Viewpoint

Patient-Centered Care: Transforming the Health Care System in Vietnam With Support of Digital Health Technology

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Abstract

Background: Over the recent decades, Vietnam has attained remarkable achievements in all areas of health care. However, shortcomings including health disparities persist particularly with a rapidly aging population. This has resulted in a shift in the disease burden from communicable to noncommunicable diseases such as dementia, cancer, and diabetes. These medical conditions require long-term care, which causes an accelerating crisis for the health sector and society. The current health care system in Vietnam is unlikely to cope with these challenges.

Objective: The aim of this paper was to explore the opportunities, challenges, and necessary conditions for Vietnam in transforming toward a patient-centered care model to produce better health for people and reduce health care costs.

Methods: We examine the applicability of a personalized and integrated Bespoke Health Care System (BHS) for Vietnam using a strength, weakness, opportunity, and threat analysis and examining the successes or failures of digital health care innovations in Vietnam. We then make suggestions for successful adoption of the BHS model in Vietnam.

Results: The BHS model of patient-centered care empowers patients to become active participants in their own health care. Vietnam's current policy, social, technological, and economic environment favors the transition of its health care system toward the BHS model. Nevertheless, the country is in an early stage of health care digitalization. The legal and regulatory system to protect patient privacy and information security is still lacking. The readiness to implement electronic medical records, a core element of the BHS, varies across health providers and clinical practices. The scarcity of empirical evidence and evaluation regarding the effectiveness and sustainability of digital health initiatives is an obstacle to the Vietnamese government in policymaking, development, and implementation of health care digitalization.

Conclusions: Implementing a personalized and integrated health care system may help Vietnam to address health care needs, reduce pressure on the health care system and society, improve health care delivery, and promote health equity. However, in order to adopt the patient-centered care system and digitalized health care, a whole-system approach in transformation and operation with a co-design in the whole span of a digital health initiative developing process are necessary.

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KEYWORDS

building blocks; digital health; eHealth; patient-centered care; telemedicine; Vietnam

Introduction

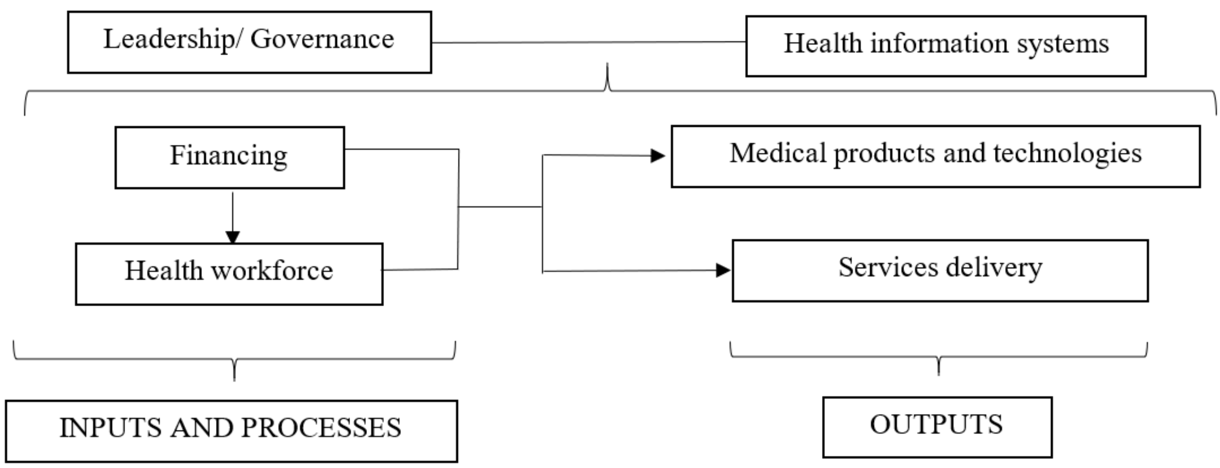
Overview

Following broad economic reforms known as Doi Moi in 1986, Vietnam has attained remarkable health care improvement, reflected in core health indicators [1]. From 1988 to 2018, life expectancy at birth increased from 69.9 years to 75.3 years, under-5 mortality rate decreased from 56‰ to 20.7‰, and infant mortality reduced from 39.6‰ to 16.5‰ [2]. Health care expenditure gradually increased and was forecasted to triple from US $15.6 billion in 2018 to US $42.9 billion in 2028 [3]. Despite these improvements, the health care system still faces significant challenges including wide disparities in health and growing health care costs. The disparities in core health indicators are particularly observed between urban and rural residents, across different regions, and among population groups [4]. For example, the maternal mortality ratio and infant mortality rate in some mountainous areas are 3 to 4 times higher than those in lowland and urban areas and almost double the national average rates [4].

Vietnam is undergoing a dramatic demographic transition resulting in an aging population. The number of people aged 65 years and over is estimated to increase from 10% of the population in 2015 to 28% in 2050 [5]. The combination of an aging population, increased industrialization, and changes in population lifestyle have created a double disease burden, with a shift from communicable to noncommunicable diseases (NCDs). Specifically, the mortality rate caused by NCDs rose from 45.5% in 2010 to 77% in 2016 and is projected to climb [3,4,6]. The double disease burden means that Vietnam is facing more costly health conditions such as dementia, cancer, and multimorbidity. In addition to this, the country still faces significant burden of infectious conditions and a number of new epidemics such as COVID-19. These health challenges must be addressed using a systemic approach by the whole government of Vietnam to improve health for its population.

To improve health care problems and the health status of the population, there is a critical need for a well-functioning health care system that can deliver services equitably and efficiently [7]. The World Health Organization (WHO) developed an evidence-based building blocks framework as a tool to help its member states analyze their health care systems. This framework allows nations to consider the multifaceted nature of their health systems and interdisciplinary and multilevel responsibility in health care [7]. The WHO framework assesses health systems using 6 core components or building blocks. Each building block and its indicators were initiated by a group of agency representatives and technical experts, shared broadly with country experts, and followed by evaluations through a series of case studies and reviews of country experiences [7]. These components focus on the key chains of the monitoring and evaluation framework developed by the International Health Partnership, namely inputs, processes, and outputs [8]. The relation between the 6 building blocks and this monitoring and evaluation framework is summarized in Figure 1. In the following section, the 6 building blocks and corresponding indicators are used to describe Vietnam's health care system, comprising financing and health workforce components (inputs and processes), medical products, technologies, and service delivery components (immediate outputs), and cross-cutting components: leadership/governance and health information systems [7].

Figure 1. Health system strengthening: relationship between the World Health Organization building blocks (6 core components, top) and International Health Partnership monitoring and evaluation framework (inputs, processes and outputs, bottom).



Health Care System in Vietnam

Health Financing

Health financing is a key building block in a national health system, largely influencing the inputs, thus affecting the availability, affordability, and accessibility of health services. A good health financing system should move toward universal health coverage, where all people have access to needed health services without financial hardship. This could be achieved through increasing total health expenditure (THE) and decreasing the proportion of households facing financial catastrophe as a result of out-of-pocket payments (OPP) [7].

With multiple health financing reforms, Vietnam's THE per capita increased from US $14 in 1995 to US $113 in 2014 [9,10], thus within the internationally defined range and enough for universal coverage of key health interventions [7]. The increase in public health expenditure (mainly comprising state budget [11] and social health insurance [12]) has increased health care coverage for some groups including the poor, ethnic minorities, under–6-year-old children, over–80-year-old people, and socially vulnerable groups through the government's subsidized schemes [13]. However, patient OPP remained high, accounting for 40.8% of THE in 2015, which was higher than that of other countries in the Asia Pacific region and the WHO recommended level [10,11]. The high OPP led to catastrophic expenditure and pushed many Vietnamese families into poverty, resulting in health care inequity [14,15]. The current model of the health care system and financing needs further reforms to address a surge in health care expenditure caused by the aging population and shifting disease pattern in Vietnam.

Health Workforce

The health workforce is another key building block to provide inputs and processes to the monitoring and evaluation chain of health systems. The ability of a country to meet its health goals largely depends on people in charge of organizing and delivering health services. Evidence of the direct and positive link between numbers of health workers and population health outcomes has been demonstrated in several studies [16,17].

The health workforce in Vietnam has gradually improved in both quantity and quality. The number of doctors and pharmacists increased from 7.2 and 1.76 per 10,000 people in 2010 to 8.0 and 2.2 per 10,000 people in 2015, respectively [4]. In 2015, 65% to 95% of the health facilities and about 90% of the health workers in hospitals at central and provincial levels were licensed [4]. Despite this significant improvement, Vietnam's health workforce was still insufficient to meet staffing norms and clinical needs [4] and inappropriately distributed across regions and levels/areas of care. The aging population and shifting disease burden to those requiring long-term care for chronic NCDs are likely to lead to severe shortages in health resources, which occur in highly specialized fields such as cancer, palliative care, and mental health and in hard-to-reach areas such as North West, Central highlands, and Mekong Delta regions [4,18-20]. The mountainous and remote areas lack not only specialists trained in advanced diagnostic and treatment approaches but also standard medical and diagnostic equipment, which diminishes the quality of health care services in these areas compared to urban regions [4]. This wide disparity in health care between the rich and the poor, urban and rural, is demonstrated in the disparity of core health indicators such as life expectancy at birth and infant and under-5 mortality rates [4].

Overcrowding in health facilities, especially in urban and specialized hospitals, is a main cause of health worker exhaustion. Nearly one-fifth of Vietnamese clinical nurses experienced burnout and occupational stress [21]. Clinician burnout directly reduces the quality of life of clinicians and adversely affects the quality of care to patients. It also indirectly contributes to the reduction of health staffing [22]. Hence, a vicious negative cycle for Vietnam's health sector is created.

Health Service Delivery

Health service delivery is reflected in the availability and readiness of services across the health care continuum. Vietnam has achieved significant service improvement in health care: for example, the ratio of hospital beds per 10,000 people increased from 21.5 in 2011 to 24.0 in 2015 [4]. The hospital quality management system was established in 2013 and available in 55.4% of hospitals throughout the country in 2015 [23].

Service provision is immediate outputs of the inputs into the health system such as financing, workforce, procurement, and supplies [7]. It will be difficult to achieve the outputs if the inputs are insufficient. Even if the inputs are adequate, whether the outputs are obtained depends very much on the efficiency of the health system's functioning. According to Bentley et al [24], there are 4 key inefficiencies: duplication of services, inefficient processes, overly expensive inputs, and medical errors. All of these forms of inefficiency occur in Vietnam's health sector.

Vietnamese patients' laboratory tests and results are not usually archived at medical facilities or shared between different health care providers. This poses a challenge as patients experience multiple visits to doctors and specialists for the same health conditions thus leading to duplication of services [3]. Public hospitals, especially in large cities, are usually overcrowded with 2 to 3 patients sharing a bed. Limited quality of health care services at the commune level leads to reduced patient trust in primary care. Also, if patients use OPP, the health care system allows them to easily bypass lower level facilities (eg, commune health stations) and seek health care services in leading tertiary hospitals in big cities without referrals (ie, inefficient processes), even just to treat common diseases that primary care is well equipped to manage (ie, overly expensive inputs) [4,25]. Consequently, higher level hospitals are drained of resources, while there is waste at lower levels due to underuse [26]. Overcrowding in high-level health facilities is associated with medication errors. A large prospective study in two urban hospitals in Vietnam revealed that medication errors occurred in more than one-third of all medication doses [27].

There are also discrepancies in health service readiness and quality across areas of health care. Vietnam has an extensive primary health care system that reaches almost every administrative jurisdiction and acts as the main entry point to public health care. However, grassroots level facilities have inadequate infrastructure required for basic health care delivery. For example, only 76% of commune health stations in Dien Bien province (a Northern mountainous province) have a source of clean water, and a significant number of district hospitals lack essential equipment such as child ventilators and electrocardiograms [28]. Also, there have been increasing concerns about the equity and quality of basic health service provisions in primary health care. These limitations were reflected in key health indicators, with the infant mortality rate among the ethnic minority population being over 4 times higher than that of Kinh and Hoa ethnic groups, who mostly live in urban areas [28].

Access to Essential Medicines

According to WHO, a well-functioning health system should be able to provide the population it serves with equitable and affordable access to essential medicines, medical products, and technologies and use this resource efficiently [7]. However, published literature consistently reported that medicine prices in Vietnam were high and unaffordable for many Vietnamese people [29-31]. A fragmented medical information system within and between health care and other sectors such as General Department of Vietnam Customs and Ministry of Finance, as well as a shortage of personnel and resources for enforcing medicine pricing policies was one of the reasons for their high price in Vietnam [32]. Because of high medicine prices, irrational selection and use of medicines, unsustainable pharmaceutical production and distribution systems, and a lack of financial support systems for medicine procurement, access to the right medicines at the times people need them remains a major challenge for the majority of the Vietnamese people [33-37].

Health Information

The health information system (HIS) is a crosscutting building block because it creates a foundation for all decision-making processes in a health system. Vietnam has achieved significant progress in this area. A number of health statistics are generated annually: for example, the Annual Health Statistic Yearbook, Joint Annual Health Review, and Statistical Yearbook. Information technology is applied widely in the health administration and management of all 63 provinces and cities across the country. Vietnam is also strongly promoting the development of a health management database for its over 90 million citizens [4].

Vietnam's HIS, however, still faces a number of issues and challenges, including data generation, validation, and uses. For example, data from health care facilities, especially from private and industrial sectors, are neither timely nor complete. Information from local death registration is incompatible with WHO recommendations. There are discrepancies in the quality of medical records across regions and levels of care, which creates challenges for continuing health monitoring, disease prevention and treatment, and management of medical errors and adverse drug reactions. Even after the data are collected, the unclear data dissemination mechanism in Vietnam will likely restrict data use [4]. Given the importance of this crosscutting building block of the health system, reform is needed to operate HIS more effectively, especially in the new era of information technology.

Leadership and Governance

Health leadership and governance is another crosscutting building block in a health care system. It mediates other building blocks by connecting all issues surrounding the accountability of various stakeholders in the system to ensure adequate resources (finance, workforce, medical supplies, and information) are available to deliver essential health services. In terms of health care governance, Vietnam has attained remarkable progress, demonstrated in the development of a strong policy framework in health care. The enactment of important laws and policies, such as health insurance and pharmacy laws [38,39], and the Health Sector Strategy for 2011-2020 with a Vision to 2030 [40] provided a solid foundation and led to the formation of regulations, guidelines, initiatives, and plans in these areas. The organizational structure of Vietnam's health system has been adjusting to meet health care needs at various levels, such as establishing information technology administration at central levels and formally affirming the function and tasks of community health services at local levels [4]. Nevertheless, health policies in Vietnam are sometimes overlap, inconsistent and lack evidence. Lack of detailed plans and information cause difficulty for the effective implementation of policies. Additionally, insufficient sanctions and a weak inspection network for policy enforcement are also shortcomings of Vietnam's health care governance [4].

