23/62, 37%) being set in tertiary care, such as academic hospitals and special care units. The largest group of studies (28/62, 45%) focused their research on the EHR overall. Of the 62 studies, 17 (27%) studied medication-related functionalities or EHR-integrated systems, such as computerized physician order entries. Approximately half (28/62, 45%) used or included a combination of physicians, nurses, and other staff such as pharmacists and administrative personnel as participants. Of the 62 studies, 26 (42%) used a combination of methods such as observations, interviews, and questionnaires, 15 (24%) used interviews as the sole method, 5 (8%) solely used questionnaires, 7 (11%) solely used observational methods, and 9 (15%) used other methods such as think-aloud protocols and documentation analysis.

Table 2. General characteristics of the included studies (N=62).

Study characteristics	Values, n (%)
Year of publication	
2010-2015	30 (48)
2016-2021	32 (52)
Study setting	
Primary care	18 (29)
Secondary care	21 (34)
Tertiary care	23 (37)
Functionalities of EHR[a] studied	
Medication-related (eg, prescribing and CPOE[b])	17 (27)
Documentation	8 (13)
Overall EHR	28 (45)
Others (eg, alert systems and authentication process)	9 (15)
Type of population	
Physicians	9 (15)
Nurses	13 (21)
Others (eg, pharmacists or administrative staff such as managers, assistants, secretary, or not mentioned)	12 (19)
Combination of users	28 (45)
Methods	
Observations	7 (11)
Interviews	15 (24)
Questionnaires	5 (8)
Others (eg, think-aloud and documentation analysis)	9 (15)
Combination of ≥1 observation, interview, questionnaire, or other	26 (42)

[a] EHR: electronic health record.

[b] CPOE: computerized physician order entry.

Validation, Refinement, and Enrichment of the SEWA Framework

Overview

Evidence for the work system components, rationales, attributes, type of impact, and possible scopes contained in the original SEWA framework was found in the included studies. Moreover, we refined and enriched the original framework with 7 rationales, 4 attributes, and 3 types of impact. The following subsections elaborate on the work system components, rationales, attributes, possible scopes, and types of impact.

Work System Components

Support for all 5 work system components was found in the included studies, as shown in Table 3. No new work system components were identified. However, we made 1 change to the work system component *EHR system*, which we renamed to *EHR system and related technology*. The latter was incorporated to also cover workarounds stemming from the use of technology other than the EHR but used in parallel with the EHR, such as scanners [25].

Table 3. Overview of work system components and related included studies.

Work components	Description	Studies
Person(s)	Health care professionals developing and using EHR[a] workarounds	[20,26-28]
EHR system and related technology	The EHR and related information technology used by health care professionals	[20,25-27,29-31]
Organization	Organizational conditions (eg, care directives and hospital policies) under which clinical tasks and EHR use are performed	[20,27,28,30,31]
Physical environment	The environment (eg, outpatient examination room and inpatient ward) and its conditions (eg, lighting and noise) in which clinical tasks are conducted by health care professionals	[20,26,27]
Task(s)	Clinical tasks performed by health care professionals	[20,26,28,30-32]

[a] EHR: electronic health record.

Rationales

The rationales for workarounds contained in the original SEWA framework were confirmed in many studies. In addition, 7 new rationales were identified.

Under the work system component *person(s)*, one rationale was added: *trust* (Table 4). Multiple studies reported that users created workarounds because of insufficient trust in the (new) system or its capabilities while frequently maintaining trust in older systems (replaced by the EHR). The related causes of a lack of trust are a lack of perceived usefulness of the (new) system and insufficient confidence in (completeness) of the data available in the EHR [33-39]. The description of the rationale *awareness* has been refined to also cover awareness of the information needs of patients and not just of colleagues [40]. Likewise, the description of the rationale *social norms* has been refined to make cultural [30,41] and collaborative [27,42] aspects more explicit.

Although extensive support in the included studies was found for all rationales under the work system component *EHR system and related technology*, except *patient data specificity*, four additional rationales were identified: *data integration*, *enforced actions*, *data quality*, and *interoperability* (Table 5). The description of the pre-existing rationale *technical issues* has been refined to cover technical issues related to ancillary technology used in conjunction with the EHR.

Multiple studies provide support for all rationales under the work system component *organization* except for the rationale *data migration policy* (Table 6). No new rationales were identified.

Although support was found for the pre-existing rationales under *task(s)*, one rationale was added: *task complexity* (Table 7). Approximately 3% (2/62) of studies described that the EHR does not always sufficiently support the execution of a complex task at hand [34-39]. Therefore, health care professionals resort to workarounds to make their workflow more digestible.

Finally, the SEIPS work system component *physical environment* was incorporated into the original SEWA framework without any rationale. However, Dudding et al [25] mentioned that a busy, fast-paced environment where interruptions are constant, such as the neonatal intensive care unit, gives rise to EHR workarounds. The rationale here is "fast-paced environment" and is described as "devising workarounds to cope with the inability to, for example, update the documentation in fast-paced care environments where interruptions are constant" [25].

Table 4. Overview of rationales for the work system component person(s) and related included studies.

Rationales	Description	Studies
Declarative knowledge	Not knowing how to use (a part of) the EHR[a] to accomplish a task	[20,33,34,39,43,44]
Procedural knowledge	Knowing how but not being proficient enough to use a part of the EHR to accomplish a task	[20,28,34,39,44]
Memory aid	Writing patient data down on paper (eg, keywords) or adding visual elements to parts of text in a progress note (eg, boldfacing, italicizing, or underlining) to remind oneself	[20,34,39,43,45-47]
Awareness	Storing patient data that are perceived important by the EHR user for other colleagues or patients to be noticed (frequently in a data field other than the intended field in the EHR)	[20,39,40,48]
Social norms	Formal or informal, collaborative, and cultural understandings among health care professionals leading to the creation and dissemination of workarounds (eg, mimicking workarounds devised by colleagues to accomplish a task or working around the system upon as friendly requested or enforced by a fellow clinician)	[20,29-31,45,49,50]
Trust (new)	Having insufficient trust in the (new) EHR system or its capabilities, lack of perceived usefulness, or insufficient confidence in the (completeness) of data	[20,33-39]

[a] EHR: electronic health record.

Table 5. Overview of rationales for the work system component EHR[a] system and related technology and related included studies.

Rationales	Description	Studies
Usability	High behavioral user cost in accomplishing a task	[20,25,28,29,31,41,42,45,46,50-56]
Technical issues	(A part of the) EHR or ancillary technology halting, crashing, or slowing down, hampering the EHR user in accomplishing a task	[20,25,28,31-33,43,44,51-53,55-61]
Data presentation	Preferring a different data view (eg, visualization by means of charts or graphs rather than plain text)	[20,55,62]
Patient data specificity	Needing to enter or request patient data with greater or lesser specificity than offered or enforced by the EHR	[20]
Data integration (new)	EHR not providing or supporting the integration of patient data necessary for care delivery	[42,45]
Enforced actions (new)	Avoiding or overriding actions enforced by the EHR (eg, bypassing the approval process of prescribing medication or using a different user account)	[29,43,48,54,63]
Data quality (new)	Unavailability of data, disparity in data formats (eg, the same data being stored in multiple different formats in the EHR), lack of standardization, and information gaps in the EHR	[31,34-36,39,41,42,44,50,57,64-67]
Interoperability (new)	Data not able to be exchanged between health care systems or institutions (eg, causing data to be unavailable at the right moment and time)	[44,50,54,56,64,65]

[a] EHR: electronic health record.

Table 6. Overview of rationales for the work system component organization and related included studies.

Rationales	Description	Studies
Efficiency	Using an alternative way of accomplishing a task that improves actual efficiency	[20,29,31,34,35,37,43,46,47,55,68-70]
Data migration policy	Not having (direct) access to required historical data because of data not having been imported from previously used systems to the current EHR[a]	[20]
Enforced data entry	EHR enforcing user to enter patient data of which neither the user nor the patient has knowledge of	[20,71,72]
Required data entry option missing	EHR not offering the required data entry option (eg, 3.75 mg rather than the available options 2.5 mg or 5 mg)	[20,32,71]

[a] EHR: electronic health record.

Table 7. Overview of rationales for the work system component task(s) and related included studies.

Rationales	Description	Studies
Task interference	Inability to perform multiple tasks at once (eg, simultaneously treating a patient on the treatment table as well as entering patient data into the EHR[a])	[20,61]
Commitment to patient interaction	Valuing patient interaction over computer interaction (ie, writing things down on paper and afterward entering this into the EHR)	[20,34,37,41,44,55,61,73]
Task complexity (new)	The high complexity of the tasks needing to be conducted	[34,39]

[a] EHR: electronic health record.

Attributes

Although several studies confirmed the previously defined attributes in SEWA, several included studies also mentioned a total of 4 new attributes (Table 8). These are concerned with whether the user is aware of using a workaround [49] (*awareness*), whether the workaround is an individual or shared practice across users [49] (*shared*), on what medium the workaround is conducted (eg, paper or computer) [34,41] (*medium*), and whether the workaround is a formal or informal practice (eg, part of a defined process or approved or promoted by management or not) [56] (*formality*).

Table 8. Overview of workaround attributes and related included studies.

Attributes	Description	Source
Cascadedness	Whether the workaround initiates the creation of 1 or multiple additional workarounds or is an isolated occurrence	[20]
Avoidability	Whether the workaround is required to proceed with one's workflow or optional	[20,32,66,74]
Anticipatedness	Whether the workaround is used at known moments in time (ie, the situation in which the workaround is used is known beforehand) or used unexpectedly	[20,74]
Repetitiveness	Whether the workaround is ingrained into the workflow (ie, becomes part of daily routines) or used temporarily to overcome workflow constraints	[20,56,74]
Awareness (new)	Whether the user is aware of using the workaround	[49]
Shared (new)	Whether the workaround is a shared practice across multiple other users of the EHR[a] or limited to 1 user	[49]
Medium (new)	On what medium the workaround is conducted (eg, paper, computer, verbal, or a combination)	[34,41]
Formality (new)	Whether the use of the workaround is approved by management and part of a defined process	[56]

[a] EHR: electronic health record.

Types of Impact

The previously defined types of impact in the SEWA framework were confirmed by many included studies. Multiple additional types of impact were also identified: *privacy/security*, *data quality*, *employee perception of EHR*, *financial*, *law/regulations*, and *workload* (Table 9). *Privacy/security* relates not only to the impact a workaround has on the security and privacy of the data but also to the patient and organization itself. Data quality concerns the impact on, for example, loss of data, or a lower data quality because of spelling or formatting mistakes in the data. Moreover, workarounds can have a positive or negative financial impact [58], may jeopardize laws and regulations [63,75], and have a positive or negative impact on the workload of the user [43].

Table 9. Overview of types of impact and related included studies.

Impact	Description	Source
Patient safety	The impact on the safety (physical and mental) of the patient	[20,28,29,41,43,46,48,53,54,58,59,67,75-77]
Effectiveness of care	The effectiveness and quality of the care process performed	[20,28,43,46,54,58,59,67]
Efficiency of care	The impact on the efficiency of the care process in terms of time and resources expended	[20,33,55,60,64,72,76]
Privacy and security (new)	Impact on the security and privacy of data related to the patient or organization	[32,39,51,52,56,63,68,75]
Data quality (new)	Impact of workarounds on data quality (eg, loss of data or decreased data quality)	[32,33,35,39,41,46,51,52,56,59,69,76]
Financial (new)	Financial implications because of the workaround	[58]
Laws and regulations (new)	Legal conflicts resulting from the use of a workaround	[63,75]
Workload (new)	An increase or decrease in workload of the EHR[a] user resulting from the use of a workaround	[43]

[a] EHR: electronic health record.

Possible Scopes

Only a few studies explicitly discussed possible scopes (ie, entities impacted) of workarounds and resonated with those in the SEWA framework [41,43,53,77] (Table 10). No new possible scopes were identified.

Table 10. Overview of possible scopes and related included studies.

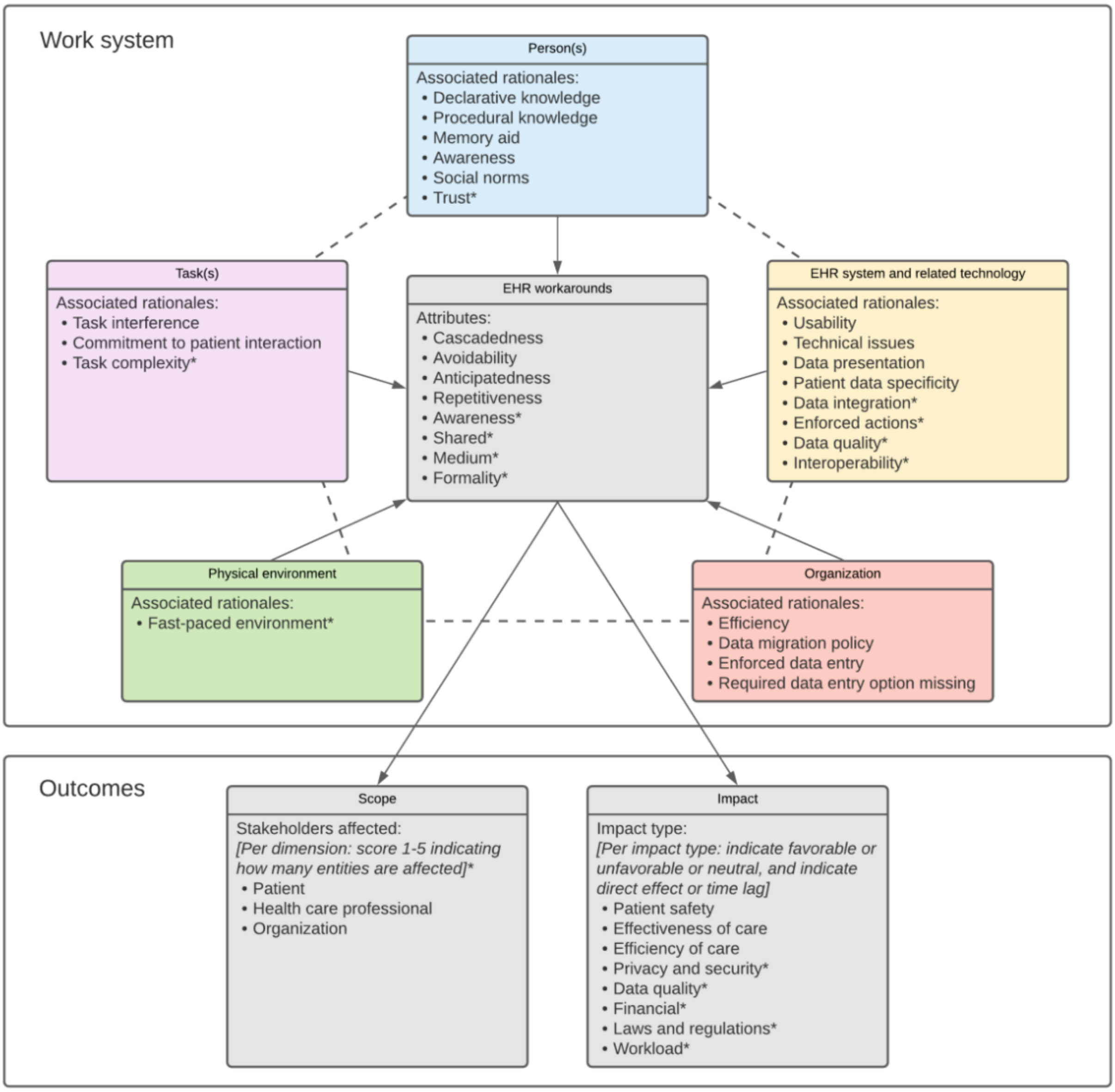
Scope	Description	Source
Patient	The workaround affects the patients in the care process	[20,43,77]
Health care professional	The workaround affects the health care professionals such as physicians, nurses, and pharmacists	[20]
Organization	The workaround affects the whole organization, including the supporting departments such as finance or legal	[20,41,53]

Revised Version of the SEWA Framework

On the basis on the foregoing results, the original SEWA framework [20] was revised to incorporate new rationales, attributes, types of impact, and possible scopes identified in the included studies (Figure 2). The revised SEWA framework still comprises 2 major parts. The first part concerns the work system and its components (inspired by the SEIPS framework), [21] constituting the context in which EHR workarounds are created.

The work system components now include 22 rationales (previously 15) for workaround creation, and EHR workarounds are now defined by 8 attributes (previously 4). The second part concerns the possible scope of workarounds in terms of types and number of entities affected (still 3), as well as their impact on patient safety, the effectiveness of care, the efficiency of care, and 5 newly introduced types of impact. All new items in the framework are marked with asterisks.

Figure 2. Revised SEWA framework with incorporated rationales, attributes, types of impact, and possible scopes identified in included studies. EHR: electronic health record; SEWA: Sociotechnical Electronic Health Record Workaround Analysis.



The recommendations [20] for using a scoring mechanism to indicate whether the impact per workaround is favorable, unfavorable, or neutral, as well as to indicate whether the impact is immediate or only observable after a certain period (*direct/time lag*) remain. However, we also recommend the inclusion of a scoring mechanism to indicate the number of patients and health care professionals and organizational units affected per applicable scope. This is in line with Carayon et al [53], who distinguished between workarounds having an impact at an individual or *team level* (eg, an entire team of nurses in a certain hospital ward). Applying a scoring mechanism allows for a more substantiated view when analyzing and prioritizing various identified workarounds for resolution.

Discussion

Principal Findings

A scoping review was performed to theoretically validate the SEWA framework [20] and refine and enrich it with newly identified rationales, attributes, types of impact, and possible scopes of EHR workarounds. The scoping review retrieved 737 studies, of which 62 (8.4%) were included. The included studies provided extensive support for nearly all the items included in the original SEWA framework. SEWA was revised and enriched with 7 new rationales, 4 attributes, and 5 types of impact of EHR workarounds mentioned in the included studies. The definitions of several existing rationales were also refined. As a result, SEWA is now grounded in the existing body of peer-reviewed empirical evidence on EHR workarounds published between 2010 and 2021. In addition, this revised version is likely also applicable in a wider range of health care settings as input for the original SEWA framework that came from a single comprehensive case study on EHR workarounds in an academic hospital.

Comparison With the Literature

The results of this scoping review are in line with prior research and reviews of EHR workarounds. In an integrative review, Fraczkowski et al [78] examined nurse workarounds in EHR use. The categories defined in the review by Fraczkowski et al [78] are similar to the work system components defined in SEWA, with the exception of *usability* being a separate rationale in the SEWA framework under the work system component *EHR system and related technology* [20]. The *patient* category in the review by Fraczkowski et al [78] is defined as an impact and scope category in SEWA [20]. Finally, Fraczkowski et al [78], similar to Koppel et al [18], did not include a work system component for *person(s)* (the users of the EHR) as a category. Our scoping review is one of the few studies that investigated the entire spectrum of EHR users. On the one hand, we included studies of all types of health care professionals in primary, secondary, and tertiary care who make use of an EHR in their clinical practice, whereas other reviews merely focused on a specific population such as physicians, nurses, or secretary personnel [78]. On the other hand, we excluded studies researching workarounds in the use of barcode medication administration systems, whereas other reviews did not [78].

Strengths and Limitations

To maximize the capture of relevant information on EHR workarounds, comprehensive and structured searches were conducted in MEDLINE, Embase, CINAHL, Cochrane, and IEEE databases. Data charting templates and analytic frames were used to extract relevant information from the reviewed studies and compare with pre-existing items in the SEWA framework.

A total of 2 research team members participated in the review process for both the title and abstract and full-text review phases, with a Cohen κ value of >0.9. This indicates an adequate interrater agreement. Despite this, our scoping review is at risk for selection bias, as we did not identify all available data, such as gray literature on EHR workarounds. There is a chance that relevant but nonincluded studies may use terminology other than the terms included in the search queries.

The broad scope of the retrieved information on EHR workarounds and the different types of studies reporting a particular issue made using a formal meta-analytic method to quantitatively assess the quality of the studies and evidence of retrieved information difficult. However, given the purpose of the scoping review to theoretically validate and refine the SEWA framework, we do not consider this limitation.

Implications for Practice and Future Research

Multidisciplinary teams (comprising, for example, physicians, nurses, management, and EHR developers) can use the revised SEWA framework to identify, analyze, prioritize, and resolve workarounds related to EHR use more accurately. Similarly, the consequences of current and future configurations of the work system (health care professionals' work processes and activities in relation to their EHR use) can be assessed and discussed in greater detail to determine how a design and redesign of the work system would positively or negatively affect the interaction between work system components. Finally, as workarounds are subject to gradual change (eg, personal changes in experience with the EHR, system updates to the EHR, and hospital policies), more detailed snapshots of the work system using SEWA can be taken over time and compared so as to gain valuable insights into how EHR workarounds evolve over time.

Concerning future research, EHR systems are continuously subject to technological evolution by developments in, for example, artificial intelligence, machine learning, and telemedicine. This may lead to the creation of hitherto unidentified rationales, attributes, possible scopes, and types of impact of workarounds on users, patients, and health care organizations. Similarly, more studies on EHR workarounds will continue to emerge that may report novel insights not incorporated into the revised SEWA framework. Therefore, we expect that SEWA needs a continuous process of refinement over time. This could be done by repeating the scoping review using the described search strategy, search queries, and inclusion and exclusion criteria.

In addition, although the revised SEWA framework is now theoretically validated, refined, and enriched, practical validation is still required. The same holds true when investigating its practicality. The firsthand experience from the application of SEWA in practice could yield suggestions for further improvement. A related suggestion is that although the framework helps in identifying and analyzing workarounds, a prioritization method for handling these issues is likely required, as workarounds are generally abundant in any organization, and resources to resolve them are finite. Therefore, the framework could benefit from being extended with prioritization mechanisms and weighting factors for deciding which workarounds require priority. Similarly, the framework could be translated into a practical tool such as a scoring matrix to facilitate use by practitioners.

Finally, the applicability of the SEWA framework could be explored for systems other than EHRs (eg, enterprise resource planning, customer relationship management, and content management) and in other settings (eg, nonacademic hospitals and general practitioner practices) and even in other industries (eg, financial services and manufacturing) after appropriate validation. Although SEWA has an explicit focus on EHRs used in health care, we expect many of the described workaround rationales and attributes to be applicable to other systems, settings, and industries.

Authors' Contributions

VB, FH, and MJ conceived and designed the study. FH collected the data. VB and FH analyzed the data and wrote the manuscript. VB and MJ edited the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Descriptive data template that was captured per included study.
[DOCX File , 13 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Analytic frame with workaround-related data captured per study.
[DOCX File , 13 KB-Multimedia Appendix 2]

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Abbreviations

EHR: electronic health record
PRISMA: Preferred Reporting Item for Systematic Reviews and Meta-Analyses
SEIPS: Systems Engineering Initiative for Patient Safety
SEWA: Sociotechnical Electronic Health Record Workaround Analysis

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Review

Physician Burnout and the Electronic Health Record Leading Up to and During the First Year of COVID-19: Systematic Review

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Abstract

Background: Physician burnout was first documented in 1974, and the electronic health record (EHR) has been known to contribute to the symptoms of physician burnout. Authors pondered the extent of this effect, recognizing the increased use of telemedicine during the first year of COVID-19.

Objective: The aim of this review was to objectively analyze the literature over the last 5 years for empirical evidence of burnout incident to the EHR and to identify barriers to, facilitators to, and associated patient satisfaction with using the EHR to improve symptoms of burnout.

Methods: No human participants were involved in this review; however, 100% of participants in studies analyzed were adult physicians. We queried 4 research databases and 1 targeted journal for studies commensurate with the objective statement from January 1, 2016 through January 31, 2021 (n=25).

Results: The hours spent in documentation and workflow are responsible for the sense of loss of autonomy, lack of work-life balance, lack of control of one's schedule, cognitive fatigue, a general loss of autonomy, and poor relationships with colleagues. Researchers have identified training, local customization of templates and workflow, and the use of scribes as strategies to alleviate the administrative burden of the EHR and decrease symptoms of burnout.

Conclusions: The solutions provided in the literature only addressed 2 of the 3 factors (workflow and documentation time) but not the third factor (usability). Practitioners and administrators should focus on the former 2 factors because they are within their sphere of control. EHR vendors should focus on empirical evidence to identify and improve the usability features with the greatest impact. Researchers should design experiments to explore solutions that address all 3 factors of the EHR that contribute to burnout.

Trial Registration: PROSPERO International Prospective Register of Systematic Reviews CRD42020201820; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=201820

International Registered Report Identifier (IRRID): RR2-10.2196/15490

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KEYWORDS

electronic health record; physician burnout; quality improvement; psychiatry; medical informatics; COVID-19; pandemic; health informatic; health care; health care professional; health care infrastructure; health care system; mental health; cognitive fatigue

Introduction

Background

This systematic review examined the state of physician burnout incident to the electronic health record (EHR), compounded by the stress of managing the pandemic in the first year of COVID-19. Neither physician burnout nor the EHR are new; however, the additional stress of managing a pandemic may make the relationship between these 2 variables clearer. The clinical psychologist Herbert Freudenberger [1] is attributed to the first mention of physician burnout in 1974, as he observed physician interaction in the drug-addled East Village of New York City. His description of burnt-out physicians mirrored the physicians' description of burnt-out patients with drug addiction in terms of a feeling of disassociation as depicted by the definition in the following sections. Physician burnout can be detrimental to physician well-being and to the quality of care provided and can result in higher turnover [2-4]. It is a significant problem that has been attributed to the EHR.

Rationale

The EHR has become a pervasive entity in the lives of all health care workers. Very few processes in the health care field are independent of the EHR. This "digital version of the patient's chart is a real-time, patient-centered record that makes information available instantly and securely to authorized users" [5]. Physician burnout is "a long-term stress reaction marked by emotional exhaustion, depersonalization, and a lack of sense of personal accomplishment" [6]. Physician burnout was already identified as a worldwide health issue before COVID-19, and digital tools such as the EHR are cited as a contributing factor to this issue [7,8]. Factors associated with the EHR cited in relation to physician burnout are usability, workflow, and documentation time [8-13]. The documentation inherent to the EHR requires significant time, as much as 2:1 hours of direct clinical face-to-face time and as much as 2 hours outside of office hours [14]. Some authors list burn-out as a new pandemic and a new normal [15,16].

A systematic review of 182 studies on a similar topic was conducted in 2018. It examined physician burnout data over a 17-year period. It identified a high incidence of physician burnout, but it failed to attribute the EHR as a contributor [17]. Another systematic review of 50 studies was conducted in 2019. It identified 4 interventions (teamwork, time management, transitions, and technology) to assuage the effects of physician burnout [10]. A systematic review in 2020 of 81 studies found interventions to decrease the digital-tool burden (training, reduced documentation and task time, expanded care teams, leveraged quality improvement and processes in workflows) in 68% of articles analyzed [9].

Objectives

The purpose of this research was to examine physician burnout issues incident to the EHR prior to and during the first year of the COVID-19 pandemic by analyzing the literature from the last 5 years. We defined physician burnout as emotional exhaustion, depersonalization, and lack of sense of personal accomplishment [6]. We examined facilitators and barriers to the adoption of mitigation strategies of burnout incident to the EHR.

Methods

Protocol and Registration

Authors of this systematic review followed the protocol by Kruse [18] for conducting a systematic review and reported results in accordance with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) [19]. The research was registered with PROSPERO on August 31, 2020.

Eligibility Criteria

To be eligible for this study, articles had to be published in English in peer-reviewed, academic journals between January 2016 and January 2021. All study designs were accepted including both quantitative and qualitative studies with humans of all ages; however, other systematic reviews were excluded from the selection.

Information Sources

On January 29, 2021, we used a standard search string to query 4 databases: PubMed (MEDLINE), CINAHL (exclude MEDLINE), Web of Science, and Science Direct. We also performed a journal-specific search of the Mayo Clinic Proceedings.

Search Strategy

We created a Boolean search string to combine key terms listed in the Medical Subject Headings (MeSH) of the US Library of Medicine [("electronic health record" OR "electronic medical record") AND ("physician burnout") AND COVID-19]. We used the same search strategy in all databases. We used similar filter strategies in each database, because not all databases offer the same tools.

Study Selection Process

In accordance with the protocol by Kruse [18], we searched key terms in all databases, filtered results, and screened abstracts for applicability. Reviewers rejected articles if they did not produce results (were not research), such as protocols, opinions, or did not address physician burnout and use of the EHR.

Data Collection Process

We used an Excel spreadsheet as a data extraction tool, collecting additional data at each step of the process. This spreadsheet was standardized in the protocol by Kruse [18]. We used a series of 3 consensus meetings. The first consensus meeting was held after abstract screening. Subsequent consensus meetings identified observations and themes.

Data Items

In accordance with the protocol by Kruse [18], we collected the following fields of data at each step: PICOS (participants, intervention, results compared to the control group, health outcomes, study design), bias, effect size, country of origin, statistics used, strength of evidence, quality of evidence, and 3 data fields specific to the objective of this systematic review (patient satisfaction, barriers, and facilitators). Data items and observations became the subject of the second and third consensus meetings.

Risk of Bias Assessment and Reporting

We observed bias and assessed the quality of each study using the Johns Hopkins Nursing tool for Evidence Based Practice (JHNEBP) [20]. We considered the instances of bias in how to interpret the results because bias can limit external validity.

Effect Measures

Because we accepted mixed methods and qualitative studies, we were unable to standardize summary measures as would be performed in a meta-analysis. Effect size was not reported in any study of the group for analysis.

Synthesis Methods

During the screening process, reviewers compared elements of the abstract against the objective statement of this review. Article abstracts that matched our objective statement were marked for inclusion. The rest of this subheading is for meta-analyses—not for systematic reviews. Although the protocol by Kruse [18] for conducting a systematic review uses elements of a meta-analysis, it falls short of this standard.

Additional Analyses

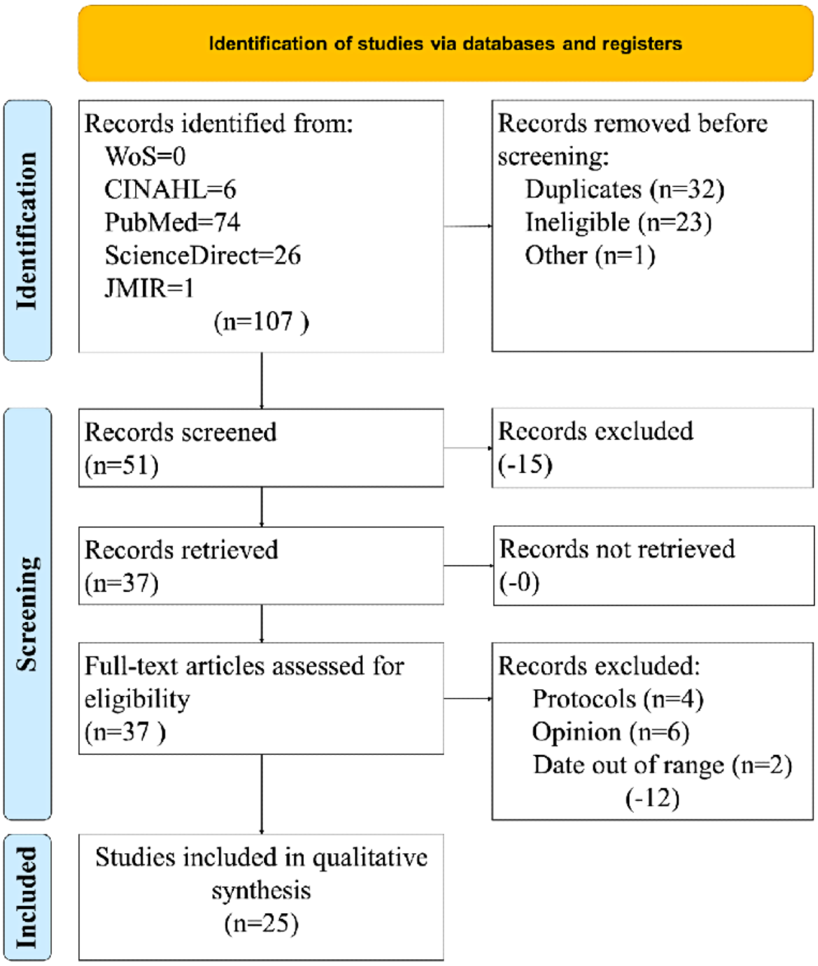
We performed a narrative analysis of the observations to convert them into themes (common threads between articles) [21]. We calculated a frequency of occurrence and reported these in a series of affinity matrices. This technique does not imply a level of importance of these observations, but instead, it simply illustrates the probability of occurrence of these observations across the group for analysis.

Results

Study Selection

Figure 1 illustrates our study selection process from the 4 databases and 1 targeted journal search. A kappa statistic was calculated based on levels of agreement between reviewers (k=0.64, moderate agreement) [22,23].

Figure 1. Study selection process. JMIR: Journal of Medical Internet Research; WoS: Web of Science.



Study Characteristics

In accordance with PRISMA 2020, a PICOS table was created from the group of articles analyzed (see Table 1). Of the 25 articles analyzed over the 5-year period, 100% of the participants were adult physicians, and all studies used the EHR as at least one of their foci in their study. Interventions ranged from using the EHR to implementing EHR training or physician partners or scribes. Results varied across studies. Many researchers found training, education, scribes, or physician partners significantly reduced symptoms of physician burnout. Additional explanation of these results will be provided below. Interventions to reduce physician burnout noted improvements in physical pain and psychological outlook. More than half (13/25, 52%) of the study designs were qualitative in nature. Studies are ordered as most recent to oldest: 2021 (n=2) [24,25], 2020 (n=4) [11,26-28], 2019 (n=6) [29-34], 2018 (n=8) [35-42], 2017 (n=2) [43,44], and 2016 (n=2) [45,46].

The 25 studies examined physician burnout with some intervention of the EHR before and during the COVID-19 pandemic. Of the 25 studies, 13 (52%) were qualitative studies, 4 (16%) were mixed methods, 2 sets of 2 (16%) were pre-post or observational, and 3 individual studies (12%) were cross-sectional, cohort, or a meta-analysis. Either scribes or physician partners to enter data into the EHR during the encounter were used in 2 studies [40,46]. This intervention resulted in a decrease in symptoms of physician burnout with zero effect on patient satisfaction. EHR training or a sprint improvement process (customizing local tools) was used by 2 studies to help physicians become more efficient with the EHR [33,41]. These studies also saw a decrease in symptoms of physician burnout with zero effect on patient satisfaction.

Table 1. PICOS (participants, intervention, results [compared with a control], outcome, and study design) characteristics of the included studies.

Authors	Participants	Intervention	Result themes	Medical outcome themes	Study design
Hu et al [24]	Adult health care professionals in the ICU[a] (1122 or 46.54% doctors, 1289 or 53.46% nurses)	EHR[b]	Low frequency of exercise, comorbidities, high-quality hospital has high expectations, more night shifts, longer on the job, few paid vacations	None reported	Qualitative
Rialon et al [25]	Adult health care professionals in pediatrics (68% male, 84% White, 42-60 years old)	EHR	Long hours or workload, no time for themselves, poor work-life balance, loss of autonomy, poor relationships with colleagues	None reported	Qualitative
Giess et al [27]	Adult nonradiologists and radiologists	EHR	Radiologists more likely to report symptoms of burnout	None reported	Qualitative
Kinslow et al [28]	Adult health care professionals (41, 50.6% identified as male; 39, 48.1% identified as female; 1, 1.2% preferred not to answer; 62, 76.5% reported being a resident in a community teaching hospital; 19, 23.5% reported being a resident in a university hospital	EHR	Women at higher risk of burnout and more likely to report suicidal ideations, poor work-life balance, long hours or workload, community-affiliated residents more likely to report suicidal ideation	None reported	Qualitative
Anderson et al [26]	Adult family medicine trainees (postgraduate years 1 through 3) and 10 family medicine faculty at the University of Arizona College of Medicine-Phoenix Family Medicine Residency	EHR	Long hours or workload	None reported	Observational
Khairat et al [11]	Adult physicians completing an EHR simulation activity, 52% female, mean age 33.2 years	EHR	Cognitive fatigue, design issues	Physical fatigue, cognitive weariness	Cross-sectional
Murphy et al [31]	Adult physicians (68% primary care physicians, 32% specialists) at 6 large health care organizations using 4 different EHR systems	EHR	Message complexity, design issues, cognitive fatigue, poor relationships with colleagues, message content	None reported	Qualitative
Tran et al [34]	Adult faculty physicians at 10 university-affiliated primary care clinics; survey sent to 190 faculty members and completed by 107 (56%) providers (86 physicians [MD/DO], 19 advanced practice providers [NP/PA], 2 providers who declined to answer the question); women = approximately two-thirds of the survey respondents; majority of the providers trained in family medicine (57%), internal medicine (27%), or pediatrics (18%)	EHR	Long hours or workload, poor work-life balance	None reported	Qualitative
Gardner et al [29]	Adult practicing physicians in Rhode Island	EHR	EHR-related or work-related stress	Work stress	Qualitative
Kroth et al [30]	Adult ambulatory primary care and subspecialty clinicians from 3 institutions (85.5% physicians, 56.7% women, 68.4% worked in primary care)	EHR	Design issues, lack of interoperability, poor work-life balance, seated position caused problems with back or wrist pain and posture	Posture, back pain	Qualitative
Sieja et al [33]	Adult clinicians in endocrinology, neurology, hematology, obstetrics, and gynecology as well as advanced practice providers	EHR Sprint process improvement	Long hours or workload	None reported	Pre-post
Quinn et al [32]	Adult physicians with an EHR	EHR	Design issues	None reported	Mixed methods
Robinson and Kersey [41]	Adult physicians from 30 specialties completing a total of 46 trainings from 2014 to 2016	EHR training	EHR improves quality and safety, readability, clinical workflow, and accuracy of documentation; efficiency gains with training; system speed and reliability issues	None reported	Mixed methods

Authors	Participants	Intervention	Result themes	Medical outcome themes	Study design
Pozdnyakova et al [40]	Adult faculty and a convenience sample (n=325) of their patients at an academic clinic (of patients: 69% Black, 65% female, 48% >65 years old); 373 patients completed surveys; 48 (13%) excluded due to incomplete data, and 325 analyzed (166 scribed and 159 nonscribed visits; Figure 1)	Scribes to assist with EHR workload	Long hours or workload	None reported	Pre-post
Marmor et al [39]	Adult physicians of internal medicine, cardiology, and gastroenterology	EHR	Time spent in EHR affects patient satisfaction	None reported	Meta-analysis
Denton et al [35]	Adult physicians at 2 urban emergency departments	EHR	EHR improves clinical workflow, door-to-doctor and time to decision, and quality and safety	None reported	Qualitative
Kroth et al [38]	Adult clinicians from 2 focus groups at 3 health care facilities with different EHRs (71% women, 98% physicians, 73% worked in primary care for an average of 11 years)	EHR	Long hours or workload, EHR-related or work-related stress, poor work-life balance	Eye strain, hand or wrist pain, back pain	Qualitative
Hauer et al [36]	Adult member and nonmember physicians practicing in Wisconsin whose email address is listed in the Wisconsin Medical Society's database	EHR	Loss of autonomy, poor relationships with colleagues, loss of autonomy, poor work-life balance	None reported	Qualitative
Young et al [42]	Adult family physician attendings, residents, and their ambulatory patients in 982 visits in clinics affiliated with 10 residencies of the Residency Research Network of Texas	EHR	Long hours or workload	None reported	Observational
Khairat et al [37]	Adult ED physicians at a large tertiary academic hospital, 50% female, 43% residents, 57% attendings	EHR	Design issues, long hours or workload, system speed or reliability issues	None reported	Mixed methods
Arndt et al [47]	Adult family medicine physicians in a single system in southern Wisconsin (100% Epic users; 43% female)	EHR	Long hours or workload	None reported	Cohort
Shahmoradi et al [44]	Adult workforce at 15 ambulatory hospitals (67% female, 75.05% with at least a BSc degree, 45.5% with age of 31-41 years, 46.67% employed <15 years)	EHR	Design issues	None reported	Qualitative
Gregory et al [43]	Adult primary care physicians at a large medical center	EHR alerts	Alert fatigue, cognitive fatigue	Physical fatigue, cognitive weariness	Mixed methods
Jamoom et al [45]	Adult physicians	EHR	Long hours or workload, longer on the job	None reported	Qualitative
Reuben et al [46]	Adult physicians were surveyed, including the pilot physicians and others who had experienced ≥1 session with a physician partner	Physician partners to help with EHR workload	Scribes or physician partners can decrease symptoms of burnout.	None reported	True experiment

[a] ICU: intensive care unit.

[b] EHR: electronic health record.

Risk of Bias Within and Across Studies

The JHNEBP quality assessment tool was used to identify the strength and quality of evidence in the literature. These are illustrated in Table 2. Of the articles, 80% (20/25) had a strength of III, and 88% (22/25) were quality B. This means a vast majority of articles were qualitative, mixed methods, nonexperimental, or quasi-experimental in nature, but their quality was still strong. Regarding the strength of evidence, level I studies were randomized controlled trials or true experiments. Level II studies were quasi-experimental in nature (no randomization). Level III studies were nonexperimental studies or qualitative studies. We did not accept any studies with a strength of evidence lower than III because these categories are opinion rather than research. Regarding the distribution of the 3 levels of evidence quality, in quality category A, research shows consistent results with sufficient sample sizes, adequate controls, and definitive conclusions. In quality category B, research shows reasonably consistent results, sufficient sample sizes, some control, and fairly definitive conclusions. As illustrated, we did not encounter any studies with a quality rating of C.

Table 2. Summary of strength and quality of evidence identified with the Johns Hopkins Nursing tool for Evidence Based Practice (JHNEBP; n=25).

Assessment	Frequency, n
Strength of evidence	
I	2
II	3
III	20
Quality of evidence	
A	3
B	22
C	0

Results of Individual Studies

Reviewers independently recorded observations for each article commensurate with the objective statement. A thematic analysis was conducted to make sense of the data. When an observation was identified more than once, it became a theme. Themes were created to summarize the observations, but they did not always exactly match the observations. These themes can be observed in Table 3. Articles are sorted by most recent to oldest. Multimedia Appendix 1 and Multimedia Appendix 2 show the observation-to-theme match. Multimedia Appendix 3 shows additional data extracted from each study.

Reviewers conducted a thematic or narrative analysis. Part of this analysis was making sense of the data. When an observation reoccurred, it became a theme. Observations without reoccurrence were just observations. Patient satisfaction, barriers, and facilitators were explored under additional analysis. Scribes and physician partners were used in 3 studies to enter data into the EHR during an appointment, but only 2 of the studies reported on patient satisfaction outcomes.

Table 3. Summary of the analysis, sorted most recent to oldest.

Authors	Patient satisfaction themes	Barrier themes	Facilitator themes
Hu et al [24]	EHR[a] time in clinic negatively affects patient satisfaction; patient dissatisfaction negatively affects doctor-patient relationship; patient dissatisfaction negatively affects physician burnout.	Not reported	Exercise relieves symptoms of burnout; annual vacation relieves symptoms of burnout.
Rialon et al [25]	Not reported	Excessive hours spent in the EHR affect work-life balance, excessive hours spent in the EHR exacerbates symptoms of physician burnout, administrative time in the EHR takes time away from clinic and patients.	Focus on mission of care relieves symptoms of burnout.
Giess et al [27]	Not reported	EHR does not help coordinate care.	Not reported
Kinslow et al [28]	Not reported	Excessive hours spent in the EHR exacerbate symptoms of physician burnout.	Small group sessions
Anderson et al [26]	Not reported	Excessive hours spent in the EHR exacerbate symptoms of physician burnout.	Not reported
Khairat et al [11]	Not reported	EHR must undergo redesign, high number of clicks per process is inefficient.	Not reported
Murphy et al [31]	Not reported	The administrative overhead of the EHR is not conducive to efficient workflow, excessive hours spent in the EHR affect work-life balance, administrative overhead of the EHR is not conducive to efficient workflow.	Local customization (eg, templates, menus) improves efficiency, localized workflow redesign relieves symptoms of burnout.
Tran et al [34]	Not reported	Excessive hours spent in the EHR exacerbate symptoms of physician burnout.	Not reported
Gardner et al [29]	Not reported	Administrative time in the EHR takes time away from clinic and patients, excessive hours spent in the EHR affect work-life balance.	Not reported
Kroth et al [30]	Not reported	EHR must undergo redesign, excessive hours spent in the EHR exacerbate symptoms of physician burnout, high number of clicks per process is inefficient, administrative time in the EHR takes time away from clinic and patients, excessive hours spent in the EHR affect work-life balance.	Not reported
Sieja et al [33]	Not reported	Administrative overhead of the EHR is not conducive to efficient workflow.	Local customization (eg, templates, menus) improves efficiency.
Quinn et al [32]	Not reported	EHR reliability and speed, some patient information is not available due to lack of interoperability, EHR must undergo redesign.	Training increases efficiency.
Robinson and Kersey [41]	Not reported	EHR training takes time away from the clinic.	Institutional endorsement of EHR increases user acceptance of EHR, training increases efficiency.
Pozdnyakova et al [40]	Patient satisfaction not affected by scribe or physician partner in clinic during exam	Some patients do not like scribes or physician partners in the exam room, excessive hours spent in the EHR exacerbate symptoms of physician burnout.	Presence of scribe or physician partner relieves symptoms of burnout, localized workflow redesign relieves symptoms of burnout.
Marmor et al [39]	Time of day affects patient satisfaction more than time spent with patient.	Excessive hours spent in the EHR exacerbate symptoms of physician burnout.	Localized workflow redesign relieves symptoms of burnout.
Denton et al [35]	Not reported	EHR must undergo redesign, high number of clicks per process is inefficient, administrative overhead of the EHR is not conducive to efficient workflow.	EHR increases safety, decreases admission decision time, and decreases length of stay.
Kroth et al [38]	Not reported	EHR must undergo redesign, EHR reliability and speed, some patient information is not available due to lack of interoperability, administrative overhead of the EHR is not conducive to efficient workflow.	Training increases efficiency, presence of scribe or physician partner relieves symptoms of burnout.

Authors	Patient satisfaction themes	Barrier themes	Facilitator themes
Hauer et al [36]	Not reported	EHR must undergo redesign, lack of supporting practice environment, EHR creates a loss of autonomy, excessive hours spent in the EHR affects work-life balance.	Not reported
Young et al [42]	Not reported	Administrative time in the EHR takes time away from clinic and patients.	Not reported
Khairat et al [37]	Not reported	EHR must undergo redesign, EHR reliability and speed.	Not reported
Arndt et al [47]	Not reported	EHR must undergo redesign, excessive hours spent in the EHR affect work-life balance, administrative overhead of the EHR is not conducive to efficient workflow.	Not reported
Shahmoradi et al [44]	Not reported	EHR reliability and speed, excessive hours spent in the EHR exacerbate symptoms of physician burnout, some patient information is not available due to lack of interoperability, administrative overhead of the EHR is not conducive to efficient workflow, EHR investment inhibits short-term profit, EHR must undergo redesign, no standardized vocabulary.	EHR enables rapid access to information, decreases duplicate testing, increases speed of delivery of care, increases accuracy of documentation, increases safety, enables computerized analysis and interpretation of data.
Gregory et al [43]	Not reported	EHR must undergo redesign, administrative overhead of the EHR is not conducive to efficient workflow.	Not reported
Jamoom et al [45]	Not reported	Not reported	Level of physician experience with EHR increases perceived usefulness of EHR
Reuben et al [46]	Patient satisfaction not affected by scribe or physician partner in clinic during exam	Scribes or physician partners cost more money.	Presence of scribe or physician partner relieves symptoms of burnout.

[a] EHR: electronic health record.

Additional Analysis

Themes and individual observations were organized into tables to reflect the probability of their occurrence in the group for analysis. These affinity matrices are shown and discussed in the following sections. In the interest of saving space, only those with the greatest number of occurrences will be discussed in detail.

Study Results

Table 4 summarizes the study results observed: 12 themes and 20 individual observations were identified by the reviewers for a total of 68 occurrences in the literature.

Of 68 occurrences, 13 (19%) identified longer hours worked and increased workload as a result of using the EHR. Researchers noted respondents to surveys worked 60-80 hours per week: The extra time was largely attributed to the EHR [25,45]. Physicians spent between 17 minutes and 217 minutes per patient in the EHR, resulting in up to 33 hours per month in the EHR after work hours: These longer hours were highly attributable to symptoms of burnout [26,34]. The nonintuitive nature of the EHR negatively impacted efficiency and contributed to the longer hours [37]. This point leads to the next item most often cited: design issues. This point occurred in 7 of 68 (10%) occurrences. Observations about design were attributed to the user interface, the long length of cut-and-paste notes required, communication and inefficient data-sharing processes, and the requirement to memorize menu and button names [11,30-32,37,44]. The long hours spent in the EHR created a poor work-life balance [25,28,30,34,36,38]. This point occurred in 6 of 68 (9%) occurrences. Many providers felt compelled to complete administrative work in the EHR from home so that they could at least be near their families while completing their workload, but this habit created tension in the household and overall impeded attempts at work-life balance. Four themes occurred 3 times (12%): EHR improves quality and safety [35,41], a general loss of autonomy [25,36], poor relationships with colleagues [25,31,36], and cognitive fatigue [11,31,43]. The increase in quality and safety appeared in the form of greater readability of notes, increased accuracy of clinician notes, a decrease in medical errors, increased clinical efficiency, and ease of data retrieval. Loss of autonomy occurred in the literature as a general lack of control over one's schedule. Poor relationships with colleagues occurred as lack of team communication, lack of supportive practice environment, and lack of time available in the clinic to build relationships. Cognitive fatigue was only subjectively queried in 1 of the 3 studies: The other 2 were objectively measured as pupillometry and a cognitive weariness index. These themes comprised 60% of the observations. Some of these themes will appear again as either facilitators or barriers to the use of the EHR to decrease physician burnout.

Table 4. Study results affinity matrix.

Study result themes or observations	Reference(s)	Frequency, n
Long hours or workload	[25,26,28,33,34,37,38,40,42,45,47]	13
Design issues	[11,30-32,37,44]	7
Poor work-life balance	[25,28,30,34,36,38]	6
EHR[a] improves quality and safety	[35,41][b]	3
Loss of autonomy	[25,36][b]	3
Poor relationships with colleagues	[25,31,36]	3
Cognitive fatigue	[11,31,43]	3
EHR-related or work-related stress	[29,38]	2
Efficiency gains with training	[41][b]	2
EHR improves clinical workflow	[35,41]	2
Longer on the job	[24,45]	2
System speed or reliability issues	[11,41]	2
EHR improves accuracy of documentation	[41]	1
EHR improves readability	[41]	1
Women more likely to report suicidal ideations	[28]	1
High-quality hospital has high expectations	[24]	1
Alert fatigue	[43]	1
Community-affiliated residents more likely to report suicidal ideations	[28]	1
Comorbidities	[24]	1
EHR improves door-to-doctor and time to decision	[35]	1
Women at a higher risk of burnout	[28]	1
Few paid vacations	[24]	1
Lack of interoperability	[30]	1
Low frequency of exercise	[24]	1
Message complexity	[31]	1
Message content	[31]	1
More night shifts	[24]	1
No time for themselves	[25]	1
Radiologists more likely to report symptoms of burnout	[27]	1
Scribes or physician partners can decrease symptoms of burnout	[46]	1
Seated position causes problems with back or wrist pain and posture	[30]	1
Time spent in EHR affects patient satisfaction	[39]	1

[a] EHR: electronic health record.

[b] Multiple occurrences observed in one study.

Medical Outcomes Identified With the EHR and Physician Burnout

Table 5 summarizes the medical outcomes observed: 3 themes and 4 individual observations were identified by the reviewers for a total of 10 occurrences in the literature. Of the 25 articles, 20 (80%) did not report medical outcomes. Back pain [30,38], physical fatigue [11,43], and cognitive weariness [11,43] were each mentioned 2 times out of 10 observations (60%). The other medical outcomes were eye strain, work stress, hand or wrist pain, and posture [29,30,38].

Table 5. Medical outcomes identified with the electronic health record (EHR) and physician burnout.

Medical outcome theme or observation	Reference(s)	Frequency, n
Back pain	[30,38]	2
Physical fatigue	[11,43]	2
Cognitive weariness	[11,43]	2
Eye strain	[38]	1
Work stress	[29]	1
Hand or wrist pain	[38]	1
Posture	[30]	1
None reported	[24-28,31-37,39-42,44-47]	20

Patient Satisfaction Impact of EHR

This section is not entirely logical. When we designed this study, we assumed we would find more experiments. We expected to find experiments with and without the presence of the EHR or experiments with control groups to objectively measure interventions to improve physician burnout incident to the EHR. The results of the study searches did not identify any true experiments. There were only 2 pre-post studies. The only experiments identified used training or scribes to help improve physician burnout. Table 6 identifies these as well as all mentions of patient satisfaction in the group of articles analyzed.

Although patients did not prefer a scribe in the room during an exam, their presence did not negatively affect patient satisfaction in a statistically significant manner [40,46]. Only 2 other articles mentioned patient satisfaction. One article mentioned that time in the EHR negatively affects patient satisfaction, and this negatively affects both symptoms of physician burnout and the doctor-patient relationship [24]. The other article identified the time of day the physician is in the EHR during clinic time has a greater effect on patient satisfaction than the amount of time spent with patients [39].

Table 6. Patient satisfaction impact of the electronic health record (EHR) and efforts to improve physician burnout.

Patient satisfaction theme or observation	Reference(s)	Frequency, n
Patient satisfaction not affected by scribe or physician partner in clinic during exam	[40,46]	2
EHR time in clinic negatively affects patient satisfaction	[24]	1
Time of day affects patient satisfaction more than time spent with patient	[39]	1
Patient dissatisfaction negatively affects physician burnout	[24]	1
Patient dissatisfaction negatively affects doctor-patient relationship	[24]	1
Not reported	[11,25-38,41-45,47]	21

Barriers Identified With the EHR and Physician Burnout

Table 7 summarizes the barriers incident to using the EHR to mitigate symptoms of physician burnout. The reviewers identified 8 themes and 8 individual observations, for a total of 56 occurrences in the literature; 2 articles did not identify barriers [24,45].

The theme of “EHR must undergo a redesign” occurred in 12 of 58 occurrences (21%) [11,30,32,35-38,43,44,47]. Researchers echoed their participants’ pleas to improve the design of the EHR; to reduce task repetition, screen clutter, number of clicks per task, and inefficient interfaces; improve the workflow; and reduce unnecessary searching and inefficient data entry. The inefficiencies take time away from patients and make the day longer for the provider, which impacts work-life balance. The inefficiencies lead to “excessive hours spent in the EHR, which exacerbate symptoms of physician burnout.” This theme occurred in 8 of 58 occurrences (14%) [25,26,28,30,34,39,40,44]. The administrative overhead associated with the EHR creates inefficiencies in the standard workflow of seeing patients. This theme occurred also occurred in 8 of 58 occurrences (14%) [31,33,35,38,43,44,47]. Examples of inefficiencies were excessive data entry, illogical workflow, high number of clicks per task, and multiple screens. These inefficiencies lead to excessive hours spent in the EHR, which adversely affects work-life balance and adds to daily frustration levels. This theme occurred in 6 of 58 occurrences (11%) [25,29-31,36,47]. To add to the inefficiencies, providers noted a level of frustration at the speed and reliability issues associated with the EHR [32,37,38,44]. Participants noted communication technologies and data-sharing processes that are cumbersome and counterproductive, unpredictable system response times, and lack of hardware and infrastructure to make the EHR faster and more reliable. On the topic of administrative time in the EHR, participants noted that administrative time in the EHR takes time away from the clinic and patients. This theme occurred 4 out of 58 occurrences (7%) [25,29,30,42]. Some of the inefficiencies highlighted by providers were that some patient information is not available due to lack of interoperability. This theme occurred in 3 of 58 occurrences (5%) [32,38,44]. This lack of availability creates data overload, which complicates data integration efforts. It often prevents linking to legacy systems, and it creates barriers with data sharing between organizations. Inefficiencies like number of clicks per process encumber efficient workflows. This theme also occurred in 3 of 58 occurrences (5%) [11,30,35]. As mentioned in the table for general results, 2 studies noted that EHR users felt a loss of autonomy [25,36]. Other observations only occurred once in the literature [27,36,40,41,44,46]. One study noted that the EHR does not coordinate care [27]. A study that used scribes or physician partners to enter data into the EHR during the exam noted that patients do not like this practice [40]. Another study that used scribes in the exam room noted the cost to the organization for this practice [40]. A study that used training to improve provider efficiency noted this training takes time away from the clinic [41]. One study noted a lack of support by the organization for EHR tools and efficiency [36]. Another study noted that the EHR does not have a standard vocabulary [44].

Table 7. Barriers to the electronic health record (EHR) and physician burnout.

Barrier theme or observation	Reference(s)	Frequency, n
EHR must undergo redesign	[11,30,32,35-38,43,44,47][a]	12
Excessive hours spent in the EHR exacerbate symptoms of physician burnout	[25,26,28,30,34,39,40,44]	8
The administrative overhead of the EHR is not conducive to efficient workflow	[31,33,35,38,43,44,47][a]	8
Excessive hours spent in the EHR affect work-life balance	[25,29-31,36,47]	6
EHR reliability and speed	[32,37,38,44]	4
Administrative time in the EHR takes time away from clinic and patients	[25,29,30,42]	4
Some patient information is not available due to lack of interoperability	[32,38,44]	3
High number of clicks per process is inefficient	[11,30,35]	3
EHR creates a loss of autonomy	[25,36]	2
EHR does not help coordinate care	[27]	1
Some patients do not like scribes or physician partners in the exam room	[40]	1
EHR training takes time away from clinic	[41]	1
Scribes or physician partners cost more money	[46]	1
Lack of supporting practice environment	[36]	1
No standardized vocabulary	[44]	1
EHR investment inhibits short-term profit	[44]	1
Not reported	[24,45]	2

[a] Multiple occurrences observed in one study.

Facilitators Identified With the EHR and Physician Burnout

Table 8 summarizes the facilitators incident to using the EHR to mitigate symptoms of physician burnout: 6 themes and 12 individual observations were identified by the reviewers for a total of 27 occurrences in the literature. Facilitators were not identified in 11 articles [11,26,27,29,30,34,36,37,42,43,47].

The theme of “presence of a scribe or physician partner relieves symptoms of burnout” occurred in 3 of 27 occurrences (11%) [38,40,46]. Although this practice incurs a cost to the organization, the use of either a scribe or a physician partner to enter data into the EHR during the encounter enables the physician to focus on the patient rather than negotiating the EHR, and the scribe’s time entering data into the EHR can easily be offset by a savings in provider administrative time later. This practice decreases appointment time and enables the provider to work a standard day instead of spending so much time after clinic hours catching up with the administrative side of the day’s encounters. Geriatrics practices that leveraged scribes in this manner experienced an average of 4 minutes less per encounter for an average of 48 minutes per 4-hour session. When the administrative time after the encounter was accounted for, the savings was 88 minutes per 4-hour session. Internal medicine experienced a 2 minute per patient savings for a total of 92 minutes per 4-hour session, counting administrative time saved. Another set of studies found training would increase physician efficiency in the EHR. This theme also occurred in 3 of 27 occurrences (11%) [32,38,41]. Training decreased their frustration with the system and shortened their work day. This practice improved work-life balance and decreased symptoms of burnout. A similar theme found localized workflow redesign relieves symptoms of burnout. This theme also occurred in 3 of 27 occurrences (11%) [31,39,40]. The most common workflow redesign was preparation for encounters, which also increased patient satisfaction. Similar to training and workflow redesign, it was discovered that customized templates also increased efficiencies. This theme occurred in 2 of 27 occurrences (7%) [31,33]. This practice also increased accuracy and completeness of documentation [44], which increases quality of care. The theme “small group sessions” also occurred in 2 of 27 occurrences (7%) [28]. This theme focused on development of young providers. This development focused on emotional and professional development. These sessions also helped establish rapport among providers. Two studies highlighted how the EHR increases safety [35,44]. The readability of orders and intelligence built into the system to alert when doses are outside of a standard range increase safety and decrease admission decision time and length of stay [35]. The other observations were only identified once [11,24,25,28-32,34-38,41,43-45,47]. One study mentioned that, although improving the EHR will help with the burden of care, it also is important to schedule regular exercise to help providers cope with the stress of care [24]. One study highlighted how a focus on the mission of care, rather than the administration of the encounter, decreases symptoms of burnout [25]. One study highlighted the ability of the EHR to rapidly access patient data, which saves the provider time searching through a paper record [44]. Based on the conclusions of other studies, it is the process of finding this information that is key. One study highlighted the importance of provider experience (years as a provider and years in the EHR) to appreciate the usefulness of this tool [45]. Institutional endorsement of the EHR is also important [41]. This is important because it increases user acceptance of the system. A study in China found that providers who take their annual vacation tended to report fewer symptoms of burnout [24]. A study in Tehran identified the capability for the EHR to enable computerized analysis; however, this capability should be found easily rather than taking time to hunt for the feature [44]. Through training programs and customization, the EHR can increase the speed of delivery of care [44].

Table 8. Facilitators to the electronic health record (EHR) and physician burnout.

Facilitator theme or observation	Reference(s)	Frequency, n
Presence of scribe or physician partner relieves symptoms of burnout	[38,40,46]	3
Training increases efficiency	[32,38,41]	3
Localized workflow redesign relieves symptoms of burnout	[31,39,40]	3
Local customization (eg, templates, menus) improves efficiency	[31,33]	2
Small group sessions	[28][a]	2
EHR increases safety	[35,44]	2
Exercise relieves symptoms of burnout	[24]	1
Focus on mission of care relieves symptoms of burnout	[25]	1
EHR enables rapid access to information	[44]	1
Level of physician experience with EHR increases perceived usefulness of EHR	[45]	1
Institutional endorsement of EHR increases user acceptance of EHR	[41]	1
Annual vacation relieves symptoms of burnout	[24]	1
EHR decreases admission decision time	[35]	1
EHR decreases length of stay	[35]	1
EHR decreases duplicate testing	[44]	1
EHR increases speed of delivery of care	[44]	1
EHR increases accuracy of documentation	[44]	1
EHR enables computerized analysis and interpretation of data	[44]	1
Not reported	[11,26,27,29,30,34,36,37,42,43,47]	11

[a] Multiple occurrences observed in one study.

Discussion

Summary of Evidence

The preponderance of evidence supports the claim that the EHR needs an overall redesign to increase efficiency of providers. However, very few empirical studies published in the studied years could be found to measure the deficiencies. One study measured pupillometry, one measured cognitive load, and another measured cognitive weariness [11,31,43], but claims of inefficiencies were largely the result of surveys. Clearly, providers spend a great deal of time in the EHR managing the administrative necessities of the system; however, studies with training and local customization of templates and workflow greatly improved efficiencies and decreased symptoms of burnout [33,41]. The creative use of scribes and physician partners to relieve providers of some of the real-time documentation burden showed statistically significant improvement in burnout symptoms, but they come at a price of an increased cost to employ them and a slight decrease in patient satisfaction (not statistically significant) [40,46].

From the practitioners' points of view, they wanted to know what factors remain in their sphere of influence to assuage the effects of physician burnout. Factors associated with the EHR cited in relation to physician burnout were usability, workflow, and documentation time [8-13]. Workflow can be redesigned and customized to the user, and documentation can be performed with the use of scribes or physician partners [40,46]. The remaining factor was usability, which can only be managed in a large redesign effort. Practitioners should focus on robust and ongoing training, customization of local templates, and workflow redesign. They should weigh the economics of scribes or physician partners against the decrease in symptoms of burnout. If increasing the prevalence of symptoms of burnout increases physician turnover [2-4], certainly reducing symptoms of burnout will decrease turnover. Some best practices identified in the literature to reduce burnout were taking annual vacation [24], focusing the organization on the mission of care rather than the administration of it [25], scheduling small group sessions to help emotionally equip young providers [28], institutional endorsement of the EHR [41], and the use of regular exercise to manage stress [24]. However, these techniques do not improve the usability of the EHR, but they were identified as practices to decrease the symptoms of burnout.

Future research should empirically measure the redesign factor of usability. What aspects of usability can be improved? Are navigation issues in the EHR specific to each vendor? Are there best practices from one vendor that can be applied to other vendors without infringing upon proprietary secrets? What mental processes in the physician workflow can be directly mapped into the menus of the EHR?

Limitations

A limitation to this review is the selection of 5 years. It was originally assumed there would be a plethora of studies on the topic of physician burnout incident to the EHR, but we found a dearth of empirical studies on the topic. There were plenty of opinion articles but very little empirical evidence. This review could have been improved by expanding the time period to 10 years, but technology advances rapidly, and reconciling the observations over a decade might have been counterproductive.

Conclusion

Although physician burnout incident to the EHR has been documented, several best practices exist to overcome 2 of the 3 factors associated with the EHR: workload and documentation time. The effect of these factors can be assuaged through workload redesign, customized templates, training, and the use of physician partners or scribes in the exam room. The third factor of usability can only be overcome through a redesign of the EHR. Practitioners should focus on the former factors, which are within their sphere of control. EHR vendors should organize empirical studies to identify targeted areas of improvement to optimize the usability of the system.

Authors' Contributions

All authors contributed equally to the preparation of this manuscript. CSK served as the lead editor and supervisor. All authors contributed to the conceptualization, methodology, study collection, study analysis, and writing.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Observation-to-theme conversion for results and medical outcomes.
[DOCX File , 24 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Observation-to-theme conversion for patient satisfaction, barriers, and facilitators.
[DOCX File , 27 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Other observations incident to review.
[DOCX File , 26 KB-Multimedia Appendix 3]

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Abbreviations

EHR: electronic health record
JHNEBP: Johns Hopkins Nursing tool for Evidence Based Practice
PICOS: participants, intervention, comparison of results to control, outcome (medical), study design
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta Analyses

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Corrigenda and Addenda

Correction: Gender-Specific Impact of Self-Monitoring and Social Norm Information on Walking Behavior Among Chinese College Students Assessed Using WeChat: Longitudinal Tracking Study

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In “Gender-Specific Impact of Self-Monitoring and Social Norm Information on Walking Behavior Among Chinese College Students Assessed Using WeChat: Longitudinal Tracking Study” (J Med Internet Res 2021;23(12):e29167), one error was noted.

The foundation number of the National Natural Science Foundation of China was mistaken. In the originally published paper, under “Acknowledgments”, the foundation information was listed as follows:

> *This research was supported by Beijing Natural Science Foundation (BNSF, 9172019), the National Natural Science Foundation of China (NSFC, 7170111)…*

This has been corrected to:

> *This research was supported by Beijing Natural Science Foundation (BNSF, 9172019), the National Natural Science Foundation of China (NSFC, 71471171)…*

The correction will appear in the online version of the paper on the JMIR Publications website on March 31, 2022, together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.

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Original Paper

Modeling Access Across the Digital Divide for Intersectional Groups Seeking Web-Based Health Information: National Survey

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Abstract

Background: The digital divide refers to technological disparities based on demographic characteristics (eg, race and ethnicity). Lack of physical access to the internet inhibits online health information seeking (OHIS) and exacerbates health disparities. Research on the digital divide examines where and how people access the internet, whereas research on OHIS investigates how intersectional identities influence OHIS. We combine these perspectives to explicate how unique context–device access pairings operate differently across intersectional identities—particularly racial and ethnic groups—in the domain of OHIS.

Objective: This study aims to examine how different types of internet access relate to OHIS for different racial and ethnic groups. We investigate relationships among predisposing characteristics (ie, age, sex, education, and income), internet access (home computer, public computer, work computer, and mobile), health needs, and OHIS.

Methods: Analysis was conducted using data from the 2019 Health Information National Trends Survey. Our theoretical model of OHIS explicates the roles of internet access and health needs for racial and ethnic minority groups' OHIS. Participant responses were analyzed using structural equation modeling. Three separate group structural equation modeling models were specified based on Black, Latine, and White self-categorizations.

Results: Overall, predisposing characteristics (ie, age, sex, education, and income) were associated with internet access, health needs, and OHIS; internet access was associated with OHIS; and health needs were associated with OHIS. Home computer and mobile access were most consistently associated with OHIS. Several notable linkages between predisposing characteristics and internet access differed for Black and Latine individuals. Older racial and ethnic minorities tended to access the internet on home and public computers less frequently; home computer access was a stronger predictor of OHIS for White individuals, and mobile access was a stronger predictor of OHIS for non-White individuals.

Conclusions: Our findings necessitate a deeper unpacking of how physical internet access, the foundational and multifaceted level of the digital divide, affects specific racial and ethnic groups and their OHIS. We not only find support for prior work on the digital divide but also surface new insights, including distinct impacts of context–device access pairings for OHIS and several relationships that differ between racial and ethnic groups. As such, we propose interventions with an intersectional approach to access to ameliorate the impact of the digital divide.

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KEYWORDS

Black; African American; first-level digital divide; health disparities; home computer; internet access; intersectionality; Latino; Latine; Hispanic; mobile; online health information seeking; public computer; structural equation modeling; work computer; mobile phone

Introduction

Background

The benefits of eHealth, or the use of the internet to facilitate health behaviors (eg, online health information seeking [OHIS]) [1], are counteracted by the digital divide. The digital divide was first used to emphasize that racial and ethnic minorities and individuals of lower socioeconomic status did not adopt new technologies to the same extent as White individuals or those of higher socioeconomic status [2]. Obtaining physical access to new technologies and, thus, web-based health information remains a paramount obstacle, particularly for Black or African American (hereafter *Black*) and Latino or Latine or Hispanic (hereafter *Latine*) individuals [3]. This is problematic, as racial and ethnic minorities are more likely to live in areas of concentrated poverty that coincide with limited health care access [4-6]. Systematic inequalities in internet access and health care for racial and ethnic minorities reinforce one another, such that those who would potentially benefit the most from OHIS are often unable to access it.

However, internet access (hereafter *access*) is not monolithic and comprises the use of different devices (eg, smartphone or computer) in various contexts (eg, at home or in public) [7]. Although mobile devices are increasingly more accessible than computers, they can be harder to navigate because of their smaller interfaces [8]. Publicly accessible devices may extend access to those who do not own such devices; however, they often entail irregular availability, which can compound poor health outcomes for minority groups [9]. Recognizing the multidimensionality of access [7] is key to understanding how access via a myriad of devices in various contexts differentially influences OHIS. Furthermore, positioning the digital divide as a health disparity is imperative to developing effective interventions [10]. As such, this study uses data from the 2019 Health Information National Trends Survey (HINTS), also known as HINTS 5, Cycle 3 [11], to bolster theoretical models of OHIS with a nuanced conceptualization of access. We also advance the perspective that the digital divide is a health disparity by applying an intersectional focus to examine how relationships with access and OHIS differ across racial and ethnic groups.

Theoretical Framework: OHIS Model

The internet has become one of the most common ways of accessing health information [12]. Health information seeking refers to those actions that individuals use to search for information about their health, risks, illnesses, and health-protective behaviors [13]. When conducted on the web (ie, OHIS), seeking out health information can positively affect health outcomes by improving the quality, expense, and efficiency of health care [10]. In addition, OHIS has demonstrated that individuals are more willing to comply with their health decisions [14]. However, those with limited access to OHIS may not experience its benefits. Health disparities faced by low-income and minority communities may be magnified by the digital divide [3,15]. However, when underserved communities are provided the means to participate in OHIS, they gain more health knowledge [16]. Thus, understanding how the digital divide affects OHIS is imperative to enhance the impact of interventions aimed at increasing access among these communities.