In summary, Vietnam has attained significant achievement and improvement in all 6 areas of the health system framework. However, shortcomings persist. To address all these systemic challenges and achieve optimal and equitable health outcomes for the population, the Vietnamese government must consider adapting the current model of health care operation to meet rapidly changing population trends, patterns of disease, and health care needs and use existing resources more efficiently while improving health infrastructure. The application of digital health technologies to underpin the health care system transformation is critical to success [41]. "The use and scale-up of digital health solutions can revolutionize how people worldwide achieve higher standards of health and access services to promote and protect their health and well-being" [42]. As in many other countries, Vietnam's health care system will need to be migrated to the patient-centered care model, which focuses on patients and their particular health care needs, and patients will need to be empowered to become active participants in their care to optimize health and economic outcomes [43]. This study was conducted to explore the opportunities, challenges, and necessary conditions for Vietnam in transforming toward a patient-centered care model to produce better health for people and reduce health care costs.

Methods

Approach

In this paper, we explored a Bespoke Health Care System (BHS) developed by Schofield et al [44] as an ideal example of a comprehensive patient-centric care model. The current Vietnamese digital health and health care landscape was examined using a strength, weakness, opportunity, and threat (SWOT) analysis to argue for the potential of developing a BHS in Vietnam. We then discuss necessary and sufficient conditions and challenges for Vietnam in transforming toward this patient-centered care model to produce better health for people and reduce health care costs.

Bespoke Health Care System

In 2019, Schofield et al [44] first introduced the concept of the BHS in the context of Australian health care, which has been adapted to other contexts [45,46]. The development of the BHS was based on the pedagogical model of flipping the classroom in modern education [47] and its application in health care [48]. In Australia, this approach has been applied by many health professionals [47]. Patients were equipped with necessary knowledge before consultations. Therefore, the consultation time was effectively used to solve health problems and make joint decisions [47]. The core component of the BHS is "increasing patient involvement in health care decisions and self-management assisted by the use of technology" [49]. In this model, patients will be educated about their illness and management options, flipping their role from passengers to drivers to manage their own health care, with clinicians playing more of a support role being the "guide by the side." Although the BHS was proposed as an ideal comprehensive patient-centric care system with several advantages and benefits, there is no one-size-fits-all approach. Novel health care solutions will work best when they are adapted to suit a country's specific conditions and have broad-based acceptance among the community, health care providers, and government agencies.

SWOT Analysis

The SWOT analysis has been used widely in policy research to provide policy makers with a sound basis for strategy development and formulation and identify new avenues for national health care reform [50]. The technique examines 4 parameters: strengths, weaknesses, opportunities, and threats. In this paper, strengths and weaknesses refer to internal factors of the proposed BHS that place it at an advantage or disadvantage over the current Vietnamese health care system, respectively. Opportunities and threats refer to external factors to the BHS that support or prevent it from being adopted in Vietnam.

Results

Strengths

The BHS brings a number of potential benefits to a health care system. First, the BHS proposes integrating electronic medical records (EMRs) into a patient-centered management platform. Currently, EMRs act as passive information depositories mainly for the purposes of health data storage or analysis. In the proposed BHS, every person would have their EMR containing all relevant personal and medical information that is shared across health care providers. As such, relevant health workers and agencies would have access to patients' real-time health information, saving time in managing people's health, saving costs of unnecessary or duplicated examinations and laboratory tests, and reducing medication errors. Studies have revealed that one-fifth of medical errors were due to insufficient patient medication information [48,51]. Clinical access to patients' real-time health information would enable tailored precision and holistic health solutions for individuals.

Second, the BHS proposes that the EMR is an active tool in promoting optimal health management. The proposed platform would remotely track symptoms, prompt patients to perform routine screening tests, allow patients to book medical appointments and remind them to attend, and provide scheduled reminders for adherence to medical recommendations. Electronic prompts and reminder alerts have been shown to assist individuals in adhering to clinical intervention effectively, particularly in managing long-term chronic conditions [49].

Third, the BHS serves as an education platform, upskilling patients and health workers. In the BHS, patients would optimally be equipped with a comprehensive understanding of their conditions, treatment options, and self-management strategies. This is an effective way to empower people to have greater ownership in managing their health. Additionally, clinicians would be provided with up-to-date, evidence-based optimal health care pathways suitable for their specific patients' conditions. This offers an ongoing mechanism to support clinicians' continuing professional development using their own case studies. Moreover, the platform might be used to upskill patient families and carers, which would strengthen community care and lessen the health care burden due to staff shortages [51]. Potentially, the BHS would facilitate reducing the health inequities in terms of accessing optimal health care, particularly for the economically disadvantaged or those living in remote areas.

In summary, adopting the BHS model may assist Vietnam in addressing the health crisis and achieving the country's health care goals in the new decade. This model can increase patient accessibility to health care facilities and state-of-the-art health management, including the most vulnerable and hard-to-reach people, thus enhancing health equity across the country. It can also increase operational efficiencies for both health care providers and users, resulting in lessening overcrowded hospitals and enabling coordinated health care, which is currently missing [3,52]. Moreover, digital solutions can assist teaching, tertiary, or specialized hospitals to deliver training or conduct eHealth consultations with satellite, primary, or secondary hospitals. Therefore, the quality of health care would be strengthened across the country.

Weaknesses

Although the BHS model has many strengths, we need to articulate inherent weaknesses in the model. First, the high cost and complexity of implementing digital health information systems, such as EMRs, may be a barrier to broad dissemination. Second, the digitalization of data and services represents a potential cybersecurity threat to privacy and trust of people in a new health care system [3]. Finally, the establishment of nationwide unique health IDs (unique codes used to identify individuals within the health care system) often takes time, especially for socially disadvantaged members of the community.

Opportunities

Vietnam has a high-level policy framework (ie, political and legal environment) supporting the transition toward the BHS. The 2017 Resolution 20-NQ/TW of the Communist Party of Vietnam has provided a strategic orientation for reforming the health care system. This includes systemic implementation of information technology in management of primary health care, prevention, disease management, and the establishment of electronic health records (EHRs) for all citizens that link to their health insurance card.

Based on this strategic orientation, the Vietnamese Ministry of Health (MOH) in 2017 set out national goals for the protection, care, and improvement of people's health in the period to 2030. One of the 5 key priorities for action to achieve the national health care goals was developing human resources, medical sciences, and technology [4,53]. Since then, a national agenda for digitalization of the health care system has been driven by MOH with a number of initiatives that aim to adopt digital solutions in health care network across the country. Vietnam is rapidly embracing digital health. Digitalized health care is perceived as a useful solution that could help to address the rapidly growing gap between service demand and capacity [44].

To implement health care digitalization, MOH issued Circular 54/2017/TT-BYT regarding assessment criteria for information technology applications in health care facilities [50] and a plan to develop smart health care during the period 2018-2025, with a vision toward 2030 [54]. In this plan, targeted smart health outcomes were specified, such as development of a national health care data center, electronic health and medical records, and electronic government and smart medicine management systems. Particularly in the field of examination and treatment, telemedicine is regulated by Circular 49/2017/TT-BYT, which provides guidelines for a range of telemedicine consultations in Vietnam (eg, allowing doctors to provide telemedicine services to patients under certain infrastructure requirements [55]).

To accelerate the application of information technology in the health sector, in 2018, MOH issued Circular 46/2018/TT-BYT regulating EMRs. According to Häyrinen et al [56], EMR was defined as "a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users. It contains retrospective, concurrent, and prospective information, and its primary purpose is to support continuing, efficient, and quality integrated health care." In the circular, EMRs include inpatient records, outpatient records, and other medical records prescribed by MOH, such as traditional medicine medical records and medical records of abortion. This is the first time Vietnam has specific guidance for EMR establishment, use, and management at health care facilities [57]. As the health care system in Vietnam is centralized under MOH and provincial health authorities, the integration of EMRs within the existing system, at least in the 47 central-level hospitals and possibly also at 419 provincial-level hospitals [58], will be easier than in countries with a more fragmented health care system.

The plan for implementing EHRs was approved by MOH in 2019 in Decision 5349/QĐ-BYT [59]. According to this decision, EHRs are medical documents that record the health care process of a person from birth to death in the form prescribed by MOH. This plan guides and directs all 61 cities and provinces of Vietnam to simultaneously deploy and make EHRs available for use by 80% and 95% of population in 2020 and 2025, respectively. If this aim is achieved, Vietnam will be perfectly positioned to adapt and adopt the BHS model. EHRs may be able to assist every citizen to understand and manage their health information continuously for life, enabling them to prevent disease proactively, and actively manage their health conditions if used as the basis for a BHS. EHRs will also support physicians in providing health care for people in real time and according to best practice health care recommendations. Importantly, EHRs will provide complete, accurate, and timely data on population health, enabling policy makers to advance evidence-based health policy and health authorities to examine the relative efficacy of treatments to manage health care expenditure more efficiently.

Supportive social and technological environments also place Vietnam in a good position to adopt advanced digital health solutions of the BHS. Today, Vietnam is benefiting from a golden population proportion with 70% of the population being of working age (aged 18 to 65 years) [6]. This generation is rapidly embracing new communication technologies. In 2020, Vietnam was the seventh highest number of Facebook users in the world [60]. On average, Vietnamese people spend about 7 hours per day on the internet [61]. The high uptake is associated with a high acceptability of digital technologies by Vietnamese people. Studies have shown that people's attitudes toward mobile health solutions is highly positive. Two-thirds of Vietnamese youth and adolescents found mobile health apps useful [62,63].

Online communication is backed by a rapid and strong development of the country's information and communication technology infrastructure: penetration rate of internet access is 67%, which is among the highest in the Asia Pacific region [64], and 95% of households are now able to use 4G network [3]. Vietnam's technology infrastructure is also embracing cloud-based services, which will facilitate innovative and cost-effective health care delivery solutions. In recent years, a number of projects have initiated and implemented digital health services in large urban hospitals, including teleradiology, teleconsultation, telediagnosis, and videoconferencing. Examples of these initiatives include raising disease awareness and encouraging people to adopt heathier behaviors [65-69], improving accessibility to health care services among disadvantaged and vulnerable target groups [70-72], and upskilling health care workers [73-80].

A supportive economic environment has resulted in an increased need for high-quality health care services and precision medicine. Strong economic growth with an average annual gross domestic product growth rate of 6.4% [81] is creating a booming middle class in the society. It is estimated that this population will increase sharply from 10% in 2015 to more than 50% in 2035 [82]. The growth in disposable income among digitally literate, educated, and wealthy individuals creates economic conditions for higher personal expenditure on easily accessible, high-quality health care. Public health facilities often do not meet their needs due to long waiting times, inadequate consultation time, overcrowding, and high-occupancy bed rates [3]. This has resulted in the rapid expansion of a private health system, which was projected to grow from US $6.6 billion in 2016 to US $8.7 billion in 2020 [83]. Smart solutions that use big data, cloud computing, and mobile technology are strongly encouraged to alleviate overcrowded public hospitals and increase quality health care overall [4].

Together, all these supportive policy, social, technological, and economic environments provide a good foundation for the health care system in Vietnam to shift toward innovative models of care that are being proposed in developed countries, such as the BHS, which focus on patient-centered care.

Threats

In Vietnam, patient medical records remain paper-based at all levels of the health care system and currently are required for legal purposes [84]. Moreover, although electronic administration management has been adopted in some large hospitals, the quality of medical records and databases varies across hospitals and clinics. In most health care facilities, the medical record system is not centralized [52]. As such, one patient can have multiple medical records. This is a barrier for timely medical information exchange and sharing between hospitals [69]. In addition, the development of EMRs and EHRs, a precondition for BHS adoption, is still in the early stages [4,44]. Although MOH has taken initial steps toward the development of EMR and EHR systems, the readiness to implement the EMR nationally in real clinical practice still requires considerable preparatory effort.

First, Vietnam needs to assign a unique patient identifier to every citizen, which is a core requirement for successfully introducing EHRs [52]. In 2019, MOH issued Decision 4376/QĐ-BYT, regulating the establishment, use, and management of IDs [85]. According to the decision, an ID will be created, comprising two series of numbers separated by a dot. The first series is the social insurance code of the individual while the second series is a product of an algorithm of administrative information including the social insurance code, full name, date of birth, gender, and place of birth. The social insurance, however, is a compulsory income protection insurance for employed people only to fully or partially offset their income that is reduced or lost due to sickness, maternity, labor accident, occupational disease, retirement, or death [86]. Although Vietnam has made significant progress in expanding social insurance coverage in recent years, enrollment rates are still low, especially in small- and medium-size enterprises due to multiple barriers such as cost of contribution, lack of trust in the government system, and administrative factors [87]. Despite large increases in government subsidies, low enrollment rates in compulsory social and health insurance still persist [88]. In May 2020, only 27% of Vietnam's workforce had social insurance [89,90], which is far short of the government's target of 50% social insurance coverage [87] and 80% health insurance coverage by 2020 [91,92]. The IDs, when established, therefore, will only cover a small proportion of the population.

Second, although many health workers and patients are aware of the advantages of using EMRs and EHRs, there are concerns about the risks of privacy violation. The Law on Network Information Security No. 86/2015/QH13, enacted in 2015, includes a requirement of "providing an adequate level of protection for personal data, following the technical standards for protection of personal data." However, there are no clear definitions of "an adequate level of protection" and "technical standards" [93]. As such, there is a lack of regulatory rigor and sanctions in managing data processors. Strengthening the legal and regulatory system to protect patient privacy and information security is fundamental for the success of EMR development and application.

Finally, since Vietnam is still in the very early stage of health care digitalization, there is no empirical evidence about the effectiveness and sustainability of digital health initiatives. Over the past few years, there have been a growing number of organizations and health startups delivering digital health solutions to improve the quality of medical services. For example, eHospital software, developed by the Corporation for Financing and Promoting Technology, was first launched in 2000 [94]. This is a comprehensive hospital management system providing supports to manage all activities relating to patients in health care facilities. In 2018, eHospital with the application of the latest 4.0 technologies such as artificial intelligence and big data was introduced. Until now, this system has been used in more than 400 hospitals and clinics in Vietnam. [95].