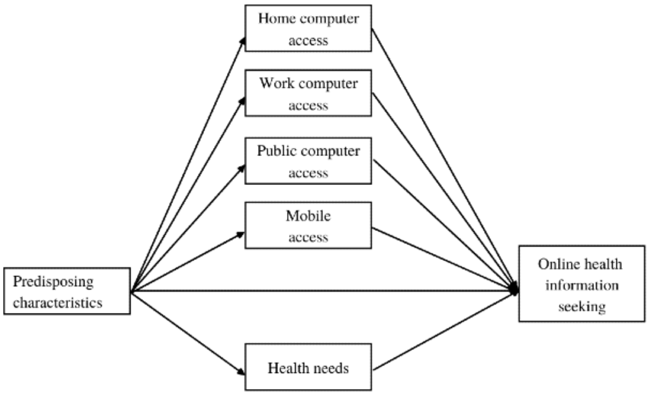
The digital divide first highlighted that certain groups of people (eg, racial and ethnic minorities and individuals of low socioeconomic status) lagged in adopting new technologies. This gradual diffusion represents the first-level factor of the digital divide, which has been situated in issues related to ownership, availability, and affordability of the technology [17]. Recent studies have identified additional second-level factors that may also impede technological adoption (eg, skills) [15,18]. Although the focus of OHIS has shifted away from access as some suggest that it has become democratized [19], we argue that it has not been democratized across devices and contexts of use as the lack of physical access remains an obstacle for marginalized groups [3,20]. Moreover, access is heterogeneous, as people can access the internet on multiple devices and at various places [7,21]. Even in populations with saturated home access, disparities can persist for other points of access and the cost to maintain them [7]. Thus, a nuanced conceptualization of access can respond to criticism that the digital divide suggests a simple binary between those who have access and those who do not [22].

Notably, some scholars have applied this multifaceted conceptualization of access to predict the likelihood of web-based activities (including OHIS). Hassani [23] found that people engaged in more OHIS as they increased their points of access (eg, home and work vs only home). Similarly, Mossberger et al [24] found that home computer access is vital to reap the benefits of web-based activities such as OHIS. Although the authors highlight the potential for mobile devices to attenuate the impacts of the digital divide, mobile access alone did little to minimize these impacts in low-income areas. Reisdorf et al [21] also suggest that simply increasing access does not lead to equal results across different contexts. However, these studies investigated OHIS as one of many web-based activities; as such, they were not grounded in theoretical models of OHIS. Moreover, studies that focused on OHIS [25,26] did not examine the impact of specific devices or contexts of use; instead, they examined the number of access points overall.

Furthermore, scholarship in this area has seldom disaggregated these connections by racial and ethnic groups. Studies that include race and ethnicity self-categorization as predictors of web-based activities [21] can unearth patterns of devices and contexts of use, such as Black (vs non-Black) individuals using mobile devices more often [24]. However, disparities among intersectional identities may still be overlooked, such as how age and race may interact to affect technology use [27]. Therefore, it is unclear where disparities in OHIS exist among intersectional identities.

Previous OHIS theorizing [14,28] highlights several factors that influence health-seeking behaviors. As such, our model includes predisposing characteristics (age, sex, education, and income), access (home computer, work computer, public computer, and mobile), health needs, and OHIS (Figure 1). Our model also focuses on the foundational level of the digital divide (ie, access). As such, our nuanced conceptualization of access helps to fill the empirical gap in OHIS research on the first-level digital divide [29]. Thus, this study offers 2 primary contributions. First, we apply a multidimensional conceptualization of access along dimensions of the context of use (eg, at home vs in public) and device type (eg, smartphone vs computer) to theoretical models of OHIS. Second, we disaggregate our models by race and ethnicity to examine how they manifest differently across racial and ethnic groups. We explicate the relationships between predisposing characteristics, access, and health needs in our model.

Figure 1. Initial online health information seeking model.



Antecedents of OHIS

Predisposing Characteristics

First, we posit associations between OHIS and predisposing characteristics. Younger individuals are more likely than older individuals to be able to navigate web-based platforms to seek out web-based health information [30,31]. Females are often expected to seek out health information because of their social roles as family caregivers [23,32]. Furthermore, education and income are generally positively associated with OHIS [33,34], as individuals with low education or income are inhibited from participating in OHIS because of low literacy [5]. Thus, we propose the following hypothesis:

> *Hypothesis 1 (H1): Demographic variables—age, sex, education, and income—will be associated with OHIS.*

Internet Access

Expanding our understanding of OHIS, we extend prior conceptualizations of access [7,21,23] and examine access by considering context and device. *Context* refers to the physical environment in which users engage in OHIS, and *device* refers to the physical technology used to engage in OHIS. We focus on four of the most common context–device pairings: home computer, work computer, public computer, and mobile (which can be used across contexts). People seek health information on the web on several devices and at several places [23]. Owing to the extent that computers and mobile devices entail different technological constraints [8], and context structures media use [35], it is crucial to consider how different context–device pairings relate to OHIS.

First, *home computer* access involves computer use at home. It facilitates the availability of OHIS in a private setting where people spend most of their time [23]. However, because of the large cost of computers, ownership trends reflect the digital divide: White individuals are more likely to own home computers than Black and Latine individuals [3,7].

Second, *work computer* access involves computer use in the workplace. Individuals may not own these devices and likely would not pay for access, making it less expensive than home-computer access. However, work computer access requires employment that involves or entails access to computers [36]. The workplace is also a less frequented and private setting than the home [23,37].

Third, *public computer* access involves computer use in public facilities [3]. Such access can be inexpensive (if not free) and occurs in typically accessible public places, enabling access for individuals who cannot afford devices with internet access [21]. However, public computer access is contingent on a variety of factors, including the hours, locations, and resources of public facilities, which restrict the availability of such services [5].

Finally, *mobile* access involves the use of mobile devices (typically smartphones) in a variety of contexts. Mobile devices allow users to connect to public Wi-Fi and data networks, enabling OHIS in a variety of public, private, and (uniquely) mobile places (eg, on the bus) [38]. However, the small size of the mobile interface may restrict more intensive tasks [8], such as OHIS.

Overall, we expect that access will be related to predisposing characteristics and OHIS. Older individuals are less likely to access the internet [7,39], and males tend to access the internet more than females [18]. Education and income are positively correlated with access [40,41]. These differences may be linked to literacy and resources, allowing certain groups to maintain [7] and navigate access [10]. Furthermore, OHIS, by definition, is contingent on internet access [42,43]. With these considerations in mind, we propose the following hypotheses:

> *Hypothesis 2 (H2): Predisposing characteristics (ie, age, sex, education, and income) will be associated with access.*
>
> *Hypothesis 3 (H3): Access will be positively associated with OHIS.*

However, it is unclear how our nuanced conceptualization of access (ie, 4 discrete context–device pairings) may differentially affect OHIS. Thus, we pose the following research question (RQ):

> *RQ1: Which access pairings have the most consistent associations with OHIS across racial and ethnic groups?*

Health Need

We conceptualize health needs as the extent to which individuals perceive that they require current or chronic medical attention. The likelihood that one may endure chronic illness is linked to group identities along the lines of age, gender, education level, and income [44]. When avoidable health differences in treatment, access to treatment, mortality, and diseases correlate with group identity, a health disparity occurs. Older individuals report greater health needs than younger individuals [45]. Although health disparities among males and females differ based on the illness, males may be more confident in their ability to maintain their health and report lower health needs [46]. Braveman at al [44] highlight that education level and income are important health determinants that predict health needs. Finally, individuals who perceive their health to be poor often demonstrate motivation to find health information on the web [28,33]. Thus, we propose the following hypotheses:

> *Hypothesis 4 (H4): Predisposing characteristics (ie, age, sex, education, and income) will be associated with health needs.*
>
> *Hypothesis 5 (H5): Health needs will be positively associated with OHIS.*

Race and Ethnicity

This study holds that existing racial and ethnic disparities exacerbate the impact of the digital divide on health disparities [22]. As such, we investigate how these inequities may affect OHIS. We explore whether hypotheses linking predisposing characteristics with OHIS (H1), access (H2), and health need (H4) differ across racial and ethnic groups. First, race and ethnicity may interact with age, sex, education, and income to predict OHIS as unique disparities in health and technology have been observed within groups that have intersecting predisposing characteristics and racial and ethnic group identities [41]. Next, race and ethnicity may interact with access to predict OHIS. Fang et al [47] provide illustrative insights, highlighting that age was a strong predictor for access but that this effect was exaggerated for some racial and ethnic minorities. Finally, race and ethnicity may interact with health needs to predict OHIS. For example, Black and Latine individuals are more likely to live in low-income areas [4,6], which is associated with exacerbated health needs [48]. As such, this study foregrounds the persistent racial and ethnic disparities in the United States to understand access and health needs from an intersectionality perspective [49].

In addition, race and ethnicity may interact with access (H3) and health need (H5) to influence OHIS. Regarding access, even when Black and Latine individuals access the internet at similar rates as White individuals, such access is often marked by greater insecurity [39]. Similarly, even with similar levels of health needs, racial and ethnic minorities may avoid seeking out web-based health information if they possess lower health and technology literacy [50,51]. Overall, our study uses previously tested models of OHIS [14,28,50-52] and seeks to extend previous theories by applying a multidimensional conceptualization of access and testing the fit of the model across racial and ethnic groups. These intersectional considerations, heightened by higher rates of internet insecurity [39] and greater health needs [4,6] because of systemic inequality, beg the following question:

> *RQ2: How will the relationships between predisposing characteristics, access, health needs, and OHIS differ across different racial and ethnic groups?*

Methods

Sample

To test our model, we used data from the 2019 HINTS, also known as HINTS 5, Cycle 3 [11]. HINTS is an annual, nationally representative survey that asks participants about their engagement with health information. Data were collected between January 2019 and April 2019. A total of 5438 individuals responded to the survey. However, of the 5438 responses, 191 (3.51%) responses were deemed ineligible by HINTS because of partial completion, leaving 5247 (96.49%) individuals. Participants who did not complete the self-categorization variables for each model were excluded (Black and White: 420/5247, 8%; Latine: 487/5247, 9.28%). In addition, participants who did not complete all model variables were excluded (Black and White: 446/5247, 8.12%; Latine: 408/5247, 7.78%). Taken together, the sample size for the final models' group was 4381 (based on Black and White self-categorization) or 4352 (based on Latine self-categorization). Owing to these different sample sizes, we report demographics and correlations for the 5247 individuals deemed eligible by HINTS. Only the variables presented in the *Measures* section were used for the purposes of this study; all other variables were excluded. Data are available in Multimedia Appendix 1. More information regarding the methodology can be found in the 2019 HINTS methodology report [53].

Ethical Considerations

An institutional review board approval was not requested because the analysis for this study was conducted using secondary data. All HINTS data sets, including the one used for analysis in this study, have been approved through expedited review by the Westat Institutional Review Board, and subsequently deemed exempt by the U.S. National Institutes of Health Office of Human Subjects Research Protections [54].

Participant Demographics

Demographic data were used to assess predisposing factors. Participants were aged 56.58 (SD 16.88) years on average. Approximately 56.62% (2971/5247) of the participants self-categorized as female, and 41.16% (2160/5247) self-categorized as male. Race and ethnicity were operationalized in comparison with those who did not self-categorize as the respective racial or ethnic group as individuals who self-categorize ethnically as Latine may still self-categorize racially as White or Black. Of the 5247 individual, 3727 (71.03%) self-categorized as White, and 1100

(20.96%) did not; 847 (16.14%) self-categorized as Black and 3980 (75.85%) did not; and 716 (13.64%) participants self-categorized as Latine and 4044 (77.07%) did not. The remaining individuals did not disclose their sex, race, or ethnicity. Participants' level of education was measured on a 5-point scale from *less than high school* (score=1) to *postbaccalaureate degree* (score=5), and participants' annual income was measured on a 7-point scale from *US$0* to *US $19,999* (score=1) to ≥ *US $200,000* (score=7). See Table 1 for a summary of participant demographics.

Table 1. Participant demographics.

Demographics	OHIS[a,b]	
	No, n (%)	Yes, n (%)
Age (years; n=5090)		
18-24	20 (0.39)	132 (2.59)
25-35	62 (1.22)	535 (10.51)
36-44	66 (1.30)	492 (9.67)
45-54	172 (3.38)	627 (12.32)
55-64	316 (6.21)	827 (16.25)
≥65	790 (15.52)	1051 (20.65)
Sex (n=5110)		
Male	652 (12.76)	1501 (29.37)
Female	798 (15.62)	2159 (42.25)
White (n=4805)		
No	344 (7.16)	746 (15.53)
Yes	977 (20.33)	2738 (56.98)
Black (n=4805)		
No	1034 (21.52)	2934 (61.06)
Yes	287 (5.97)	550 (11.45)
Latine (n=4745)		
No	1015 (21.39)	3016 (63.56)
Yes	237 (4.99)	477 (11.45)
Education (n=5087)		
Less than high school	200 (3.93)	108 (2.12)
High school graduate	445 (8.75)	448 (8.81)
Some college	441 (8.67)	1093 (21.49)
Received a bachelor's degree	230 (4.52)	1130 (22.21)
Received a postbaccalaureate degree	117 (2.30)	875 (17.2)
Income (US $; n=4637)		
0-19,999	411 (8.86)	441 (9.51)
20,000-34,999	213 (4.59)	380 (8.19)
35,000-49,999	173 (3.73)	433 (9.34)
50,000-74,999	182 (3.92)	639 (13.78)
75,000-99,999	116 (2.5)	461 (9.94)
100,000-199,999	106 (2.29)	764 (16.48)
>200,000	36 (0.78)	282 (6.08)

[a] OHIS: online health information seeking.

[b] Percentages reflect those who responded to the OHIS item.

Measures

Overview

Correlations between all variables are displayed in Tables 2-4.

Table 2. Descriptive statistics and correlations between study variables (age, sex, and White).

Predictors	Values, mean (SD)	Age		Sex		White	
		r	*P* value	*r*	*P* value	*r*	*P* value
Age (years)	56.58 (16.88)	1	—[a]	—	—	—	—
Sex[b]	0.42 (0.49)	0.04	.01	1	—	—	—
White[c]	0.77 (0.42)	0.04	.005	0.07	<.001	1	—
Black[d]	0.18 (0.38)	–0.01	.64	–0.09	<.001	–0.79	<.001
Latine[e]	0.15 (0.36)	–0.10	<.001	0.01	.68	0.10	<.001
Education	3.36 (1.16)	–0.17	<.001	0.03	.07	0.08	<.001
Income	3.76 (1.93)	–0.17	<.001	0.12	<.001	0.14	<.001
Home computer	1.15 (0.84)	–0.17	<.001	0.10	<.001	0.15	<.001
Work computer	0.70 (0.90)	–0.45	<.001	0.03	.06	0.06	<.001
Public computer	0.16 (0.39)	–0.20	<.001	0.01	.69	–0.07	<.001
Mobile	1.27 (0.85)	–0.51	<.001	–0.04	.004	0.08	<.001
Health needs	2.58 (0.94)	0.16	<.001	–0.02	.29	–0.09	<.001
Online health information seeking (OHIS)	0.71 (0.45)	–0.31	<.001	–0.04	.01	0.05	.001

[a] Not applicable.

[b] Coded as female=0 and male=1.

[c] Coded as non-White=0 and White=1.

[d] Coded as non-Black=0 and Black=1.

[e] Coded as non-Latine=0 and Latine=1.

Table 3. Descriptive statistics and correlations between study variables (Black, Latine, education, and income).

Predictors	Black		Latine		Education		Income	
	r	*P* value	*r*	*P* value	*r*	*P* value	*r*	*P* value
Age (years)	—[a]	—	—	—	—	—	—	—
Sex[b]	—	—	—	—	—	—	—	—
White[c]	—	—	—	—	—	—	—	—
Black[d]	1	—	—	—	—	—	—	—
Latine[e]	–0.10	<.001	1	—	—	—	—	—
Education	–0.12	<.001	–0.17	<.001	1	—	—	—
Income	–0.20	<.001	–0.12	<.001	0.47	<.001	1	—
Home computer	–0.15	<.001	–0.16	<.001	0.41	<.001	0.38	<.001
Work computer	–0.09	<.001	–0.08	<.001	0.40	<.001	0.46	<.001
Public computer	0.07	<.001	–0.01	.76	0.11	<.001	–0.03	.03
Mobile	–0.08	<.001	–0.04	.005	0.33	<.001	0.37	<.001
Health need	0.10	<.001	0.07	<.001	–0.25	<.001	–0.31	<.001
Online health information seeking (OHIS)	–0.07	<.001	–0.07	<.001	0.34	<.001	0.28	<.001

[a] Not applicable.

[b] Coded as female=0 and male=1.

[c] Coded as non-White=0 and White=1.

[d] Coded as non-Black=0 and Black=1.

[e] Coded as non-Latine=0 and Latine=1.

Table 4. Descriptive statistics and correlations between study variables (home computer, work computer, public computer, mobile, and health need).

Predictors	Home computer		Work computer		Public computer		Mobile		Health need	
	r	*P* value	*r*	*P* value	*r*	*P* value	*r*	*P* value	*r*	*P* value
Age (years)	—[a]	—	—	—	—	—	—	—	—	—
Sex[b]	—	—	—	—	—	—	—	—	—	—
White[c]	—	—	—	—	—	—	—	—	—	—
Black[d]	—	—	—	—	—	—	—	—	—	—
Latine[e]	—	—	—	—	—	—	—	—	—	—
Education	—	—	—	—	—	—	—	—	—	—
Income	—	—	—	—	—	—	—	—	—	—
Home computer	1	—	—	—	—	—	—	—	—	—
Work computer	0.38	<.001	1	—	—	—	—	—	—	—
Public computer	0.15	<.001	0.13	<.001	1	—	—	—	—	—
Mobile	0.48	<.001	0.48	<.001	0.21	<.001	1	—	—	—
Health need	–0.18	<.001	–0.23	<.001	–0.02	.14	–0.20	<.001	1	—
Online health information seeking (OHIS)	0.41	<.001	0.30	<.001	0.14	<.001	0.46	<.001	–0.10	<.001

[a] Not applicable.

[b] Coded as female=0 and male=1.

[c] Coded as non-White=0 and White=1.

[d] Coded as non-Black=0 and Black=1.

[e] Coded as non-Latine=0 and Latine=1.

Internet Access

Participants reported how often they access the internet on a computer at home, at work, in a public place, and on a mobile device. A single item was used to measure each mode of access. Items were measured on 3-point scales, including *not applicable or never* (score=0), *sometimes* (score=1), and *daily* (score=2). There were varied responses for home computer (mean 1.14, SD 0.84), work computer (mean 0.70, SD 0.90), public computer (mean 0.16, SD 0.39), and mobile (mean 1.27, SD 0.85) access.

Health Need

Health needs were operationalized as perceived general health [14]. Thus, it was measured with a single item: “In general, how would you say your health is?” The item was measured on a 5-point scale from *excellent* (score=1) to *poor* (score=5; mean 2.58, SD 0.94). As measured, greater values represent greater health needs or poorer general health.

OHIS Measure

Participants reported using a single item, whether they used a computer, smartphone, or other electronic means to look for health or medical information for themselves in the past 12 months. Responses were *no* (score=0) or *yes* (score=1; mean 0.71, SD 0.45).

Statistical Analysis

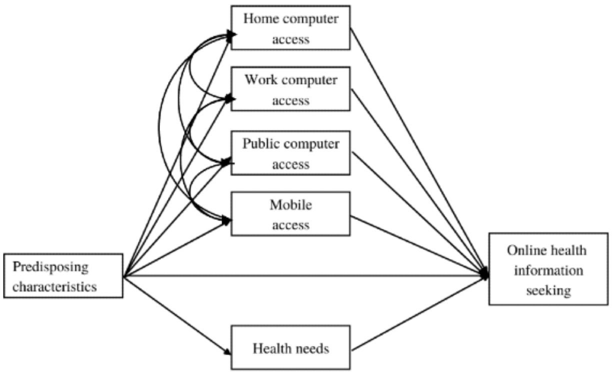
The initial demographic data were cleaned and analyzed using SPSS Statistics (version 27, IBM Corporation; Multimedia Appendix 1). Three group structural equation modeling models were specified based on the Black, Latine, and White self-categorization using Mplus 8.4 (Muthen and Muthén) [55]. Owing to the dichotomous outcome, diagonally weighted least squares mean and variance adjusted estimators were used instead of maximum likelihood to estimate the models, and odds ratios (ORs; vs standardized coefficients) were used to interpret relationships with OHIS. These models evaluated relationships between predisposing characteristics, access, health needs, and OHIS (H1-H5) and determined the access pairings most predictive of OHIS (RQ1). To test differences across racial and ethnic groups (RQ2), we constrained individual paths and compared each model with its respective baseline model, using chi-square tests for difference testing to account for the diagonally weighted least squares mean and variance estimation method.

Results

Model Fit

Our proposed models grouped by Black, Latin, and White self-categorization displayed poor fit statistics [56]. Modification indices suggested the addition of correlations between all the access variables. Individuals who partake in OHIS are likely to do so in multiple ways [23,57]—thus, these correlations were incorporated into the models (Figure 2). The resulting models yielded appropriate fit statistics [56] for all 3 models, grouped by Black (root mean square error of approximation [RMSEA]=0.026; comparative fit index [CFI]=0.997; standardized root mean square residual [SRMR]=0.008), Latine (RMSEA=0.021; CFI=0.998; SRMR=0.007), and White (RMSEA=0.026; CFI=0.997; SRMR=0.007) self-categorization.

Figure 2. Final online health information seeking model.



Theoretical Model

First, we examined whether predisposing characteristics were associated with OHIS (H1). Age was negatively associated with OHIS, and education was positively associated with OHIS across all models and groups. Income was positively associated with OHIS for individuals who self-categorized as White (OR 1.122, 95% CI 1.048-1.202; *P*<.001), non-White (OR 1.121, 95% CI 0.989-1.271; *P*=.02), non-Black (OR 1.124, 95% CI 1.052-1.201; *P*<.001), and non-Latine (OR 1.123, 95% CI 1.051-1.200; *P*<.001). Sex was negatively associated with OHIS, such that White (OR 0.572, 95% CI 0.513-0.638; *P*<.001), non-Black (OR 0.591, 95% CI 0.530-0.660; *P*<.001), Latine (OR 0.601, 95% CI 0.474-0.762; *P*=.009), and non-Latine (OR 0.656, 95% CI 0.581-0.741; *P*<.001) females were more likely to engage in OHIS. These findings lent partial support for H1.

Next, we investigated whether predisposing characteristics were associated with access (H2) and whether access was associated with OHIS (H3). Age was negatively associated with all forms of access for all the models and groups. Education was positively associated with all forms of access for all models and groups, except public computer access for Latine individuals (β=.087; *P*=.10). Income was positively associated with home computer access, work computer access, and mobile access—but negatively associated with public computer access—for all models and groups. Sex was negatively associated with mobile access for all models and groups and negatively associated with work computer access for Black individuals (β=−.097; *P*=.003), such that females who self-categorized with these groups accessed the internet more frequently than males within these context–device pairings. However, sex was positively associated with home computer access for individuals who self-categorized as White (β=.071; *P*<.001), non-Black (β=.074; *P*<.001), and non-Latine (β=.063; *P*<.001) as well as public computer access for individuals who self-categorized as non-Black (β=.035; *P*=.04) and non-Latine (β=.033; *P*=.048), such that males who self-categorized with these groups accessed the internet more frequently than females. This provided partial support for H2.

Turning to OHIS, mobile and home access were positively associated with OHIS across all models and groups. Public computer access was positively associated with OHIS for non-White (OR 1.307, 95% CI 0.706-2.418; *P*=.04) individuals. Finally, work computer access was not associated with OHIS in any model and for any group. This provided partial support for H3. Regarding RQ1, mobile and home computer access were associated with OHIS more consistently across groups than public computer access and work computer access.

Then, we examined whether predisposing characteristics were associated with health needs (H4) and whether health needs were associated with OHIS (H5). Age was positively associated with health needs across all models and groups. Education and income were negatively associated with health needs across all models and groups, except for the relationship between education and health needs for non-White (β=−.061; *P*=.08) and Black (β=−.072; *P*=.06) individuals. Sex was not associated with health needs for any group. This provided partial support for H4. Turning to OHIS, health needs were positively associated with OHIS across all models and groups apart from non-White (OR 1.182, 95% CI 0.958-1.458; *P*=.07) and Latine (OR 1.091, 95% CI 0.869-1.369; *P*=.58) individuals. This provided partial support for H5.

Intersectional Differences

Finally, we investigated whether significant differences in H1 to H5 emerged for different groups (RQ2). We found that certain relationships between predisposing characteristics and access differed for each type of access; all reported relationships were significant at *P*<.05. Significant differences emerged for the relationship between home computer access and age, income, and sex. The negative association with age was stronger for non-White, Black, and Latine individuals. The positive association with income was stronger for non-White and Black individuals. The association with sex was stronger for non-Black individuals; males were more likely to have home computer access than females among non-Black individuals. Significant differences also emerged for the association of work computer access with age and sex. The negative association with age was significantly stronger for non-Latine individuals. The association with sex was stronger for Black individuals; females were more likely to have work computer access than males among Black individuals. Next, the negative association between public computer access and age was stronger for non-White and Black individuals. Finally, the positive association between mobile access and education was significantly stronger for non-White and Latine individuals.

Other relationships also differed across racial and ethnic groups. For predisposing characteristics and OHIS, sex had a stronger negative association with OHIS for non-Black and White individuals, such that the gap between females and males engaging in OHIS was greater for these groups. For access and OHIS, home computer access had a significantly stronger positive association with OHIS for White, non-Black, and non-Latine individuals. Mobile access had a significantly stronger positive association with OHIS for non-White individuals. There were no significant differences in other dimensions of access or health needs. Tables 5-7 display the ORs and standardized coefficients for the final models, and our general analysis scripts are available in the Multimedia Appendix 1.

Table 5. Standardized coefficients and odds ratios for theorized OHIS[a] models (for Black and non-Black individuals)[b].

Path	Group			
	Black		Non-Black	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	*P* value[e]	Standardized coefficient or odds ratio (95% CI)	*P* value
Predisposing characteristics → OHIS				
Age (years)	0.982[f] (0.967-0.996)	.003	0.976[f] (0.970 -0.982)	<.001
Sex	1.134[f] (0.721-1.783)	.74	0.591[g] (0.530-0.660)	<.001
Income	1.081[f] (0.939-1.245)	.15	1.124[f] (1.052-1.201)	<.001
Education	1.499[f] (1.126-1.995)	<.001	1.439[f] (1.259-1.644)	<.001
Predisposing characteristics → access				
Home computer				
Age (years)	–0.146[f]	<.001	–0.056[g]	<.001
Sex	–0.036[f]	.44	0.074[g]	<.001
Income	0.329[f]	<.001	0.170[g]	<.001
Education	0.213[f]	<.001	0.292[f]	<.001
Work computer				
Age (years)	–0.294[f]	<.001	–0.368[f]	<.001
Sex	–0.097[f]	.003	0.018[g]	.20
Income	0.374[f]	<.001	0.283[f]	<.001
Education	0.177[f]	<.001	0.186[f]	<.001
Public computer				
Age (years)	–0.255[f]	<.001	–0.180[g]	<.001
Sex	0.033[f]	.39	0.035[f]	.04
Income	–0.122[f]	.003	–0.115[f]	<.001
Education	0.104[f]	.01	0.135[f]	<.001
Mobile				
Age (years)	–0.446[f]	<.001	–0.444[f]	<.001
Sex	–0.105[f]	<.001	–0.060[f]	<.001
Income	0.226[f]	<.001	0.220[f]	<.001
Education	0.167[f]	<.001	0.131[f]	<.001
Access → OHIS				
Home computer	1.491[f] (0.990-2.246)	.001	1.981[g] (1.554-2.526)	<.001
Work computer	0.877[f] (0.663-1.161)	.55	0.939[f] (0.822-1.073)	.92
Public computer	1.368[f] (0.692-2.706)	.06	1.118[f] (0.801-1.560)	.16
Mobile	2.158[f] (1.175-3.962)	<.001	1.833[f] (1.440-2.333)	<.001
Predisposing Characteristics → health need				
Age (years)	0.098[f]	.005	0.102[f]	<.001
Sex	0.001[f]	.98	0.022[f]	.16

Path	Group			
	Black		Non-Black	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	P value[e]	Standardized coefficient or odds ratio (95% CI)	P value
Income	–0.202[f]	<.001	–0.245[f]	<.001
Education	–0.072[f]	.06	–0.117[f]	<.001
Health need → OHIS	1.235[f] (0.970-1.572)	.03	1.222[f] (1.078-1.385)	.004

[a] OHIS: online health information seeking.

[b] Comparisons were made for each model per row.

[c] Standardized coefficients are displayed for paths predicting nondichotomous outcomes; negative relationships are indicated by negative signs. For standardized coefficients, 95% CI values are not available.

[d] Odds ratios are presented for paths predicting dichotomous outcomes (ie, OHIS) and were generated using Monte Carlo integration because of model complexity; negative relationships are indicated by values <1.

[e] Significance values were based on the primary models (ie, without Monte Carlo integration).

[f] Coefficients or odds ratios differ significantly from those denoted by footnote *g* at *P*<.05.

[g] Coefficients or odds ratios differ significantly from those denoted by footnote *f* at *P*<.05.

Table 6. Standardized coefficients and odds ratios for theorized OHIS[a] models (for Latine and non-Latine individuals)[b].

Path	Group			
	Latine		Non-Latine	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	*P* value[e]	Standardized coefficient or odds ratio (95% CI)	*P* value
Predisposing characteristics → OHIS				
Age (years)	0.979[f] (0.966-0.993)	.002	0.977[f] (0.971-0.983)	<.001
Sex	0.601[f] (0.474-0.762)	.009	0.656[f] (0.581-0.741)	<.001
Income	1.058[f] (0.930-1.204)	.42	1.123[f] (1.051-1.200)	<.001
Education	1.393[f] (1.075-1.804)	<.001	1.481[f] (1.291-1.699)	<.001
Predisposing characteristics → access				
Home computer				
Age (years)	–0.185[f]	<.001	–0.054[g]	<.001
Sex	0.060[f]	.08	0.063[f]	<.001
Income	0.181[f]	<.001	0.203[f]	<.001
Education	0.324[f]	<.001	0.254[f]	<.001
Work computer				
Age (years)	–0.249[f]	<.001	–0.374[g]	<.001
Sex	0.019[f]	.57	–0.006[f]	.68
Income	0.265[f]	<.001	0.301[f]	<.001
Education	0.259[f]	<.001	0.171[f]	<.001
Public computer				
Age (years)	–0.257[f]	<.001	–0.188[f]	<.001
Sex	–0.024[f]	.57	0.033[f]	.048
Income	–0.152[f]	.002	–0.142[f]	<.001
Education	0.087[f]	.10	0.128[f]	<.001
Mobile				
Age (years)	–0.462[f]	<.001	–0.439[f]	<.001
Sex	–0.069[f]	.03	–0.072[f]	<.001
Income	0.139[f]	<.001	0.232[f]	<.001
Education	0.206[f]	<.001	0.114[g]	<.001
Access → OHIS				
Home computer	1.294[f] (0.861-1.945)	.04	1.950[g] (1.541-2.467)	<.001
Work computer	1.121[f] (0.772-1.627)	.19	0.917[f] (0.806-1.044)	.49
Public computer	1.500[f] (0.574-3.919)	.08	1.117[f] (0.824-1.513)	.15
Mobile	1.739[f] (1.057-2.861)	<.001	1.912[f] (1.491-2.452)	<.001
Predisposing characteristics → health need				
Age (years)	0.140[f]	<.001	0.093[f]	<.001
Sex	–0.039[f]	.30	0.028[f]	.07

Path	Group			
	Latine		Non-Latine	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	*P* value[e]	Standardized coefficient or odds ratio (95% CI)	*P* value
Income	–0.178[f]	<.001	–0.243[f]	<.001
Education	–0.147[f]	<.001	–0.113[f]	<.001
Health need → OHIS	1.091[f] (0.869-1.369)	.58	1.242[f] (1.093-1.411)	.001

[a] OHIS: online health information seeking.

[b] Comparisons were made for each model per row.

[c] Standardized coefficients are displayed for paths predicting nondichotomous outcomes; negative relationships are indicated by negative signs. For standardized coefficients, 95% CI values are not available.

[d] Odds ratios are presented for paths predicting dichotomous outcomes (ie, OHIS) and were generated using Monte Carlo integration because of model complexity; negative relationships are indicated by values <1.

[e] Significance values were based on the primary models (ie, without Monte Carlo integration).

[f] Coefficients or odds ratios differ significantly from those denoted by footnote *g* at *P*<.05.

[g] Coefficients or odds ratios differ significantly from those denoted by footnote *f* at *P*<.05.

Table 7. Standardized coefficients and odds ratios for theorized OHIS[a] models (for White and non-White individuals)[b].

Path	Group			
	White		Non-White	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	*P* value[e]	Standardized coefficient or odds ratio (95% CI)	*P* value
Predisposing characteristics → OHIS				
Age (years)	0.975[f] (0.967-0.983)	<.001	0.982[f] (0.971-0.994)	<.001
Sex	0.572[f] (0.513-0.638)	<.001	1.123[g] (0.757-1.665)	.84
Income	1.122[f] (1.048-1.202)	<.001	1.121[f] (0.989-1.271)	.02
Education	1.456[f] (1.267-1.673)	<.001	1.427[f] (1.119-1.819)	<.001
Predisposing characteristics → access				
Home computer				
Age (years)	–0.047[f]	.003	–0.158[g]	<.001
Sex	0.071[f]	<.001	0.014[f]	.62
Income	0.176[f]	<.001	0.265[g]	<.001
Education	0.282[f]	<.001	0.280[f]	<.001
Work computer				
Age (years)	–0.370[f]	<.001	–0.298[f]	<.001
Sex	–0.001[f]	.95	0.010[f]	.71
Income	0.289[f]	<.001	0.329[f]	<.001
Education	0.182[f]	<.001	0.205[f]	<.001
Public computer				
Age (years)	–0.178[f]	<.001	–0.242[g]	<.001
Sex	0.033[f]	.06	0.038[f]	.26
Income	–0.122[f]	<.001	–0.129[f]	<.001
Education	0.131[f]	<.001	0.126[f]	.001
Mobile				
Age (years)	–0.450[f]	<.001	–0.432[f]	<.001
Sex	–0.069[f]	<.001	–0.065[f]	.01
Income	0.223[f]	<.001	0.202[f]	<.001
Education	0.121[f]	<.001	0.199[g]	<.001
Access → OHIS				
Home computer	2.002[f] (1.558-2.573)	<.001	1.458[g] (1.005-2.116)	<.001
Work computer	0.921[f] (0.806-1.052)	.63	0.931[f] (0.712-1.218)	.96
Public computer	1.098[f] (0.787-1.532)	.25	1.307[f] (0.706-2.418)	.037
Mobile	1.776[f] (1.398-2.256)	<.001	2.379[g] (1.281-4.419)	<.001
Predisposing characteristics → health need				
Age (years)	0.097[f]	<.001	0.123[f]	<.001
Sex	0.027[f]	.09	–0.015[f]	.64

Path	Group			
	White		Non-White	
	Standardized coefficient[c] or odds ratio[d] (95% CI)	*P* value[e]	Standardized coefficient or odds ratio (95% CI)	*P* value
Income	–0.246[f]	<.001	–0.226[f]	<.001
Education	–0.124[f]	<.001	–0.061[f]	.08
Health need → OHIS	1.237[f] (1.085-1.411)	.002	1.182[f] (0.958-1.458)	.07

[a] OHIS: online health information seeking.

[b] Comparisons were made for each model per row.

[c] Standardized coefficients are displayed for paths predicting nondichotomous outcomes; negative relationships are indicated by negative signs. For standardized coefficients, 95% CI values are not available.

[d] Odds ratios are presented for paths predicting dichotomous outcomes (ie, OHIS) and were generated using Monte Carlo integration because of model complexity; negative relationships are indicated by values <1.

[e] Significance values were based on the primary models (ie, without Monte Carlo integration).

[f] Coefficients or odds ratios differ significantly from those denoted by footnote *g* at *P*<.05.

[g] Coefficients or odds ratios differ significantly from those denoted by footnote *f* at *P*<.05.

Discussion

Principal Findings

This study applied a nuanced conceptualization of access to theoretical models of OHIS and identified how relationships with OHIS differed between racial and ethnic groups (ie, Black, Latine, and White individuals). We found partial support for all hypotheses, and results regarding the RQs provided deeper insight into the predicted relationships. By examining access as 4 unique context–device pairings, we found that home computer and mobile access were most consistently associated with OHIS. In addition, disaggregating models by racial and ethnic self-categorization identified different patterns between predisposing characteristics and access for different groups, highlighting how the digital divide affects intersectional groups.

Our findings suggest that predisposing characteristics are associated with OHIS for different racial and ethnic groups (H1). Education was positively associated with OHIS, and age was negatively associated with OHIS. These findings align with previous research, such that those with more education and younger individuals are more likely to possess the skills to navigate web-based platforms [30,31,33,58]. However, income only had a positive association with OHIS for individuals who self-categorized as White, non-Black, or non-Latine. Although education and income are often correlated with OHIS [9,59,60], our findings suggest that education may better index the foundational knowledge necessary to take advantage of web-based health information. Finally, although females sought out health information more frequently than males [23,32], this pattern did not hold for those who self-categorized as Black. This may reflect how factors of socioeconomic status are typically stronger determinants of access to technology and health services for racial minorities than sociodemographic factors [44,61].

Our findings also suggest that some predisposing characteristics are associated with access for some racial and ethnic groups (H2). Age was negatively associated with all forms of access. Older individuals used all 4 context–device pairings less frequently than younger individuals, which may indicate their use of nondigital means (eg, print media and interpersonal) to obtain health information [47]. Females of all groups accessed the internet on mobile devices more frequently than males, as well as work computers among Black individuals. However, White males (vs females) accessed the internet on home computers more frequently. Although males and females may have similar access overall [62], combining a multifaceted conceptualization of access with an intersectional approach highlights that disparities in access based on sex are grounded in devices and contexts of use, as well as race and ethnicity. White males and females are more likely to access the internet on home computers and mobile devices, respectively, suggesting that internet access may be a zero-sum game, such that having access in one place reduces the need to have access elsewhere [21]. However, this trade-off did not emerge for other groups, suggesting important boundary conditions based on race and ethnicity [61]. Furthermore, income and education consistently demonstrated a positive association with access, as maintaining access requires sustainable resources afforded by income and education [7]. However, income was negatively associated with public computer access, suggesting that individuals with lower income may be more reliant on public resources to access the internet [39,57].

Our findings generally confirm that access is associated with OHIS (H3). As suggested by previous research [14,28,50-52], OHIS is unlikely without a means to access the internet. Specifically, mobile access was positively associated with OHIS for all groups, suggesting that the ubiquity of mobile phones may help bridge this particular gap of the digital divide [3,5,21]. Home computer access was also associated with OHIS for all groups. Public computer access was positively associated with OHIS for non-White individuals. Work computer access was not associated with OHIS across all groups. These findings are corroborated by the fact that certain contexts of OHIS (eg, home computer and mobile) provide a level of privacy that other contexts do not [23,37], thus facilitating searches for private health information. Our results highlight that certain groups (particularly non-White individuals) face access disparities based on affordance and maintenance of that privacy [7,63].

Predisposing characteristics were also associated with health needs (H4), such that older individuals and individuals with less education and income were more likely to describe their health as poor. Older individuals and individuals with less education and income often face barriers to quality health options [44]. However, education was not significantly associated with health needs for Black and non-White individuals. Research on minority groups (eg, Black individuals) finds that educational advancement may not overcome the aggregated stress of marginalization, which contributes to negative health outcomes [64]. However, sex was not associated with health needs for any group, likely because of counterbalancing of health issues that disproportionately affect males and females separately [45].

Furthermore, those with greater health needs were more likely to partake in OHIS, apart from non-White and Latine individuals (H5). Past research has found that greater health needs are associated with increased OHIS among Latine individuals [58]. However, our findings support previous findings that Latine individuals may be less trusting of health information on the web and may rely on different (eg, interpersonal) means of seeking out health information [65]. Reconciliation of these contradicting findings may be a result of area, as the national sample is not limited to patterns that may only exist in larger cities with more resources to provide access [58].

Finally, our exploratory analyses provide insight into RQ2; however, additional research may be required to fully explicate certain patterns in our model in which stronger relationships were detected for specific racial and ethnic groups. In terms of access, several relationships were stronger for Black individuals. Greater income was associated with more frequent home computer access across all groups; however, this relationship was stronger for Black (vs non-Black) individuals. Income inequality among Black individuals appears to be a stark determinant of home computer access [39]. Individuals with higher income can afford the cost of maintenance that comes with home computer access, which is apparent across the models [7]. However, Black individuals with lower income may face additional hurdles to home computer access, such as living in areas without the infrastructure to support maintenance [3]. Similarly, the negative relationship between age and public computer access was stronger for Black (vs non-Black) individuals. The restricted availability of public computers [5] and limited accessibility of web-based platforms for older individuals [7] may be particularly profound for Black individuals. As Black individuals have been historically disadvantaged in access, both community resources and technological skills of the older generation may be stunted [5,39]. Furthermore, the relationship between sex and access differed, such that Black females reported more frequent access via work computers than Black males. In contrast, non-Black males were more likely to use home computers. For specific sex, racial, and ethnic groups, finding access to the internet via 1 mode may be sufficient, which could reduce the need to have access elsewhere [21]. Finally, non-White (vs White) individuals, or racial and ethnic minorities in general, demonstrated a stronger negative relationship between age and home computer access and a stronger positive relationship between education and mobile access. Older racial and ethnic minorities tend to have less access to the internet [39], including at home. Although racial and ethnic minorities lag in home computer ownership, the stronger relationship with education and mobile access may be interpreted as a route to attenuate the digital divide or as exacerbating the digital divide within racial minority groups. As such, lower education levels seem to inhibit access more intensely among Latine individuals.

In addition to access, the relationship between sex and OHIS differed, such that non-Black (vs Black) females demonstrated a stronger association with OHIS. The extent to which females relieve the burden of family health knowledge [32] may differ across racial and ethnic groups, as these groups are often disproportionately affected by health disparities [4,6]. Moreover, the positive relationship between home computer access and OHIS was weaker for non-White (vs White) individuals, whereas the positive relationship between mobile access and OHIS was stronger. Mobile devices remained a key factor not only for establishing access for racial and ethnic minorities [3] but also for OHIS. Although the mobile interface may be more difficult for tasks such as OHIS [8], having at least one point of access is critical for web-based health behaviors [9,24]. Although some OHIS research suggests that access has been democratized [19], the above results highlight the overlap in health and technology disparities for racial and ethnic minority groups [4-6].

Contributions

Our first contribution—applying a multidimensional conceptualization of access to theoretical models of OHIS—revealed that different context–device pairings offer distinct OHIS profiles. Mobile and home computer access were more consistently associated with OHIS than work computer and public computer access. This implies that privacy is important when assessing the digital divide, as home computers and mobile devices can be used in more private contexts [23,37]. Furthermore, for racial and ethnic minority participants, the link between home computer access and OHIS was weaker, and the relationship between mobile access and OHIS was stronger. These differences primarily emerged in the non-White versus White models because of reduced power in the other models and the fact that Black individuals were included as non-Latine individuals (and vice versa). Racial and ethnic minorities may rely more on mobile (vs home computer) access for OHIS because of the lower cost and flexibility of mobile devices [66]. Public and work computer access were not consistently associated with OHIS, although public computer access was generally associated with OHIS for non-White individuals. Contexts that typically do not require ownership may provide access for groups that lack other means of access. Discrepancies among home computer, work computer, public computer, and mobile access highlight that devices and contexts of use do not provide access equally [7].

Our second contribution was to unpack the digital divide using an intersectional approach, as it is crucial to understand which groups have limited access to the internet. We found discrepancies in access for specific groups. Older individuals who self-categorized as a racial or ethnic minority engaged in less frequent home and public computer access. Older (vs younger) individuals and racial and ethnic minorities (vs majorities) tend to access the internet less frequently [39], and we find that this gap is magnified for home and public computer access. In addition, for non-White (vs White) individuals, there were stronger positive relationships between education and mobile access, as well as mobile access and OHIS. Although formal education may minimize the digital divide via mobile access, disparities in access to the education needed to operate the devices should also be considered. Discrepancies between predisposing characteristics, access, health needs, and OHIS for different racial and ethnic groups demonstrate the need for future OHIS theorizing to adopt an intersectional approach.

Practical Implications

This study supports the criticism that the digital divide is not a dichotomy between access and lack thereof [22]. In response to this criticism, interventions combating the digital divide must consider how context–device access pairings can be leveraged among specific racial and ethnic groups. Home computer and mobile were the most frequently used means of access and were both consistently positively related to OHIS. This implies that people typically engage in OHIS on home computers or mobile devices. As such, improving access within these contexts may be valuable for interventions to support OHIS across racial and ethnic groups. Our findings suggest that work and public computer access are less ideal for OHIS. These pairings may lack accessibility [5] or privacy [23,37]. The association between public computer access and OHIS for racial and ethnic minorities could be explored further as a means of increasing OHIS for Latine and Black individuals. Work and public computer access remain important to the extent that increasing access points overall supports OHIS [21,25,26]. However, public computer access may also replace more expensive yet more private modes of access (eg, home computer). In general, interventions could reinforce existing strengths (eg, home computer and mobile access) or bolster existing weaknesses (eg, work and public computer access).

These 2 courses of action can also apply to future interventions aimed at addressing the digital divide and OHIS among specific groups. For racial and ethnic minorities, we found weaker positive relationships between home computer access and OHIS and stronger positive relationships between mobile access and OHIS. Interventions can strengthen the established relationship between mobile devices and OHIS or bolster the weaker link for home computer access. Although home computer access is considered a more easily navigable interface [8], it may not be scalable, given its cost. As such, interventions with limited financial resources may benefit from working with providers of web-based health information to develop mobile-friendly interfaces to make health information more accessible. Furthermore, this study shines a spotlight on older racial and ethnic minorities, who experienced consistent discrepancies in access and may have the highest health needs. The negative relationship between age and public computer access was stronger for Black individuals, suggesting a drop-off in public computer access for older Black adults. As public computer access was associated with OHIS for racial and ethnic minorities, future interventions could increase the accessibility of public computers for older Black adults, with attention toward local libraries and community centers in predominately older Black neighborhoods [5]. Overall, a deep understanding of current community strengths must be balanced with efforts to provide equitable access to web-based health information to not overlook the key interactions between multiple social positions that create compounding experiences of oppression [67].

Limitations and Future Research

Some limitations should be considered when interpreting these findings. This study used secondary cross-sectional data. Thus, potentially relevant variables (eg, mobile use at home vs at work vs in public) were not measured, and causality or directionality cannot be determined. Future research could measure additional constructs and use longitudinal designs. In addition, this analysis used self-reported data. Future work could use log and GPS data in tandem to paint a more accurate picture of OHIS. Furthermore, our primary outcome variable (OHIS) was dichotomous, and other variables (eg, access) were trichotomous or single-item measures. Future research should use continuous variables for OHIS and access to better capture the temporal variety of digital media use. Finally, we did not examine second-level digital divide variables (eg, experience, perceived utility, beliefs, and skills) [28,50,51,68,69]. However, before receiving and interpreting information, those who seek information on the web must choose a device and context to seek that information.

Conclusions

This study holds that a nuanced conceptualization of access is necessary to understand how the digital divide differentially affects racial and ethnic groups. Our theoretical model identified variables that predict OHIS while distinguishing the type (ie, device) and location (ie, context) of access, testing these associations for different racial and ethnic groups and examining intersectional characteristics among these groups (ie, age, sex, education, and income). By interlacing a thorough understanding of the first-level digital divide with an awareness of the unique impacts of the digital divide for specific groups, we further theorize on OHIS and suggest important considerations for more targeted interventions. As we continue to understand the complexities of the digital divide and its relationship with health, racial, and ethnic disparities, our perspective highlights how web-based health resources may not be accessed by those who need them the most.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Data and syntax.
[ZIP File (Zip Archive), 227 KB-Multimedia Appendix 1]

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Abbreviations

CFI: comparative fit index
HINTS: Health Information National Trends Survey
OHIS: online health information seeking
OR: odds ratio
RMSEA: root mean square error of approximation
RQ: research question

SRMR: standardized root mean square residual

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Review

The Effectiveness of Mobile Phone Messaging–Based Interventions to Promote Physical Activity in Type 2 Diabetes Mellitus: Systematic Review and Meta-analysis

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Abstract

Background: The prevalence of type 2 diabetes mellitus (T2DM) is increasing worldwide. Physical activity (PA) is an important aspect of self-care and first line management for T2DM. SMS text messaging can be used to support self-management in people with T2DM, but the effectiveness of mobile text message–based interventions in increasing PA is still unclear.

Objective: This study aims to assess the effectiveness of mobile phone messaging on PA in people with T2DM by summarizing and pooling the findings of previous literature.

Methods: A systematic review was conducted to accomplish this objective. Search sources included 5 bibliographic databases (MEDLINE, Cochrane Library, CINAHL, Web of Science, and Embase), the search engine *Google Scholar* (Google Inc), and backward and forward reference list checking of the included studies and relevant reviews. A total of 2 reviewers (MA and AA) independently carried out the study selection, data extraction, risk of bias assessment, and quality of evidence evaluation. The results of the included studies were synthesized narratively and statistically, as appropriate.

Results: We included 3.8% (6/151) of the retrieved studies. The results of individual studies were contradictory regarding the effectiveness of mobile text messaging on PA. However, a meta-analysis of the results of 5 studies showed no statistically significant effect (P=.16) of text messages on PA in comparison with no intervention. A meta-analysis of the findings of 2 studies showed a nonsignificant effect (P=.14) of text messages on glycemic control. Of the 541 studies, 2 (0.4%) found a nonsignificant effect of text messages on anthropometric measures (weight and BMI).

Conclusions: We could not draw a definitive conclusion regarding the effectiveness of text messaging on PA, glycemic control, weight, or BMI among patients with T2MD, given the limited number of included studies and their high risk of bias. Therefore, there is a need for more high-quality primary studies.

Trial Registration: PROSPERO International Prospective Register of Systematic Reviews CRD42020156465; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=156465

(J Med Internet Res 2022;24(3):e29663) doi: 10.2196/29663

KEYWORDS

type 2 diabetes mellitus; physical activity; mobile phone messaging; systematic review; meta-analysis

Introduction

Background

The burden of diabetes is increasing, and the number of people with type 2 diabetes mellitus (T2DM) worldwide has reached 387 million and is expected to increase to 592 million by 2035 [1]. This prevalence imposes a high and rising burden of lifelong multiorgan complications, leading to increased disability and risk of premature deaths, mainly in low- and middle-income countries [2]. A considerable amount of literature suggests that better management of T2DM delays the onset of short- and long-term complications among people diagnosed with T2DM [3-5]. Over the past decades, physical activity (PA) has been part of the first line T2DM care management [6]. PA includes all movements that increase energy use; however, there are three main types of exercise: aerobic, strength training, and flexibility work [7]. PA can help people with T2DM achieve a variety of goals, including increased vigor, improved glycemic hemoglobin control, decreased insulin resistance, increased cardiorespiratory fitness, improved lipid profile, blood pressure reduction, and maintenance of weight loss [8]. Unfortunately, patients with T2DM are less likely to engage in regular PA, with recent estimates demonstrating a lower participation rate compared with the national average [9]. There have been many attempts to explore alternative approaches to improve PA in people with T2DM, and the mobile phone messaging revolution has brought entirely new opportunities and increased access to self-management education [1]. The literature shows that text messaging–based interventions can be effective in improving health-related behaviors and bridging the gaps between patients and health care services for people living with chronic diseases [10,11]. Text messaging may be 1-way (unidirectional) or 2-way (bidirectional); they can be standardized or tailored to specific patients and sent at varied frequencies based on the intervention design [12]. Multiple meta-analyses have demonstrated the overall success of mobile phone messaging in promoting various aspects of behavior change for PA and mental health–related disorders [1,13,14].

Research Problem and Aim

Several studies have assessed the effect of mobile text messaging on the PA of patients with T2DM. It is crucial to summarize and aggregate the findings of such studies to produce more generalizable and definitive conclusions about the effectiveness of such interventions. A total of 4 previous systematic reviews did not provide evidence from studies with text messaging interventions that specifically targeted PA. Specifically, the first review focused on the impact of education on T2DM delivered via mobile text messaging [15]. The second review assessed the effectiveness of text messaging interventions on glycated hemoglobin (HbA_{1c}) in patients with T2DM, including all self-management strategies [1]. The third review identified randomized trials conducted to improve glycemic control in T2DM, which involved the delivery of behavior change content through a range of digital platforms and approaches (eg, SMS text messaging, multimedia message service, or instant messaging such as WhatsApp) [12]. The fourth review assessed the effectiveness of technology-based interventions to promote PA in T2DM; for this review, technology included mobile phones and text messages, websites, CD-ROMs, and computer learning–based technology [16]. This review was conducted approximately 7 years ago, but studies involving technology-based interventions are rapidly emerging and there may be new published evidence. Therefore, this study aims to assess the effectiveness of mobile phone messaging on PA in patients with T2DM by summarizing and pooling the findings of previous literature.

Methods

Overview

A systematic review was conducted and reported in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Multimedia Appendix 1) [17]. The protocol for this review was registered at PROSPERO (ID: CRD42020156465).

Search Strategy

Search Sources

We used the following electronic databases in our search: MEDLINE, Cochrane Library, CINAHL, Web of Science, and Embase. These databases were searched on April 19, 2020, by the first author (MA). Auto alerts were set after searching the databases to conduct an automatic search weekly for 16 weeks (ending on August 9, 2020) and send us the retrieved studies. We also searched the search engine *Google Scholar* (Google Inc) to identify gray literature. To identify further studies of relevance to the review, we screened the reference lists of included studies (ie, backward reference list checking) and identified and screened studies that cited the included studies (ie, forward reference list checking).

Search Terms

The search terms were identified by consulting 2 experts in eHealth interventions for patients with diabetes and by checking systematic reviews of relevance to the review. These terms were chosen based on the target population (eg, type 2 diabetes, diabetes type 2, and type II diabetes), target intervention (eg, text messaging, text messages, and short messages), target outcome (eg, PA, physical exercise, HbA_{1c}, and weight), and target study design (eg, trial, experiment, and randomized controlled trial [RCT]). Multimedia Appendix 2 shows the detailed search query used for searching MEDLINE.

Study Eligibility Criteria

The population of interest was adult patients (≥18 years) with T2DM, regardless of their gender and ethnicity. We excluded patients with type 1 diabetes mellitus, gestational diabetes, and prediabetes. The target intervention in this review was mobile phone text messages (SMS text messaging and multimedia message service), but not mobile apps, web-delivered interventions, wearables, or emails. The aim of the text messages was to improve solely PA but not diet, lifestyle, diabetic literacy, or other aspects of self-care. The primary outcomes of interest were subjectively or objectively measured PA (eg, step counts), glycemic control (eg, HbA_{1c} and fasting glucose), and anthropometric measures (eg, change in weight and BMI). Only RCTs were eligible for inclusion in this review. We considered studies published only in the English language. No restrictions were applied to the year of publication, country of publication, comparator, type of publication, or study setting.

Study Selection

We followed 2 steps of the study selection process. In the first step, 2 reviewers (MA and AA) independently sifted the titles and abstracts of all retrieved studies. In the second step, the 2 reviewers independently scrutinized the full texts of the studies included in the first step. In both steps, any disagreements among the reviewers were resolved through discussion and consensus. Cohen κ in this review indicated a very good level of interrater agreement in the first (0.88) and second step (0.95) of the selection process [18].

Data Extraction

Multimedia Appendix 3 shows the data extraction form that was used in this review to precisely and systematically extract the data from the included studies. A total of 2 reviewers (MA and AA) independently conducted data extraction from the included studies, and they resolved any disagreements through discussion and consensus. Cohen κ showed a very good level of interrater agreement among the reviewers (0.85) [18].

Risk of Bias Assessment

To assess the risk of bias in the included studies, we used the Risk of Bias 2 tool, which is recommended by the Cochrane Collaboration [19]. This tool assesses RCTs in terms of five domains: randomization process, deviations from intended interventions, missing outcome data, measurement of the outcome, and selection of the reported result [19]. Then, the overall risk of bias was determined for each study based on the risk of bias judgments in the five domains [19]. A total of 2 reviewers (MA and AA) independently assessed the risk of bias in the included studies, and any disagreements were resolved through discussion and consensus. Interrater agreement among the reviewers was very good (Cohen κ=0.86) [18]. We presented the results of the risk of bias assessment using a graph showing the reviewers' judgments about each *risk of bias* domain in the *Results* section. We also showed reviewers' judgments about each *risk of bias* domain for each included study using a figure in Multimedia Appendix 4 [10,20-24].

Data Synthesis

We synthesized the extracted data using narrative and statistical approaches. Specifically, meta-analysis was carried out when at least two studies assessed the same outcome of interest and reported sufficient data for the analysis (eg, mean difference, SD, and number of participants in each intervention group). When the abovementioned conditions were not met, we narratively synthesized findings of the included studies. We grouped and synthesized the findings according to the measured outcomes (ie, PA, glycemic control, and weight change).

We conducted a meta-analysis using Review Manager 5.4, which is a software developed by Cochrane. We used the mean difference to assess the effect of each trial and the overall effect when the outcome data were continuous, and the outcome measure of each outcome was identical in the meta-analyzed studies. However, we used the standardized mean difference when, among studies, the outcome was measured using different tools. We selected a random effects model in the analysis because of the clinical heterogeneity among the meta-analyzed studies in terms of intervention characteristics (eg, its directionality, purpose, and frequency) and population characteristics (eg, sample size and mean age).

We assessed the clinical heterogeneity of the meta-analyzed studies by inspecting the characteristics of their interventions, outcomes, participants, and comparators. Further, we evaluated the statistical heterogeneity of the meta-analyzed studies. To do so, we calculated a chi-square P value and I^2 to evaluate the statistical significance of heterogeneity and degree of heterogeneity, respectively. We judged the meta-analyzed studies as heterogeneous when the chi-square P value was ≤.05 [25]. The degree of heterogeneity was considered unimportant, moderate, substantial, or considerable when I^2 ranged from 0% to 40%, 30% to 60%, 50% to 90%, or 75% to 100%, respectively [25].

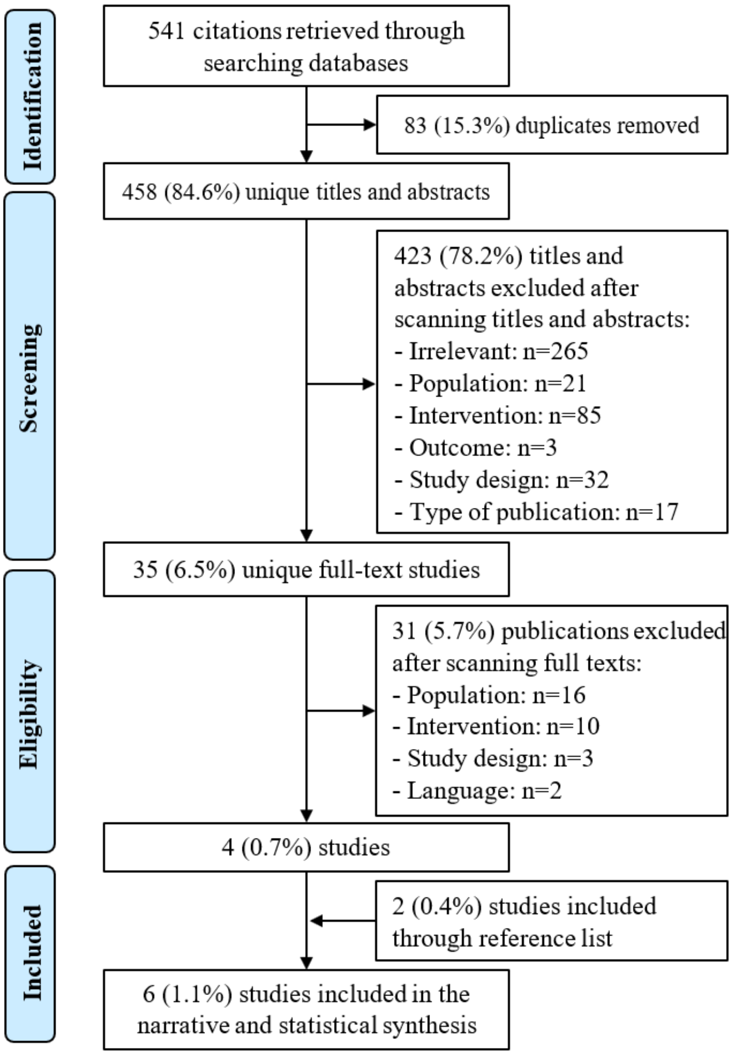
The overall quality of meta-analyzed evidence was examined using the Grading of Recommendations Assessment, Development, and Evaluation approach [26,27]. This approach assessed the quality of evidence based on five main criteria: risk of bias, inconsistency (ie, heterogeneity), indirectness, imprecision, and publication bias [26]. A total of 2 reviewers (MA and AA) independently assessed the overall quality of the meta-analyzed evidence, and any disagreements were resolved through discussion and consensus. Interrater agreement among the reviewers was very good (Cohen κ=0.81) [18].

Results

Search Results

We retrieved 541 citations by searching the 6 bibliographic databases (Figure 1). Of these 541 citations, 83 (15.3%) duplicates were identified and excluded. We screened the titles and abstracts of the remaining 84.6% (458/541) citations and excluded 78.2% (423/541) citations owing to reasons shown in Figure 1. By checking the full texts of the remaining 35 (6.5%) studies, 31 (5.7%) studies were not eligible for this review for several reasons (Figure 1). We identified 2 additional studies by backward reference list checking. Overall, we included 6 studies in this review [10,20-24]. At all steps, consensus was agreed between the 2 reviewers (MA and AA), and referral to a third reviewer was not required.

Figure 1. Flow chart of the study selection process.



Characteristics of Included Studies

As detailed in Table 1, all the included studies were RCTs. The included studies were conducted in 3 countries: the United States (n=3), Iran (n=2), and Indonesia (n=1); 4 of the studies were published in 2018. The sample size in the included studies ranged between 28 and 138, with an average of 81 (SD 40.03).

The mean age of participants in the included studies varied from 44.6 to 65.5 years, with an average of 51.6 years (SD 6.7). The percentage of men in the included studies ranged from 23.3% to 57.9%, with an average of 42.2% (SD 12.1). All studies recruited patients with T2DM. The included studies recruited participants from health care (n=5) and community (n=1).

Table 1. Characteristics of studies and population.

Study	Year	Country	Study design	Sample size	Age (years), mean (SD)	Sex (male)	Health condition	Setting
Agboola et al [20]	2016	United States	RCT[a]	126	51.4 (11.5)	48.4%	T2DM[b]	Health centers
Arovah et al [21]	2018	Indonesia	RCT	43	65.5 (5.8)	37.2%	T2DM	Public hospital
Lari et al [10]	2018	Iran	RCT	73	47.6 (9.1)	53.4%	T2DM	Diabetes clinics
Lari et al [22]	2018	Iran	RCT	76	48.2 (8.8)	57.9%	T2DM	Diabetes clinics
Polgreen et al [23]	2018	United States	RCT	138	44.6 (15.9)	23.3%	T2DM	Community
Ramirez and Wu [24]	2017	United States	RCT	28	52 (9.0)	33%	T2DM	Ambulatory care clinic

[a] RCT: randomized controlled trial.

[b] T2DM: type 2 diabetes mellitus.

The interventions in the included studies were text messages only (n=1), text messages and educational CD about PA (n=1), and text messages and pedometers (n=4; Table 2). Text messages were unidirectional (n=1), bidirectional (n=4), and both (ie, most messages were unidirectional, and some messages were bidirectional; n=1). The purpose of the text messages in the included studies was to educate participants about PA (n=4), remind them to wear the pedometer, review goals, or self-monitor and record their steps (n=4), provide them with feedback about their previous day's activity (n=3), motivate them to walk and exercise more (n=2), and set step goals (n=1). The frequency of text messages sent to participants ranged between 2 per week and 3 per day. The intervention was delivered for 12 weeks in 4 studies and 24 weeks in 2 studies. The intervention in 5 studies was theoretically informed. Specifically, the following theories or models were used to develop the intervention: Social Cognitive Theory (n=2), Health Promotion Models (n=2), and Transtheoretical Model and Grounded Theory (n=1).

Table 2. Characteristics of interventions.

Study	Intervention	Directionality	Purpose	Frequency	Period	Theory used
Agboola et al [20]	SMS and pedometers	1- and 2-way	Education, motivation, reminder, and feedback	2/day	24 weeks	Transtheoretical model and grounded theory
Arovah et al [21]	SMS and pedometers	2-way	Motivation and reminder	1-3/day	12 weeks	Social Cognitive Theory
Lari et al [10]	SMS	2-way	Education	Phase 1: 2-3/day; phase 2: 2/week	Phase 1: 2 weeks; Phase 2: 10 weeks	Health promotion models
Lari et al [22]	SMS + educational CD	1-way	Education	2/week	12 weeks	Health promotion models
Polgreen et al [23]	Intervention 1: SMS text messaging (reminder) + SMS text messaging (goal setting) + pedometer; intervention 2: SMS text messaging (reminder)+pedometer	2-way	Reminders, feedback, and setting goals	Intervention 1: 2/day; intervention 2: 1/day	24 weeks	N/A[a]
Ramirez and Wu [24]	Intervention 1: SMS text messaging + pedometer	2-way	Education reminders and feedback	≥4/week	12 weeks	Social Cognitive Theory

[a] N/A: not applicable.

The comparison group received pedometers in 4 of the studies or no intervention in 2 studies (Table 3). The pedometers were used by the participants for 12 weeks (n=2) or 24 weeks (n=2). The follow-up period ranged from 4 weeks to 24 weeks. The following outcomes of interest were assessed in the included studies: PA (n=6), glycemic control indicators (n=3), weight (n=1), and BMI (n=1). Step count was the most common outcome measure used in the included studies (n=4), followed by HbA_{1c} (n=2), weight scale (n=2), and metabolic equivalent of task questionnaire (n=2).

Table 3. Characteristics of comparators and outcomes.

Study	Comparator	Period (week)	Follow-up (week)	Outcome	Outcome measure
Agboola et al [20]	Pedometers	24	24	PA[a], glycemic control, and weight	Step count, weight scale, and HbA_{1c}[b]
Arovah et al [21]	Pedometers	12	12 and 24	PA and glycemic control	Step count, PAR[c] questionnaire, HbA_{1c}, fasting glucose, and 2-hour glucose
Lari et al [10]	No intervention	N/A[d]	4 and 12	PA	MET[e] questionnaire
Lari et al [22]	No intervention	N/A	4 and 12	PA	MET questionnaire
Polgreen et al [23]	Pedometers	24	12 and 24	PA and BMI	Step count, weight scale, and stadiometer
Ramirez and Wu [24]	Pedometers	12	6 and 12	PA	Step count

[a] PA: physical activity.

[b] HbA_{1c}: glycated hemoglobin.

[c] PAR: physical activity rating.

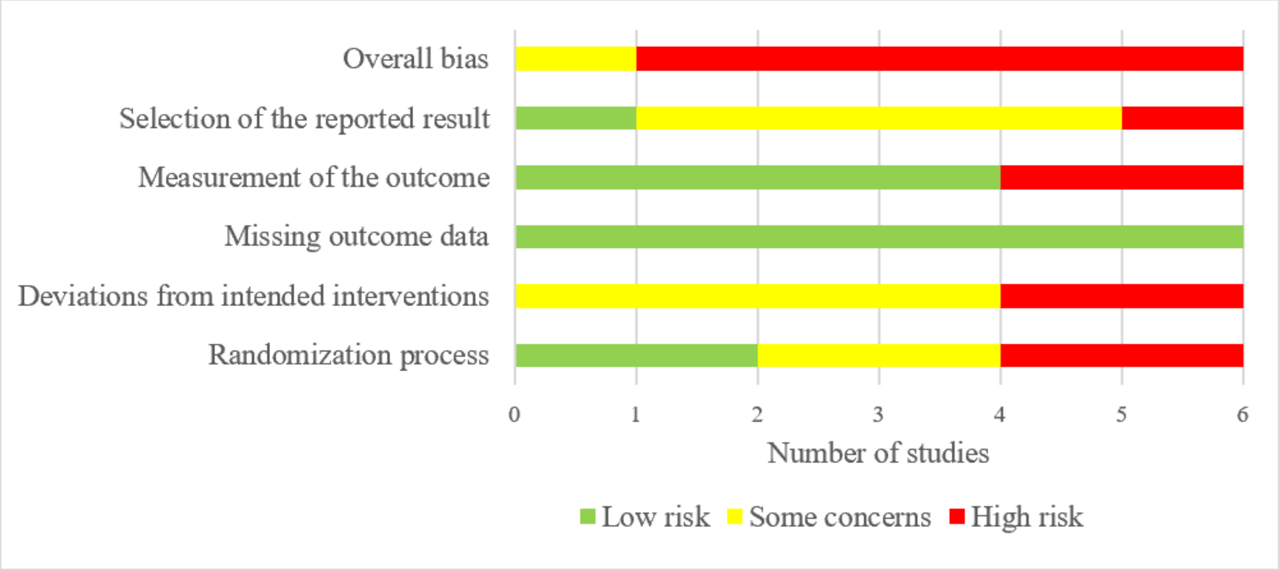
[d] N/A: not applicable.

[e] MET: metabolic equivalent of task.

Risk of Bias Results

Although all studies used an appropriate random allocation sequence for the randomization process and had comparable groups, only 2 studies concealed the allocation sequence until participants were enrolled and assigned to interventions. Accordingly, only these 2 studies were rated as having a low risk of bias in the randomization process (Figure 2). In all studies, participants, their health care professionals, researchers, or individuals delivering the interventions were aware of the assigned intervention during the trial. The study also did not report any information about whether a deviation from the intended intervention occurred owing to the experimental context. Thus, none of the studies were rated as having a low risk of bias in deviations from the intended interventions (Figure 2).

Figure 2. Review authors' judgments about each risk of bias domain.



Outcome data were not available for all participants in the included studies, and there was no evidence that the findings were not biased by missing outcome data. However, the reasons for missing outcome data were not related to the true value of the outcome in all studies. Thus, all studies were judged as having a low risk of bias in the domain of missing outcome data.

In 4 studies, the outcomes of interest were assessed using appropriate measures (eg, pedometer and HbA_{1c}), which were comparable between the intervention groups. Therefore, these studies were rated as having a low risk of bias when measuring the outcome. However, the remaining 2 studies were judged as having a high risk of bias in this domain because they used subjective outcome measures that depended on participants' recall, and participants and outcome assessors were not blinded in the 2 studies (Figure 2).

Only 1 study was judged as having a low risk of bias in the selection of the reported studies (Figure 2). This judgment is attributed to the fact that the remaining studies did not publish a prespecified analysis plan or reported outcome measurements and analyses different from those specified in the analysis plan. Given that 5 studies were judged as having a high risk of bias in at least one domain, they were rated as high risk in the domain of overall bias. The remaining study was judged to raise some concerns in the domain of overall bias, as it had some concerns in one of the domains. Reviewers' judgments about each *risk of bias* domain for each included study are presented in Multimedia Appendix 4.

Results of Studies

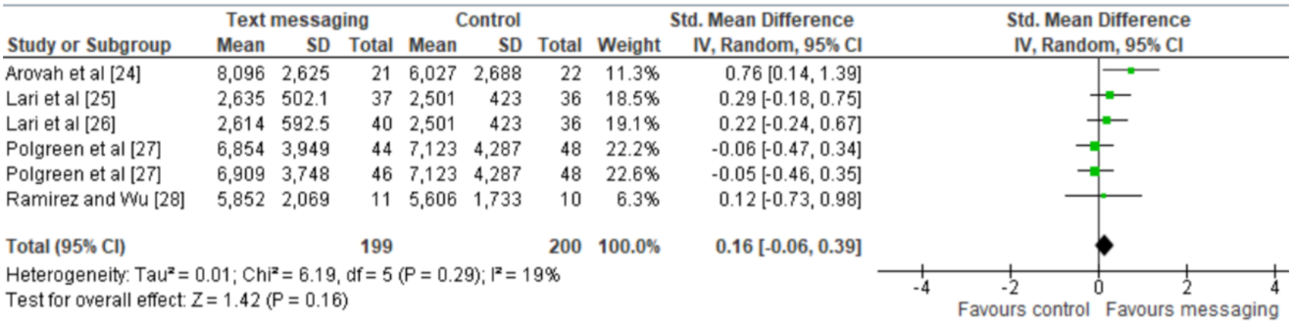
Effect on PA

All included studies assessed the effect of using text messages on PA among patients with T2DM. A total of 3 studies showed a statistically significant effect of text messages on PA [10,21,22,24]. To be more precise, Arovah et al [21] compared the effect of text messages plus pedometers to only pedometers on PA as measured by daily step count, self-reported walking (min/week), and self-reported moderate-to-vigorous-intensity PA (min/week). The study showed a statistically significant effect of 12-week text messages plus pedometers to only pedometers on daily steps (*P*<.001), self-reported walking (*P*=.001), and moderate-to-vigorous-intensity PA (*P*<.001) [21]. In 2 further studies, where data were analyzed from different arms of a single RCT in each *study*, Lari et al [10] compared the effect of text messages only and text messages plus educational CD [22] to no intervention on PA as measured by the metabolic equivalent of task questionnaire. Both studies found a statistically significant effect of text messages only (*P*<.001) [10] and text messages plus educational CDs (*P*<.001) [22] on PA compared with no intervention.