Another example is the Hospital Information System of the Vietnam Posts and Telecommunications Group, which was introduced in 2015. This solution with its three levels of management—state, hospital and patient—aims at supporting provincial health authorities and hospital managers to make well-informed decisions for health care improvement and assisting patients to facilitate and adhere to their health care appointments online. This allegedly leads to increasing transparency and reducing overcrowding in health care facilities [96]. Nevertheless, these initiatives have not been rigorously evaluated. Lack of evaluation results will prevent the government from evidence-based policymaking and hinder the broader implementation of existing projects or development of new initiatives.

Discussion

Necessary Conditions for Successful Adoption of the BHS Model in Vietnam

Vietnam has identifiable opportunities to adopt the BHS model and implement digitalization in health care. To grasp these opportunities, the following strategies are recommended.

First, establishing a national ID for each individual based on their social insurance code is one core requirement for successfully introducing EHRs. In a recent Organisation for Economic Co-operation and Development policy report, recommendations have been proposed for the Vietnamese government to increase the enrollment rates of social insurance. They include reducing obstacles to participation (eg, simplifying administration processes for paying insurance), introducing incentive scheme for employees to participate (eg, providing government subsidies for participation of low-income people in the voluntary system), and adopting a systematic approach to social protection (eg, considering the interaction between various social protection mechanisms) [87].

Second, successful adoption of the BHS requires a whole-system approach involving the support of different sectors in the society. Obviously, MOH would have to play a key role in this adoption process but would need to collaborate with related ministries—in particular, the Ministry of Science and Technology and the Ministry of Information and Communications—in developing and implementing a digital health strategy. The resources needed to improve the health care system are sizeable. MOH would need to garner funding from different sources, both domestic and foreign agencies: government, social entrepreneurs, or private businesses [69,70].

Third, integrating personal data in EHR and EMR systems will increase the risk of privacy violation and cybersecurity breaches. The Vietnamese government needs to improve the security of information technology platforms in general and health care in particular to protect patient privacy and information security [70].

Fourth, to improve the adoption of evidence-based practices, it will be necessary to provide resources to demonstrate the effectiveness and impact of digital health initiatives and establish a network of collaborators including health care administrators, clinicians, community representatives, digital health researchers, information technology developers, and public health education experts [69]. This will be a great opportunity for further enhancing strong collaborations between multisectors and multistakeholders at various levels, which are essential for successfully reforming the health care system in Vietnam. BHS implementation would require the involvement of local educators to provide education for communities, raising awareness of the benefits the system could bring to individuals and society, coaching to enhance self-management behaviors, and increasing engagement with the system [97]. Strong evidence about the effectiveness of digital health initiatives in Vietnam will encourage the government to develop appropriate health policies and increase opportunities for ongoing projects to scale-up by attracting funding and support [70]. Thus, there is a substantial need for further research in this area in the future.

Finally, to increase the acceptability and feasibility of digital health initiatives, a co-design approach is crucial. Co-design is defined as the “collective creativity as it is applied across the whole span of a design process” [98]. In the design process, diverse experts such as researchers, designers or developers and potential customers and users work closely together to understand the needs and preferences of end users [99,100]. A co-design approach is likely to increase scalability and dissemination of the initiative [99].

Conclusions

The overarching goal of the BHS is, with the support of digital technologies, to deliver best practice health care and reduce pressure on the current health care system by empowering people to direct their own health care, regardless of their geographical location and economic status [44]. The BHS offers a promising and intelligent health care that which may be efficient and suitable for Vietnam in the new era of the Fourth Industrial Revolution [101]. Vietnam has tremendous opportunities and a favorable policy, social, technological, and economic environment to adopt this model of comprehensive patient-centric health care. In order to uptake, adapt, and implement the BHS successfully, Vietnam needs to apply a whole-system approach in transformation and operation processes.

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Conflicts of Interest

None declared.

References

1. The World Bank in Vietnam. Hanoi: The World Bank; 2019. URL: https://www.worldbank.org/en/country/vietnam/overview [accessed 2020-05-24]
2. The World Bank indicators. Washington: World Bank; 2020. URL: https://data.worldbank.org/indicator/ [accessed 2020-08-16]
3. Digital health in Vietnam: a guide to market. Australian Trade and Investment Commission. 2019. URL: https://www.austrade.gov.au/ArticleDocuments/4569/Digital%20Health%20in%20Vietnam%20Report.pdf.aspx [accessed 2021-05-23]
4. Plan for people’s health protection, care and promotion 2016-2020. Hanoi: Ministry of Health of Vietnam; 2016. URL: http://faolex.fao.org/docs/pdf/vie179587.pdf [accessed 2021-05-23]
5. World population prospects: the 2015 revision. Department of Economic and Social Affairs, Population Division, United Nations. 2015 Jun 12. URL: https://esa.un.org/unpd/wpp/Publications/Files/Key_Findings_WPP_201pdf [accessed 2020-05-24]
6. Statistical yearbook of Vietnam 2018. Hanoi: General Statistics of Vietnam; 2019. URL: https://www.gso.gov.vn/wp-content/uploads/2019/10/Nien-giam-2018-1.pdf [accessed 2021-05-24]

7. Monitoring the building blocks of health systems: a handbook of indicators and their measurement strategies. Geneva: World Health Organization; 2010. URL: https://www.who.int/healthinfo/systems/WHO_MBHSS_2010_full_web.pdf?ua=1 [accessed 2021-05-24]
8. Boerma T, Abou - Zahr C, Bos E, Hansen P, Addai E, Low - Beer D. Monitoring and evaluation of health systems strengthening: an operational framework. Geneva: World Health Organization; 2009. URL: https://www.who.int/healthinfo/HSS_MandE_framework_Nov_2009.pdf [accessed 2021-05-24]
9. Hoang VM, Oh J, Tran TA, Tran TGH, Ha AD, Luu NH, et al. Patterns of health expenditures and financial protections in Vietnam 1992-2012. J Korean Med Sci 2015 Nov;30 Suppl 2:S134-S138 [FREE Full text] [doi: 10.3346/jkms.2015.30.S2.S134] [Medline: 26617446]
10. Ministry of Health of Vietnam and Department of Planning and Finance. National health account: implemented in Vietnam period 1998-2012. Hanoi: Statistical Publishing House; 2014.
11. Health financing strategy in Asia-Pacific region (2010-2015). Geneva: World Health Organization; 2009. URL: https://apps.who.int/iris/bitstream/handle/10665/207746/9789290614586_eng.pdf?sequence=1&isAllowed=y [accessed 2021-05-24]
12. Health financing in Vietnam. Geneva: World Health Organization URL: https://www.who.int/vietnam/health-topics/health-financing [accessed 2020-08-22]
13. The Prime Minister of Vietnam. Decision of the Prime Minister No. 139/2002/QD-TTG on examination and treatment of poverty people. Hanoi: Legal library; 2002. URL: https://thuvienphapluat.vn/van-ban/the-thao-y-te/Quyet-dinh-139-2002-QD-TTg-kham-chua-benh-cho-nguoi-ngheo-50086.aspx [accessed 2020-08-22]
14. Xu K, Evans DB, Kawabata K, Zeramdini R, Klavus J, Murray CJL. Household catastrophic health expenditure: a multicountry analysis. Lancet 2003 Jul 12;362(9378):111-117. [doi: 10.1016/S0140-6736(03)13861-5] [Medline: 12867110]
15. van Doorslaer E, O'Donnell O, Rannan-Eliya RP, Somanathan A, Adhikari SR, Garg CC, et al. Effect of payments for health care on poverty estimates in 11 countries in Asia: an analysis of household survey data. Lancet 2006 Oct 14;368(9544):1357-1364. [doi: 10.1016/S0140-6736(06)69560-3] [Medline: 17046468]
16. Anand S, Bärnighausen T. Health workers and vaccination coverage in developing countries: an econometric analysis. Lancet 2007 Apr 14;369(9569):1277-1285. [doi: 10.1016/S0140-6736(07)60599-6] [Medline: 17434403]
17. Speybroeck N. Reassessing the relationship between human resources for health, intervention coverage and health outcomes: the world health report 2006. Geneva: World Health Organization; 2006. URL: https://www.who.int/hrh/documents/reassessing_relationship.pdf [accessed 2021-05-24]
18. Krakauer EL, Cham NTP, Khue LN. Vietnam's palliative care initiative: successes and challenges in the first five years. J Pain Symptom Manage 2010 Jul;40(1):27-30 [FREE Full text] [doi: 10.1016/j.jpainsymman.2010.04.009] [Medline: 20619210]
19. Health at a glance Asia/Pacific 2016. Organisation for Economic Co-operation and Development. 2016. URL: https://www.oecd-ilibrary.org/health-at-a-glance-asia-pacific-2016_5jlsgjk4ktxs.pdf?itemId=%2Fcontent%2Fpublication%2Fhealth_glance_ap-2016-en&mimeType=pdf [accessed 2021-05-24]
20. Vuong DA, Van Ginneken E, Morris J, Ha ST, Busse R. Mental health in Vietnam: burden of disease and availability of services. Asian J Psychiatr 2011 Mar;4(1):65-70. [doi: 10.1016/j.ajp.2011.01.005] [Medline: 23050918]
21. Nguyen HTT, Kitaoka K, Sukigara M, Thai AL. Burnout study of clinical nurses in Vietnam: development of job burnout model based on Leiter and Maslach's Theory. Asian Nurs Res (Korean Soc Nurs Sci) 2018 Mar;12(1):42-49 [FREE Full text] [doi: 10.1016/j.anr.2018.01.003] [Medline: 29463486]
22. Shanafelt T, Dyrbye L. Oncologist burnout: causes, consequences, and responses. J Clin Oncol 2012 Apr 10;30(11):1235-1241. [doi: 10.1200/JCO.2011.39.7380] [Medline: 22412138]
23. Circular 19/2013/TT-BYT: Specifying implementation guidelines for healthcare service quality management in hospitals. Hanoi: Ministry of Health of Vietnam; 2013. URL: https://vanbanphapluat.co/circular-19-2013-tt-byt-implementation-guidelines-healthcare-service-quality-management-hospitals [accessed 2021-05-24]
24. Bentley TGK, Effros RM, Palar K, Keeler EB. Waste in the U.S. health care system: a conceptual framework. Milbank Q 2008 Dec;86(4):629-659 [FREE Full text] [doi: 10.1111/j.1468-0009.2008.00537.x] [Medline: 19120983]
25. Nguyen TKT, Cheng T. Vietnam's health care system emphasizes prevention and pursues universal coverage. Health Aff (Millwood) 2014 Nov;33(11):2057-2063. [doi: 10.1377/hlthaff.2014.1141] [Medline: 25354953]
26. Le D, Kubo T, Fujino Y, Pham T, Matsuda S. Health care system in Vietnam: current situation and challenges. Asian Pac J Dis Manag 2010;4(2):23-30. [doi: 10.7223/apjdm.4.23]
27. Nguyen H, Nguyen T, van den Heuvel ER, Haaijer-Ruskamp FM, Taxis K. Medication errors in Vietnamese hospitals: prevalence, potential outcome and associated factors. PLoS One 2015;10(9):e0138284 [FREE Full text] [doi: 10.1371/journal.pone.0138284] [Medline: 26383873]
28. Demombynes G, Hurt K. Quality and equity in basic health care services in Vietnam: findings from the Vietnam District and Commune Health Facility Survey. Washington: World Bank; 2015. URL: https://microdata.worldbank.org/index.php/catalog/2728/download/39045 [accessed 2021-05-24]
29. Falkenberg T, Nguyen TB, Larsson M, Nguyen TD, Tomson G. Pharmaceutical sector in transition—a cross sectional study in Vietnam. Southeast Asian J Trop Med Public Health 2000 Sep;31(3):590-597. [Medline: 11289028]