The 3 remaining studies did not find a statistically significant effect of text messages on PA [20,23,24]. Specifically, Agboola et al [20] compared the effect of text messages plus pedometers to pedometers only on PA, as measured by the monthly step count. Although the study found that step counts over 6 months were higher in the intervention group than in the control group, this difference was not statistically significant (*P*=.17) [20]. Another study assessed the effect of text messages plus pedometers and only pedometers on PA, as assessed by daily steps [24]. The study did not show any statistically significant difference (*P*=.78) in PA between the 2 groups [24]. In a previous study, Polgreen et al [23] compared the effect of 2 interventions to only pedometers on PA, as measured by daily step count. The first intervention was pedometers plus text message reminders to wear the pedometers (reminders and pedometers), whereas the second intervention was the same as the first intervention plus text messages asking participants to set a step goal (goal setting, reminders, and pedometers) [23]. The study found no statistically significant differences in PA among the 3 groups [23].

A total of 5 studies were included in the statistical analysis (ie, meta-analysis), as they reported sufficient and appropriate data for the analysis [10,21-24]. The meta-analysis contained 6 comparisons as we included a comparison from each of the 4 studies [10,21,22,24] and 2 comparisons from the remaining study [23], which compared two types of text messages to no intervention. The meta-analysis showed no statistically significant difference in the PA (*P*=.16) between the text message group and the control group (standardized mean difference 0.16, 95% CI –0.06 to 0.39; Figure 3). The heterogeneity of the evidence was not a concern (*P*=.29; I^2=19%). The quality of the evidence was very low because of the high risk of bias and impression (Multimedia Appendix 5).

Figure 3. Forest plot of 6 studies assessing the effect of text messaging on physical activity.



	Text messaging			Control				Std. Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Random, 95% CI
Arovah et al [24]	8,096	2,625	21	6,027	2,688	22	11.3%	0.76 [0.14, 1.39]
Lari et al [25]	2,635	502.1	37	2,501	423	36	18.5%	0.29 [-0.18, 0.75]
Lari et al [26]	2,614	592.5	40	2,501	423	36	19.1%	0.22 [-0.24, 0.67]
Polgreen et al [27]	6,854	3,949	44	7,123	4,287	48	22.2%	-0.06 [-0.47, 0.34]
Polgreen et al [27]	6,909	3,748	46	7,123	4,287	48	22.6%	-0.05 [-0.46, 0.35]
Ramirez and Wu [28]	5,852	2,069	11	5,606	1,733	10	6.3%	0.12 [-0.73, 0.98]
Total (95% CI)			**199**			**200**	**100.0%**	**0.16 [-0.06, 0.39]**

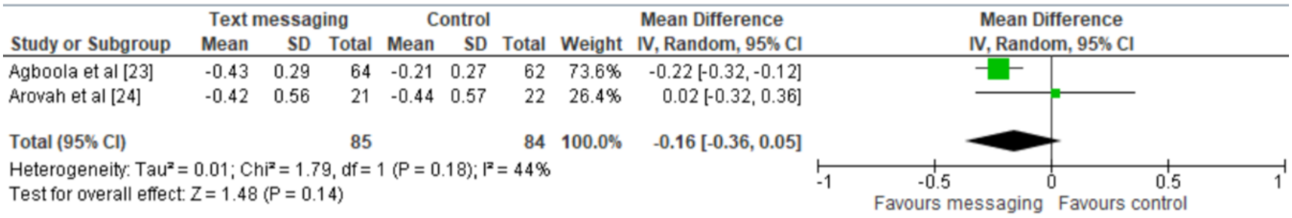
Heterogeneity: Tau² = 0.01; Chi² = 6.19, df = 5 (P = 0.29); I² = 19%

Test for overall effect: Z = 1.42 (P = 0.16)

Glycemic Control

A total of 2 studies examined the effect of text messages on glycemic control, as assessed by HbA_{1c} [20,21]. The results of both studies were meta-analyzed. The meta-analysis showed no statistically significant difference (*P*=.14) between the intervention and control groups, with no difference observed between text messages plus pedometers and only pedometers on HbA_{1c} (mean –0.16, 95% CI –0.36 to 0.05; Figure 4). There was moderate heterogeneity of the evidence (I^2=44%), but the difference was not statistically significant (*P*=.18; Figure 4). The quality of evidence was low as it was downgraded by 1 level owing to a high risk of bias (Multimedia Appendix 5). It is worth mentioning that 1 of the 2 studies compared the effect of text messages plus pedometers with only pedometers on glycemic control as measured by fasting plasma glucose and 2-hour plasma glucose [21]. The study did not find a statistically significant difference between the groups in terms of fasting plasma glucose (*P*=.18) and 2-hour plasma glucose (*P*=.90) [21].

Figure 4. Forest plot of 2 studies assessing the effect of the text messaging on HbA_{1c}.



Anthropometric Measures

A total of 2 studies assessed anthropometric measures as outcomes (weight or BMI) [20,23]. The results of the 2 studies could not be statistically synthesized, as they assessed different outcomes. The first study showed no statistically significant difference between the intervention and control groups, with no effect of text messages plus pedometers on weight (P=.77) compared with pedometers alone [20]. In the second study, Polgreen et al [23] compared the effects of 2 interventions with only pedometers on BMI. The first intervention was pedometers plus text message reminders to wear the pedometers (reminders and pedometers), whereas the second intervention was the same as the first intervention plus text messages asking participants to set a step goal (goal setting, reminders, and pedometers) [23]. The study found no statistically significant differences in BMI among the 3 groups [23].

Other Outcomes

Secondary outcome measures reported in the examined studies included the following variables and parameters: reports of usability, satisfaction and adherence to the RCT as discussed in the study by Agboola et al [20], and quality of life or psychological outcomes (eg, self-efficacy, outcome expectations, self-regulation, and social support) as discussed in Arovah et al [21]. Lari et al [10,22] assessed the Health Promotion Model constructs (eg, perceived benefits, perceived barriers, perceived social support, and self-efficacy). Ramirez and Wu [24] also investigated the feasibility, perceived usefulness, and potential effectiveness.

Discussion

Principal Findings

This systematic review assessed the effectiveness of mobile text messaging as a method of promoting PA alone in people with T2DM. The meta-analysis of the results of 5 studies (6 comparisons) showed no statistically significant effect of mobile text messaging on PA in comparison with no intervention. The insignificant effect may be attributed to the fact that 3 studies showed a statistically significant effect of mobile text messaging on PA, whereas 2 studies did not find any significant effect of text messages on PA. There are several potential reasons for the significant increase in PA in 3 studies. First, the intervention in 1 study [21] was combined with pedometers, and some studies have found greater effects when using objective measures compared with subjective measures [28]. It is possible that participants in these studies were more active because of the knowledge that they were wearing the pedometer [29]. The remaining 2 RCTs [10,22] were rated as having a high risk of bias because they used self-recall questionnaires to measure PA. However, these measures can present limitations in capturing PA because of poor reliability and validity, participant recall bias, and differences in the interpretation of questions [30]. Our findings are consistent with previous reviews that assessed the effect of text messaging on PA in participants with different chronic conditions [31]. Some studies observed only small improvements in daily steps and self-reported PA; other studies did not observe any statistically significant changes in PA despite the use of different PA measurement strategies [31].

Our review found no statistically significant effect of mobile text messaging on glycemic control as assessed by HbA_{1c}, fasting plasma glucose, and 2-hour plasma glucose. Our findings are consistent with those of previous studies that showed no significant difference in HbA_{1c} levels in people with T2DM following text messaging interventions [32]. This could be attributed to the duration effect, which had short interventions and follow-up durations (median 12 weeks); thus, outcomes such as HbA_{1c} are less likely to change over a short timescale (3 months). In other words, it might take longer for the intervention effects to become apparent [33].

The narrative synthesis in this review showed no statistically significant effect of mobile text messaging on either weight or BMI. We could not synthesize these measures in our meta-analysis because of the high heterogeneity in the included studies. Our findings are consistent with those of previous reviews, and a meta-analysis showed no statistically significant association between BMI and weight following mobile messaging interventions in people with T2DM [34]. However, it is important to be realistic about the period of intervention, and a longer period is required to determine the desired improvements in such clinical outcomes [35]. The aforementioned studies had short interventions (median 12 weeks); thus, outcomes such as weight and BMI are less likely to change on a short timescale [33].

Strengths and Limitations

Strengths

Our study is the first review and meta-analysis that focused on the effectiveness of text messages targeting only PA among T2DM patients. This enabled us to ensure that the effect of text messaging on PA outcomes is attributed to PA-related message content and to no other content such as diet, lifestyle, and general diabetes education. Our study is considered a robust and high-quality review given that we followed well-recommended guidelines (ie, PRISMA) in developing, executing, and reporting it.

To run as sensitive a search as possible, we searched the most popular databases in the health and information technology fields using a very comprehensive list of search terms. The risk of publication bias is minimal in this review because we searched gray literature databases (ie, Web of Science and Google Scholar) and conducted backward and forward reference list checking. We did not restrict our search to specific countries of publication, year of publication, comparators, or settings; thus, this resulted in a more comprehensive review.

The risk of selection bias was minimal in the current review as 2 authors (MA and AA) independently selected the studies, extracted data, and assessed the risk of bias and quality of evidence, and they had a very good interrater agreement in all processes. When possible, we meta-analyzed the results of the included studies, and this improved the power of studies and the estimates of the likely size of the effect of text messaging on different outcomes.

Limitations

The intervention of interest in this review was restricted to PA-related text messaging, so we did not examine the impact of other digital interventions, such as mobile apps, wearables, or other eHealth tools. We also focused on patients with T2DM, rather than patients with other types of diabetes. Accordingly, our results may not be generalizable to other eHealth interventions or patients with type 1 diabetes mellitus or gestational diabetes mellitus. In this review, we included only RCTs published in the English language; thus, it is possible that we missed results from some non-English RCTs. We applied these restrictions owing to the high internal validity of RCTs over other study designs [36] and lack of resources to translate non-English studies. The included studies were conducted in only 3 countries (the United States, Iran, and Indonesia); therefore, the generalizability of our findings to other countries may be limited. The findings were based on a small number of studies that met the review criteria. Although 6 studies were included in this review, 2 (33%) of the studies were from a single RCT where 2 separate analyses were undertaken with data taken from different arms. Only 2 studies were included in each of the 2 meta-analyses conducted in this review. This is attributed to the lack of reported data that were appropriate for the analysis and incomparable outcome measures and comparators between studies. As such, it is not possible to draw firm conclusions about effectiveness.

Implications for Research

The current review found relatively few studies assessing the effectiveness of text messages in promoting PA in T2DM; thus, RCTs with larger sample sizes are needed. Future studies should seek to include objective outcome measures (eg, PA, glycemic control, and anthropometric measures), be consistent in terms of selected outcome measures, and measure outcomes after longer follow-up periods to be able to compare study findings and make firm conclusions about intervention effectiveness. More research is needed to determine the type of text message content, frequency of messaging, and duration of intervention that is most likely to result in positive outcomes. Additional research needs to include an estimation of the cost-effectiveness of text messages and an examination of their long-term impact.

Conclusions

We could not draw a definitive conclusion regarding the effectiveness of text messaging on PA, glycemic control, weight, or BMI among patients with T2MD, given the low number of included studies and their high risk of bias. Thus, the findings of this study suggest that texting messaging should not substitute but rather supplement clinical support. In addition, there is a pressing need for further RCTs with large sample sizes, low risk of bias, and more consistency regarding intervention duration, outcome measures, follow-up period, and comparator.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analyses) checklist.
[DOCX File , 23 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Search query used for searching MEDLINE.
[DOCX File , 15 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Data extraction form.
[DOCX File , 16 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Reviewers' judgements about each "risk of bias" domain for each included randomized controlled trial.
[DOCX File , 64 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Grading of Recommendations Assessment, Development, and Evaluation profile.
[DOCX File , 16 KB-Multimedia Appendix 5]

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Abbreviations

HbA_{1c}: glycated hemoglobin
PA: physical activity
PRISMA: Preferred Reporting Item for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial
T2DM: type 2 diabetes mellitus

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Review

Community Health Programs Delivered Through Information and Communications Technology in High-Income Countries: Scoping Review

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Abstract

Background: The COVID-19 pandemic has required widespread and rapid adoption of information and communications technology (ICT) platforms by health professionals. Transitioning health programs from face-to-face to remote delivery using ICT platforms has introduced new challenges.

Objective: The objective of this review is to scope for ICT-delivered health programs implemented within the community health setting in high-income countries and rapidly disseminate findings to health professionals.

Methods: The Joanna Briggs Institute's scoping review methodology guided the review of the literature.

Results: The search retrieved 7110 unique citations. Each title and abstract was screened by at least two reviewers, resulting in 399 citations for full-text review. Of these 399 citations, 72 (18%) were included. An additional 27 citations were identified through reviewing the reference lists of the included studies, resulting in 99 citations. Citations examined 83 ICT-delivered programs from 19 high-income countries. Variations in program design, ICT platforms, research design, and outcomes were evident.

Conclusions: Included programs and research were heterogeneous, addressing prevalent chronic diseases. Evidence was retrieved for the effectiveness of nurse and allied health ICT-delivered programs. Findings indicated that outcomes for participants receiving ICT-delivered programs, when compared with participants receiving in-person programs, were either equivalent or better. Gaps included a paucity of co-designed programs, qualitative research around group programs, programs for patients and carers, and evaluation of cost-effectiveness. During COVID-19 and beyond, health professionals in the community health setting are encouraged to build on existing knowledge and address evidence gaps by developing and evaluating innovative ICT-delivered programs in collaboration with consumers and carers.

(J Med Internet Res 2022;24(3):e26515) doi: 10.2196/26515

KEYWORDS

telemedicine; delivery of health care; pandemics; community health services; information and communications technology; mobile phone

Introduction

Background

Health professionals, working across community and acute health care settings, have responded rapidly to the COVID-19 pandemic by adopting information and communications technology (ICT) to continue delivering health programs [1-3]. Internationally, there has been an upward surge in the use of ICT to facilitate videoconferencing and telephone consultations to meet physical distancing requirements [4-6]. In Australia, this shift to telehealth in the community health setting required a temporary restructure to government funding models [7]. COVID-19 has been a catalyst for global adoption and focus on the prioritization of ICT in health, particularly in the community health setting (primary care, ambulatory care, home-based care, and outpatient hospital care) where primary and secondary prevention health programs are delivered [3,8-13].

Digital health, *eHealth*, and *telehealth* (including telemedicine) are terms used interchangeably and broadly defined as the use of ICT platforms for the remote delivery of health care to consumers [3,14,15]. Examples include videoconferencing and telephone consultations, web-based platforms, electronic health records, SMS text messaging, and smartphone apps (or mobile health, which can include telemonitoring platforms) [14]. Globally, there is increasing support for the use of ICT platforms to improve the accessibility of health services, particularly for health promotion and disease prevention [14,16]. This is evidenced by a surge in research evaluating the usability and effectiveness of ICT-delivered health [17,18], including programs addressing chronic disease risk factors [19-23], patient education and health literacy [24,25], and chronic disease self-management [18,26-28].

Barriers to the adoption of ICT platforms by health professionals are well documented and include a lack of ICT familiarity, lack of time to implement ICT programs, design and technical concerns, and attitudes toward ICT [29-32]. There has been little scope to address these barriers during the pandemic, where there has been a greater focus on the use of ICT in COVID-19 surveillance [33-35], and delivery of telehealth consultations [3,36]. To support health professionals in transitioning community health programs to remote delivery using ICT during COVID-19, a collaborative group was established between 4 Australian universities and 2 regional health services in April 2020. A review working group was formed, with the purpose of engaging directly with health professionals to understand knowledge gaps regarding program delivery using ICT. During the consultation phase (May to June 2020), health professionals voiced concerns regarding the transition of community health programs (particularly group programs) to an ICT platform and the potential for reduced program effectiveness. Similar concerns have been shared by other health professionals internationally [37].

Approaches to undertaking reviews to inform evidence-based decision-making in health care vary [38]. Engaging stakeholders in the review process is suggested to generate more relevant review findings and enable prompt dissemination into practice [39]. An initial search was undertaken of MEDLINE Ovid, Cochrane Database of Systematic Reviews, Joanna Briggs Institute's (JBI) Evidence Synthesis, and PROSPERO for existing reviews (or proposed reviews) examining ICT-delivered health programs implemented in the community health care setting in high-income countries (HIC). No recent reviews were located that mapped the evidence for community health ICT-delivered programs, justifying the need for a scoping review [40]. The review was limited to HIC because advanced use of ICT platforms is more likely with similarities in resourcing [14]. Capturing a broad range of ICT platforms across various health disciplines and specialties was important for participating health professionals seeking to innovate and engage consumers in programs. Responding to these needs, researchers and health professionals in the review working group collaborated to develop the review question, objectives, and inclusion and exclusion criteria.

Review Questions and Objectives

The review question is as follows:

What is the evidence for the development and implementation of health programs delivered through ICT for consumers in the community health care settings in HIC?

The specific review objectives include the following:

1. to scope for evidence examining the development and implementation of ICT-delivered health programs in the community health care setting in HIC,
2. to scope for consumer co-design processes used to develop health programs,
3. to examine strategies to facilitate the sharing of consumer lived experience and peer interaction through an ICT platform, and
4. to scope for any andragogical or pedagogical principles or theories, informing program design.

Methods

Overview

This scoping review examined the evidence around ICT-delivered health programs implemented in HIC community health care settings. This review used the JBI's scoping review methodology [41]. Search terms were developed for the population, concept, and context. The review question, objectives, inclusion and exclusion criteria, and search strategies were developed and documented in advance (Section S1 in

Multimedia Appendix 1 [41-141]). The PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) was adhered to (Table S1 in Multimedia Appendix 1) [42-141].

Search Strategy

The JBI 3-step search process was used [142]. A preliminary search was undertaken in Ovid MEDLINE and CINAHL using keywords. A tailored search was then developed for each information source using keywords. For databases, a combination of Boolean operators, truncations, and Medical Subject Headings were used to form search strings (Multimedia Appendix 1). Health librarian assistance was obtained for developing the initial Ovid MEDLINE search strategy and translating searches. Reference lists of included studies were also searched for additional studies.

The databases searched included Ovid MEDLINE, CINAHL (EBSCOhost), Embase (Elsevier), and Cochrane Database of Systematic Reviews (Table S2 in Multimedia Appendix 1). Multiple platforms were searched for gray literature (Table S3 in Multimedia Appendix 1). Database searches were conducted on June 16, 2020. Gray literature searches were conducted between June 15 and 30, 2020.

Inclusion Criteria and Exclusion Criteria

The literature was selected according to the inclusion and exclusion criteria presented in Table 1). Health programs (excluding infectious disease screening, surveillance, antenatal and postnatal, and postoperative rehabilitation programs) delivered by a health professional using an ICT platform to all populations (including carers and family members) in the community health context of HIC, as defined by the Organization for Economic Co-operation and Development (OECD) [142], were included. All types of literature published from January 1, 2010, to June 16, 2020, were included to capture a broad range of ICT platforms and health programs. Only studies published in English were included because of resource constraints.

Table 1. Inclusion and exclusion criteria.

	Inclusion criteria	Exclusion criteria
Population	Health programs delivered for infants, children, young people, and adults, including those delivered for consumers, carers, and family or friends of consumers	No exclusions
Concept	Health programs (interventions, models of health care, and services, including, but not limited to, health education, self-management, health promotion and rehabilitation for secondary prevention of disease) delivered by health professionals (including psychologists, speech therapists, speech pathologists, occupational therapists, physiotherapists, physical therapists, podiatrists, exercise physiologists, dietitians, social workers, audiologists, nurses, and doctors) addressing health conditions including, but not limited to, chronic disease (eg, cardiovascular disease, respiratory disease, diabetes, renal disease, cancer, and mental illness) or risk factors for developing chronic disease including, but not limited to, obesity, physical inactivity, poor health literacy, and alcohol misuse using information and communications technology (eg, mobile health, eHealth, telehealth, web-based interventions, and digital health)	Infectious disease screening and surveillance programs, antenatal and postnatal programs, with the exception of gestational diabetes mellitus and postoperative rehabilitation programs
Context	Health programs implemented in the community health context in high-income countries (according to the Organization for Economic Co-operation and Development criteria), including primary care clinics and hospital outpatient clinics	Programs delivered in low- and middle-income countries

Study Selection and Data Extraction

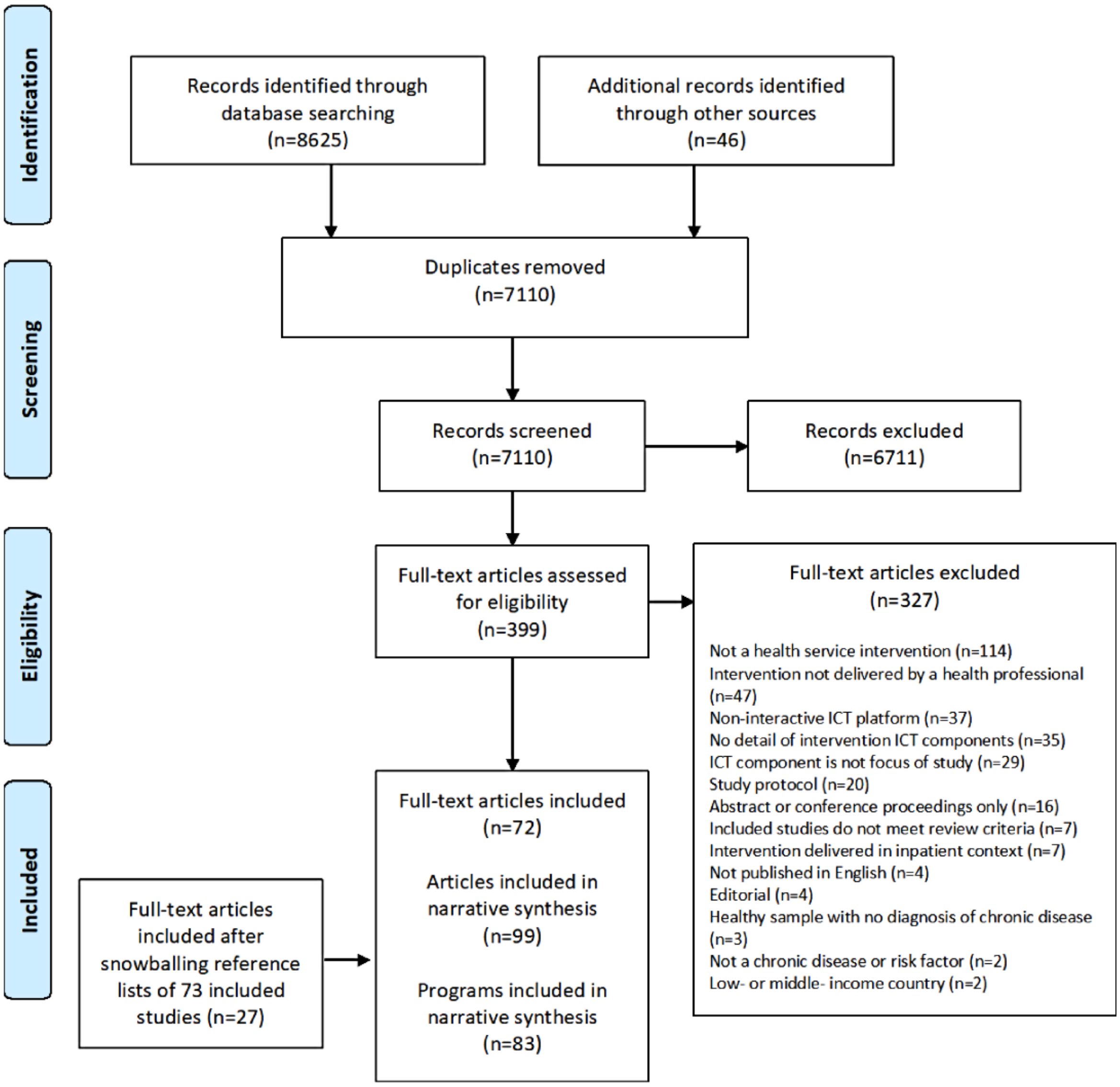
Searches were undertaken with the assistance of librarians skilled in systematic reviews. Citations were imported into Covidence (Veritas Health Innovation) for screening. Titles and abstracts were screened independently by at least two reviewers with conflicts resolved through mediation with an independent reviewer. All authors were involved in either screening, resolving conflicts, or both. Authors only resolved conflicts for citations that they did not screen. Full-text review and data extraction was then undertaken. For articles not meeting the inclusion criteria, reasons were noted (Table S4 in Multimedia Appendix 1). Reference lists of the included citations were screened for additional literature. Data extraction was tabulated (Section S1 in Multimedia Appendix 1), and findings were synthesized using a descriptive approach informed by the review objectives [41]. Consistent with scoping review methods and to enable rapid dissemination of findings, a quality assessment of the studies was not undertaken [143,144].

Results

Overview

Of the 399 citations eligible for full-text screening, 72 (18%) met the inclusion criteria. An additional 27 citations were identified from the reference lists of the included citations, resulting in 99 citations examining 83 programs (Figure 1). Reasons for exclusion were provided (Table S4 in Multimedia Appendix 1).

Figure 1. PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analyses) flow diagram. ICT: information and communications technology.



Heterogeneity of Programs Using ICT Platforms

The included health programs (n=83) were heterogeneous in design and use of ICT platforms, addressing a variety of chronic diseases (cancer, 3/83, 4%; cardiovascular disease [CVD], 12/83, 14%; diabetes [including gestational diabetes], 30/83, 36%; chronic obstructive pulmonary disease [COPD], 14/83, 17%; other chronic diseases, 11/83, 13%; and chronic pain, 2/83, 2%) and risk factors for developing chronic disease (11/83, 13%; Table S5 in Multimedia Appendix 1). The most frequently used ICT platform for program delivery was the telephone (24/83, 29%) and then internet-based platforms (21/83, 25%), telehealth (telemonitoring; 15/83, 18%), and videoconferencing (11/83, 13%). Some programs used a combination of ICT: telephone and internet-based platforms (1/83, 1%); telephone and mobile apps (2/83, 2%); telemonitoring and an internet-based platform (6/83, 7%); and telehealth (telemonitoring), videoconferencing, and telephone (2/83, 2%). Most programs were delivered by nurses (30/83, 36%) or a multidisciplinary health care team (24/83, 29%), dietitians (8/83, 10%), physiotherapists (7/83, 8%), diabetes educators (4/83, 5%), and psychologists (4/83, 5%). Diverse community health settings were captured where the programs were delivered. Most programs were delivered in outpatient hospital settings (51/83, 61%), followed by home-based settings (12/83, 15%; delivered by other community health organizations that were not primary care practices or hospitals), primary care practices (10/83, 12%), and other community health centers, including multidisciplinary centers (7/83, 8%) and community cancer centers (3/83, 4%).

The included health programs were from 19 OECD HIC. The United States had the highest number of programs (31/83, 37%), followed by Australia (14/83, 17%), Canada (7/83, 8%), Spain (5/83, 6%), the United Kingdom (5/83, 6%), Denmark (4/83, 5%), Norway (3/83, 4%), Italy (3/83, 4%), the Netherlands (2/83, 2%), Belgium (2/83, 2%), Taiwan (2/83, 2%), Greece (2/83, 2%), France (2/83, 2%), Japan (1/83, 1%), Finland (1/83, 1%), Germany (1/83, 1%), South Korea (1/83, 1%), Singapore (1/83, 1%), and Switzerland (1/83, 1%). A total of 2 programs were implemented in >1 country, accounting for 88 sites of program implementation across all included studies [76,86].

Program Design: Group Programs, Co-design, and Guiding Theories

The programs primarily targeted only patients (76/83, 92%). Fewer programs were for patients and carers (7/83, 8%) and included 2 programs for cancer management [43,44], 1 telemonitoring program for CVD [56], 1 rehabilitation program for acquired brain injury [61], 1 pediatric asthma management program [64,65], 1 coping skills training program for COPD [78], and 1 self-management program for psychological distress [133].

Of the 83 programs, 16 (19%) were either delivered to groups of participants or included a component that involved groups of participants. Of these 16 programs, 5 (31%) targeted diabetes education, self-management, and behavior change coaching [101,102,108,116,125]; 4 (25%) programs were CVD rehabilitation (secondary prevention) or counseling programs [46,47,52,53,55,57]; 4 (25%) addressed risk factors for chronic disease through education and behavior change coaching [131,132,136,141]; 1 (6%) involved group cognitive behavioral therapy (CBT) for participants experiencing insomnia [66]; 1 (6%) involved pharmacist-led group education for hepatitis C [73]; and 1 (6%) involved group education for osteoarthritis [70].

No studies included strategies to facilitate the sharing of consumer lived experience and peer interaction in group ICT-delivered programs. A qualitative study evaluating 1 group program (CVD rehabilitation program) reported that participants engaged in group sessions but did not provide information regarding participants’ experiences [46]. There was limited information of any co-design processes used with consumers or participants to develop programs. Only 2 studies investigating 2 different programs mentioned collaboration with consumers or community organizations to develop interventions; however, no detail about the collaboration was provided [70,119].

None of the studies used specific andragogical or pedagogical principles to inform the delivery of ICT programs to adult or child participants. A total of 12 citations referred explicitly to health behavior theories that informed program development or delivery. Constructs of social cognitive theory (SCT) were used to inform a diabetes self-management support program (Health Education Access Through Information Technology and Utilization Program) [123], a diabetes telemedicine program [111], a pedometer-based intervention for the secondary prevention of CVD [50], a telephone-based Living Well with Diabetes program [104], a telephone-based symptom management program for people with lung cancer and their carers [76], and a telephone-based health coaching program for the secondary prevention of CVD [58,59]. Strategies were implemented to optimize program participation and adherence by promoting SCT constructs (eg, self-efficacy). Examples of strategies included supporting participants to engage in goal setting (eg, related to physical activity) [50], encouraging participants to seek support and rewarding achievements [104], and equipping participants with skills (through cognitive restructuring, problem solving, or self-soothing) to enhance self-efficacy [76].

Other theories included self-determination theory, which informed the development of a telephone-based coaching program targeting physical activity and quality of life for inactive adults through self-management [132]. Using self-determination theory as a conceptual framework, the program integrated motivational interviewing and CBT approaches to coaching [132]. The chronic care model developed by Wagner et al [145] and the transtheoretical model [146] were also used to guide a diabetes self-management education program [119], enabling self-management education and management goals to be provided and set specifically for the stage of change participants were at. The transtheoretical model was also used to inform the content and delivery of pediatric asthma management programs delivered to children and their carers [64,65] and a telehealth diabetes self-management program, along with the health belief model [102].

Research Evidence: Study Designs, Findings, and Limitations

Heterogeneity was evident in the research design of included citations (n=99) when evaluating the effectiveness, feasibility, or acceptability of the included programs (n=83; Table S6 in Multimedia Appendix 1). Most studies used a randomized controlled trial (RCT) design (58/99, 59%), followed by a single cohort study design (12/99, 12%), a cohort study with 2 or more groups (7/99, 7%), a qualitative design (5/99, 5%), an economic evaluation of an RCT (4/99, 4%), a mixed methods study design (3/99, 3%), or a survey design (2/99, 2%). The remaining citations used other non-RCTs or experimental study designs (8/99, 8%).

Primary and secondary outcomes, and approaches to measuring outcomes (eg, use of validated questionnaires or devices) varied between studies and conditions (Table S6 in Multimedia Appendix 1). For RCTs, the reported effect was categorized as positive (ICT intervention was effective or more effective than control), neutral (effects were equivalent to control), or negative (ICT intervention was not effective or less effective than control) where appropriate, to provide an indication of the effectiveness of programs using ICT platforms. Of the 58 studies able to be categorized, 30 (52%) reported positive effects on the primary and secondary outcomes attributed to the ICT intervention, when compared with the control group, whereas 28 (48%) studies reported a neutral effect. No RCTs reported that outcomes were worse in the ICT intervention group than in the control group. Owing to the heterogeneity of primary and secondary outcome measures and program design, the most frequently reported outcome measures for condition groups used in RCTs are reported in Table 2, with the effects categorized. From the studies included in this table, there was consistency in the findings of RCTs of COPD programs reporting on health service use outcome measures. The effect of programs on the rate of hospitalization of the ICT intervention and control groups were found to be neutral. However, for RCTs of programs using clinical, anthropometric, or physical activity outcome measures, there was a mix of positive and neutral effects. The length of the final follow-up periods in RCTs ranged from 6 weeks to 5 years (with a median follow-up period of 12, IQR 6-15 months).

Table 2. Most frequently reported primary outcome measures in included RCTs[a].

Study	Reported effect and results
Outcome measure: HbA $_{1c}$ [b] (diabetes programs)	
Baron et al [94]	Neutral: Program did not achieve a clinically significant reduction in HbA_{1c}.
Blackberry et al [96]	Neutral: At 18-months follow-up, the effect on HbA_{1c} did not differ between the intervention and control (mean difference 0.2, 95%CI −0.2 to 0.2; *P*=.84).
Buysse et al [97]	Positive: Both groups received tele-education at different time points (delayed access [control] and immediate access [study group]) and demonstrated an overall significant impact of tele-education on HbA_{1c} reduction (−0.5% control and −0.4% study group, respectively).
Carter et al [98]	Positive: Patients enrolled in intervention were 4.58 times more likely to achieve an HbA_{1c} target <7%.
Charpentier et al [99]	Positive: At 6 months, mean HbA_{1c} was lower in the intervention group than in the control group (8.41 vs 9.10, respectively).
Davis et al [102]	Positive: A significant reduction in HbA_{1c} was found in the intervention group, compared with usual care (9.4 to 8.2 in the intervention group, compared with 8.8 to 8.6 in usual care).
Fountoulakis et al [107]	Positive: Significant reduction in HbA_{1c} in the intervention group at 3 and 6 months, when compared with that in the control group.
Greenwood et al [108]	Positive: The intervention group had a statistically significant difference of 0.41 percentage points at 6 months when compared with the control group.
Klingeman et al [117]	Positive: Average HbA_{1c} reduced by 1.7% in the intervention group, compared with 0.3% in the control group.
Sood et al [124]	Neutral: No statistically significant differences between the intervention and control groups at 18 months.
Varney et al [127]	Positive: The intervention group experienced a greater mean change in adjusted HbA_{1c} than the controls between baseline and 12 months; however, this was not sustained.
Wakefield et al [129]	Neutral: Participants in the intervention group experienced decreased HbA_{1c} during the 6-month intervention period when compared with the control group; however, 6 months after the intervention was withdrawn, the intervention groups were comparable with the control group.
Weinstock et al [113]	Positive: Intervention was associated with improved HbA_{1c} over 5 years, when compared with control.
Wild et al [110]	Positive: Clinically and statistically significant improvements were observed in the intervention group at 9 months, when compared with the control group.
Outcome measure: rate of hospitalization (COPD[c] programs)	
Antoniades et al [75]	Neutral: No significant difference between the intervention and control groups at 12 months.
Blumenthal et al [78]	Neutral: No significant difference between the intervention and control groups up to 4.4 years follow-up
Fairbrother et al [84]	Neutral: No significant difference between the intervention and control groups at 12 months.
Pinnock et al [85]	Neutral: No significant difference between the intervention and control groups at 12 months.
Kessler et al [86]	Neutral: No significant difference between the intervention and control groups at 12 months.
Tabak et al [89]	Neutral: No significant difference between the intervention and control groups at 2 months.
Outcome measure: PA[d] or capacity (cardiovascular disease programs)	
Lear et al [47]	Positive: Intervention group participants who received support from a health professional through an internet-based platform had a greater increase in maximal time on the treadmill by 45.7 seconds (95% CI 1.04-90.48) compared with the usual care group over the 16 months (*P*=.045).
Furber et al [50]	Positive: After the 6-week intervention, improvements in total PA time, total PA sessions, walking time, and walking sessions were all significantly greater in the intervention group who received telephone support than in the control who received 2 education pamphlets and no support via telephone.
Hawkes et al [59]	Neutral: No significant difference between the PA of participants in the intervention and control groups at 6 months follow-up.
Hwang et al [52,53]	Neutral: No difference was found between the PA of participants receiving the telerehabilitation intervention when compared with the control group who received center-based care, and it was less costly than center-based heart failure rehabilitation.
Nolan et al [57]	Positive: More telehealth participants than control participants reported adherence to exercise and diet after treatment at a 6-month follow-up.