30. Aït-Khaled N, Auregan G, Bencharif N, Camara LM, Dagli E, Djankine K, et al. Affordability of inhaled corticosteroids as a potential barrier to treatment of asthma in some developing countries. Int J Tuberc Lung Dis 2000 Mar;4(3):268-271. [Medline: 10751075]
31. Nguyen A, Knight R, Mant A, Cao M, Auton M. Medicine prices, availability, and affordability in Vietnam. Southern Med Review 2009;2(2):2-9 [FREE Full text] [doi: 10.1016/b978-0-12-813166-4.00012-7]
32. Nguyen T. Medicine Prices and Pricing Policies in Vietnam [Thesis]. Sydney: UNSWorks; 2011.
33. Nguyen T, Vitry A, Roughead E. Pharmaceutical policy in Vietnam. In: Babar Z, editor. Pharmaceutical Policy in Countries with Developing Healthcare Systems. 1st Edition. Cham: Springer International Publishing; 2017:75-94.
34. Nguyen T, Roughead E. Pharmaceutical pricing policies in Vietnam. In: Pharmaceutical Prices in the 21st Century. 1st Edition. Cham: Springer International Publishing; 2015:321-342.
35. Nguyen T, Knight R, Mant A, Razee H, Brooks G, Dang T. Inflated medicine prices in Vietnam: a qualitative study. Health Policy Plann Jun 2017;32(5):647-656. [doi: 10.1093/heapol/czw174] [Medline: 28160482]
36. Nguyen TA, Knight R, Mant A, Razee H, Brooks G, Dang TH, et al. Corruption practices in drug prescribing in Vietnam: an analysis based on qualitative interviews. BMC Health Serv Res 2018 Jul 28;18(1):587 [FREE Full text] [doi: 10.1186/s12913-018-3384-3] [Medline: 30055601]
37. Wang H, Sun Q, Vitry A, Nguyen TA. Availability, price, and affordability of selected essential medicines for chronic diseases in 11 countries of the Asia Pacific Region: a secondary analysis. Asia Pac J Public Health 2017 May;29(4):268-277. [doi: 10.1177/1010539517700472] [Medline: 28397532]
38. The Congress of Vietnam. Heath insurance law. Hanoi: Legal library; 2014. URL: https://thuvienphapluat.vn/van-ban/Bao-hiem/Luat-Bao-hiem-y-te-sua-doi-2014-238506.aspx [accessed 2020-08-23]
39. The Congress of Vietnam. Pharmaceutical law. Hanoi: Legal library; 2016. URL: https://thuvienphapluat.vn/van-ban/The-thao-Y-te/Luat-Duoc-2016-309815.aspx [accessed 2020-08-23]
40. The Prime Minister of Vietnam. Health sector strategy for 2011-2020 with a vision to 2030. Hanoi: Legal library; 2013. URL: http://www.chinhphu.vn/portal/page/portal/chinhphu/hethongvanban?class_id=2&mode=detail&document_id=165437 [accessed 2020-09-23]
41. Kay M, Santos J, Takane M. mHealth: New Horizons for Health Through Mobile Technologies. Geneva: World Health Organization; 2011.
42. Digital health. Geneva: World Health Organization; 2020. URL: https://www.who.int/health-topics/digital-health#tab=tab_1 [accessed 2020-08-23]
43. Reynolds A. Patient-centered care. Radiol Technol 2009;81(2):133-147. [Medline: 19901351]
44. Schofield P, Shaw T, Pascoe M. Toward comprehensive patient-centric care by integrating digital health technology with direct clinical contact in Australia. J Med Internet Res 2019 Jun 04;21(6):e12382 [FREE Full text] [doi: 10.2196/12382] [Medline: 31165713]
45. Bergmann J, Sams A. Flip Your Classrom: Reach Every Student in Every Class Every Day. Washington: International Society for Technology in Education; 2019.
46. Lage MJ, Platt GJ, Treglia M. Inverting the classroom: a gateway to creating an inclusive learning environment. J Econ Educ 2000;31(1):30. [doi: 10.2307/1183338]
47. Mate KS, Salinas G. Flipping primary health care: a personal story. Healthc (Amst) 2014 Dec;2(4):280-283. [doi: 10.1016/j.hjdsi.2014.10.003] [Medline: 26250637]
48. Roughhead L, Semple S, Rosenfeld E. Literature review: medication safety in Australia. Sydney: Australian Commission on Safety and Quality in Health Care; 2013. URL: https://www.safetyandquality.gov.au/sites/default/files/migrated/Literature-Review-Medication-Safety-in-Australia-2013.pdf [accessed 2021-05-27]
49. Alkhaldi G, Hamilton FL, Lau R, Webster R, Michie S, Murray E. The effectiveness of prompts to promote engagement with digital interventions: a systematic review. J Med Internet Res 2016;18(1):e6 [FREE Full text] [doi: 10.2196/jmir.4790] [Medline: 26747176]
50. Circular promolgating the criteria of application of information technology application at medical examination and treatment establishments. Hanoi: Ministry of Health of Vietnam; 2017. URL: https://vanbanphapluat.co/circular-54-2017-tt-byt-assessment-of-information-technology-application-at-health-facilities [accessed 2021-05-24]
51. Schaller S, Marinova-Schmidt V, Setzer M, Kondylakis H, Griebel L, Sedlmayr M, et al. Usefulness of a tailored ehealth service for informal caregivers and professionals in the dementia treatment and care setting: the ehealth monitor dementia portal. JMIR Res Protoc 2016 Apr 05;5(2):e47 [FREE Full text] [doi: 10.2196/resprot.4354] [Medline: 27050401]
52. Hochwarter S, Do D, Nguyen T, Larsson M. Towards an electronic health record system in Vietnam: a core readiness assessment. J Health Inform Devel Countr 2014;8(2):1 [FREE Full text]
53. Vietnamese Party's Central Committee. Resolution 20-NQ/TW. Hanoi: Law library of Vietnam; 2017. URL: https://thuvienphapluat.vn/van-ban/the-thao-y-te/Nghi-quyet-20-NQ-TW-2017-tang-cuong-cong-tac-bao-ve-cham-soc-nang-cao-suc-khoe-nhan-dan-365599.aspx [accessed 2021-06-03]
54. Electronic Health Administration. Smart health development in the period of 2019-2025, vision to 2030. Hanoi: Ministry of Health of Vietnam; 2019. URL: https://ehealth.gov.vn/?action=News&newsId=47145 [accessed 2021-06-07]

55. Ministry of Health of Vietnam. Circular regulations on telemedicine activities. Hanoi: Legal library; 2017. URL: https://thuvienphapluat.vn/van-ban/The-thao-Y-te/Circular-49-2017-TT-BYT-on-telemedicine-374119.aspx [accessed 2020-06-07]
56. Häyrinen K, Saranto K, Nykänen P. Definition, structure, content, use and impacts of electronic health records: a review of the research literature. Int J Med Inform 2008 May;77(5):291-304. [doi: 10.1016/j.ijmedinf.2007.09.001] [Medline: 17951106]
57. Electronic Health Administration. Circular No. 46/2018/TT-BYT regulating electronic medical records. Hanoi: Ministry of Health of Vietnam; 2018. URL: https://ehealth.gov.vn/Index.aspx?action=GioiThieu&MenuChildID=391&Id=4262 [accessed 2020-06-13]
58. Hospitals in Vietnam. Geneva: World Health Organization; 2020. URL: https://www.who.int/vietnam/health-topics/hospitals [accessed 2020-06-08]
59. Plan for implementing Electronic Health Records. Hanoi: Ministry of Health of Vietnam; 2019. URL: https://thuvienphapluat.vn/van-ban/the-thao-y-te/Quyet-dinh-5349-QD-BYT-2019-phe-duyet-Ke-hoach-trien-khai-ho-so-suc-khoe-dien-tu-428071.aspx [accessed 2020-06-13]
60. Doan EZ. Vietnam: number of Facebook users 2017-2023. Statista. 2020. URL: https://www.statista.com/statistics/553800/facebook-penetration-in-vietnam/ [accessed 2020-06-08]
61. Vietnamese people spend much of their time online. Hanoi: Vietnam News; 2018. URL: https://vietnamnews.vn/economy/481777/vietnamese-people-spend-much-of-their-time-online.html#:~:text=The%20figures%20released%20by%20the,of%203.55%20hours%20per%20day [accessed 2021-05-26]
62. Do TTT, Le MD, Van Nguyen T, Tran BX, Le HT, Nguyen HD, et al. Receptiveness and preferences of health-related smartphone applications among Vietnamese youth and young adults. BMC Public Health 2018 Jun 19;18(1):764 [FREE Full text] [doi: 10.1186/s12889-018-5641-0] [Medline: 29921258]
63. Tran BX, Zhang MW, Le HT, Nguyen HD, Nguyen LH, Nguyen QLT, et al. What drives young Vietnamese to use mobile health innovations? Implications for health communication and behavioral interventions. JMIR Mhealth Uhealth 2018 Nov 30;6(11):e194 [FREE Full text] [doi: 10.2196/mhealth.6490] [Medline: 30251704]
64. Individuals using the internet (% of population)—Vietnam. World Bank. 2021. URL: https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=VN [accessed 2021-05-31]
65. Vu LTH, Nguyen NTK, Tran HTD, Muhajarine N. mHealth information for migrants: an e-health intervention for internal migrants in Vietnam. Reprod Health 2016 May 14;13(1):55 [FREE Full text] [doi: 10.1186/s12978-016-0172-6] [Medline: 27180147]
66. Ngan TT, Do VV, Huang J, Redmon PB, Minh HV. Willingness to use and pay for smoking cessation service via text-messaging among Vietnamese adult smokers, 2017. J Subst Abuse Treat 2019 Sep;104:1-6. [doi: 10.1016/j.jsat.2019.05.014] [Medline: 31370973]
67. Tran BX, Le XTT, Nguyen PN, Le QNH, Mai HT, Nguyen HLT, et al. Feasibility of e-Health interventions on smoking cessation among Vietnamese active internet users. Int J Environ Res Public Health 2018 Dec 20;15(1):1 [FREE Full text] [doi: 10.3390/ijerph15010165] [Medline: 29361694]
68. Bates LA, Hicks JP, Walley J, Robinson E. Evaluating the impact of Marie Stopes International's digital family planning counselling application on the uptake of long-acting and permanent methods of contraception in Vietnam and Ethiopia: a study protocol for a multi-country cluster randomised controlled trial. Trials 2018 Aug 04;19(1):420 [FREE Full text] [doi: 10.1186/s13063-018-2815-0] [Medline: 30075739]
69. Nguyen QT, Naguib RNG, Abd Ghani MK, Bali RK, Lee IM. An analysis of the healthcare informatics and systems in Southeast Asia: a current perspective from seven countries. Int J Electron Healthc 2008;4(2):184-207. [doi: 10.1504/IJEH.2008.019792] [Medline: 18676343]
70. Lam JA, Dang LT, Phan NT, Trinh HT, Vu NC, Nguyen CK. Mobile health initiatives in Vietnam: scoping study. JMIR Mhealth Uhealth 2018 Apr 24;6(4):e106 [FREE Full text] [doi: 10.2196/mhealth.8639] [Medline: 29691214]
71. McBride B, Nguyen LT, Wiljer D, Vu NC, Nguyen CK, O'Neil J. Development of a maternal, newborn and child mHealth intervention in Thai Nguyen province, Vietnam: protocol for the mMom Project. JMIR Res Protoc 2018 Jan 11;7(1):e6 [FREE Full text] [doi: 10.2196/resprot.7912] [Medline: 29326095]
72. McBride B, O'Neil JD, Hue TT, Eni R, Nguyen CV, Nguyen LT. Improving health equity for ethnic minority women in Thai Nguyen, Vietnam: qualitative results from an mHealth intervention targeting maternal and infant health service access. J Public Health (Oxf) 2018 Dec 01;40(suppl_2):ii32-ii41 [FREE Full text] [doi: 10.1093/pubmed/fdy165] [Medline: 30252117]
73. Sabin LL, Larson WA, Le BN, Herman AR, Viet NH, Albanese RR, et al. Benefits and limitations of text messages to stimulate higher learning among community providers: participants' views of an mHealth intervention to support continuing medical education in Vietnam. Glob Health Sci Pract 2017 Jun 27;5(2):261-273 [FREE Full text] [doi: 10.9745/GHSP-D-16-00348] [Medline: 28655802]
74. Larson Williams A, Hawkins A, Sabin L, Halim N, Le Ngoc B, Nguyen VH, et al. Motivating HIV providers in Vietnam to learn: a mixed-methods analysis of a mobile health continuing medical education intervention. JMIR Med Educ 2019 Apr 18;5(1):e12058 [FREE Full text] [doi: 10.2196/12058] [Medline: 30998220]

75. Gill CJ, Le NB, Halim N, Chi CTH, Nguyen VH, Bonawitz R, et al. mCME project V.2.0: randomised controlled trial of a revised SMS-based continuing medical education intervention among HIV clinicians in Vietnam. BMJ Glob Health 2018;3(1):e000632 [FREE Full text] [doi: 10.1136/bmjgh-2017-000632] [Medline: 29527350]
76. Bonawitz R, Bird L, Le NB, Nguyen VH, Halim N, Williams AL, et al. Implementing the mobile continuing medical education (mCME) project in Vietnam: making it work and sharing lessons learned. Mhealth 2019;5:7 [FREE Full text] [doi: 10.21037/mhealth.2019.02.01] [Medline: 30976599]
77. Pollack TM, Nhung VTT, Vinh DTN, Hao DT, Trang LTT, Duc PA, et al. Building HIV healthcare worker capacity through telehealth in Vietnam. BMJ Glob Health 2020;5(4):e002166 [FREE Full text] [doi: 10.1136/bmjgh-2019-002166] [Medline: 32337087]
78. Davis MC, Can DD, Pindrik J, Rocque BG, Johnston JM. Virtual interactive presence in global surgical education: international collaboration through augmented reality. World Neurosurg 2016 Mar;86:103-111 [FREE Full text] [doi: 10.1016/j.wneu.2015.08.053] [Medline: 26342783]
79. Hersh D, Hersch F, Mikuletic L, Neilson S. A Web-based approach to low-cost telemedicine. J Telemed Telecare 2003;9 Suppl 2:S24-S26. [doi: 10.1258/135763303322596174] [Medline: 14728752]
80. Imamura K, Tran TTT, Nguyen HT, Kuribayashi K, Sakuraya A, Nguyen AQ, et al. Effects of two types of smartphone-based stress management programmes on depressive and anxiety symptoms among hospital nurses in Vietnam: a protocol for three-arm randomised controlled trial. BMJ Open 2019 Apr 08;9(4):e025138 [FREE Full text] [doi: 10.1136/bmjopen-2018-025138] [Medline: 30962230]
81. GDP growth (annual %)—Vietnam. Washington: World Bank; 2020. URL: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=VN [accessed 2020-06-08]
82. Vietnam 2035: toward prosperity, creativity, equity and democracy. Washington: World Bank; 2016. URL: https://openknowledge.worldbank.org/bitstream/handle/10986/23724/9781464808241.pdf?sequence=12&isAllowed=y [accessed 2021-05-24]
83. Das K. Vietnam: growing demand for healthcare services. Hanoi: Vietnam Briefing; 2018 Sep 14. URL: https://www.vietnam-briefing.com/news/vietnam-growing-demand-healthcare-services.html/?hilite=%27Growing%27%2C%27Demand%27%2C%27Healthcare%27%2C%27Services%27 [accessed 2020-06-08]
84. The Congress of Vietnam. The law of disease examination and treatment. Hanoi: Government of the Socialist Republic of Vietnam; 2009. URL: http://vanban.chinhphu.vn/portal/page/portal/chinhphu/hethongvanban?class_id=1&_page=1&mode=detail&document_id=92348 [accessed 2020-07-25]
85. Electronic Health Administration. Decision 4376/QĐ-BYT, promulgating the regulation on the establishment, use and management of health identifications. Hanoi: Ministry of Health of Vietnam; 2019. URL: https://ehealth.gov.vn/Index.aspx?action=Detail&MenuChildID=&Id=4372 [accessed 2020-06-13]
86. The Congress of Vietnam. Social insurance Law. Hanoi: Law library; 2014. URL: https://thuvienphapluat.vn/van-ban/bao-hiem/Luat-Bao-hiem-xa-hoi-2014-259700.aspx [accessed 2020-07-25]
87. Castel P, Pick A. Increasing social insurance coverage in Viet Nam's SMEs. OECD. 2018. URL: https://www.oecd.org/dev/inclusivesocietiesanddevelopment/Increasing_social_insurance_coverage_in_Vietnam_SMES.pdf [accessed 2021-05-24]
88. Somanathan AT, Dao H, Hurt K, Fuenzalida-Puelma H. Moving toward universal coverage of social health insurance in Vietnam—assessment and options. Washington: World Bank; 2014. URL: http://documents1.worldbank.org/curated/en/383151468138892428/pdf/Moving-toward-universal-coverage-of-social-health-insurance-in-Vietnam-assessment-and-options.pdf [accessed 2021-05-24]
89. Press release on labor and employment situation in the first quarter of 2019. Hanoi: General Statistics Office of Vietnam; 2019. URL: https://www.gso.gov.vn/en/employment/ [accessed 2021-05-26]
90. Thoa D. The number of people participating in compulsory social insurance decreases and voluntary social insurance increases. Hanoi: Vietnam Communist Party electronic newspaper; 2020. URL: http://dangcongsan.vn/bao-hiem-xa-hoi-bao-hiem-y-te-vi-an-sinh-xa-hoi/tin-tuc/so-nguoi-tham-gia-bao-hiem-xa-hoi-bat-buoc-giam-bao-hiem-xa-hoi-tu-nguyen-tang-556718.html [accessed 2020-07-26]
91. Prime Minister of Vietnam. Decision 538/QD-TTg: Approving the project on implementation of program to comprehensive health insurance period 2012-2015 and toward 2020. Hanoi: Legal library; 2013. URL: https://thuvienphapluat.vn/van-ban/bao-hiem/quyet-dinh-538-qd-ttg-nam-2013-phe-duyet-de-an-thuc-hien-lo-trinh-bhyt-toan-dan-179586.aspx [accessed 2020-06-08]
92. Takashima K, Wada K, Tra TT, Smith DR. A review of Vietnam's healthcare reform through the Direction of Healthcare Activities (DOHA). Environ Health Prev Med 2017 Oct 30;22(1):74 [FREE Full text] [doi: 10.1186/s12199-017-0682-z] [Medline: 29165160]
93. National Assembly of Vietnam. Law on network information security No. 86/2015/QH13. Hanoi: Legislation web portal; 2015. URL: https://vanbanphapluat.co/law-no-86-2015-qh13-on-cyberinformation-security-2015 [accessed 2020-06-08]
94. Do N. MoH partners with FPT to build smart medical model. Hanoi: Vietnam Economic Times; 2018 Aug 16. URL: http://vneconomictimes.com/article/society/moh-partners-with-fpt-to-build-smart-medical-model [accessed 2020-07-27]
95. FPT launches hospital management solution applying 4.0 technology. FPT. 2018. URL: https://fpt.com.vn/en/ir/featured-news/fpt-launches-hospital-management-solution-applying-4-0-technology [accessed 2020-07-27]

96. Tuyet M. VNPT introduces solution to improving healthcare. Hanoi: Vietnam Economics Times; 2015 Jun 26. URL: http://www.vneconomictimes.com/article/business/vnpt-introduces-solution-to-improving-healthcare [accessed 2020-07-27]
97. Schneider H, Hill S, Blandford A. Patients know best: qualitative study on how families use patient-controlled personal health records. J Med Internet Res 2016 Feb 24;18(2):e43 [FREE Full text] [doi: 10.2196/jmir.4652] [Medline: 26912201]
98. Sanders EB, Stappers PJ. Co-creation and the new landscapes of design. CoDesign 2008 Mar;4(1):5-18. [doi: 10.1080/15710880701875068]
99. Bate P, Robert G. Bringing User Experience to Healthcare Improvement: The Concepts, Methods and Practices of Experience-based Design. Oxford: Radcliffe Publishing; 2007.
100. Steen M, Manschot M, de Koning KN. Benefits of co-design in service design projects. Int J Des. 2: 5; 2011. URL: http://www.ijdesign.org/index.php/IJDesign/article/view/890/346 [accessed 2021-05-24]
101. Fourth industrial revolution. World Economic Forum. 2020. URL: https://www.weforum.org/focus/fourth-industrial-revolution [accessed 2020-06-14]

Abbreviations

BHS: Bespoke Health Care System
EHR: electronic health record
EMR: electronic medical record
HIS: health information system
MOH: Ministry of Health of Vietnam
NCD: noncommunicable disease
OPP: out-of-pocket payment
SWOT: strength, weakness, opportunity, and threat analysis
THE: total health expenditure
WHO: World Health Organization

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Original Paper

The Effects of Log-in Behaviors and Web Reviews on Patient Consultation in Online Health Communities: Longitudinal Study

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Abstract

Background: With the rapid development of information technology and web-based communities, a growing number of patients choose to consult physicians in online health communities (OHCs) for information and treatment. Although extant research has primarily discussed factors that influence the consulting choices of OHC patients, there is still a lack of research on the effects of log-in behaviors and web reviews on patient consultation.

Objective: This study aims to explore the impact of physicians' log-in behavior and web reviews on patient consultation.

Methods: We conducted a longitudinal study to examine the effects of physicians' log-in behaviors and web reviews on patient consultation by analyzing short-panel data from 911 physicians over five periods in a Chinese OHC.

Results: The results showed that the physician's log-in behavior had a positive effect on patient consultation. The maximum number of days with no log-ins for a physician should be 20. The two web signals (log-in behavior and web reviews) had no complementary relationship. Moreover, the offline signal (ie, offline status) has different moderating effects on the two web signals, positively moderating the relationship between web reviews and patient consultation.

Conclusions: Our study contributes to the eHealth literature and advances the understanding of physicians' web-based behaviors. This study also provides practical implications, showing that physicians' log-in behavior alone can affect patient consultation rather than complementing web reviews.

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KEYWORDS

online health communities; digital health; patient consultation; log-in behavior; web reviews; offline status

Introduction

Background

With the development of Health 2.0 technologies, the number of people using the internet to meet their health-related needs is increasing [1]. Online health communities (OHCs) have become prevalent in recent years, and research has focused on two of them: web-based physician-patient communities and web-based patient communities. A web-based physician-patient community is a platform that connects physicians with patients where patients can consult physicians on health issues and disease treatments anytime and anywhere. The object of this study is this kind of OHC, namely, the web-based physician-patient community.

Unlike other types of services, health care services have several characteristics. First, the disease of each patient is unique [2]. Second, life and death matter [3]. Third, serious information asymmetry exists between physicians and patients [4]. The choice of an appropriate physician has always been the focus of research in the health care field. The emergence of OHCs has effectively alleviated the problem of information asymmetry between physicians and patients. Unlike traditional health care services, OHCs give patients the opportunity to review the abundant amount of information about various physicians and then use this information to choose the physician whom they want to consult [5]. Although numerous studies have explored the factors that influence patients' choices of consulting [5-14], they are not the only ones; thus, more research is needed.

As health care service providers, physicians' web behaviors, such as knowledge-sharing behaviors [9], interactions with patients [5,6], and written and telephone consultations [13], provide important information when patients make consulting choices. However, for physicians, the premise of providing web-based health care services and conducting these behaviors involves logging into their accounts of the OHC. As physicians work full time in hospitals or clinics [14], they can only use off-duty hours to provide web-based services [15], which suggests that there are different log-in patterns in OHCs. Web-based behaviors reflect the degree of the physician's activeness and effort, as well as the quality of the service process [5,6,14,16]. In addition, as one kind of information generated by patients who have experienced health care services, web reviews can reflect the service outcome [14,16] and influence patients to make consulting choices [8-10]. The assessment of service quality should focus on both the outcome and delivery process they receive [17]. Log-in behavior and web reviews were evaluated in this study. Therefore, whether log-in behavior is related to patient consultation and its relationship with web reviews is worth studying.

As a web-based health platform may provide multiple signaling mechanisms simultaneously [18], there are multiple signals that influence patient consultation. This study focuses on both web-based and offline signals. According to the signaling theory [19], which indicates how the information receiver interprets signals along with information from the sender, log-in behaviors and web reviews can be considered as two web signals provided by a physician to assist patients in making consulting choices [6,11,20]. In addition, considering that people live in a mixed environment comprising web-based and offline worlds, the status of a physician's offline world (ie, offline status) as an offline signal may affect the relationship between web signals and patient consultation.

The objective of this study is to investigate how a physician's log-in behavior and web reviews affect patients' choices for consultation using data from a Chinese OHC. The main research questions are as follows:

1. How does a physician's log-in behavior affect patient consultation in OHCs?
2. How does a physician's log-in behavior and web reviews complement each other in affecting patient consultation?
3. How does the offline status of physicians moderate the effects of web signals (ie, log-in behavior and web reviews) on patient consultation?

To answer these three research questions, we collected data from 911 physicians over five periods and proposed a research model based on the signaling theory.

Related Research

With the development of information technologies, many physicians and patients are using OHCs. An OHC is a web-based community that presents a medical ecosystem, including patients and physicians, and is a core communication platform wherein patients can obtain physicians' web-based services, knowledge about diseases, and emotional support [20,21]. As health care service characteristics [2-4], the patient's choice of an appropriate physician for health care consultation has been the focus of research in the health care field. Table 1 summarizes the studies on patient consultation with OHCs. Although there are many factors that influence patients' choices of consulting [5-14], not all of them have been studied. More research is needed to better understand how information affects patient consultation in OHCs.

Table 1. Studies of patient consultation in online health communities.

Study	Theory	Influencing factors
Cao et al [5]	ELM[a]	The number of current patients who repeatedly interact with the physician, voting heating, service star, disease knowledge, and disease risk
Deng et al [6]	N/A[b]	Physician effort and web reputation
Li et al [7]	ELM	Technical quality, interpersonal quality, votes, high-privacy disease, and private doctor service
Li et al [9]	N/A	Web-based rating and activeness
Li et al [8]	N/A	Technical skills, interpersonal skills, and gender
Liu et al [11]	Signaling theory	The physician's web reputation and offline reputation; the hospital's web reputation and offline reputation
Liu et al [10]	N/A	Web-based service reviews, offline service reviews, and disease risk
Lu and Wu [12]	Service quality theory	Technical quality, functional quality, and disease risk
Wu and Lu [13]	N/A	Written consultation, telephone consultation, and doctor reputation
Yang et al [14]	Signaling theory	System-generated information and patient-generated information

[a]ELM: elaboration likelihood model.

[b]N/A: not applicable.

An OHC is a web-based platform wherein physicians can provide more types of health care services than offline hospitals or clinics [22], such as network consultation, phone consultation, and appointment registration. Furthermore, physicians can update their personal information, publish articles, respond to consultations, and manage patients. In the literature, many scholars have investigated physicians' web-based behaviors, such as knowledge-sharing behaviors [9,23,24], interactions with patients [5,6], written and telephone consultations [13], and contribution behaviors [25-27].

Although several web-based behaviors of physicians have been studied, not all of them have been evaluated. Log-in behavior is a web-based behavior of physicians that involves launching profile home pages in health websites and logging into their accounts. Log-in behavior is the first step for physicians to participate in OHCs and conduct other web-based behaviors. Many physicians offer services in both OHCs and hospitals or clinics. Owing to the heavy workload at hospitals or clinics (offline services), they can only use their spare time to provide patients with web-based services [15]. Thus, physicians have unique log-in behaviors. Previous research has shown that information about physicians' web-based behaviors is an important factor influencing patients' consultation choices [5,6,13]. However, less attention has been paid to log-in behaviors in OHCs. Therefore, the aim of this study is to explore physicians' log-in behaviors and their roles in OHC consulting choices.

Research Model and Hypotheses

Signaling Theory

The signaling theory is used to describe the behaviors of two parties (individuals or organizations) when accessing different information and has been applied in studies of investment decisions, entrepreneur-investor relationships [4], and web-based social trading [28]. The primary parties in the signaling theory include signalers and receivers as well as the signal itself. A signaler sends signals to the receiver to reflect quality [19]. The receiver evaluates the quality of the signaler and acts. As the two parties hold different amounts and levels of information, significant information asymmetry exists between the signalers and receivers [29]. Hence, the signal conveyed by signalers affects the degree of information asymmetry and can affect the receivers' behaviors.

Parties in OHCs include physicians and patients. Patients are at a disadvantage, as they must rely on physicians to provide health care services [30]. Physicians, as signalers, can provide information (eg, titles, workplaces, web-based behaviors, or reviews) to receivers (patients) [11], which can help patients choose physicians to serve their needs. Referring to past studies [11,14], this study used the signaling theory to explain the effects of log-in behavior and web reviews on patient consultation choices.

Log-in Behavior and Web Reviews

For patients, web-based behavior is often an important factor in choosing a physician. On the one hand, web-based behavior indicates the level of active participation that stems from internet motivation within the web-based community. Activeness has a certain influence on the number of patient consultations [9]. On the other hand, web-based behavior is a positive indicator of a physician's effort and popularity. Patients can gain insight into a physician's past efforts through web-based behaviors, which may influence their attitudes toward the physician, thereby influencing the likelihood of selecting that physician [6]. Most importantly, physicians' web-based behaviors are important cues for evaluating service process quality [14,16]. Combined with health care service characteristics [2-4], patients prefer to choose physicians who can provide a high-quality service process.

As the web-based behavior of a physician, log-in behavior reflects the degree of active participation in the OHC and the physician's efforts. Given that a physician may log in many times each day to check for new messages, log-in is the basis for any active actions for physicians in OHCs. Li et al [31] believed that log-in behavior belongs to the central working sphere, and log-in patterns could indicate a physician's central efforts related to the work, as well as the physician's attitude toward service provision, participation degree, and responsibility. Bitner et al [32] revealed that customers' perceptions of service depend on service providers' efforts, and their behaviors will raise the purchase intentions or continuous purchase intentions of customers [33], thus having a positive effect on marketing sales or organizational performance [34]. Physicians as providers of web-based health care services also apply to this phenomenon [9]. On the one hand, physicians with a higher-frequency log-in are more likely to make more task-related efforts to attract a greater number of patients, and subsequent patients would consider this for references. On the other hand, a higher-frequency log-in appears to be more responsive and involved than others [35], with those physicians logging in more frequently being more likely to ensure timeliness in service delivery, leading to attracting more patients. Therefore, the following hypothesis is proposed:

> *Hypothesis 1: a physician's log-in behavior has a positive effect on patient consultation.*

Web reviews are a particular type of user-generated content or electronic word-of-mouth, are the most important information source in customers' decision-making processes [36], and are deemed more successful in influencing customer behaviors than traditional marketing, information provided by products or service providers, or promotion messages from third-party websites [37-39].

OHCs provide a feedback channel where patients can express their views on the physician's service and share treatment experiences on the web. This information can help patients understand a physician's service quality at a minimal cost. In OHCs, web reviews are generated by patients who have experienced health care services. The more web reviews about a physician presented in the OHC, the more patients have selected the physician for consultation [16]. The web reviews generated by patients with similar experiences are more objective and credible signals than traditional information from acquaintances [40], which can increase other patients' trust in the physician and reduce perceived risks [41]. Web reviews are signals that reflect a physician's service outcome [14,16].

Positive web reviews mean a higher outcome quality of the physician, which has been shown to influence patients to make consulting choices [5,8,9,12,14].