Study	Reported effect and results
Outcome measure: weight loss or prevention of weight gained (risk factors for chronic disease programs)	
Ferrara et al [135]	Positive: Compared with those receiving usual care, women in the lifestyle intervention had reduced weekly rate of gestational weight gain (mean 0.26 vs 0.32 kg/week).
Padwal et al [138]	Neutral: Face to-face or web-based delivery of intensive self-management program was no more effective than the once off provision of educational materials and were more costly.
Weinstock et al [141]	Positive: Mean percent weight loss at 2-year follow-up was higher for the conference call group than for the individual call group (−5.6% compared with −1.8%).

[a] RCT: randomized controlled trial.

[b] HbA_{1c}: glycated hemoglobin A_{1c}.

[c] COPD: chronic obstructive pulmonary disease.

[d] PA: physical activity.

Of the 7 studies using qualitative inquiry (including mixed methods studies using qualitative inquiry), 3 (43%) studies examined the attitudes of participants (a videoconferencing education workshop for inflammatory arthritis, a COPD telemonitoring program, and a telemonitoring program for diabetes) [71,88,109], 2 (29%) examined perceptions of a T2DM smartphone app [118,121], 1 (14%) measured the patient experience of being involved in a web-based cardiac rehabilitation program [46], and 1 (14%) examined the perceptions of both patients and health professionals involved with a COPD telemonitoring service [83]. Themes varied but generally related to the accessibility of ICT programs [46] and general participant satisfaction [88]. A study also reported no difference in feedback obtained from participants who attended an in-person program compared with those who attended videoconferencing [71]. Another study reported limitations of using ICT platforms, including frustration with using smartphones [118], whereas other studies reported that technology was acceptable [83,88,109,121].

Studies providing an economic evaluation of an ICT-delivered program, in conjunction with either an RCT [49,52,54,132] or a case-control study [51], supported the potential for the cost-effectiveness of ICT-delivered programs when compared with in-person programs. When examining telerehabilitation for CVD, Hwang et al [52] found the intervention to be as effective and less costly than center-based rehabilitation. Ho et al [51] reported that a telehealth program for CVD was more cost-effective and more likely to prevent hospitalizations than usual care. However, a telemonitoring program for CVD was reportedly not cost-effective because the intervention had higher costs (including equipment costs) than usual care, and no significant difference was found in quality-adjusted life years [54].

Research limitations frequently reported included high attrition rates, small sample sizes (or not statistically powered for outcome measures), and limited external validity. The total attrition rates of RCTs ranged from 1% to 63%, with a median attrition rate of 18% (IQR 10%-25%). Difficulty in recruiting participants was also reported by some researchers. An RCT conducted a survey of why participants declined to participate in the trial and found personal reasons and concerns with technology were frequently cited by respondents [54].

Discussion

Principal Findings

This review provides a broad overview of research examining ICT-delivered programs implemented in the community health setting in 19 countries, providing a sample of programs from 24% (19/80) of OECD HIC [144]. The highest proportion of included ICT-delivered programs was implemented in the United States, the country with the highest financial investment in health care (16.9% of gross domestic product in 2018) [147] and a growing investment in digital health [148]. Although this review was limited to programs implemented by OECD HIC, other studies have identified a surge in ICT programs and innovations in low- and middle-income countries [149-151]. Because of the COVID-19 pandemic, it is anticipated that ICT-delivered health programs and innovations will continue to increase as global health care systems are transformed [152].

Included programs and citations were diverse, addressing a range of chronic diseases and risk factors, using a variety of ICT platforms delivered by different health professionals across different community health settings. Programs mostly targeted highly prevalent chronic diseases and risk factors, such as CVD, COPD, diabetes, and obesity or being overweight [153,154], and were delivered in the outpatient hospital setting. The need to facilitate a greater adoption of ICT in other community health settings (eg, primary care practices) has been identified by other international research and is supported by the review findings [155]. Furthermore, there were few self-management and education programs addressing cancer and mental health conditions, other chronic diseases that pose a significant burden on global populations [153]. During the COVID-19 pandemic, the need for improved accessibility to mental health programs has also been identified [156]. There were also few programs implemented for patients and carers. There is an increasing focus on the importance of carer engagement, particularly for dementia care [157] and mental health [158], and research around the role of ICT programs in supporting carers [159].

A high proportion of programs were delivered using the telephone, internet, and telemonitoring. With a surge in the use of mobile health technologies through smartphone apps and other innovations (eg, activity monitoring devices), this finding suggests that the telephone remains an important ICT platform for improving patient accessibility to health professionals, particularly for self-management and behavior change coaching. This is evident by the use of telehealth during COVID-19 in countries such as Australia, where telephone consultations have had a higher uptake in primary care settings compared with videoconferencing delivered via web-based platforms [160]. The usefulness of videoconferencing for delivering group education, behavior change coaching, and self-management programs is also indicated by the review findings. Although this review reports little about the acceptability of ICT-delivered group programs and strategies to facilitate peer interaction, other reviews have found that group programs delivered through videoconferencing have been acceptable and feasible to participants [161]. Future research needs to examine how to facilitate group interaction in ICT programs [162].

Although the included studies had a range of research designs (a finding of another systematic review examining emergent eHealth interventions [163]), the findings from this review supported the effectiveness of nurse-led ICT programs in improving pain associated with cancer [43], improving quality-of-life outcomes and reducing hospital admissions for patients with CVD [56], improving health outcomes for patients with CVD [58,59], and improving quality of life in carers of children with asthma [64,65]. Findings also indicated the effectiveness of ICT-delivered programs by allied health professionals, including a telenutrition program delivered by dietitians [60] and a chronic pain program delivered by physiotherapists [91]. The results from included RCTs comparing participant outcomes of an ICT program to a control group (receiving mostly in-person care) were either equivalent or better for ICT programs. Other reviews examining ICT interventions, such as nurse and allied health, delivered telehealth interventions [164], and electronic CBT [165], also concluded that delivering health interventions through ICT platforms does not lead to poorer health outcomes for patients.

Substantial gaps in research evidence relating to ICT programs delivered in the community health setting by health professionals were identified. There were few co-designed ICT programs (and no documentation of co-design processes) and no reference to specific pedagogical or andragogical educational principles guiding program delivery—gaps identified by other reviews [166,167]. Engaging stakeholders in program development through co-design processes is thought to create programs that are more useful and acceptable to end users [168]. Some programs were developed or guided by theories; however, further research is required to examine whether using theories (eg, SCT) to develop and guide programs results in better outcomes for participants [169]. Few studies have examined participant acceptability, experience, and perceptions of ICT programs through qualitative inquiry. However, qualitative findings resonate with other reviews that have found that participants are generally satisfied with telehealth [170]. Findings indicate that there is a need for greater consumer engagement in the process of developing ICT programs and evaluating effectiveness [171]. There is also a need for more economic evaluations of ICT programs delivered in the community health setting, which is also lacking in broader health services research [172,173].

Engaging with health professionals to understand knowledge gaps regarding community health ICT program delivery during COVID-19 and codevelopment of the scoping review question, objectives, and inclusion and exclusion criteria are strengths of this review. A summary of review findings was rapidly disseminated to health professionals involved, and findings were discussed during a short webinar. The limitations of the review include only a brief search of international gray literature due to the need to rapidly disseminate findings to health professionals. Undertaking a more thorough search of the international gray literature could have minimized publication bias. There is potential that relevant citations were not included in the review owing to this constraint. Despite this, every effort was made to review the reference lists of included citations for additional studies. Studies published in a language other than English were not captured by this review owing to resource constraints.

Conclusions

This review identified heterogeneity in available evidence examining ICT-delivered programs in community health settings in HIC. There is promising evidence for the effectiveness of nurse and allied health delivered ICT programs. From RCTs, outcomes for participants receiving ICT programs, compared with those receiving in-person programs, were either equivalent or better. Gaps identified included a paucity of co-designed programs; qualitative research relating to consumer acceptability, experience, and interactions in group programs; and cost-effectiveness of ICT programs and programs targeting patients and carers. It is expected that because of COVID-19, there will be a surge in the innovation, development, and evaluation of community health programs delivered using ICT platforms, providing an opportunity for health professionals and researchers to build on existing knowledge and address evidence gaps.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Included studies characteristics, search strategies, protocol, excluded studies, and PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist.
[DOCX File , 180 KB-Multimedia Appendix 1]

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Abbreviations

CBT: cognitive behavioral therapy
COPD: chronic obstructive pulmonary disease
CVD: cardiovascular disease
HIC: high-income countries
ICT: information and communications technology
JBI: Joanna Briggs Institute
OECD: Organization for Economic Co-operation and Development
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
RCT: randomized controlled trial
SCT: social cognitive theory

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Original Paper

The Mediating Role of Patients' Trust Between Web-Based Health Information Seeking and Patients' Uncertainty in China: Cross-sectional Web-Based Survey

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Abstract

Background: In the physician-patient relationship, patients' uncertainty about diseases and the lack of trust in physicians not only hinder patients' rehabilitation but also disrupt the harmony in this relationship. With the development of the web-based health industry, patients can easily access web-based information about health care and physicians, thus reducing patients' uncertainty to some extent. However, it is not clear how patients' web-based health information–seeking behaviors reduce their uncertainty.

Objective: On the basis of the principal-agent theory and the perspective of uncertainty reduction, this study aims to investigate the mechanism of how web-based disease-related information and web-based physician-related information reduce patients' uncertainty.

Methods: A web-based survey involving 337 participants was conducted. In this study, we constructed a structural equation model and used SmartPLS (version 3.3.3; SmartPLS GmbH) software to test the reliability and validity of the measurement model. The path coefficients of the structural model were also calculated to test our hypotheses.

Results: By classifying patients' uncertainties into those concerning diseases and those concerning physicians, this study identified the different roles of the two types of patients' uncertainty and revealed that web-based disease-related information quality and web-based physician-related information can act as uncertainty mitigators. The quality of disease-related information reduces patients' perceived information scarcity about the disease ($\beta=-.588$; $P<.001$), and the higher the information scarcity perceived by patients, the higher their uncertainty toward the disease ($\beta=.111$; $P=.02$). As for physician-related information, web-based word-of-mouth information about physicians reduces patients' perceived information scarcity about the physician ($\beta=-.511$; $P<.001$), mitigates patients' fears about physician opportunism ($\beta=-.268$; $P<.001$), and facilitates patients' trust ($\beta=.318$; $P<.001$). These factors further influence patients' uncertainty about the physician. In addition, from the test of mediating effect, patients' trust in the physician fully mediates the relationship between their perceived information scarcity about the physician's medical service and their uncertainty about the physician. Patients' trust also partially mediates the relationship between their fear of the physician's opportunism and their uncertainty about the physician. As for the two different types of uncertainty, patients' uncertainty about the physician also increases their uncertainty about the diseases ($\beta=.587$; $P<.001$).

Conclusions: This study affirms the role of disease-related web-based information quality and physician-related web-based word-of-mouth information in reducing patients' uncertainties. With regard to the traits of principal-agent relationships, this study describes the influence mechanism based on patients' perceived information scarcity, fears of physicians' opportunism, and patients' trust. Moreover, information about physicians is effective in reducing patients' uncertainties, but only if the information enhances patients' trust in their physicians. This research generates new insights into understanding the impact of web-based health information on patients' uncertainties.

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KEYWORDS

patient trust; online health information quality; online word-of-mouth; patient uncertainty; principal-agent theory; physician-patient relationship

Introduction

Background

In a physician-patient relationship, it is always difficult for patients to evaluate medical services and their physicians because medical services are typical credence products [1,2]. Patients also lack the specialized knowledge to judge whether a physician's treatments would be helpful before the treatments begin. Therefore, as principals, in this typical principal-agent relationship, patients face many uncertainties.

Previous research has explored how to achieve better treatment outcomes by reducing patients' uncertainty [3-6]. The uncertainty in this principal-agent relationship is caused by information problems [7], such as hiding information and hiding behaviors; therefore, to reduce patients' uncertainties, it is important to provide patients with more information. With the rapid development of patient-centered care [8], the physician-patient relationship is gradually changing from the traditional physician-led model to a new type of patient-centered diagnosis and treatment, with increasing emphasis on the role of patients [9]. The role of patients is changing from passive information recipients to active participants in medical decision-making [10]. The development of the eHealth industry has led to an increase in the number of patients who become electronic patients, namely, e-patients [9]. The channels for e-patients to obtain information about diseases and physicians have expanded, and this information can enhance patient-centered care [8]. For example, in a survey by Wong and Cheung [11], 97.32% (1162/1194) of the respondents used the internet, of which 87.44% (1016/1162) had used the internet to find health information. In a survey by Hedges and Couey [12], 90% of patients used web-based reviews to evaluate their physicians. By actively acquiring information about diseases and physicians through electronic information technology, e-patients can enhance their understanding of their medical condition and have a sense of control over their health, while reducing their uncertainties about the consultation processes and the physicians.

Although web-based information can reduce patients' uncertainty to some extent, information overload can pose a major challenge [13], leading to confusion in e-patients. Incorrect information does not effectively reduce patients' uncertainty. Moreover, this information may undermine patients' trust and have a counterproductive effect [14]. Therefore, it is important to understand how patients' web-based information consumption reduces their uncertainty, so that information providers can improve the design of information to better help patients. With this as the objective, this study intends to answer the following research questions: how do patients' web-based information-seeking behaviors reduce their uncertainties about diseases and physicians? In addition, how does web-based information, such as information related to diseases and physicians, alleviate problems in this principal-agent relationship and then reduce patients' uncertainty?

To address these research questions, based on the framework of *uncertainty mitigator–uncertainty antecedent–uncertainty*, this study explores how web-based health information mitigates patients' uncertainty. The contributions of this study are as follows. First, based on the principal-agent theory and the uncertainty reduction theory (URT), this study explores the mechanism of how patients' web-based health behaviors can reduce their uncertainty. Second, following the classification of consumers' uncertainty about products and sellers by Dimoka et al [15], this study also distinguishes between patients' uncertainty about diseases and physicians; the influence chain is also investigated. Finally, this study emphasizes the significant role of trust. Additional information can help reduce patients' uncertainty, but only if it can enhance patients' trust in their physicians.

Principal-Agent Theory

Originating from the field of enterprise management, the principal-agent theory describes the relationship in which one entity (the principal) delegates work to another entity (the agent) who performs the work under a mutually agreed contract [16]. The relationship between enterprise owners and professional managers is a typical principal-agent relationship. This relationship applies to all transactional relationships in socioeconomic systems where opportunism, information asymmetry, and limited rationality exist. Owing to the separation of ownership and management rights of enterprises, the goals of principals and agents are inconsistent, which will lead to adverse selection before the contract [17] and the moral hazard of hidden behaviors after the contract [18].

The physician-patient relationship is also a typical principal-agent relationship in which the physician acts as an agent to provide medical services to the patient (the client) under a contract [19,20]. Patients, as principals, receive diagnoses of the disease, treatment plans, and medical care services from the agents (ie, physicians). Physicians and patients have inconsistent goals and asymmetrical information. Compared with physicians, patients are always at a disadvantage in information about diseases and physicians' medical services. Patients want to receive superior medical services at a low cost to improve their health, whereas physicians want to provide medical services at a higher fee and lower cost (to themselves) to increase their income and reputation.

Perceived Information Scarcity

Owing to the principal-agent relationship and the specialization of medical services, there is natural information asymmetry between physicians and patients [21]. Compared with physicians, patients have limited information about diseases and physicians, leading to patients' perception of information scarcity. Previous literature defined scarcity as the limitation or unavailability of objects (eg, commodity) [22]. In the research of Wells et al [23], an individual's degree of prepurchase information scarcity related to the product of interest is operationalized as whether a consumer had any prior information or experience with products offered on web-based shopping websites. Compared with physicians, patients lack professional medical education process and clinical experience; therefore, patients will be aware of the information scarcity regarding diseases and the physician's medical service. In this study, patients' perceived scarcity of information about diseases is defined as patients' perception of their limited information related to diseases, whereas perceived scarcity of information about the physician's medical service information is defined as patients' perception of their limited information related to the physician's medical service.

In the web-based environment, the emergence of information systems can help alleviate the principal–agent problem to some extent. For example, the website and product information can reduce customers' information scarcity about products, thereby reducing customers' worries about the platform's opportunism and their purchase uncertainty [24]; the implementation of information systems within organizations, such as hospitals, was also found to be an effective means of improving information transparency [25]. Similarly, the disease-related and physician-related information obtained by patients through web-based searches can respectively help patients understand diseases and their physicians better. Web-based disease-related and physician-related information can reduce patients' perceived scarcity of information about diseases and their physicians.

However, the information quality is unevenly distributed in the problem of information asymmetry [24], but existing studies failed to take into account the impact of the information quality of search behavior, especially because web-based health information lacks accuracy and credibility [26]. Information quality is always measured by the perceived information quality, which represents information receivers' subjective perception about four dimensions of information quality, namely, relevance, adequacy, usefulness, and understandability of the information [27]. Higher-quality information can lead to better descriptions about the targets, and it is more useful than lower-quality information [28]. With a higher quality of diseases information in the web-based environment, patients will perceive the information as more relevant, adequate, and useful, thereby increasing their information about the diseases. As a result, the higher the quality of disease-related information sought by patients, the lower the perceived scarcity of information about the disease, leading to the following hypothesis: web-based health information quality reduces patients' perceived scarcity of information regarding diseases (H1).

In addition to disease-related information, web-based health information provides patients with physician-related information, such as web-based word-of-mouth information about physicians, which represents other patients' visiting experiences. In traditional offline hospitals, patients had very limited access to physicians' medical service information, which was often confined to the small reach of word-of-mouth communication, making it difficult to obtain a large amount of word-of-mouth physician information. Web-based word-of-mouth information can effectively reduce asymmetries of products information [29,30]. Web-based word-of-mouth information can inform later customers about the details of the products or the service [28,31]. Similarly, physicians' web-based ratings are also found to reflect their quality perceived by offline patients [32]. Web-based word-of-mouth information about physicians obtained by patients before their visit helps patients to know the physicians better, such as the physicians' manner, treatments, and knowledge. Therefore, web-based word-of-mouth information can reduce patients' perceived scarcity of information about their physician's medical services, leading to our second hypothesis: patients' perceived web-based word-of-mouth information about physicians reduces patients' perceived scarcity of information regarding the physicians' medical services (H2).

Fear of Physicians' Opportunistic Behaviors

In the principal-agent relationship, both parties expect to maximize their own interests [16]. The agents will work to increase their benefits, but some of their behaviors may even increase principals' costs, leading to agents' opportunistic behaviors [33]. As principals, patients are concerned about whether the physicians have opportunistic behaviors because patients cannot accurately evaluate physicians' behaviors, especially in China. Owing to the imperfections of the medical systems in China, opportunistic behaviors of medical service providers have caused widespread concerns [34,35], such as whether physicians receive kickbacks, prescribe high-priced drugs [36], or ask patients to do excessive or unnecessary examinations or treatments [36], all of which are beneficial to physicians' own interests but harm patients' interests [37]. Opportunistic behaviors are also harmful to the physician-patient relationship because these behaviors reduce patients' trust in physicians [38].

Patients can not only obtain health information such as diagnoses and treatments through eHealth data but also browse web-based reviews about physicians. Compared with offline word-of-mouth information, web-based word-of-mouth information has a greater impact on consumers' behaviors because of its extensive sources, large coverage, and convenient dissemination [39]. Positive web-based word-of-mouth information can effectively reduce principals' concerns about agents' opportunistic behaviors [24,40]. Web-based word-of-mouth information about physicians helps improve the transparency of medical services and enhance patients' confidence in medical decisions [41]. It also reflects the experiences of other patients with similar diseases [42]. With more web-based word-of-mouth information about the physicians, patients can evaluate the likelihood of the physicians' opportunistic behaviors, and then they can choose physicians who are less likely to engage in those opportunistic behaviors. Therefore, positive web-based word-of-mouth information helps reduce patients' concerns about physicians' opportunism. Physicians' opportunism, in this study, is defined as the behaviors of physicians who do not provide good services but charge high prices, conduct excessive and unnecessary examinations, and receive rebates to prescribe high-priced drugs [36]. With better web-based word-of-mouth information about physicians, patients will be less apprehensive of the physicians' opportunistic behaviors, leading to the following hypothesis: patients' perceived web-based word-of-mouth information about a physician reduces patients' fear of the physician's opportunism (H3).

Trust

In the principal-agent relationship, trust is the most valuable aspect [43], because if the relationship occurs under ideal conditions, there is no need for trust [44,45]. Trust is the expectation that an individual or a group will make an effort of good faith to behave following commitments (both explicit and implicit), to be honest, and not to take excessive advantage of others, even when the opportunity exists [46]. Owing to the scarcity of patients' information about clinical diagnoses and treatments, the asymmetry of physicians' medical service information between patients and physicians makes it difficult for patients to determine whether the physicians are trustworthy [24]; therefore, in the physician-patient relationship, the information scarcity of physicians' medical services impedes patients' trust in the physicians, leading to hypothesis 4: patients' perceived information scarcity about physicians' medical service information reduces patients' trust in physicians (H4).

In the principal-agent relationship, as agents, patients' fear of physicians' opportunistic behaviors also influences patients' trust in physicians. Existing research has confirmed that opportunistic behavior in web-based banking leads to low levels of trust of users in internet banking [47]. In the e-commerce environment, fear of sellers' opportunism also harms buyers' trust [33]. In the physician-patient relationship, opportunistic behaviors are also harmful because these behaviors reduce patients' trust in physicians [38]. Although physicians' behaviors are not always immoral, patients still worry about the possibility of physicians' opportunistic behaviors because the principal-agent relationship is favorable for physicians to act immoral behaviors. This worry will be enhanced if the possibility of the physicians' opportunism is high. Physicians' opportunistic behavior benefits their own interests but harms the interests of patients, which also impedes patients' trust in them. Patients cannot monitor physicians' behaviors, and they worry that their physicians will act opportunistic behaviors; thus, the fear of physicians' opportunism reduces patients' trust, leading to hypothesis 5: the fear of physicians' opportunism reduces patients' trust in physicians (H5).

Web-based word-of-mouth information is an important factor affecting potential customers' purchase intentions and behaviors [48,49], because web-based word-of-mouth information reflects previous consumers' evaluation of the products. In medical situations, some studies have also explored the impact of web-based physician reviews on patients' decision-making behavior. For example, higher web-based ratings of physicians increase patients' intention to consult them [50]. Web-based word-of-mouth information about physicians also increases physicians' offline visits [51]. Acting as the previous patients' evaluation cue, physicians' web-based word-of-mouth information serves as an important reference for the selection of physicians by patients. The better the patients perceive web-based word-of-mouth information about the physicians, the more favorable it is for the patients to trust in the physicians, leading to the following hypothesis: patients' perceived web-based word-of-mouth information about physicians increases patients' trust in the physicians (H6).

URT Overview

In the principal-agent relationship, uncertainty arises because the principal cannot fully monitor the agent's behavior, resulting in adverse selection [17] and the moral hazard of hidden behaviors [18]. It is important to understand how to reduce uncertainty in this relationship. For example, reducing uncertainty can increase consumers' purchase intention and lead to an actual purchase [24]; reducing uncertainty can also increase users' trust in the web-based world so that they can effectively use a tool [52]. Originating from the field of interpersonal communication, the URT posits that uncertainty occurs when people cannot predict the future behavior of others or when they do not meet their own expectations [52,53]. URT is widely used in fields such as organizational behavior and information systems, among others [52]. For example, Srivastava and Chandra [52] considered 3 ways to reduce users' uncertainty to enhance their trust and use intention in the web-based world. The three ways include acquiring information passively through observation, acquiring information actively through third-party search, digital signatures, and third-party authentication, and acquiring information from interactions, such as direct interaction with the target object [52].

In the medical scenario, patients' uncertainties, that is, their inability to accurately predict the state of their disease because of a lack of information, exist in every aspect of their diagnoses and treatments. Uncertainties in the principal-agent relationship are caused by specific information problems (eg, hiding information and hiding behavior), and these problems can be alleviated by the use of information systems [24]. In the physician-patient relationship discussed previously, the disclosure of information comes from the agent (eg, medical information provided by the physician), and it reduces only a few uncertainties of patients, but with the development of technology, medical and health information is no longer only in the hands of the medical providers (agents). The client can actively acquire medical and health information from a third party [20], enabling patients to overcome the restrictions of time and space and actively obtain information about the causes of diseases, treatments, and reputations of physicians and hospitals through the internet. With the active information acquisition method [52] to reduce uncertainty, patients' web-based search behavior can help actively reduce uncertainty, but the influence mechanism of how web-based information acquired by patients reduces uncertainty is not yet clear.

Patients' Uncertainty

Uncertainty in the medical context refers to a cognitive state in which the meaning of medical events cannot be determined [3,4]. Uncertainty, as a medical experience characterized by unpredictability, unfamiliarity, and ambiguity, is associated with poor medical outcomes and psychological states (eg, fear, stress, and loss of control) [43]. Existing research on uncertainties in the medical field has mainly focused on information uncertainty related to diseases, diagnoses, and treatments [5]. Uncertainties regarding illness can be divided into the medical providers' uncertainty about diseases and the patients' uncertainty about diseases. Previous research has mainly focused on the physician's uncertainty of expressing disease-related information during patients' visits and its impact [54]. The latter, that is, patients' uncertainty about diseases, is the focus of this study.

Patients' uncertainty means that the patients are unable to determine the meaning of disease-related events or accurately predict the outcomes of such events [5,6]. In the uncertainty in illness theory presented by Mishel [3], the antecedents (eg, symptom stimulus, patients' cognitive abilities, and physicians' information authorities), the appraisal process, the coping mechanism, and the adaptation outcomes of patients' uncertainty in diseases are concluded, and the scale of patient uncertainty about illness is developed. This theory is effective in guiding interventions to manage patients' uncertainty [55].

In web-based markets, as sellers cannot fully describe the product or predict the products' future performances, consumers' uncertainty about products and sellers should be distinguished, between which the former uncertainty is related to the description and performance of products, and the latter uncertainty is related to sellers' adverse selection and moral hazard [15]. The uncertainty about sellers also increases uncertainty about products, and the two types of uncertainties reduce price premiums [15]. Similarly, in the physician-patient relationship, as physicians cannot fully describe the diseases or predict the effectiveness of treatments, patients' uncertainty in the process may be not only about the diseases but also about the physicians. Owing to the traits of principal-agent relationship, patients, who are the inferior party because of the scarcity of information, tend to question the rationality of physicians' advised medical treatments. However, in the medical context, few researchers have focused on patients' uncertainty about physicians. Given this, considering the principal-agent relationship between physicians and patients, we follow the classification of customers' uncertainties about sellers and products by Dimoka et al [15] to distinguish between patients' uncertainty about diseases and patients' uncertainty about physicians. In this way, this study can contribute to research on patients' uncertainty.

In the principal-agent relationship, how much information principals have played a key role in their uncertainty [23,24]. The lower the availability of product information, the greater the consumers' uncertainty about the product quality [23]; therefore, in our context, patients' perception of scarcity of disease information can increase patients' uncertainties about the diseases, and we hypothesize the following: patients' perceived information scarcity about diseases increases patients' uncertainty about the diseases (H7).

Owing to information scarcity, it is difficult for patients to judge the quality of physicians' medical services. Less information about physicians' medical services leads to patients' stronger sense of uncertainty about physicians. According to research on the uncertainty of patients regarding disease [3], the causative factors include event familiarity. When patients have more knowledge about the physicians' medical services, it helps to reduce their uncertainty about the physicians' medical services, leading to the following hypothesis: patients' perceived information scarcity about physicians' medical services information increases patients' uncertainty about the physicians (H8).

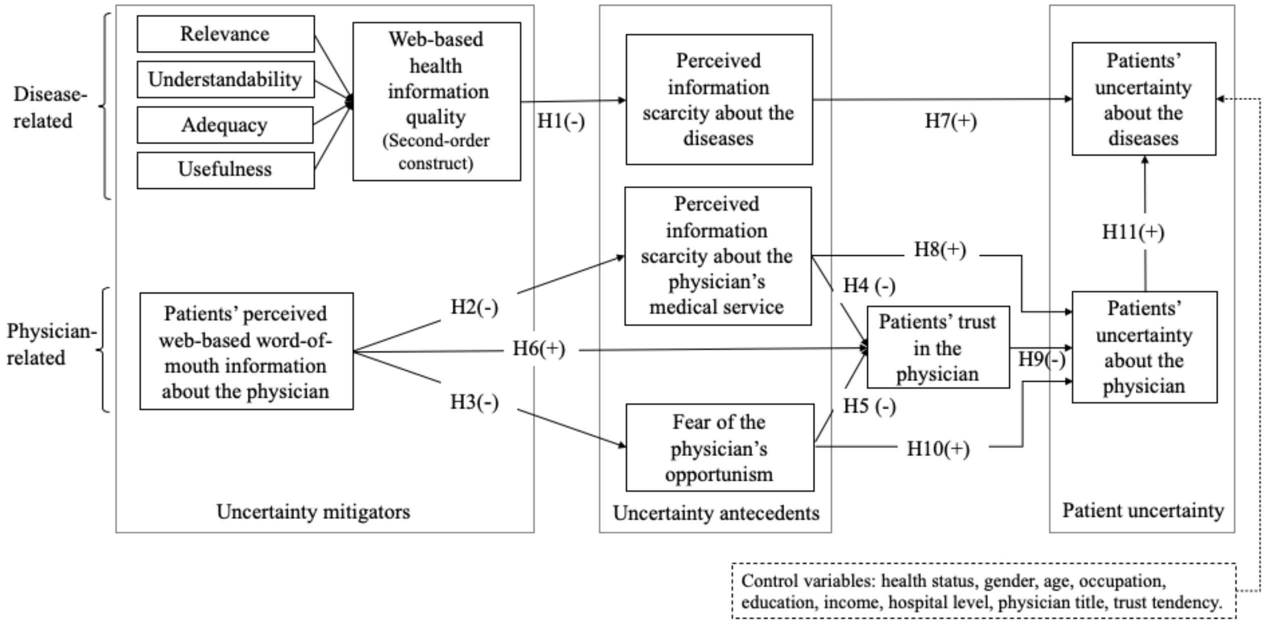
Trust can overcome uncertainty, and trust is necessary only when the environment is uncertain [45]. When patients trust their physicians, they can predict their physicians' behaviors based on their belief in the physicians' integrity, benevolence, and competence under uncertain circumstances. They believe that their physicians are honest and have great capabilities. Therefore, this study believes that a patient's trust in a physician will help reduce the patient's uncertainty about the physician, leading to hypothesis 9: a patient's trust in a physician can mitigate the patient's uncertainty in that physician (H9).

Because of the internally inconsistent goals between physicians and patients, physicians' opportunistic behaviors are inevitable, such as physicians taking kickbacks to prescribe expensive drugs, unnecessary tests, and overtreatment. Patients often lack professional information to judge the rationality of physicians' treatment plans and examination procedures, which leads to a sense of uncertainty about the rationality of physicians' treatment behaviors. In China, concern about physicians' opportunistic behavior is an important factor that leads to patients' sense of uncertainty [37,56]. Possible opportunistic behavior of vendors' drug prescription also leads to more uncertainty for buyers [45], and thus we hypothesize the following: patients' fear of the physician's opportunism increases patients' uncertainty in the physician (H10).

Consumers' uncertainty about sellers is distinct from the uncertainty about products, between which the former uncertainty can increase the latter uncertainty [15]. The process of patient consultation entails providing a series of examinations, diagnoses, and other services by the physician to identify the disease and determine other relevant treatments for the patient. If patients are uncertain about the rationality of the medical services provided by physicians and doubt the rationality of the physician's examination and treatment plans, it will be detrimental to patients' certainty about the disease; therefore, we hypothesize the following: patients' uncertainty about the physician increases patients' uncertainty about their diseases (H11).

In summary, based on existing literature, this study uses the principal-agent theory and the URT to develop a research model to explain the mechanism of how web-based information search by patients can reduce their uncertainties, as shown in Figure 1. In the context of patients' active information acquisition, we hypothesize that two types of web-based health information (ie, web-based disease-related information quality and web-based physician-related information) as uncertainty mitigators to reduce patients’ uncertainty. When identifying the antecedents of uncertainty and its consequences, we followed the descriptions by Pavlou et al [24] and Srivastava and Chandra [52] on the use of unique and specific variables related to customers’ uncertainty. Principals’ perception of information scarcity and principals’ concern about agents’ opportunistic behaviors are the causes of the principals’ uncertainty. Principals’ trust in the agents acts as a mediator when the uncertainty antecedents reduce principals’ uncertainty. Following the classification of customers’ uncertainty about sellers and products by Dimoka et al [15], we classified patients’ uncertainties into uncertainty about diseases and uncertainty about physicians. Our research model is depicted in Figure 1.

Figure 1. Research conceptual model. H: hypothesis.



Methods

Ethical Considerations

An ethics review was not applicable for this study because the online survey measured the subjects’ perceptions and did not influence their perceptions or attitudes.

Data Collection

This study adopted the survey method to collect data. A total of 108 questionnaires were collected for the pilot test before the formal survey. The wording of some items and typesetting in the questionnaire were modified according to the feedback of the participants. A professional survey company (Wenjuanxing) was responsible for collecting the formal data. The survey started in May 2020 and lasted for a month. Each questionnaire corresponding to a separate IP address provided a reward of RMB 14 (US $2.20). The questionnaire was also set to ensure that valid respondents should answer all the questions before submitting. At the beginning of the questionnaire, the background of the survey was introduced, and screening questions were set to meet the 3 requirements for the survey. Only those who might have a certain disease and have seen a physician offline within 3 months, who had engaged in web-based disease information search behavior, and who had read the web-based word-of-mouth information of the visited physicians were eligible.

Specifically, our questionnaire first used 3 questions to exclude invalid respondents. The first question was “Did you suffer a certain disease and have any experience of offline medical treatments in the past three months?” The respondents who answered “Yes” proceeded to the next question, and the respondents who answered “No” were regarded as invalid respondents, and their questionnaires were terminated. Then, at the top of each page, there was a statement “Please recall the most recent experience of seeing a physician within the past three months, and based on this experience, answer the following questions.” The second question to screen out the invalid respondents was “Before the consultation, have you searched for disease-related information on the internet for this consultation?” Similarly, respondents who answered “No” were prompted to end answering the questionnaire, and those who answered “Yes” continued to the next question. The third screening item was “Do you know the evaluation of the physician (based on the most recent visit within three months) on the Internet?” Only respondents who answered “Yes” continued to answer the questions about the perception of web-based word-of-mouth information, and respondents who answered “No” were prompted to end answering the questionnaire.

To ensure that the respondents responded seriously, the question regarding the evaluation of physicians’ medical services appeared twice in different places in the questionnaire. Questionnaires with completely inconsistent answers (eg, strongly disagree and very agree) were excluded. A total of 40 invalid respondents were screened out, and the final sample size was 337. This sample size meets the requirement that the sample size should be 5-10 observations for each estimated parameter [57,58].