The coexistence of log-in behavior and web reviews may complement each other in driving patient consultation. As service is delivered via the interaction between the service provider and the receiver, the assessment of service quality includes not only the delivery process but also the outcome [17]. As per the preceding discussion, log-in behavior may send web signals reflecting the service delivery process from the physicians themselves. A physician with a positive log-in behavior is usually associated with a positive attitude toward the consultation service. Furthermore, web reviews send another web signal from patients who have visited the physician before, which represents the service outcome. A physician with positive web reviews is usually associated with positive outcome quality. On the basis of the characteristics of health care services [2-4], patients judging a physician rely on two types of web signals: service process quality (ie, log-in behavior) and service outcome quality (ie, web reviews). Physicians with both high outcome quality and process quality are scarce resources [18], and the demand of these physicians on the platform should be large, so a large number of patients choose these patients. As a result, log-in behavior and web reviews should complement each other. From the preceding discussion, we propose the following hypothesis:

> *Hypothesis 2: a physician's log-in behavior and web reviews have a complementary relationship that affects patient consultation.*

Moderating Effect of Offline Status

Offline status reflects a physician's abilities and performance in providing health care services in hospitals or clinics [11,13], referring to a physician's career titles, ranking, and position in the hospital [11,42]. Such information can help patients evaluate a physician's offline competence [9].

In traditional health care services, patients can only judge a physician's ability through limited information. In the case of other factors being considered to be the same, patients tend to choose physicians with a higher status or professional titles [18]. To a certain extent, physicians with a high-level offline status might have a heavy workload but not enough time to contribute via the internet [18]. For this reason, the log-in behaviors of physicians with high-level offline statuses have a weaker impact on patient consultation. Therefore, the following hypothesis is proposed:

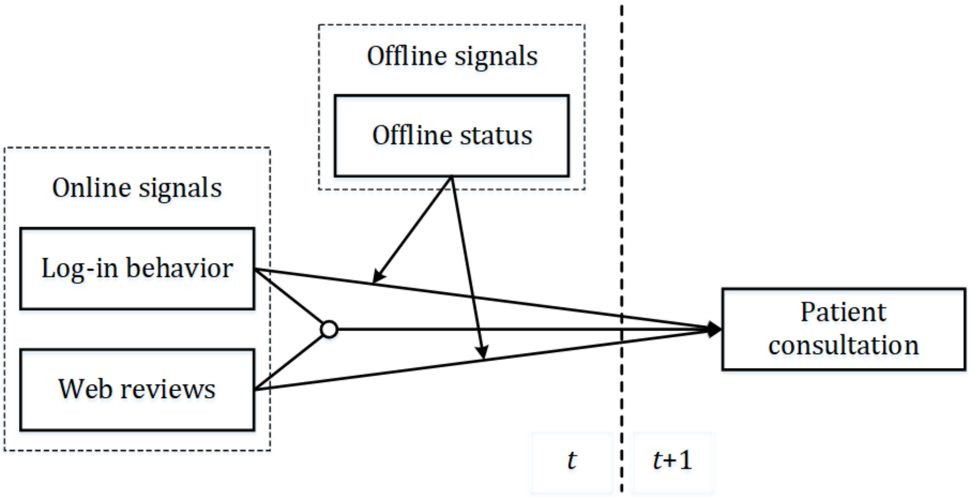
> *Hypothesis 3: the relationship between log-in behavior and patient consultation is negatively moderated by the physician's offline status.*

When patients choose physicians on the web, they rely mostly on offline and web signals. However, most patients regard offline signals as more reliable sources and treat web signals as additional information sources that supplement offline signals. Status may have a negative moderating effect on web signals [18]. When a physician has a high status, the offline signal will be sufficient for patients to make a decision. People are willing to accept the services of physicians with a high-level status as *credence services* instead of considering the service outcome reflected in web signals [25]. As physicians with high-level statuses may attract more patients, the effect of web reviews on patient consultation will be weakened. Hence, the following hypothesis is proposed:

> *Hypothesis 4: the relationship between web reviews and patient consultation is negatively moderated by a physician's offline status.*

The research model is shown in Figure 1.

Figure 1. Research model.



Methods

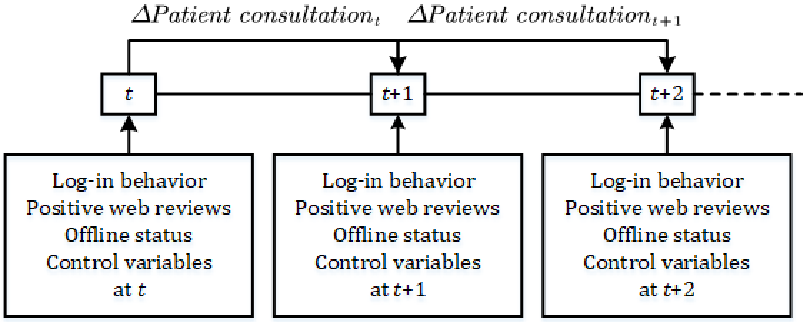
Research Context and Data Collection

The data used in this study were collected from Good Physician Online, which is one of the most popular and professional OHCs in China. It was founded in 2006 and, currently, more than 8000 hospitals and 500,000 physicians' information is presented on this website. Studying such a large and popular OHC can increase the generality of the results. Moreover, physicians registered on the Good Physician Online website have a profile home page, which contains information, such as physicians' background (name, medical title, academic title, hospital department, specialty, brief introduction, etc), patients' reviews, and information about web-based services. The information in a physician's profile home page is considerable and can help patients understand the physician and make a decision. Figure 2 shows an example of physician information shown on the OHC.

Figure 2. An example of physician information in online health communities.

To reduce the influence of disease types, we only included physicians who treated patients with coronary heart disease as our sample. Using web crawler technology, we collected data from February 2019 to July 2019 (once every month during these six periods), which covered public information of hospitals and physicians presented on this website. We designed a longitudinal study to investigate whether a physician's log-in behavior and web reviews would change patient consultation choices. The data collection process is illustrated in Figure 3. After deletion of invalid data, short-panel data from 911 physicians over five periods were obtained for a total of 4555 physician data points. These physicians were currently active on the website, and the most recent log-in time was within 1 month.

Figure 3. Data collection and processing.



Variable Measurement

Table 2 presents the variable description. The dependent variable in this study was patient consultation. We used the number of patients before time *t* as a proxy for patient consultation, in accordance with previous research [5,14]. The number of patients included those who only consulted via the internet and those who consulted again after offline consultation. This study used the difference between the two periods as the dependent variable to reduce the causal relationship between the dependent and independent variables.

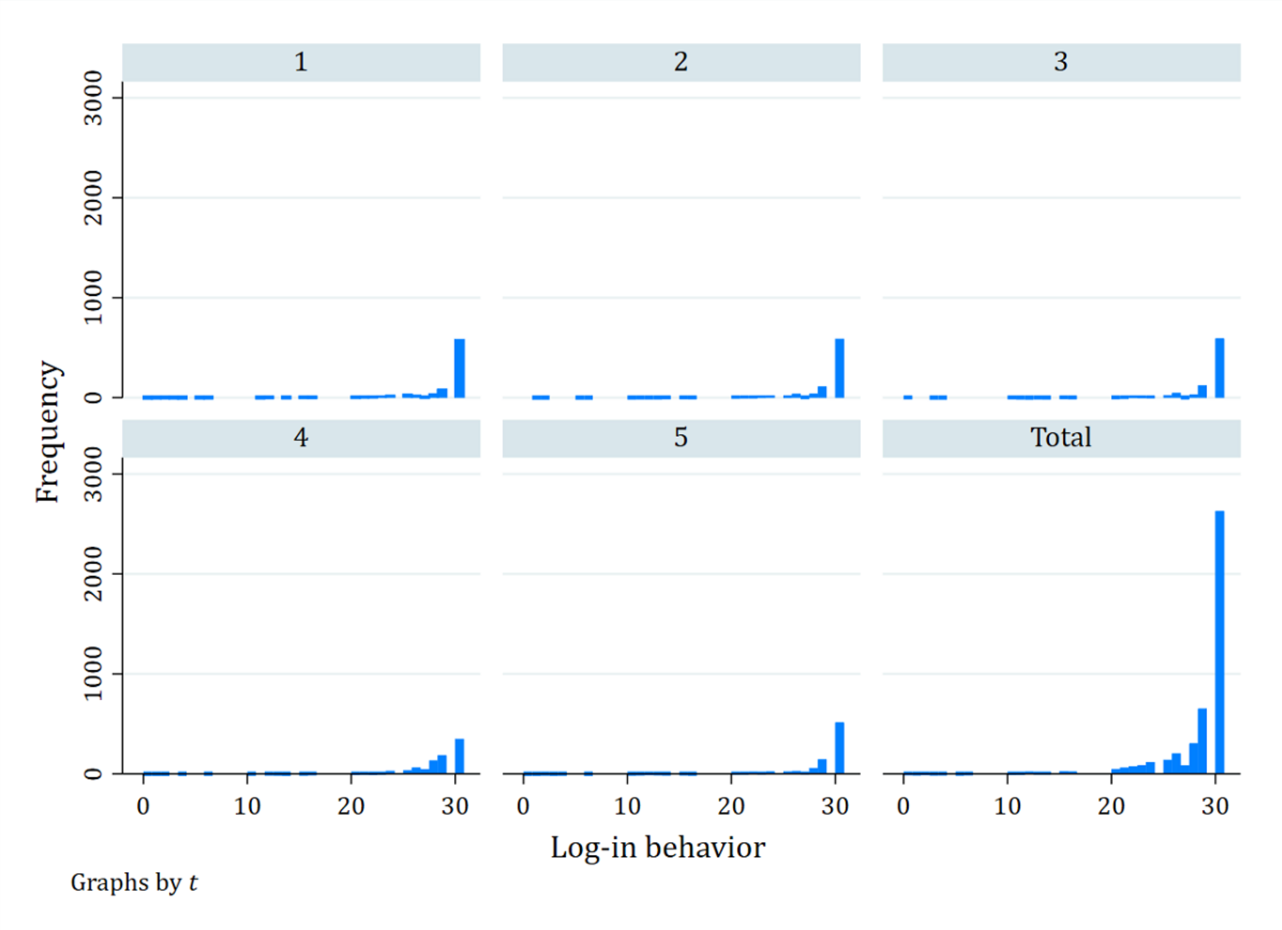
Table 2. Variable description.

Variables	Description	Proxy
Dependent variable		
Patient consultation	Patients evaluate the information about a physician and make the decision to consult online.	Patients
Independent variable		
Log-in behavior	One kind of online behavior that a physician launches his profile home page and log-ins his accounts.	Last web date
Positive web reviews	Positive reviews written by patients who have experienced a physician's health care service.	Thank-you letters
Moderating variable		
Offline status	The offline prestige of a physician in the career.	Medical title, academic title, or hospital ranking
Control variable		
Gender	The gender of a physician, 0 is male, 1 is female.	Gender
Usage years	The number of years that a physician using the OHC[a].	Usage years
Visits	The number of patients for visiting a physician’s profile home page.	Visits
Articles	The number of articles that a physician post on his or her profile home page.	Articles
Service stars	The number of service stars displayed on a physician’s profile home page.	Service stars
Written consultation	One type of online service. If a physician provided online written service, then 1; If not provided then 0.	Written consultation
Phone consultation	One type of online service. If a physician provided online phone service, then 1; If not provided then 0.	Phone consultation

[a]OHC: online health community.

The independent variables included physician’s log-in behavior and positive web reviews. In this study, log-in behavior was measured by the last date a physician was on the web at time *t*. If the physician logged in today, the log-in behavior is marked as 30; if the last on the web date is 30 days ago, the log-in behavior is marked as 0. The values are decremented individually. Figure 4 shows the frequency statistics of physicians’ log-in behaviors over five periods. It can be seen that physicians’ log-in patterns are different, and it is worth studying.

Figure 4. The frequency of physicians' log-in behaviors in online health communities.



After the web-based consultation on the Good Physician Online website, patients can express their satisfaction or dissatisfaction with the physician's service by sharing their treatment experience and writing a thank-you letter. The difference between a treatment experience and a thank-you letter is that the latter is a positive web review, and the patient who chooses to write a thank-you letter is definitely satisfied with the physician's service. Referring to previous research [14,27], we used the number of thank-you letters a physician received from patients at time *t* to measure the physician's positive web reviews.

The moderating variable in our research model is offline status, which mainly reflects the offline prestige in the physician's career. According to previous research [27,42], we used the physician's occupational title ranking and hospital standing at time *t* as a proxy for physicians' offline status. A physician's occupational title indicates the duties of a physician in a hospital, which is a manifestation of the physician's professional expertise, health knowledge, and experience. A physician's occupational title ranking includes medical title (chief physician, deputy chief physician, attending physician, and resident physician, coded from 4 to 1) and academic title (professor, deputy professor, and lecturer, coded from 3 to 1). Hospital standing can reflect an advantage in human capital, experience, health facilities, and technology, which is ranked as 3, 2, and 1. According to the methodology of previous research [43], this study integrated three variables to represent offline status. We standardized three variables by subtracting the means and dividing by the SEs, as shown in equation (1). Thus, the offline status of a physician was measured using equation (2).

$$STD(x) = \frac{(x - \bar{x})}{\delta_x} \quad \textbf{(1)}$$

Offline status = STD [STD (medical title) + STD (academic title) + STD (hospital ranking)] **(2)**

The control variables included the physician's gender, usage years, number of visits, articles, service stars, written consultation, and phone consultation provided before time *t*. This information about the physician has been shown to be relevant to patients making consulting choices [5,7-9,13,14]. Gender is coded with "0" for male and "1" for female. Usage years are measured by the difference between the launching time of a physician's personal website and time *t*. The number of visits, articles, and service stars is the information displayed on the physician's profile home page before time *t*. Written consultation and phone consultation are two important types of services that physicians can provide on the Good Physician Online website. As the distributions of visits and articles are nonnormal, *ln* (*x*+1) transformations were also used for them.

Results

Descriptive Statistics and Correlation Results

Tables 3 and 4 show the descriptive statistics and correlations of variables, respectively. As shown in Table 4, log-in behavior is positively correlated with patient consultation and positive web reviews, and the β coefficients were .169 and .219, respectively. Log-in behavior and web reviews have positive correlations with offline status, with β coefficients of .047 and .284, respectively.

Table 3. Descriptive statistics of variables (n=4555).

Variables	Values		
	Mean (SD)	Min	Max
Gender	0.157 (0.364)	0	1
Usage years	5.127 (3.176)	0	11.340
Visits	718,657.100 (1,780,896.000)	27	1.80e+07
Articles	18.704 (72.534)	0	1314
Service stars	0.818 (1.217)	0	5
Written consultation	0.503 (0.500)	0	1
Phone consultation	0.643 (0.479)	0	1
Last web-based date	28.025 (4.105)	0	30
Thank-you letters	38.225 (93.953)	0	1606
Medical title	3.095 (0.850)	0	4
Academic title	1.186 (1.241)	0	3
Hospital ranking	2.940 (0.351)	0	3
Patients	18.013 (38.372)	0	678

Table 4. Correlations of variables (n=4555).