Measurements

All items in this study are from mature scales, as shown in Table 1. Web-based information quality is a formative construct and the measurements were from Zahedi and Song [59]. The modified scale for perceived web-based word-of-mouth information about physicians was derived from Collins and Stevens [60]. As mentioned previously, there is a filter item—"Do you know the evaluation of the physician (based on the most recent visit within three months) on the Internet?"—which asked the respondent whether he or she had browsed through the web-based word-of-mouth information about the physician from those who had previously consulted that physician. With this filter item, we could ensure that the respondent's answers to web-based word-of-mouth information and other items were for the same physician. The measurement of perceived information scarcity about disease and physicians' medical service was derived from Wells et al [23], who developed reflective measures to assess individuals' degree of prepurchase information scarcity about products. The measurement of fear of physicians' opportunism was from the measurement of fear of sellers' opportunism [24,40], which referred to patients' concerns about the rationality of the visited physicians' treatment behaviors (eg, excessive examination and high-priced drugs). Patients' trust measurement was modified from that suggested by McKnight et al [61] and Zhou et al [62]. Patients' uncertainty about diseases was measured using the community scale of uncertainty in illness (Mishel Uncertainty in Illness Scale–Community form) [3]. Patients' uncertainty about physicians was modified from the perceived uncertainty scale [63], which referred to patients' uncertainty about the rationality of medical services provided by physicians. Respondents in this study are native Chinese speakers; therefore, all items were translated into Chinese. We conducted translation–back-translation procedure to ensure the validity of our questionnaire. Specifically, the translated questionnaire was evaluated by 2 doctoral students with relevant research backgrounds. Some adjustments were made to the wording and expression of the questionnaire based on their feedback. Items of constructs (ie, perceived web-based word-of-mouth information about physicians, perceived information scarcity, fear of the physician's opportunism, perceived uncertainty, and trust) were measured by a 5-point Likert scale ranging from complete disagreement (1) to complete agreement (5). Items of the 4 dimensions of information quality were measured by the extent to which the internet health information conforms to the description in the item (eg, 1 point for a very low level and 5 points for a very high level).

Table 1. Construct measurement.

Construct, label, and source	Item
IQ[a] [59]	
Relevance1	For your health information needs, to what degree do you believe the internet health information provided by the website was applicable to your needs?
Relevance2	For your health information needs, to what degree do you believe internet health information provided by the website was related to your needs?
Relevance3	For your health information needs, to what degree do you believe internet health information provided by the website was pertinent to your needs?
Relevance4	For your health information needs, to what degree do you believe internet health information provided by the website was relevant to your needs?
Understandability1	For your health information needs, to what degree do you believe internet health information provided by the website was clear in meaning?
Understandability2	For your health information needs, to what degree do you believe internet health information provided by the website was easy to read?
Understandability3	For your health information needs, to what degree do you believe internet health information provided by the website was easy to comprehend?
Understandability4	For your health information needs, to what degree do you believe internet health information provided by the website was understandable?
Adequacy1	For your health information needs, to what degree do you believe internet health Information provided by the website was sufficient?
Adequacy2	For your health information needs, to what degree do you believe internet health information provided by the website was complete?
Adequacy3	For your health information needs, to what degree do you believe internet health information provided by the website was adequate?
Adequacy4	For your health information needs, to what degree do you believe internet health information provided by the website contained the necessary topics or categories?
Usefulness1	For your health information needs, to what degree do you believe internet health information provided by the website was informative?
Usefulness2	For your health information needs, to what degree do you believe internet health information provided by the website was valuable?
Usefulness3	For your health information needs, to what degree do you believe internet health information provided by the website was helpful?
Usefulness4	For your health information needs, to what degree do you believe internet health information provided by the website was useful?
PWOM[b] [60]	
PWOM1	In online reviews, the physician is very popular and many patients come to see the physician.
PWOM2	In online reviews, patients who visited the physician had a good experience.
PWOM3	According to online reviews, the physician is a good physician.
PWOM4	According to online reviews, the physician has a good relationship with patients.
PSD[c] [23]	
PSD1	I have a good idea of the disease-related information (eg, symptoms, causes of disease, treatment methods, etc).
PSD2	I have sufficient information about the disease (eg, symptoms, cause of disease, treatment, etc).
PSD3	I possess adequate knowledge about the disease-related information (eg, symptoms, causes of disease, treatment methods, etc).
PSPMS[d] [23]	
PSPMS1	I have a good idea of the medical services of the physician whom I visited this time.
PSPMS2	I have sufficient information about the medical services of the physician for this visit.
PSPMS3	I possess adequate knowledge about the medical service information of the physician whom I visited this time.

Construct, label, and source	Item
FPO[e] [24]	
FPO1	In this visit, the physician might not have provided good service but charged a high price.
FPO2	In this visit, the physician might have overexamined, unnecessarily examined, or overtreated me.
FPO3	In this visit, the physician might have received a rebate for prescribing an overpriced drug (eg, imported drug).
FPO4	In this visit, the physician might have breached formal or informal agreements to his or her benefit.
T[f] [61,62]	
T1	The physician is sincerely concerned about my medical issues
T2	The physician is honest in his or her medical practices
T3	I believe that the physician does a very good job
T4	I feel that I can count on the physician to help me with my medical problems
MUIS[g] [3]	
MUIS1	I don't know what is wrong with me
MUIS2	I have a lot of questions without answers.
MUIS3	It is difficult to know if the treatments or medications I am getting are helping.
MUIS4	Because of the unpredictability of my illness, I cannot plan for the future.
MUIS5	The effectiveness of the treatment is undetermined.
PU[h] [63]	
PU1	I think the rationality of the medical services provided by the physician involves a high degree of uncertainty.
PU2	I think the rationality of the medicine prescribed by the physician is uncertain.
PU3	I think the rationality of the disease examination and treatment plan is uncertain.
PU4	The rationality of the services provided by the physician is uncertain (ie, the service I received may not be exactly what I wanted).
PU5	I feel the uncertainty associated with the rationality of the medical services provided by the physician is high.
TD[i] [64]	
TD1	I generally trust other people.
TD2	I generally have faith in humanity.
TD3	I feel that people are generally reliable.
TD4	I generally trust other people unless they give me reasons not to.

[a] IQ: web-based health information quality.

[b] PWOM: perceived web-based word-of-mouth information about physicians.

[c] PSD: perceived information scarcity about the diseases.

[d] PSPMS: perceived information scarcity about the physicians' medical services.

[e] FPO: fears of physician's opportunism.

[f] T: patients' trust in the physician.

[g] MUIS: patients' uncertainty about diseases.

[h] PU: patients' uncertainty about the physician.

[i] TD: trust tendency.

To reduce other possible influences on our model, we considered control variables in 3 ways, although these variables are not our interest in this study. To reduce the possible influence of individual differences, demographic information, such as gender, age, education level, income per month, and occupation, is controlled. To reduce the possible influence of the impact of medical treatment, health-related and medical experience-related factors are also controlled, such as the respondent's health status, the physician's title (an official certification of a physician's quality by the government) [65], and the hospital's level (an official certification of a hospital's quality by the government) [65]. To reduce the possible influence of the respondent's characteristic of trust, the respondents' trust tendency was also controlled. For example, with the same word-of-mouth information about a physician, some patients may easily trust the physician, whereas others may still doubt the physician.

Trust tendency [64] was also measured by a 5-point Likert scale ranging from complete disagreement (1) to complete agreement (5).

Results

Overview

As the model measured in this study has a formative construct, partial least squares (PLS) structural equation modeling is suitable for data analysis. SmartPLS (version 3.3.3, SmartPLS GmbH) software was used in this study. In addition, PLS is also widely used in information systems research owing to its relaxed requirements for the normal distribution of samples, its ability to process data with small sample size, and its applicability to development theory rather than test theory [66]. We first used SmartPLS (version 3.3.3, SmartPLS GmbH) software to test the reliability and validity of the measurement model and then tested the path coefficients of the structural model.

Descriptive Statistics

The respondents’ demographic information, health-related information, and medical experience–related information are shown in Table 2. More respondents were female (231/337, 68.5%). In terms of age distribution, age groups 21-30 years (165/337, 49%) and 31-40 years (117/337, 34.7%) were the most represented. Education level was relatively high, with high school and below accounting for only 4.5% (15/337). The monthly income distribution was relatively even. The surveyed samples were mainly working people, with enterprise employees accounting for 68.2% (230/337). The physicians’ titles and hospitals’ levels are also relatively high.

Table 3 lists the descriptive statistics of the constructs involved in the model.

Table 2. Demographic profile, health-related information, and medical experience–related information (N=337).

Characteristic	Value, n (%)
Gender	
Female	231 (68.5)
Male	106 (31.5)
Age (years)	
18-20	23 (6.8)
21-30	165 (49)
31-40	117 (34.7)
41-50	32 (9.5)
Education	
Postgraduate or above	25 (7.4)
Undergraduate	246 (73)
3-year college	51 (15.1)
High school	11 (3.3)
Middle school or below	4 (1.2)
Monthly income (RMB [US $])	
≤3000 (471.60)	55 (16.3)
3000-5999 (471.60-943.20)	40 (11.9)
6000-8999 (943.20-1414.80)	87 (25.8)
9000-11,999 (1414.80-1886.40)	85 (25.2)
12,000-14,999 (1886.40-2358)	43 (12.8)
≥15,000 (2358)	27 (8)
Occupation	
Student	46 (13.6)
Enterprise worker	230 (68.2)
Civil servant	39 (11.6)
Individual operator	15 (4.5)
Others	7 (2.1)
Health status	
Excellent	14 (4.1)
Very good	56 (16.6)
Good	124 (36.8)
Fair	134 (39.8)
Poor	9 (2.7)
Physician’s title	
Assistant physician	103 (30.6)
Associate physician	123 (36.5)
Chief physician	87 (25.8)
Not sure	24 (7.1)
Hospital’s level	
Primary hospital	52 (15.4)
Intermediate hospital	72 (21.4)
Senior hospital	203 (60.2)

Characteristic	Value, n (%)
Not sure	10 (3)

Table 3. Descriptive statistics[a].

Construct and item	Minimum value	Maximum value	Mean (SD)
PWOM[b]			
PWOM1	2	5	4.04 (0.66)
PWOM2	1	5	4.16 (0.80)
PWOM3	1	5	4.08 (0.88)
PWOM4	1	5	4.09 (0.85)
PSD[c]			
PSD1	1	5	2.38 (0.83)
PSD2	1	5	2.62 (1.03)
PSD3	1	5	2.48 (0.97)
PSPMS[d]			
PSPMS1	1	5	2.24 (0.76)
PSPMS2	1	5	2.25 (0.90)
PSPMS3	1	5	2.23 (0.87)
FPO[e]			
FPO1	1	5	2.44 (1.04)
FPO2	1	5	2.40 (1.19)
FPO3	1	5	2.06 (1.07)
FPO4	1	5	1.90 (1.08)
T[f]			
T1	1	5	4.03 (0.76)
T2	2	5	4.12 (0.78)
T3	1	5	4.02 (0.79)
T4	1	5	4.10 (0.81)
MUIS[g]			
MUIS1	1	5	2.27 (0.94)
MUIS2	1	5	2.70 (1.12)
MUIS3	1	5	2.60 (1.15)
MUIS4	1	5	2.35 (1.14)
MUIS5	1	5	2.64 (1.05)
PU[h]			
PU1	1	5	2.63 (1.04)
PU2	1	5	2.28 (1.13)
PU3	1	5	2.32 (1.18)
PU4	1	5	2.43 (1.13)
PU5	1	5	2.34 (1.08)
TD[i]			
TD1	1	5	3.73 (0.74)
TD2	1	5	3.91 (0.78)
TD3	1	5	3.72 (0.90)
TD4	1	5	3.78 (0.91)

[a] The web-based health information quality is a formative construct; therefore, the details of this construct are described in the *Measurement Model* section.

[b] PWOM: perceived web-based word-of-mouth information about physicians.

[c] PSD: perceived information scarcity about the diseases.

[d] PSPMS: perceived information scarcity about the physicians' medical services.

[e] FPO: fears of physician's opportunism.

[f] T: patients' trust in the physician.

[g] MUIS: patients' uncertainty about diseases.

[h] PU: patients' uncertainty about physicians.

[i] TD: trust tendency.

Common Method Variance

As with all self-reported data, we should examine the potential common method variance. We follow the suggestions of Podsakoff et al [67] to minimize potential common method biases. First, we tried procedural remedies of Podsakoff et al [67]. To reduce respondents' evaluation apprehension and avoid their answers being socially desirable, at the beginning of the questionnaire, we reminded them that their answers are anonymous and there are no right or wrong answers to our questions. All items in the questionnaire were designed in a random order to ensure that the measurement of predictor and criterion variables are psychologically separated for respondents. To ensure that the scale items are specific, concise, and clear, we also conducted the pilot test before the formal survey. We modify the wording according to the feedback of the participants to reduce ambiguity.

Second, the Harman single-factor test was conducted to diagnose whether the common method bias is a problem [68]. We ran an exploratory factor with all variables included [23]. The results showed that more than one factor can be extracted from the unrotated solution, and the variance contribution rate of the first factor was not more than 50% (23.7%), so there was no one single major factor that can reflect the majority covariance of all items, indicating that common method bias was not serious [57].

Moreover, based on our survey context and the suggestions of Podsakoff et al [67], we conducted a single-common-method-factor approach by controlling for the effects of a single unmeasured latent method factor to control the common method variance. Following Liang et al [69], we included in the PLS model a common method factor whose indicators included all the indicators of the constructs in this study. We calculated each indicator's factor loadings and variances substantively explained by the construct and by the method factor. Multimedia Appendix 1 provides the detailed procedure and results [67,69,70]. As shown in Table S1 in Multimedia Appendix 1, most factor loadings of the method factor are insignificant. The average substantively explained variance of the indicators is 0.594, whereas the average method-based variance is 0.002. The ratio of substantive variance to method variance was 297:1, indicating the variance of each observed indicator explained by its substantive construct is substantially greater than the variance explained by the method factor. Therefore, based on the studies by Liang et al [69] and Williams et al [70], we further conclude that common method bias is not a serious problem in this study.

Measurement Model

First, we tested the reliability and validity of the formative indicators (ie, web-based information quality). As web-based health information quality is a second-order formative construct, this study follows the method suggested by Wetzels et al [71]. In the structural equation model, four first-order reflective constructs (ie, information relevance, understandability, adequacy, and usefulness) point to the second-order constructive variable (information quality). A total of 16 items in the first order are taken as the measurement items of second-order constructs. PLS and Bootstrap were used to test the reliability and validity of the model and the outer weight of second-order formative constructs. First, the results of reliability and validity test of first-order reflective constructs showed information relevance (Cronbach α=.641; composite reliability [CR]=0.786; average variance extracted [AVE]=0.480), information understandability (Cronbach α=.726; CR=0.830; AVE=0.551), information usefulness (Cronbach α=.699; CR=0.816; AVE=0.526), and information adequacy (Cronbach α=.868; CR=0.910; AVE=0.717) all have good reliability and validity. Then, we tested the reliability and validity of the information quality of the second-order formative index, and the weight of the information quality (0.263, 0.314, 0.293, and 0.463) was >0.2 and significant at the level of $P<.001$, which passed the reliability and validity test of the formative construct. The variance inflation factors among all items were <2, satisfying the multicollinearity test, and the outer weight was significant and >0.2 [72].

Second, reflective indicators of this model were tested. We followed the methods suggested by Lewis et al [58] and Straub et al [73] to test the reliability and validity of the measurement model. The results are listed in Table 4. First of all, we tested the reliability of the constructs. The results show that the component reliability of each construct is >0.7 with good internal consistency [74,75]. The average variance extraction is also >0.5, which has good convergent validity [76]. In most cases, Cronbach α is >.7, and in all cases, the values are >0.6, which are within the acceptable range [66].

Table 4. Construct reliability and validity.

Construct and item	Item loading	Cronbach α	CR[a]	AVE[b]
PWOM[c]		.653	0.793	0.500
PWOM1	0.703			
PWOM2	0.695			
PWOM3	0.712			
PWOM4	0.689			
PSD[d]		.740	0.852	0.658
PSD1	0.797			
PSD2	0.832			
PSD3	0.805			
PSPMS[e]		.695	0.830	0.620
PSPMS1	0.758			
PSPMS2	0.784			
PSPMS3	0.820			
FPO[f]		.852	0.900	0.692
FPO1	0.821			
FPO2	0.811			
FPO3	0.863			
FPO4	0.831			
PU[g]		.890	0.919	0.694
PU1	0.861			
PU2	0.828			
PU3	0.828			
PU4	0.803			
PU5	0.844			
MUIS[h]		.797	0.861	0.554
MUIS1	0.663			
MUIS2	0.772			
MUIS3	0.790			
MUIS4	0.706			
MUIS5	0.783			
T[i]		.731	0.832	0.554
T1	0.710			
T2	0.759			
T3	0.805			
T4	0.699			
TD[j]		.760	0.846	0.580
TD1	0.834			
TD2	0.796			
TD3	0.740			
TD4	0.666			

[a] CR: composite reliability.

[b] AVE: average variance extracted.

[c] PWOM: perceived web-based word-of-mouth information about physicians.

[d] PSD: perceived information scarcity about the diseases.

[e] PSPMS: perceived information scarcity about the physicians' medical services.

[f] FPO: fears of physician's opportunism.

[g] PU: patients' uncertainty about physicians.

[h] MUIS: patients' uncertainty about diseases.

[i] T: patients' trust.

[j] TD: trust tendency.

As shown in Table 5, we also tested the discriminant validity of the measurement model. The square root of the AVE (ie, italicized number on the diagonal line) for each factor in the table is larger than the correlation coefficient between the factor and other factors, so this measurement model has good discriminant validity [76]. Therefore, all the reflective constructs of this measurement model have good reliability and validity.

Table 5. Discriminant validity analysis[a].

Construct	IQ[b]	PU[c]	PSPMS[d]	PWOM[e]	T[f]	FPO[g]	MUIS[h]	PSD[i]
IQ	—[j]	—	—	—	—	—	—	—
PU	−0.323	*0.833*	—	—	—	—	—	—
PSPMS	−0.506	0.258	*0.788*	—	—	—	—	—
PWOM	0.405	−0.336	−0.511	*0.700*	—	—	—	—
T	0.379	−0.539	−0.473	0.532	*0.744*	—	—	—
FPO	−0.154	0.711	0.118	−0.268	−0.380	*0.832*	—	—
MUIS	−0.365	0.678	0.301	−0.279	−0.497	0.507	*0.744*	—
PSD	−0.588	0.255	0.487	−0.273	−0.334	0.068	0.296	*0.811*

[a] The italicized values represent the square root of the average variance extracted for each construct.

[b] IQ: web-based health information quality.

[c] PU: patients' uncertainty about the physician.

[d] PSPMS: perceived information scarcity about the physicians' medical services.

[e] PWOM: perceived web-based word-of-mouth information about physicians.

[f] T: patients' trust in the physician.

[g] FPO: fears of physician's opportunism.

[h] MUIS: patients' uncertainty about diseases.

[i] PSD: perceived information scarcity about the diseases.

[j] Not applicable.

Construct Model and Results

We used PLS to test the hypotheses of this model and the Bootstrap method to test the significance of path coefficients [77]. The results are shown in Figure 2, and the path coefficients and T values are shown in Table 6. The control variables were also included in the model as predictors of the finally dependent variable (ie, patients' uncertainty about the diseases). From Figure 2, the R^2 of this model for patients' uncertainty in diseases is 0.515. Both the disease- and physician-related uncertainty mitigators have significant effects on the uncertainty antecedents. Specifically, web-based health information quality can reduce patients' perceived information scarcity about diseases (β=−.588; *P*<.001), supporting H1. Patients' perceived web-based word-of-mouth information about physicians can reduce patients' perceived information scarcity about the physician's medical service (β=−.511; *P*<.001) and fears of physicians' opportunism (β=−.268; *P*<.001), thus supporting H2 and H3. Patients' perceived web-based word-of-mouth of physicians also increases patients' trust in the visited physician (β=.318; *P*<.001), supporting H6.

Figure 2. Structural equation model results. H: hypothesis.

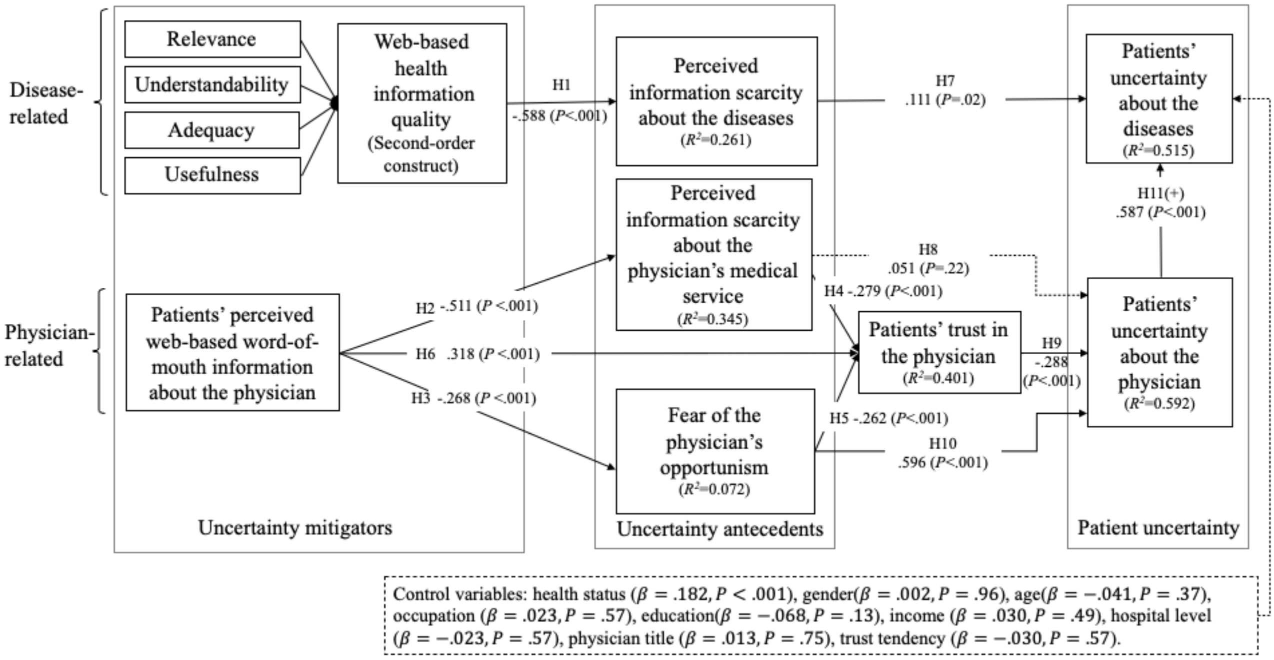


Table 6. Hypotheses test results.

Hypothesis	Path	Path coefficient (SD)	*P* value	Result
H1	IQ[a]→PSD	−.588 (0.035)	<.001	Supported
H2	PWOM[b]→PSPMS[c]	−.511 (0.045)	<.001	Supported
H3	PWOM→FPO[d]	−.268 (0.048)	<.001	Supported
H4	PSPMS→T[e]	−.279 (0.062)	<.001	Supported
H5	FPO→T	−.262 (0.050)	<.001	Supported
H6	PWOM→T	.318 (0.068)	<.001	Supported
H7	PSD[f]→MUIS[g]	.111 (0.045)	.02	Supported
H8	PSPMS→PU[h]	.051 (0.045)	.22	Rejected but fully mediated by patients' trust in the physician
H9	T→PU	−.288 (0.043)	<.001	Supported
H10	FPO→PU	.596 (0.047)	<.001	Supported and partially mediated by patients' trust in the physician
H11	PU→MUIS	.587 (0.043)	<.001	Supported

[a] IQ: web-based health information quality.

[b] PWOM: perceived web-based word-of-mouth information of the physician.

[c] PSPMS: perceived information scarcity about the physicians' medical services.

[d] FPO: fears of physician's opportunism.

[e] T: patients' trust in the physician.

[f] PSD: perceived information scarcity about the diseases.

[g] MUIS: patients' uncertainty about diseases.

[h] PU: patients' uncertainty about the physician.

Patients' perceived information scarcity about the physician's medical service reduces their trust in the visited physician (β=−.279; *P*<.001), supporting H4. Fear of physicians' opportunism reduces patients' trust in the visited physician (β=−.262; *P*<.001), supporting H5. Patients' perceived information scarcity about the diseases increases patients' uncertainty in diseases (β=.111; *P*=.02), supporting H7. However, patients' perceived information scarcity about physicians' medical services has no significant influence on patients' uncertainty in the visited physician (β=.051; *P*=.22), thus rejecting H8. Patients' trust in the visited physician can reduce patients' uncertainty in the visited physician (β=−.288;

P<.001), supporting H9. Fear of physicians' opportunism has the most significant positive effect to increase patients' uncertainty about the physician (β=.596; *P*<.001), supporting H10. Finally, uncertainty about the visited physician can increase patients' uncertainty in diseases (β=.587; *P*<.001), supporting H11.

Besides respondents' perception about their health status, other control variables have no significant influence on the model. Health status has a significantly negative impact on the model, which means that compared with patients who feel their health status is poor, patients who feel they are healthy perceive a higher level of uncertainty about the diseases.

To further explore the possible explanation of the rejection of H8, we conducted the Sobel test [78,79] to investigate the mediation role of trust in the relationship between the uncertainty antecedents and patients' uncertainty about the physician. From the results in Table 7, after introducing patients' trust in their physicians, the relationship between patients' perceived information scarcity about physicians and their uncertainty about the physicians becomes nonsignificant, indicating that patients' trust in their physicians fully mediates the relationship of H8; therefore, the direct relationship of H8 is rejected, and only when more information can increase patients' trust, their uncertainty about physicians can be reduced. Moreover, increasing physicians' medical service information can be effective in reducing patients' uncertainty about their physicians. The relationship between patients' fear of the physician's opportunism and their uncertainty about the physician is still significant, indicating patients' trust in their physicians partially mediates the relationship of H10. The Sobel test statistics [80] are also significant, which further confirms that patients' trust in their physicians plays the role of mediation.

Table 7. The Sobel test of the mediating effect of patients' trust in the physician.

Hypothesis and path	Path coefficient (SD)	Sobel test statistic	*P* value
Hypothesis 8[a]	N/A[b]	6.5734	<.001
PSPMS[c]**→PU**[d]			
Without mediator	.120 (0.054)	N/A	.02
With mediator	−.055 (0.052)	N/A	.29
PSPMS→T[e]	−.476 (0.053)	N/A	<.001
T→PU	−.492 (0.051)	N/A	<.001
Hypothesis 10[f]	N/A	5.2280	<.001
FPO[g]**→PU**			
Without mediator	.656 (0.040)	N/A	<.001
With mediator	.579 (0.047)	N/A	<.001
FPO→T	−.380 (0.047)	N/A	<.001
T→PU	−.281 (0.041)	N/A	<.001

[a] Fully mediated.

[b] N/A: not applicable.

[c] PSPMS: perceived information scarcity about the physicians' medical services.

[d] PU: patients' uncertainty about the physician.

[e] T: patients' trust in the physician.

[f] Partially mediated.

[g] FPO: fears of physician's opportunism.

Discussion

Principal Findings

This study investigated the mechanism of how web-based health information search behavior reduces patients' uncertainty. Our empirical test results supported most of our hypotheses, except H8. Patients' perceived web-based word-of-mouth information about physicians and the quality of web-based health information can effectively reduce patients' uncertainty about diseases and physicians. The uncertainty reduction effect is achieved by affecting the antecedent factors of patients' uncertainty, including patients' fears of physicians' opportunism, patients' perceived information scarcity, and patients' trust, which are all the traits of principal-agent relationship.

Specifically, the higher the possibility of the physician's opportunism and information scarcity perceived by patients, the greater their uncertainty. Among the antecedents of patient uncertainty, patients' fear of physicians' opportunism has the most significant impact on patients' uncertainty about physicians. By segmenting patients' uncertainty, this research discussed the relationship between patients' uncertainty about the diseases and patients' uncertainty about physicians. The results show that patients' uncertainty about physicians has a significant positive impact on patients' uncertainty about diseases.

In addition, this study also demonstrated the significant role of patients' trust in physicians. Patients' perceived web-based word-of-mouth information about physicians can enhance patients' trust in physicians. Patients' having more information and less fear of physicians' opportunistic behaviors also increases patients' trust. However, from the result of the mediation test, only when the information can increase patients' trust in their physicians, patients' uncertainty about physicians can be reduced; thus, increasing physicians' medical service information can be effective in reducing patients' uncertainty about their physicians. Patients' trust in their physicians fully mediates the relationship between their perception of information scarcity about the physicians' medical service and their uncertainty about their physicians.

Theoretical Contributions

First, on the basis the principal-agent theory and from the perspective of reducing patient uncertainty, this study is the first to explore the influence mechanism of web-based disease-related information quality and web-based word-of-mouth information received by patients on patients' uncertainty. It is to be noted that information can reduce uncertainty, but the mechanism of how information reduces uncertainty is not clear. Therefore, we propose our *uncertainty mitigators–uncertainty antecedents–uncertainty* framework to explore the mechanism. On the basis of the URT, web-based information quality and web-based word-of-mouth information of physicians effectively reduce the antecedents of patients' uncertainty, including perceived information scarcity, fears of physicians' opportunism, and trust. Thus, patients' uncertainty about the disease and the physician are reduced.

Second, this study enriches the literature on patients' uncertainty by classifying patients' uncertainties into patients' uncertainty about the diseases and patients' uncertainty about their physicians. Following the classification of consumers' uncertainty about sellers and products by Dimoka et al [15], we also found that patients' uncertainty about diseases and physicians should be distinguished. In particular, we explored the role of patients' uncertainty about physicians, which has been rarely studied in the existing literature. Reducing patients' uncertainty about their physicians can further reduce their uncertainty about diseases.

Third, this study emphasizes the significant role of patients' trust. As an important factor in principal-agent relationships, trust is the most valuable aspect [43]. We also found that without trust, just increasing patients' information does not help reduce their uncertainty about their physicians. This result further supports the fact that building trust is crucial to address the principal–agent problem.

Practical Contributions

First, this study found that the better the web-based word-of-mouth information of a physician and information quality obtained by patients, the better the reduction in patients' uncertainty. Therefore, for physicians in the internet era, attention should be paid to the role of web-based health information. More authoritative, more reliable, and higher-quality web-based platforms should be provided to meet patients' demands for health information. In addition, physicians should encourage offline patients to participate in web-based word-of-mouth evaluations, maintain their own web-based word-of-mouth information, and provide more information about their services to potential patients [81]. Web-based word-of-mouth information can reach a wider audience and has a greater impact than offline word-of-mouth information. Web-based word-of-mouth information can effectively nudge physicians to improve their service quality and help patients acquire relevant information about physicians, thereby reducing patients' uncertainty [39].

Second, from the full mediator role of trust, web-based information is effective only when this information can help build patients' trust in their physicians. This suggests that web-based platforms that provide information (ie, web-based word-of-mouth information about physicians) should strictly check the quality of the information. More importantly, platforms can provide some cues to inform patients that the information is trustworthy, such as third-party certifications and guarantees. Only when patients can trust their physicians through this information can it help reduce their uncertainties.

Limitations and Future Directions

First, as for the sample composition, there are 3 prerequisites for this study. Only those who might have a certain disease and had seen the physicians offline within the past 3 months, read the web-based word-of-mouth information about physicians, and engaged in web-based disease information search behaviors were eligible, which resulted in a large overrepresentation of younger people in our sample. More than 90.5% (305/337) of our respondents were aged <40 years, so the sample had possible self-selection bias and a bias of young age. Second, regarding the collection time of data, the research data were collected in May 2020 after the COVID-19 epidemic in China. The external validity of the results may be jeopardized. Then, this study only considered the influence mechanism of web-based word-of-mouth information about physicians on offline patients' trust. Future studies can further consider the situation of web-based health consultation and investigate the possible differences in web-based health information on the physician-patient relationship in different channels. Moreover, because the focus of this study is the information about diseases and physicians, the respondents' health status is controlled, and the result shows that respondents' perception of their health status influences their uncertainty. Future studies can further discuss and explain the effect of health status. Finally, the study data were cross-sectional subjective data, which were provided by the same subjects at the same time, and future studies can use longitudinal analysis or experiments to better test the causal relationships in the model.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

The procedure and results of common method variance.
[DOCX File , 425 KB-Multimedia Appendix 1]

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Abbreviations

AVE: average variance extracted
CR: composite reliability
PLS: partial least squares
URT: uncertainty reduction theory

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Original Paper

Contextualizing Engagement With Health Information on Facebook: Using the Social Media Content and Context Elicitation Method

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Abstract

Background: Most of what is known regarding health information engagement on social media stems from quantitative methodologies. Public health literature often quantifies engagement by measuring likes, comments, and/or shares of posts within health organizations' Facebook pages. However, this content may not represent the health information (and misinformation) generally available to and consumed by platform users. Furthermore, some individuals may prefer to engage with information without leaving quantifiable digital traces. Mixed methods approaches may provide a way of surpassing the constraints of assessing engagement with health information by using only currently available social media metrics.

Objective: This study aims to discuss the limitations of current approaches in assessing health information engagement on Facebook and presents the social media content and context elicitation method, a qualitatively driven, mixed methods approach to understanding engagement with health information and how engagement may lead to subsequent actions.

Methods: Data collection, management, and analysis using the social media content and context elicitation method are presented. This method was developed for a broader study exploring how and why US Latinos and Latinas engage with cancer prevention and screening information on Facebook. The study included 20 participants aged between 40 and 75 years without cancer who participated in semistructured, in-depth interviews to discuss their Facebook use and engagement with cancer information on the platform. Participants accessed their Facebook account alongside the researcher, typed *cancer* in the search bar, and discussed cancer-related posts they engaged with during the previous 12 months. Engagement was defined as liking, commenting, and/or sharing a post; clicking on a post link; reading an article in a post; and/or watching a video within a post. Content engagement prompted questions regarding the reasons for engagement and whether engagement triggered further action. Data were managed using MAXQDA (VERBI GmbH) and analyzed using thematic and content analyses.

Results: Data emerging from the social media content and context elicitation method demonstrated that participants mainly engaged with cancer prevention and screening information by viewing and/or reading content (48/66, 73%) without liking, commenting, or sharing it. This method provided rich content regarding how US Latinos and Latinas engage with and act upon cancer prevention and screening information on Facebook. We present 2 emblematic cases from the main study to exemplify the additional information and context elicited from this methodology, which is currently lacking from quantitative approaches.

Conclusions: The social media content and context elicitation method allows a better representation and deeper contextualization of how people engage with and act upon health information and misinformation encountered on social media. This method may be applied to future studies regarding how to best communicate health information on social media, including how these affect assessments of message credibility and accuracy, which can influence health outcomes.

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KEYWORDS

mixed methods; data collection; social media; cancer; health information; Facebook; digital health

Introduction

Background

The rise of health misinformation in today's social media landscape has prompted a need to better understand how and why individuals engage with this content, as well as its ramifications on health outcomes. Although this topic has gained notoriety in light of the COVID-19 pandemic and its accompanying infodemic, calls for research addressing health misinformation and its unique impact on underserved populations have been present since late 2018 [1]. These calls acknowledge that in addition to defining the prevalence and trends of health misinformation, researchers need to develop approaches that better understand the context of misinformation exchange on social media, the intra- and interpersonal dynamics that influence engagement with content, and how health consequences may stem from these interactions [1].

Reaching populations with evidence-based content through social media has become an important effort to counteract the spread of health misinformation [2,3]. If leveraged correctly, these platforms can be used to encourage participatory communication by fostering user engagement via posts, pictures, videos, and other forms of information sharing [4]. This conceptualization of social media as participatory frames engagement as a way for health organizations to communicate with audiences directly [5] and is typically assessed by evaluating how users respond to content posted on the platform. By playing an active role in conversations about health topics, organizations can also ensure that trust and credibility are established through the dissemination of accurate information [5].