Variables	Gender	Usage years	ln(Visits+1)	ln(Articles+1)	Service stars	Written consultation	Phone consultation	Log-in behavior	Reviews	Status	Consultation
Gender	1	—[a]	—	—	—	—	—	—	—	—	—
Usage years	−0.056	1	—	—	—	—	—	—	—	—	—
ln(Visits+1)	−0.068	0.717	1	—	—	—	—	—	—	—	—
ln(Articles+1)	−0.150	0.321	0.502	1	—	—	—	—	—	—	—
Service stars	−0.041	0.082	0.223	0.188	1	—	—	—	—	—	—
Written consultation	0.021	−0.118	−0.203	−0.148	−0.068	1	—	—	—	—	—
Phone consultation	0.037	−0.152	−0.268	−0.195	−0.088	0.750	1	—	—	—	—
Log-in behavior	−0.035	0.066	0.131	0.109	0.259	−0.039	−0.037	1	—	—	—
Reviews	−0.088	0.448	0.647	0.292	0.498	−0.128	−0.174	0.219	1	—	—
Status	0.148	0.443	0.388	0.117	0.097	−0.029	−0.050	0.047	0.284	1	—
Consultation	−0.032	0.125	0.288	0.210	0.562	−0.020	−0.048	0.169	0.455	0.168	1

[a]Not applicable.

Estimation Model

As can be seen from Table 3, the dependent variables (patients) were nonnegative integers and their variance was greater than the mean; therefore, the negative binomial regression model was suitable for this study. The negative binominal probability function is as shown in equation (3), which has two parameters, θ and λ. Parameter θ captures overdispersion in the data, and parameter λ is the expected value of the distribution.

$$Pr(Y=y\,|\,\lambda,\theta)=\frac{\Gamma(y+\theta)}{\Gamma(y+\theta)\Gamma(\theta)}\left(\frac{\theta}{\theta+\lambda}\right)^{\theta}\left(\frac{\lambda}{\theta+\lambda}\right)^{y} \quad \textbf{(3)}$$

To test the hypotheses, the negative binomial regression model with fixed effects is explicitly expressed as shown in equation (4).

$$\triangle Patient\ consultation = Patient\ consultation_{i,t+1} - Patient\ consultation_{i,t}$$

$= \alpha_0 + \alpha_1 Gender_i + \alpha_2 Usage\ years_{i,t} + \alpha_3 ln(Visits_{i,t} + 1) + \alpha_4 ln(Articles_{i,t} + 1) + \alpha_5 Service\ stars_{i,t} + \alpha_6 Written\ consultation_{i,t} + \alpha_7 Phone\ consulatation_{i,t} + \alpha_8 Log\text{-}in\ behavior_{i,t} + \alpha_9 Positive\ web\ reviews_{i,t} + \alpha_{10} Service\ stars_{i,t} \times Positive\ web\ reviews_{i,t} + \alpha_{11} Offline\ status_{i,t} + \alpha_{12} Log\text{-}in\ behavior_{i,t} \times Offline\ status_{i,t} + \alpha_{13} Positive\ web\ reviews_{i,t} \times Offline\ status_{i,t} + \varepsilon_{i,t}$ **(4)**

Let i=1, 2, 3,..., n be the index of physicians. For equation (4), α_0 to α_{13} are the parameters to be estimated.

Regression Results

This study estimated the models using STATA software version 15.0 (StataCorp). The result of the Hausman test (χ^2_{14}=534.0; *P*<.001) indicated that the fixed effects model was suitable for this study. Table 5 shows the results of the fixed effects model hierarchically. Model 1 contains only constant and control variables, and model 2-model 5 add independent variables and interaction terms.

Table 5. Regression results (fixed effects model).

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	α[a] (SE)	*P* value	α (SE)	*P* value	α (SE)	*P* value	α (SE)	*P* value	α (SE)	*P* value
Constant	−1.005 (0.324)	.002	−1.449 (0.344)	<.001	−1.059 (0.474)	.02	−1.074 (0.357)	.003	−.280 (0.347)	.42
Gender	−.269 (0.098)	.006	−.266 (0.098)	.007	−.241 (0.097)	.01	−.367 (0.101)	<.001	−.338 (0.100)	.001
Usage years	.034 (0.016)	.04	.033 (0.016)	.04	.035 (0.016)	.03	.015 (0.017)	.37	.016 (0.017)	.32
ln(Visits+1)	.199 (0.031)	<.001	.199 (0.031)	<.001	.135 (0.036)	<.001	.176 (0.031)	<.001	.110 (0.036)	.002
ln(Articles+1)	−.126 (0.027)	<.001	−.126 (0.027)	<.001	−.110 (0.027)	<.001	−.118 (0.027)	<.001	−.106 (0.027)	<.001
Service stars	.118 (0.015)	<.001	.112 (0.015)	<.001	.101 (0.015)	<.001	.111 (0.015)	<.001	.106 (0.015)	<.001
Written consultation	.104 (0.086)	.001	.106 (0.031)	.001	.106 (0.031)	.001	.107 (0.031)	.001	.104 (0.030)	.001
Phone consultation	−.302 (0.086)	<.001	−.311 (0.086)	<.001	−.303 (0.085)	<.001	−.323 (0.087)	<.001	−.319 (0.085)	<.001
Log-in behavior	—[b]	—	.016 (0.004)	<.001	.014 (0.011)	.20	.016 (0.004)	<.001	—	—
Positive reviews[c]	—	—	—	—	.105 (0.122)	.39	—	—	.128 (0.037)	.001
Log-in behavior×positive reviews	—	—	—	—	.001 (0.004)	.86	—	—	—	—
Offline status	—	—	—	—	—	—	.220 (0.142)	.12	−.023 (0.088)	.80
Log-in behavior×offline status	—	—	—	—	—	—	−.001 (0.005)	.80	—	—
Positive reviews×offline status	—	—	—	—	—	—	—	—	.070 (0.027)	.009
Log likelihood	−9349.410	—	−9341.811	—	−9336.253	—	−9331.336	—	−9329.970	—
Wald chi-square (*df*)	282.6 (7)	—	296.0 (8)	—	311.9 (10)	—	317.9 (10)	—	334.1 (10)	—
P value	<.001	—	<.001	—	<.001	—	<.001	—	<.001	—

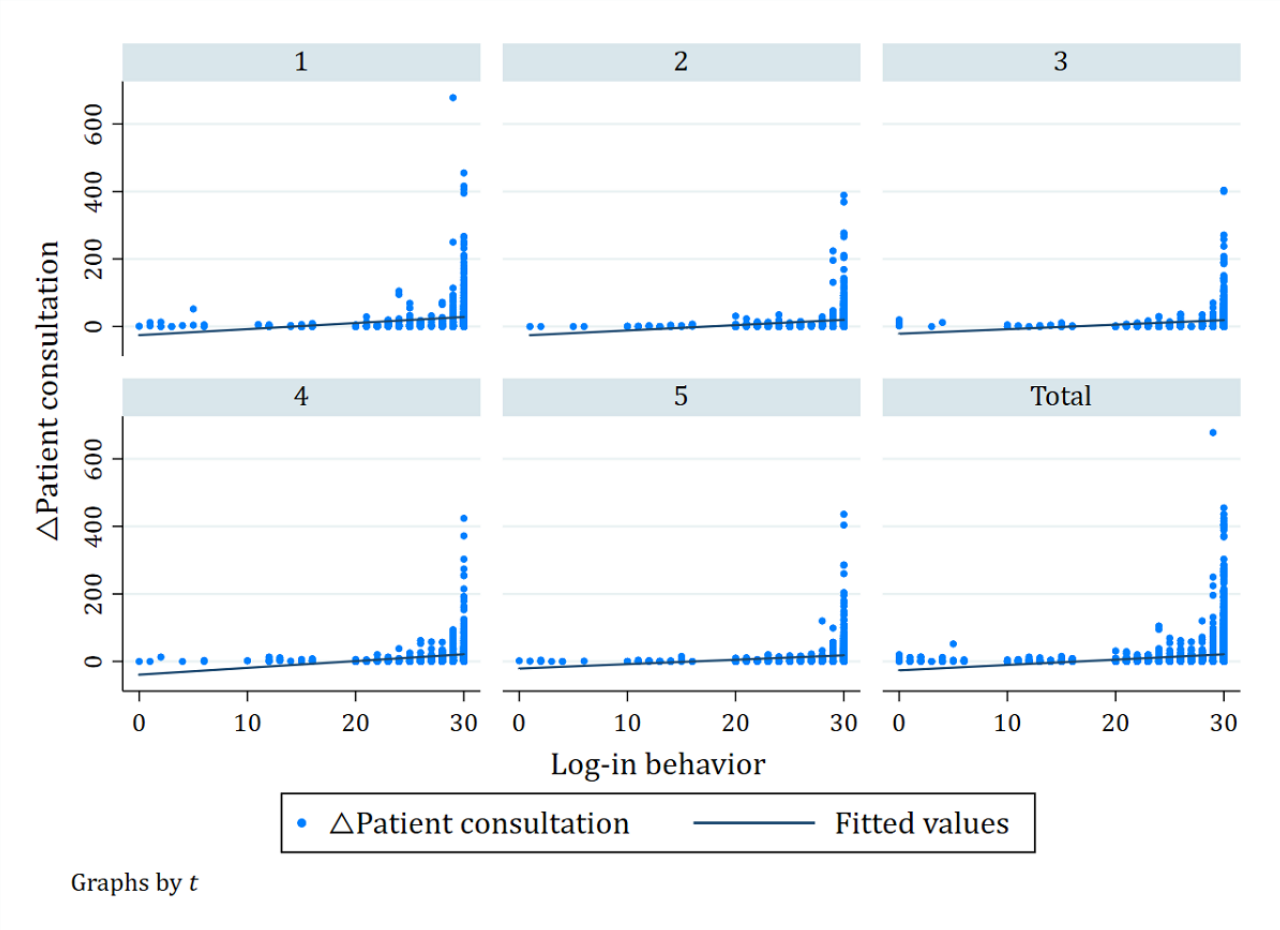
[a]Coefficient of the variable.

[b]Not applicable.

[c]Positive reviews: positive web reviews.

From model 2, the coefficient of log-in behavior (α=.016; *P*<.001) is positive and statistically significant, which supports hypothesis 1. The effects of log-in behavior on patient consultation are shown in Figure 5. As the number of log-in behaviors increases, the number of △patient consultation increases. When log-in behavior was less than 10 or 15, △patient consultation was 0 or <0. A comprehensive view of the regression lines of the five periods shows that the value of log-in behavior is ≤10, with the lowest number of patients making consulting choices.

Figure 5. The effect of log-in behavior and patient consultation on online health communities.



The results of model 3 show that the interaction between log-in behavior and web reviews (α=.001) is positive but not significant. This finding suggests that log-in behavior and web reviews do not have a complementary relationship that affects patient consultation. Therefore, hypothesis 2 is not supported.

The results of model 4 show that the interaction between log-in behavior and offline status (α=−.001) is negative but not significant. This means that the relationship between a physician's log-in behavior and patient consultation is not negatively moderated by offline status. Therefore, hypothesis 3 is contradicted.

The results of model 5 show that the interaction between web reviews and offline status (α=.070; *P*=.009) is positive and significant. This finding means that the effect of web reviews on patient consultation is stronger for physicians with a high status. Therefore, hypothesis 4 is contradicted.

Robustness Check

This study added the time effect to the estimation model, equation (5), and used the two-way fixed effects model to recheck the robustness of the results. Time is defined as a dummy variable, and *t*1 (February 2019) is used as the base period. The new estimation model is shown in equation (5). Table 6 shows the results of the robustness check, which are consistent with the results of the previous model (Table 5). In addition, the joint significance of the time dummy variable was tested, and it was confirmed that the time effect should be included in the estimation model. The robustness check results suggest that hypothesis 1 is supported.

$$\triangle \textit{Patient consultation} = \textit{Patient consultation}_{i,t+1} - \textit{Patient consultation}_{i,t}$$

$$= \beta_0 + \beta_1 \textit{Gender}_i + \beta_2 \textit{Usage years}_{i,t} + \beta_3 \textit{ln(Visits}_{i,t} + 1) + \beta_4 \textit{ln(Articles}_{i,t} + 1) + \beta_5 \textit{Service stars}_{i,t} + \beta_6 \textit{Written consultation}_{i,t} + \beta_7 \textit{Phone consulatation}_{i,t} + \beta_8 \textit{Log-in behavior}_{i,t} + \beta_9 \textit{Positive web reviews}_{i,t} + \beta_{10} \textit{Service stars}_{i,t} \times \textit{Positive web reviews}_{i,t} + \beta_{11} \textit{Offline status}_{i,t} + \beta_{12} \textit{Log-in behavior}_{i,t} \times \textit{Offline status}_{i,t} + \beta_{13} \textit{Positive web reviews}_{i,t} \times \textit{Offline status}_{i,t} + \beta_{14} t_2 + \beta_{15} t_3 + \beta_{16} t_4 + \beta_{17} t_5 + \varepsilon_{i,t} \quad \textbf{(5)}$$

Let *i*=1, 2, 3,..., *n* be the index of physicians. For equation (5), β_0 to β_{17} were the parameters to be estimated.

Table 6. Robustness check (fixed effects model).