Quantitative methods have undoubtedly helped identify health misinformation trends on social media [6-9]. However, these data are increasingly difficult to obtain [10], do not provide important contextual information regarding what motivates engagement and dissemination among vulnerable populations with poor health outcomes, and cannot capture the effects of misinformation on behavior. Mixed methods approaches that explore the role of these components in the spread of misinformation are necessary to design interventions that minimize and halt dissemination. Mixed methods research comprehensively and purposefully uses both qualitative and quantitative techniques to address an overarching research question that cannot be fully explored and contextualized by either method independently [11]. As such, this paper presents the social media content and context elicitation method, which is a novel approach that incorporates qualitative methods to better contextualize engagement with health information on social media and how this may lead to subsequent actions. This paper first discusses the limitations of the current operationalizations of engagement with health information on social media. This is followed by a detailed description of the social media content and context elicitation method, which was developed to obtain survey data, interviews, and computer screen recordings of cancer-related posts on Latino and Latina participants' Facebook accounts for quantitative and qualitative analysis. Then, 2 case studies are presented to exemplify the additional information elicited from this methodology, which is currently lacking from other approaches. Finally, we discuss how incorporating qualitative methods, such as those outlined in this paper, allows a better representation of how people engage with health information in reality and provides insights for researchers interested in this type of work.

Assessing Engagement With Health Information on Facebook

Facebook is among the most popular social media platforms worldwide, with >2.3 billion active users [12]. Second in popularity only to YouTube, 74% of US Facebook users visit the platform on a daily basis [13]. Entertainment, social interaction, and passing time are among the reasons individuals report using Facebook [14]. Facebook has also been a source of health information and social support [15], making it a useful place to engage with general audiences about health topics. Many public health organizations have established a presence on Facebook by creating a Facebook page, which provides a space for businesses and organizations to publicly share information with platform users. Facebook pages provide a direct way for these organizations to deliver evidence-based health information to Facebook users, which is of paramount importance in a social media environment with increasingly unreliable information [3]. Facebook page administrators also have the ability to monitor social media metrics, providing a way for health organizations to operationalize audience engagement with posted content.

Assessing engagement with health-related information on social media is of particular importance as it is a precursor to multiple outcomes, such as increased awareness, knowledge, and behavior change [16,17]. Most studies have assessed engagement by collecting and analyzing data on the likes, comments, and/or shares of posts within an organization's Facebook page [18-24]. For example, Strekalova and Krieger [24] reported that cancer-related posts on the National Cancer Institute's Facebook page had a significantly higher number of likes, comments, and shares when they contained images (vs videos, embedded links, or text). Similarly, Srivastava et al [18] found that posts on the American Cancer Society's Facebook page were more likely to be liked or shared when they contained images or videos, whereas text-based posts were more likely to elicit user comments. Meanwhile, Klippert and Schaper [25] expanded their definition of engagement by including metrics for post reach and clicks on embedded links—both of which are also available to Facebook page administrators. Finally, other studies have captured engagement with cancer information publicly available on Facebook [19,20,26] or Facebook groups [27-30]. Facebook groups differ from Facebook pages in that they can be public or private but do not offer detailed social media metrics and audience insights (although group administrators may extract raw data for analysis through Facebook's application programming interface). In such cases, engagement has been assessed by quantifying likes, comments, and shares, as these metrics are visible to anyone with access to the posted content.

Limitations of Quantitative Assessments of Engagement

Measuring engagement with health-related content through these metrics is useful for organizations wanting to assess the success of a social media campaign. It can also provide insight into message factors that may enhance engagement with health information on social media [31]. However, the existing metrics have important limitations. On Facebook, one of these limitations relates to how users are exposed to content. In order for a post from a Facebook page to appear on a person's news feed, a person must either follow the page or have a Facebook friend who engages with a post from the page. Additional ways users can be exposed to health-related content from a Facebook page are through paid advertising or a Facebook video recommendation, which is based on a video's popularity or other people and pages a person follows [32]. Even then, the appearance of this content on a person's news feed is influenced by Facebook's constantly changing algorithm, which favors content that individuals engage with most often [33]. This has an impact on whether specific health information emerges on a person's news feed when they log into their Facebook account. As such, engagement with content on a health-related Facebook page may not be emblematic of how the general population engages with such information on Facebook. It is likely that many individuals following a health-related Facebook page are already interested in that particular topic. However, there are many people who may not have an active interest in health information that health organizations are trying to reach, such as healthy individuals who are the target audience for prevention and screening messages. Furthermore, focusing on measuring engagement with evidence-based content posted by health organizations does not fully capture the health information landscape on Facebook, which includes user-generated or shared health misinformation that may not come from reliable sources (eg, a COVID-19–related post dispelling misinformation about vaccine efficiency shared by a Facebook friend with no links to original sources).

Another limitation to quantifying likes, comments, and shares is that these are crude measures of engagement. Although these metrics allow researchers to quantify how some Facebook users visibly engage with health information that is publicly available or posted within a Facebook group, they exclude individuals who do not perform these actions yet still consume health information on the platform [18,24]. Information consumption and lurking—generally defined as reading posts on the web without responding—have been seen as an active and participative form of web-based behavior [34]. Lurking may occur because of environmental, relationship, security, and individual reasons [35]. For example, the quality of a message may be poor (environmental), the user may not feel part of the web-based community (relationship) or have privacy concerns (security), or the person's needs may be satisfied by just reading a post (individual) [35].

Moreover, although newer Facebook applications, such as CrowdTangle, allow researchers to capture additional engagement metrics (such as post views) [36], these metrics are limited in only establishing general trends with content that is publicly available on the platform. Furthermore, these crude measures fail to capture if and how engagement with health information and misinformation may influence individuals to act upon this information elsewhere. Potential actions may be as small as discussing the information with a friend through messaging apps or as large as incorporating preventive behavior into one's lifestyle. Understanding these complexities inevitably requires new approaches to help contextualize the impact of engagement on health outcomes.

In response to these needs, we developed the social media content and context elicitation method. This method elicits data concurrently during one-on-one in-person encounters where the participants access their social media profile, scroll through relevant content, and contextualize content engagement with the researcher. In the following sections, we outline the process of collecting, managing, and analyzing elicited data and provide examples of the robust findings that this method provides. We hope that such detail—particularly surrounding data collection and management—enables other scholars to replicate and/or adapt these methods for related studies.

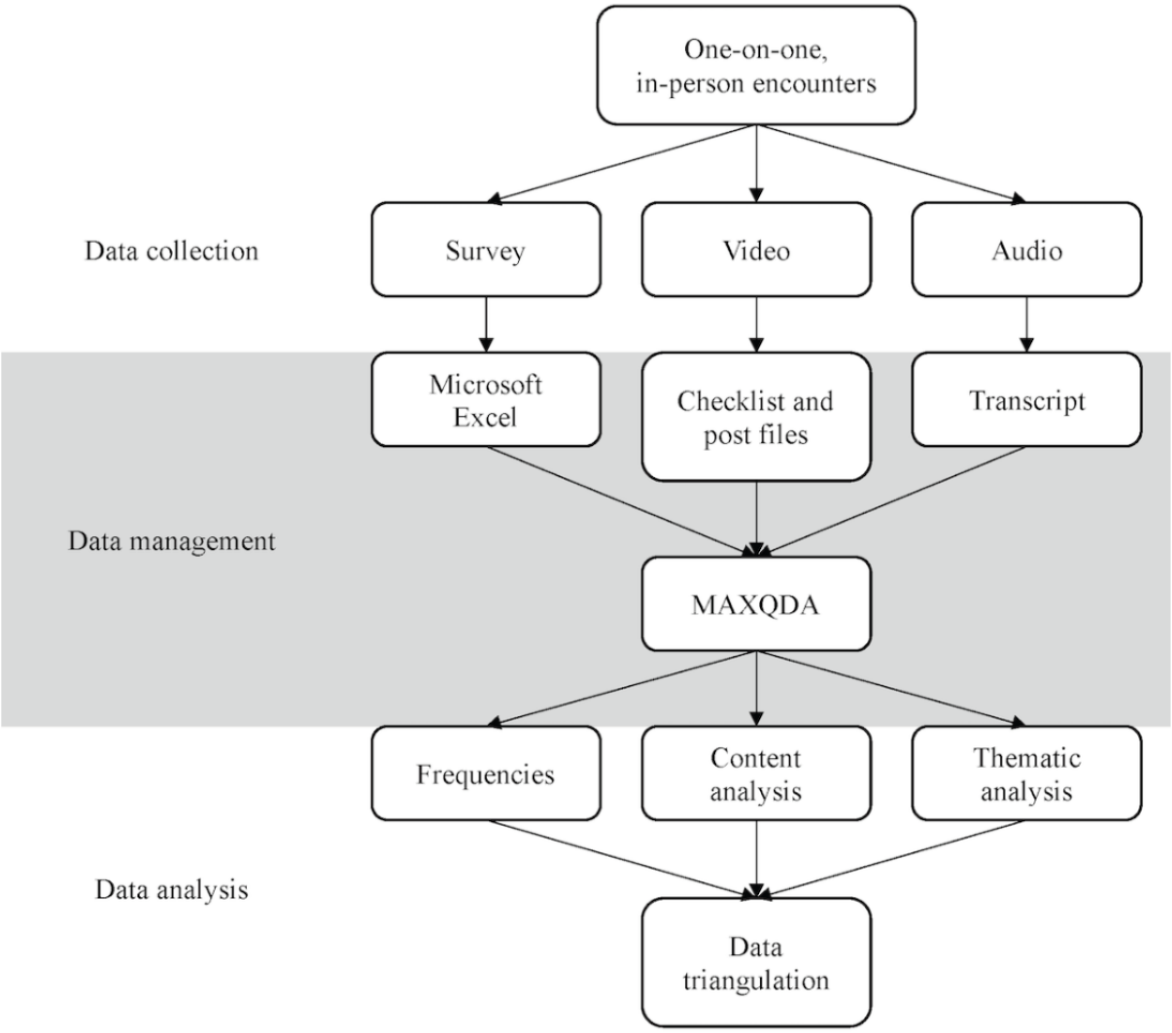
Methods

Overview

The methods discussed in this paper were developed for an exploratory, convergent parallel study assessing how and why Latino and Latina adults aged 40 to 75 years without a history of cancer engage with and act upon cancer prevention and screening information or misinformation on Facebook (published elsewhere) [37]. For this study, 20 self-identified Latinos and Latinas aged 40 to 75 years with no history of cancer participated in semistructured, in-depth interviews to discuss their Facebook use and engagement with cancer information on the platform. This diverse population not only avidly uses Facebook but also faces high cancer health disparities: cancer is the leading cause of death among US Latinos and Latinas [38], and cancer incidence rates are highest for screenable cancers linked to preventable behaviors (breast, prostate, and colorectal) [39]. Please refer to the original publication for a full description of the study and the main findings [37].

The social media content and context elicitation method developed for this study comprised three parts: (1) a short survey collecting demographics, health-related information seeking, and Facebook use data; (2) computer screen recordings of cancer posts appearing on participants' Facebook during the past 12 months; and (3) semistructured, in-depth interviews discussing Facebook use and engagement with cancer posts on Facebook (Figure 1). Participants were recruited through flyers, word of mouth, and Facebook advertisements. Interviews were conducted in the participants' language of preference (English or Spanish) by the lead researcher, who is bilingual. All interviews were conducted during the summer of 2018 and lasted approximately 2 hours.

Figure 1. Study design using the social media content and context elicitation method to capture engagement with cancer information on Facebook. Each participant underwent all points of data collection.



Data Collection

After providing oral consent, participants completed a short survey collecting demographic variables, basic health-related information seeking, and Facebook use information. This survey provided descriptive insight into the uses and gratifications experienced by Latinos and Latinas on Facebook and other contextual factors that may affect engagement with cancer prevention and screening information on the platform. Following the survey, the researcher began the semistructured interviews, which were audio recorded in their entirety. Using the survey responses as a guide, the researcher asked participants to elaborate on their regular Facebook use patterns and interactions, the extent to which they encountered health information (including cancer information) on Facebook, and what they believed Facebook's role was in sharing information. Afterward, participants logged into their Facebook account using a private browser on a research laptop and proceeded to turn off the Facebook Messenger feature to avoid being interrupted during the study. The researcher then documented the total number of friends, groups, and pages the participants followed, including how many of these were cancer-related groups or pages.

The participants then went to the search feature on Facebook, which allows Facebook users to search for content posted on the platform. This feature allows users to sort search results using multiple filters, such as *Sort by*, *Posted by*, and *Date posted*. For this study, participants were asked to enter the term *cancer* into the search bar. Once the search results emerged, they were filtered chronologically (*Sort by Most recent*) and by friends and groups the participant followed on Facebook (*Posted by Your friends and groups*). The resulting posts represented all posts that included the word *cancer* that could have potentially appeared on participants' news feeds when they previously logged into Facebook and corresponded to content either posted by their friends or groups or any other publicly available posts that a friend liked or commented on. The researcher then proceeded to explain the process of jointly scrolling through the past 6 to 12 months of cancer-related posts to discuss posts they recalled seeing and engaging with. Any questions that participants had about the process were discussed before beginning.

Once the participant agreed, the researcher began recording the computer screen using QuickTime Player (version 10.4; Apple), which captures both audio and the computer screen. The researcher and participants jointly scrolled through the content to identify any posts the participants recalled having seen and whether they engaged with the post. Engagement was defined as any combination of the following: liking a post; commenting on a post; sharing a post; clicking on a post link; reading an article in a post; or watching a video within a post. If the post included any video or embedded link, participants were asked if they recalled watching the video or clicking on the link. If so, these were opened to capture the full content.

In addition to capturing the cancer posts that appeared on participants' Facebook through computer screen recordings, engagement with content prompted the researcher to use a semistructured, in-depth interview guide to ask questions regarding the reasons participants interacted with the post and whether engagement triggered further action. Examples of action included (but were not limited to) searching for additional cancer information or scheduling a cancer screening appointment. In-depth interviews were selected for this study as they allow for the exploration of new issues in depth and elaborate on individuals' thoughts and behaviors [40], an important facet in exploring how source and content characteristics influence engagement with cancer information on Facebook and any potential subsequent action. Interview guide questions were informed by the Uses and Gratification Theory [41] and the Comprehensive Model of Information Seeking [42,43]. The interview guide covered the following domains: reasons for engagement with cancer information, relationship to the cancer information source, roles of the cancer information source in delivering information on Facebook, perceptions about posted cancer information content and attributes, the ways that source credibility and content accuracy are assessed, and actions triggered by engagement with this information. In cases where participants recalled engaging with a post in ways other than liking, commenting, and/or sharing the post, the participant was asked to elaborate on this type of engagement. The researcher also collected notes regarding each post the participant either recalled or engaged with using a checklist.

Throughout the scrolling process, multiple participants had copious amounts of cancer-related information emerging in their searches, most of which were not specific to prevention and screening topics (eg, survivorship, cancer research, and fundraising). As the purpose of this study was to understand how participants specifically engaged with cancer prevention and screening information, searches were refined midway through the interview. The search terms *cancer prevention* and *cancer screening* were entered in all interviews approximately 30 minutes into the scrolling process to narrow the search results. For each refined search term, the content was scrolled through up to 12 months prior and discussed as previously stated. On several occasions, when guided by the participant and the discussion at hand, additional search terms were added to find specific cancer prevention and screening information participants recalled engaging with. For example, one participant specifically recalled engaging with a post containing information about cancer and soursop (*guanábana*), a Latin American fruit commonly assumed to have curative properties. The post was elicited by searching for *cancer guanábana*. Similarly, another participant recalled a post about cancer diets and asked to search for *cancer diet*. A final search was performed using the term *cancer* and the filter *Posted by you*. This revealed any cancer information posted by the participant on their own Facebook profile.

After discussing the posts, participants were asked wrap-up questions regarding what would make cancer information more appealing on Facebook, who they considered the most influential and trustworthy sources of cancer information among their Facebook friends, and whether Facebook was a source of cancer information they trusted. Notes were taken throughout the interviews and used to inform data management and analysis.

Data Management

The data collection processes described above elicited rich data: in addition to survey responses, >20 hours of computer screen video and >30 hours of interview audio were captured (Figure 1). Survey responses were entered into a Microsoft Excel spreadsheet. Interview audio recordings were deidentified and transcribed verbatim. The process of capturing discussed posts and deidentifying data recorded on the computer screen is described in the following sections.

The first step in managing all computer screen recordings was to develop a checklist to document all the decision points for each interview video. This checklist collected the time stamps for both the audio and video versions of each interview, which allowed the research team to map interview transcripts with the discussed posts during analysis. Audio and video time stamps were collected at the beginning of the video recording and at the beginning of each post discussed. In addition to marking the time stamps for each post, the checklist was used to summarize the content of each post and to highlight relevant points discussed during the interview. These notes were incorporated as memos associated with each post during the analysis. The checklist was also used to document any search term refinements and outline preliminary codes for subsequent codebook development.

After using the checklist to document each post discussed in the interview, the post was captured through a screen grab and deidentified by cropping and/or covering any identifying images or names with white boxes and saved as a new file identified with the participant's unique ID; 2 additional files were saved in addition to the post screen grabs when applicable. First, if the post also included a video, the video was captured in its entirety in one of two ways: (1) if the video was part of a publicly available post, the lead researcher recorded the full video by searching for the post on Facebook or (2) if the video was no longer available on Facebook, the segment of the recorded computer screen was trimmed and cropped using iMovie to ensure that the video was deidentified. Second, if a post included a link to an external website that was visited during the interview, the website was captured in one of two ways: (1) if the website link was still accessible, the lead researcher saved a web archive and PDF version of the website page or (2) if the website link was broken or no longer accessible, the recorded segment was deidentified, as described above. All deidentified files (posts, videos, web archives, surveys, and interview transcripts) were saved in a secure cloud-based file sharing and file storage service through the Johns Hopkins University and in an encrypted folder on a password-protected computer. The deidentified data were managed using the MAXQDA (Version 12; VERBI GmbH).

Data Analysis

The last step was to analyze multiple data elicited through the aforementioned methods. This was performed using traditional data analysis approaches (ie, frequencies, content analysis, and thematic analysis) that were triangulated to explain how and why engagement with cancer prevention and screening content occurred and how this engagement led to further actions. In the following sections, we summarize these analytical approaches; a detailed description of these analyses can be found in the original study [37].

First, we conducted descriptive statistics on all survey data. These findings were used to assist in contextualizing our sample. Then, a content analysis was conducted on all cancer prevention and screening information participants engaged with on their Facebook accounts. Content analysis was used to assess message patterns in a variety of formats, including those available on internet platforms [44]. A codebook was developed using the preliminary codes documented in the checklist during the data management process described in the previous section. The initial coding framework was applied to a sample of 10 cancer posts publicly available on Facebook by the lead researcher and a second bilingual study team member. Discrepancies were discussed and resolved, and a final codebook was developed [37]. Codes were developed for the following areas: post features, post source, post content, and credibility assessment. A total of 2 coders independently coded 10% of the sample. Intercoder reliability was calculated (0.89-1.0) [45], and any discrepancies were discussed until consensus was reached. The lead researcher coded the remaining posts, and code frequencies were calculated upon completion.

Finally, a thematic analysis was conducted on all the interview transcripts. This method allowed for the identification, analysis, and interpretation of patterns or themes in rich interview data sets [46,47], allowing a detailed description of how multiple themes and factors work together to explain engagement with cancer information. Transcriptions were analyzed in their original language to ensure that no meanings were lost in translation. The transcripts were preliminarily coded using emerging codes that aligned with the research questions using a constant comparison method [48]. A coding tree was created to outline the discovered themes and concepts. In addition, memos were composed with exemplary quotes for each theme; any exemplary quotes collected in Spanish were translated into English. Memos were discussed with the study team to ensure dependability and credibility in theme development [49]. The data were placed into larger themes and factors to comprehensively explain how the phenomena occurred. Further data validation was conferred by triangulating the thematic analysis results with those of the content analysis [50] and is discussed in the original paper [37].

Ethics Approval

This study was approved by the Johns Hopkins School of Public Health institutional review board (IRB8484).

Results

Overview

Our study sample comprised 20 self-identified Latino and Latina Facebook users aged 40 to 75 years without a history of cancer (average age 54.2, SD 7.4 years) and represented 7 distinct Latin American subethnic groups from the Caribbean, Central America, and South America; 9 (45%) participants were fully bilingual, 6 (30%) preferred Spanish, and 5 (25%) preferred English. Participants were mainly female (15/20, 75%) and heavy Facebook users, with most (17/20, 85%) reporting checking their Facebook at least once a day. Facebook was most commonly used for social interaction (17/20, 85%) and information sharing (15/20, 75%). Participants had a median value of 357 (IQR 189.5-544.5) Facebook friends and followed a median of 20 (IQR 4.5-56) Facebook groups; only one of the participants followed cancer-related Facebook groups. A detailed description of the sample is available in the main study [37].

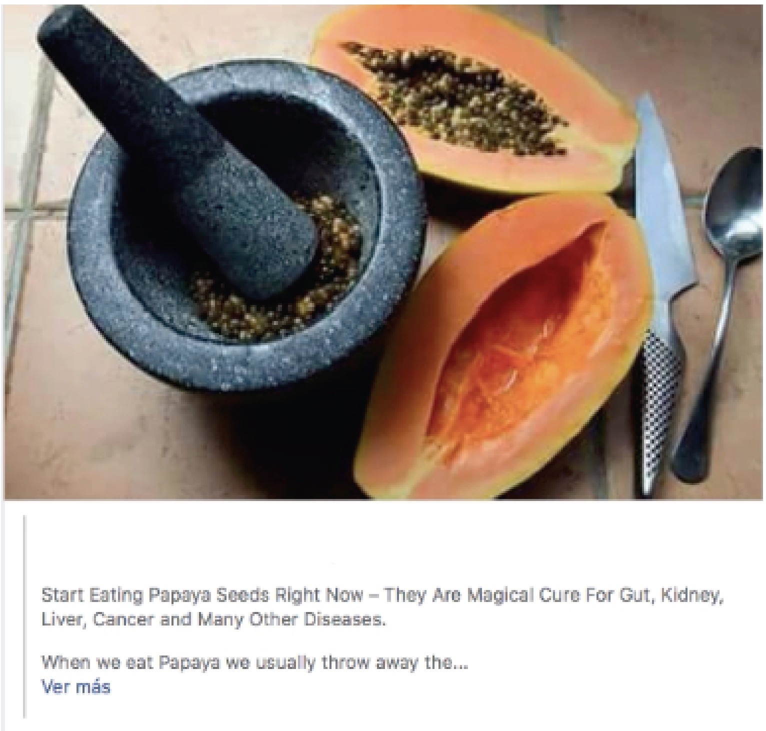
Overall, participants reported engaging with 66 posts containing cancer prevention and screening information (4.1 average posts per participant) in the previous year. Data emerging from the social media content and context elicitation method demonstrated that participants mostly engaged with cancer prevention and screening information by viewing and/or reading content (48/66, 73% posts) rather than by liking, commenting, or sharing posts (18/66, 27% posts). Furthermore, it provided rich content regarding how Latinos and Latinas engage with and act upon cancer prevention and screening information on Facebook [37]. In the following sections, we explore 2 sample cases to illustrate how a mixed methods approach provides rich insight that is otherwise missed when quantitative methods are used alone. These 2 cases were selected as they were emblematic of the broad range of information elicited from our sample that goes beyond only quantifying engagement. Participants' names have been changed to protect their identities.

Case 1: Rogelio

Rogelio was a bilingual Cuban male aged 61years. He had >1800 Facebook friends and followed 131 Facebook groups, none of which were related to cancer. He considered himself a very active Facebook user, logging in multiple times a day and using the platform for social interactions, searching for and sharing information, seeing what others are doing, and maintaining his cultural identity. During the interview, 13 cancer-related posts were discussed, all of which had a video or image, for he believed that "if it doesn't enter through the eyes, it doesn't reach you." Although he engaged with all 13 posts by reading the content, he did not like, comment, or share any of these on his profile. All but 1 of these posts were shared by friends in his network; the other was shared by a Facebook group to which he belonged. A total of 6 posts were related to natural remedies or foods with curative properties against cancer, 1 was about a free skin cancer screening event, and 1 was about free colorectal and prostate cancer educational sessions for Latino men; the remaining posts were related to cancer survivorship and prayer requests.

Although Rogelio used his Facebook account frequently throughout the day, he explained that he rarely liked, commented, or shared content on his profile as he could not let others know he was on Facebook during work hours. Therefore, instead of engaging with a post through these metrics, he would send himself interesting posts through Facebook Messenger (the platform's messaging tool). In this manner, he could read the post at a later time. He also explained how he and his wife regularly shared information related to diet and foods with preventive and/or curative properties through Facebook Messenger. Many times, after discussing content that either one engaged with on Facebook, he would decide whether they would incorporate these natural remedies into their daily lifestyle; he mentioned doing this with the 6 posts discussed during the interview. For example, he described how he and his wife started to eat papaya seeds after he read a post stating that "they are [sic] magical cure for gut, kidney, liver, cancer and many other diseases" (Figure 2). This post described how to consume papaya seeds and outlined 8 benefits, including that papaya seeds "have agents that can stop the growth of tumors and cancer cells, [and] contain isothiocyanate, which helps with breast, colon, leukemia, lung and prostate cancer."

Figure 2. Image of the papaya seed post that Rogelio discussed.



Start Eating Papaya Seeds Right Now – They Are Magical Cure For Gut, Kidney, Liver, Cancer and Many Other Diseases.

When we eat Papaya we usually throw away the...
Ver más

Rogelio also stated that, although Facebook was one of his main sources of information, he rarely—if ever—verified the information he engaged with on the platform. Instead, he relied on the seriousness of the people who post content on their profiles, stating that his friends from church or those aged >40 years are serious and do not share *fake news*. He also relied on his previous knowledge about a topic and believed that posts about the curative properties of foods are more credible than other topics. For Rogelio, engaging with information through a post was sufficient for him and his wife to incorporate natural remedies into their diets, regardless of whether the post cited an information source.

Finally, his cultural values and Cuban heritage came up frequently during the interview. He tended to have a fatalistic view about cancer, which emerged in multiple discussions. For example, he recalled seeing a post pertaining to 2 educational events for men about colorectal and prostate cancer. When he saw it, he immediately said he never attended such events as speaking about these topics is like inviting the disease into your life:

> *It's like not wanting to speak about the topic, so it doesn't happen to me. As if talking about [colorectal or prostate cancer] puts it in my cabinet.*

He believed this avoidance is a very negative Latin American custom; however, he claimed Latinos and Latinas rather *look the other way* when these topics emerge.

Case 2: Luisa

Luisa was a Puerto Rican female aged 63 years who preferred English. She had 370 Facebook friends and followed 268 Facebook groups, none of which were related to cancer. She also considered herself an avid Facebook user, logging on multiple times a day and using the platform for social interactions, searching for and sharing information, passing time, entertainment, relaxing, expressing her opinions, seeing what others are doing, advocacy, and convenience. During the interview, 11 cancer-related posts were discussed, 5 of which contained cancer prevention and screening information she engaged with. Another 2 posts containing cancer prevention and screening information were discussed as they grabbed her attention during the interview; she had not recalled seeing them previously but stated that she would have read them if she had as they were posted by a friend who she deemed a trustworthy source of health information. The remaining discussed cancer-related posts pertained to cancer survivorship and requests for prayer for survivors of cancer. She shared only 1 post on her profile; she did not like, comment, or share any of the other posts discussed.

When discussing her Facebook use patterns, Luisa stated that she sometimes did not engage through likes, comments, or shares as she was just scrolling through her timeline and did not stop to perform these actions. However, she said this does not mean that she failed to read or watch the content. She gave an example of being at the grocery store line while scrolling through her Facebook: she might watch an interesting video but does not stop to share it with others, only sharing content when "relaxed."

Luisa was very interested in topics pertaining to cancer prevention, particularly those related to a healthy diet. She discussed superfoods frequently and stated her preference for natural remedies over medication. For example, when discussing a video that included "10 alkaline foods that prevent and treat diabetes, gout, heart disease, and cancer," she stated that it was the images of different superfoods that initially grabbed her attention, not the cancer prevention claims. She also mentioned that repetition surrounding the benefits of superfoods confirms the credibility of such information. She gave an example of this while discussing engagement with a post about soursop, which stated that it "has been used by many people to fight against cancer cells." Luisa said that she was familiar with the curative properties of soursop as she had heard this often from friends and family in Puerto Rico. In fact, she had tried to incorporate it into her diet but had not been able to find it in any local supermarket.

Throughout the interview, Luisa continuously mentioned having seen a post about juicing as a way of preventing cancer. She recalled having seen the post on Facebook and copying the recipe on her phone's notepad app. In discussing this, she also mentioned using Facebook Messenger to send herself articles. At the end of the interview, we were able to find the post by entering the search term *cancer juice*. The post claimed that the super juice recipe "is designed to help us combat breast cancer, as well as helping to starve off all potential cancer cells within the body." It also stated that the juice cannot be blended as it is a *therapy tonic* that must be prepared using a juicer. The recipe called for broccoli, kale, cauliflower, fresh ginger root, apples, and carrots. She shared that she had since incorporated this juice into her diet, asking for it to be prepared for her when she goes to the supermarket. When asked, she said she decided to include this juice as part of her diet as she considered the friend who posted the recipe to be an extremely trustworthy source of health information. This friend came up 4 times during the interview as she often shared information about natural remedies against many diseases on Facebook, a topic Luisa was very interested in. As Luisa considered this person a trustworthy source of information, she said she rarely further verified the content she posts and might instead just send her any questions through Facebook Messenger. She trusted that her friend had already verified the content shared, although all the websites shared by her friend lacked sources of evidence-based information. When she does decide to verify any information she finds on Facebook, she goes to Google and WebMD.

Discussion

Principal Findings

This study presented a qualitatively driven, mixed methods approach to explore how individuals engage with health information on Facebook (specifically, cancer prevention and screening information) and the impact engagement may have on subsequent behavior. In doing so, it expands upon what is known regarding cancer information engagement on social media, which predominantly stems from quantitative methodologies. The current literature operationalizes engagement with information on Facebook through likes, comments, and shares, with some studies further categorizing engagement into levels by type of engagement [16,18-20,25,31]. However, the social media content and context elicitation method adds yet another layer of nuance to public health's current conceptualization of engagement by providing insight into the different ways people may process and act upon information, particularly individuals who would rather not like, comment, or share posts they consume. As exemplified in the aforementioned case studies, individuals may choose to read, discuss, or even change their behavior based on cancer prevention and screening information they consume without liking, commenting, and/or sharing the information. The aforementioned case studies also show that some individuals may circumvent liking, commenting, and/or sharing by using other messaging platforms to store or share information with others, such as Facebook Messenger and WhatsApp. These findings highlight the importance of exploring how platform interconnectivity affects health information engagement. As such, the presented methodology can assist in developing more comprehensive models describing engagement with health information on social media, responding to calls for a more thorough understanding of engagement on the social media landscape [15].

Consistent with previous literature [35], there are many reasons individuals do not engage with content in ways visible to others on social media. However, this decision is not indicative of a lack of engagement: both cases discussed in this study demonstrate ways in which individuals engage with and even disseminate posts while circumventing likes, comments, and shares. Discounting these aspects of engagement provides a limited explanation of the impact of health information in the social media landscape. This is of paramount importance in the current web-based environment, which is increasingly bombarded with misinformation on a broad range of topics. The social media content and context elicitation method is able to obtain a robust account of how individuals engage with health misinformation, what grabs their attention, how they perceive it, and how they incorporate this information into their daily lives. These insights are necessary to counteract the impact misinformation may have on the uptake of cancer prevention and screening recommendations, which is a growing area of research interest [1]. Although we explore the ramifications of engagement with cancer prevention and screening misinformation in a forthcoming publication, other researchers have already adapted the social media content and context elicitation method to explore the factors related to engagement and disengagement with COVID-19 information on the web [51]. As such, the social media content and context elicitation method may be of particular interest to public health efforts developing social media campaigns targeting misinformation among populations with lower digital and/or health literacy. This method can also provide further insight into features that affect engagement and contribute to the dissemination of accurate cancer information, particularly those conveying prevention and screening recommendations. This method may also be applied to future studies regarding how to best communicate health information on these platforms, an important step toward addressing health disparities.

The process of developing this mixed methodology led to several insights. First, it is important to have a thorough understanding of the social media platform to be explored and its features to maximize how data can be accessed and used for research. In this study, understanding the features that Facebook provides when searching for content on the platform allowed the development of a detailed process to access content alongside participants that may otherwise not be accessible. It also allowed researchers to chronologically discuss content in person with participants, which overrides any algorithms that may affect the visibility of content, while also providing a glimpse to the overall cancer information landscape participants encounter on Facebook. This content not only included cancer prevention and screening information but also information about cancer survivorship, treatment, research, and other cancer topics. In fact, posts with cancer information unrelated to prevention and screening were more common than posts about cancer prevention and screening. Another important observation is that research teams must adapt to the quickly changing nature of social media platforms when embarking on such research efforts. For example, midway during data collection, it was observed that Facebook added a new filter option to their search, which enables users to look only at *Posts you've seen*. Although details on how Facebook determines which posts a person has seen are not readily available, including this filter in future research using the methods described in this paper would reduce potential participant recall bias [52].

There are also important ethical considerations researchers must take into account when developing new methodologies to explore content in an increasingly unreliable information landscape on social media. One of these considerations entails privacy concerns. This study took place several months after Facebook's Cambridge Analytica scandal, where the information of 50 million American Facebook users was used to identify voters' personalities and influence voting behaviors in the 2016 election [53]. In an additional measure of clarity, the study team developed an additional information sheet for participants that outlined privacy expectations, what data would be captured, and what would and would not be done with captured data once deidentified. It also included images that provided an example of how the discussed posts would be deidentified before analysis. This sheet was discussed in person during the informed consent process and served as a useful resource to ensure participants fully understood the study methods and measures taken to protect the privacy of secondary data. Thus, it is important to be up to date on current events pertaining to social media platforms and issues concerning privacy and other policies that may increase perceptions of mistrust among the general public. It is also important to ensure that potential participants are extremely clear in their understanding of data safeguards in studies that use the aforementioned methods or any other mixed methodologies that capture information from a participant's social media account or accounts.

This study has several limitations. First, on a practical level, the method described is labor intensive and requires a detailed data collection and management protocol, increasing the resources needed to conduct similar research on a larger scale. This approach may also not be appropriate for more sensitive health topics or individuals who may find these in-depth methods too strenuous. Second, although participants accessed their Facebook accounts on a study laptop, 60% (12/20) of participants reported only accessing their accounts on their cell phones. The visual layout of Facebook's website version is different from that of its mobile app. This difference in visualization may have affected the ability of some participants to fully recall some posts they previously engaged with as they looked different on the computer screen. Future studies conducting this type of methodology may want to explore using a mobile device to collect data. They may also incorporate the aforementioned new *Posts you've seen* filter to minimize recall bias more generally, as self-reported recall may capture only content that people more deeply engaged with rather than all content to which they were exposed and maybe glanced over. Finally, only posts that included the search terms in the text emerged in the search during the data collection process, inevitably excluding posts that did not contain some kind of text feature (eg, posts with only a picture or a direct link to a video). It also excluded posts that discussed cancer-related topics but did not, at minimum, include the word *cancer*, whereas it included posts unrelated to the disease (eg, astrology-related posts or those equating current events in Latin American politics to cancer). Future studies should ensure they possess a comprehensive list of search terms encompassing multiple areas of the study topic while understanding that an increase in search terms adds time to the interview.

Conclusions

The social media content and context elicitation method shows potential for a deeper contextualization of engagement with health information on social media. Conducting interviews to complement the quantitative content analysis of elicited posts allows a deeper understanding of the reasons and ways engagement with health information on social media occurs, which cannot be done by observing web-based content alone [54] or by asking questions that require recall about a topic that may not be salient to most (ie, cancer prevention and screening information engagement). This mixed methodology also allows a discussion of how message engagement may be a result of offline interactions and relationships and how these affect assessments of message credibility and accuracy. Our findings provide insight into the preferred source and content characteristics of information on social media that triggers engagement and subsequent action among specific groups and vulnerable populations, laying foundational work for the development of future measures and empirical research exploring innovative and participatory health communication on social media platforms. Future steps for the research described in this paper include data integration and the development of a final conceptual model to help visualize the process of engagement with cancer prevention and screening information on Facebook among Latinos and Latinas in the United States.

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Conflicts of Interest

None declared.

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