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	β[a] (SE)	*P* value	β (SE)	*P* value	β (SE)	*P* value	β (SE)	*P* value	β (SE)	*P* value
Constant	−.896 (0.338)	.008	−1.283 (0.356)	<.001	−.736 (0.466)	.11	−.966 (0.368)	.009	.141 (0.356)	.69
Gender	−.298 (0.101)	.003	−.294 (0.100)	.003	−.236 (0.098)	.02	−.392 (0.104)	<.001	−.329 (0.101)	.001
Usage years	.067 (0.018)	<.001	.065 (0.018)	<.001	.072 (0.017)	<.001	.046 (0.018)	.01	.055 (0.018)	.002
ln(Visits+1)	.219 (0.032)	<.001	.220 (0.032)	<.001	.084 (0.038)	.02	.200 (0.033)	<.001	.062 (0.038)	.10
ln(Articles+1)	−.090 (0.029)	.002	−.090 (0.029)	.002	−.056 (0.028)	.049	−.081 (0.029)	.006	−.056 (0.029)	.049
Service stars	.133 (0.014)	<.001	.128 (0.014)	<.001	.109 (0.014)	<.001	.128 (0.014)	<.001	.112 (0.014)	<.001
Written consultation	.002 (0.040)	.96	.003 (0.040)	.94	.001 (0.039)	.98	−.001 (0.040)	.97	−.001 (0.038)	.98
Phone consultation	−.185 (0.096)	.06	−.197 (0.096)	.04	−.178 (0.094)	.06	−.202 (0.097)	.04	−.196 (0.093)	.04
Log-in behavior	N/A[b]	N/A	.014 (0.004)	.001	.020 (0.010)	.06	.015 (0.004)	<.001	N/A	N/A
Positive reviews[c]	N/A	N/A	N/A	N/A	.346 (0.114)	.002	N/A	N/A	.278 (0.040)	<.001
Log-in behavior×positive reviews	N/A	N/A	N/A	N/A	−.003 (0.004)	.46	N/A	N/A	N/A	N/A
Offline status	N/A	N/A	N/A	N/A	N/A	N/A	.294 (0.135)	.03	−.141 (0.092)	.13
Log-in behavior×offline status	N/A	N/A	N/A	N/A	N/A	N/A	−.004 (0.004)	.36	N/A	N/A
Positive reviews×offline status	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	.109 (0.028)	<.001
T										
2	−.391 (0.024)	<.001	−.391 (0.024)	<.001	−.389 (0.024)	<.001	−.392 (0.024)	<.001	−.390 (0.023)	<.001
3	−.443 (0.033)	<.001	−.442 (0.033)	<.001	−.452 (0.032)	<.001	−.444 (0.033)	<.001	−.451 (0.031)	<.001
4	−.461 (0.025)	<.001	−.456 (0.025)	<.001	−.472 (0.024)	<.001	−.451 (0.025)	<.001	−.467 (0.024)	<.001
5	−.540 (0.025)	<.001	−.537 (0.025)	<.001	−.560 (0.025)	<.001	−.530 (0.025)	<.001	−0.552 (0.024)	<.001
Log likelihood	−9103.221	N/A	−9096.944	N/A	−9075.380	N/A	−9087.928	N/A	−9064.380	N/A
Wald chi-square (*df*)	1001.0 (11)	N/A	1015.4 (12)	N/A	1103.6 (14)	N/A	1040.8 (14)	N/A	1161.3 (14)	N/A
P value	<.001	N/A	<.001	N/A	<.001	N/A	<.001	N/A	<.001	N/A

[a]Coefficient of the variable.

[b]N/A: not applicable.

[c]Positive reviews: positive web reviews.

Discussion

Principal Findings

In contrast to previous studies on physicians' web-based behaviors, our research focused on log-in behavior and found that it had a positive effect on patient consultation. The results were consistent with those of Li et al [31], who believed that physicians with higher-frequency log-ins are more likely to attract patients, because they seem to be more responsible and have a timely service process. The results also indicated that physicians' web-based behaviors positively influence patients' consulting choices [6,9,13], including log-in behavior. Our research also found that when a physician did not log in to the OHC for more than 20 days, the number of patients who chose them was small, even 0.

Our research used web reviews generated by patients after receiving health care services as a web signal to represent service outcomes. Our research found that a physician's log-in behavior and web reviews did not have a complementary relationship in affecting patient consultation, which was different from the findings of previous research on service quality [12,14]. On the one hand, it may be that log-in behavior and web reviews have separate effects on patient consultation, and patients do not consider both. On the other hand, although log-in behavior is a web-based behavior, it may not be directly related to the delivery process of a physician's response to consultation.

Patients mostly rely on both offline and web signals to choose a physician. This study found that web reviews were positively moderated by offline status. This is inconsistent with the findings of previous research, which suggests that web signals should be negatively moderated by offline signals [18]. However, offline status cannot moderate log-in behavior. A possible explanation is that most patients view offline signals as a more reliable source than web signals. Compared with the degree of initiative and effort, offline prestige (ie, offline status) in a physician's career can better reflect the service outcome quality.

Theoretical Implications

This study offers theoretical contributions in the following ways. First, previous studies have explored the influencing factors related to patients' consultation choices, including some web-based behaviors of physicians, such as publishing articles, providing written consultation, and phone consultation. However, the literature on the role of physicians' log-in behavior is inadequate. Logging is the central working sphere and is the first step for a physician to provide health care services. Log-in behavior represents the central effort, activeness, and service process quality. Our research found that log-in behavior could influence patients' consulting choices. This finding extends the understanding of physicians' web-based behaviors and may also be used in other service fields.

Second, although some signaling literature in the context of eHealth has discussed web reviews, no research considers web reviews as service outcomes with the log-in behavior of physicians. However, this study found that log-in behavior and web reviews did not have a complementary relationship that affected patient consultation. Therefore, these findings contribute to research on patient consultation in OHCs.

Third, a clear distinction exists between web and offline signals. This study investigated the main effects of web signals (log-in behavior and web reviews) and their interactions with offline signals (offline status). The results revealed that the moderating effects of offline status on these two signals were different. From this perspective, this study extended the understanding of multiple signal interactions.

Implications for Practice

This study has several practical implications. First, for health care service providers, our evidence-based research demonstrates that log-in behavior is also an important factor in influencing patients' choice of consultation. Apart from other web-based behaviors, patients can judge a physician's activeness, efforts, and service process quality by relying on their log-in behavior. Physicians should value their web-based behaviors and log in to OHCs proactively, transmitting signals of active participation and timely responses to patients. Furthermore, operators of OHCs should pay attention to physicians' log-in issues. The more actively physicians participate in web-based platforms, the more successful the OHCs will be.

Second, the results show that log-in behavior and web reviews do not have a complementary relationship that affects patient consultation. Physicians should distinguish between log-in behavior and other web-based behaviors. Although web-based behaviors can reflect a physician's activeness and effort, there may be differences in service process quality.

Third, the results show that multiple signals from different signaling mechanisms affect patient consultation. Offline signals can have positive moderating effects on web signals. Hence, physicians should value the impacts of both web-based and offline service quality, and offline service quality is more credible than web-based service quality for patients.

Limitations and Future Research

This study has certain limitations. First, this study used physician data from only one OHC and one disease type. However, interpretation of the results may be limited. Therefore, it is necessary to collect data from physicians with various expertise on different platforms simultaneously to further verify the research model. Second, the study used the physician's last date displayed on the web on the day of crawling data to measure log-in behavior, which has certain limitations. In future research, we could measure log-in behavior through other methods, such as counting physicians' log-in times within a month. Third, the control variables selected in this study may have ignored some important variables, especially those related to patients. As websites tend to obscure customer names to protect privacy, it is difficult to obtain these data from the website.

Conclusions

Drawing on the signaling theory, this study explores the effects of physicians' log-in behavior and web reviews on patient consultation in OHCs. This study hypothesized that two signals (ie, log-in behavior and web reviews) and their interaction affect patients' consultation choices, and the relationships between web signals and patient consultation were moderated by offline signals (ie, offline status). Short-panel data over five periods were used to test these hypotheses. Our research found that a physician's log-in behavior positively affects patient consultation, and a physician's no–log-in days should be no more than 20 days. Log-in behavior and web reviews had no complementary relationship that affects patient consultation. Furthermore, offline status could only positively moderate web reviews instead of log-in behavior.

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Conflicts of Interest

None declared.

References

1. Wang X, Zhao K, Street N. Analyzing and predicting user participations in online health communities: a social support perspective. J Med Internet Res 2017 Apr 24;19(4):e130 [FREE Full text] [doi: 10.2196/jmir.6834] [Medline: 28438725]
2. Marx GT. Soft surveillence: a growth of mandatory volunteerism in collecting personal information — "Hey Buddy Can You Spare a DNA?". FC 2006;2(1):33-46 [FREE Full text] [doi: 10.32855/fcapital.200601.004]
3. Fichman RG, Kohli R, Krishnan R. Editorial overview—the role of information systems in healthcare: current research and future trends. Inf Syst Res 2011;22(3):419-428. [doi: 10.1287/isre.1110.0382]
4. Akçura MT, Ozdemir ZD. A strategic analysis of multi-channel expert services. J Manag Inf Syst 2017 Apr 20;34(1):206-231. [doi: 10.1080/07421222.2017.1297637]
5. Cao X, Liu Y, Zhu Z, Hu J, Chen X. Online selection of a physician by patients: empirical study from elaboration likelihood perspective. Comput Human Behav 2017 Aug;73:403-412. [doi: 10.1016/j.chb.2017.03.060]
6. Deng Z, Hong Z, Zhang W, Evans R, Chen Y. The effect of online effort and reputation of physicians on patients' choice: 3-wave data analysis of China's good doctor website. J Med Internet Res 2019 Mar 08;21(3):e10170 [FREE Full text] [doi: 10.2196/10170] [Medline: 30848726]
7. Li C, Zhang E, Han J. Adoption of online follow-up service by patients: an empirical study based on the elaboration likelihood model. Comput Human Behav 2021 Jan;114:106581. [doi: 10.1016/j.chb.2020.106581]
8. Li S, Lee-Won RJ, McKnight J. Effects of online physician reviews and physician gender on perceptions of physician skills and Primary Care Physician (PCP) selection. Health Commun 2019 Oct 24;34(11):1250-1258. [doi: 10.1080/10410236.2018.1475192] [Medline: 29792519]
9. Li Y, Ma X, Song J, Yang Y, Ju X. Exploring the effects of online rating and the activeness of physicians on the number of patients in an online health community. Telemed J E Health 2019 Nov 23;25(11):1090-1098. [doi: 10.1089/tmj.2018.0192] [Medline: 30676279]
10. Liu F, Li Y, Ju X. Exploring patients' consultation behaviors in the online health community: the role of disease risk. Telemed J E Health 2019 Mar;25(3):213-220. [doi: 10.1089/tmj.2018.0033] [Medline: 29927721]
11. Liu X, Guo X, Wu H, Wu T. The impact of individual and organizational reputation on physicians' appointments online. Int J Electron Commer 2016 Jun 20;20(4):551-577. [doi: 10.1080/10864415.2016.1171977]
12. Lu N, Wu H. Exploring the impact of word-of-mouth about physicians' service quality on patient choice based on online health communities. BMC Med Inform Decis Mak 2016 Nov 26;16(1):151 [FREE Full text] [doi: 10.1186/s12911-016-0386-0] [Medline: 27888834]
13. Wu H, Lu N. Online written consultation, telephone consultation and offline appointment: an examination of the channel effect in online health communities. Int J Med Inform 2017 Dec;107:107-119. [doi: 10.1016/j.ijmedinf.2017.08.009] [Medline: 29029686]
14. Yang H, Guo X, Wu T, Ju X. Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision. Electron Commer Res Appl 2015 May;14(3):192-203. [doi: 10.1016/j.elerap.2015.04.001]
15. Lagu T, Hannon NS, Rothberg MB, Lindenauer PK. Patients' evaluations of health care providers in the era of social networking: an analysis of physician-rating websites. J Gen Intern Med 2010 Sep;25(9):942-946 [FREE Full text] [doi: 10.1007/s11606-010-1383-0] [Medline: 20464523]
16. Chen Q, Yan X, Zhang T. Converting visitors of physicians' personal websites to customers in online health communities: longitudinal study. J Med Internet Res 2020 Aug 26;22(8):e20623-e20709 [FREE Full text] [doi: 10.2196/20623] [Medline: 32845248]
17. Parasuraman A, Zeithaml VA, Berry LL. A conceptual model of service quality and its implications for future research. J Mark 1985;49(4):41. [doi: 10.2307/1251430]

18. Li J, Tang J, Jiang L, Yen DC, Liu X. Economic success of physicians in the online consultation market: a signaling theory perspective. Int J Electron Commer 2019 Mar 26;23(2):244-271. [doi: 10.1080/10864415.2018.1564552]
19. Connelly BL, Certo ST, Ireland RD, Reutzel CR. Signaling theory: a review and assessment. J Manage 2010 Dec 20;37(1):39-67. [doi: 10.1177/0149206310388419]
20. Wu H, Lu N. How your colleagues' reputation impact your patients' odds of posting experiences: evidence from an online health community. Electron Commer Res Appl 2016 Mar;16:7-17. [doi: 10.1016/j.elerap.2016.01.002]
21. Yan L, Tan Y. Feeling blue? Go online: an empirical study of social support among patients. Inf Syst Res 2014 Dec;25(4):690-709. [doi: 10.1287/isre.2014.0538]
22. Wu H, Lu N. Service provision, pricing, and patient satisfaction in online health communities. Int J Med Inform 2018 Feb;110:77-89. [doi: 10.1016/j.ijmedinf.2017.11.009] [Medline: 29331257]
23. Yan Z, Wang T, Chen Y, Zhang H. Knowledge sharing in online health communities: a social exchange theory perspective. Inf Manag 2016 Jul;53(5):643-653. [doi: 10.1016/j.im.2016.02.001]
24. Zhang X, Liu S, Deng Z, Chen X. Knowledge sharing motivations in online health communities: a comparative study of health professionals and normal users. Comput Human Behav 2017 Oct;75:797-810. [doi: 10.1016/j.chb.2017.06.028]
25. Liu G, Zhou L, Wu J. What affects patients' online decisions: an empirical study of online appointment service based on text mining. In: Proceedings of the International Conference on Smart Health. 2018 Presented at: International Conference on Smart Health (ICSH); July 1–3, 2018; Wuhan, China p. 204-210. [doi: 10.1007/978-3-030-03649-2_20]
26. Wang J, Chiu Y, Yu H, Hsu Y. Understanding a nonlinear causal relationship between rewards and physicians' contributions in online health care communities: longitudinal study. J Med Internet Res 2017 Dec 21;19(12):e427 [FREE Full text] [doi: 10.2196/jmir.9082] [Medline: 29269344]
27. Yang H, Du HS, He W, Qiao H. Understanding the motivators affecting doctors' contributions in online healthcare communities: professional status as a moderator. Behav Inf Technol 2019 Oct 23;40(2):146-160. [doi: 10.1080/0144929x.2019.1679887]
28. Kromidha E, Li MC. Determinants of leadership in online social trading: a signaling theory perspective. J Bus Res 2019 Apr;97:184-197. [doi: 10.1016/j.jbusres.2019.01.004]
29. Stiglitz J. Information and the change in the paradigm in economics. New Front Econ 2004;92(3):27-67. [doi: 10.1017/CBO9780511754357.004]
30. Evans RG. Supplier-induced demand: some empirical evidence and implications. In: The Economics of Health and Medical Care. London: Palgrave Macmillan; 1974:162-173.
31. Li J, Deng Z, Evans RD, Liu S, Wu H. How doctors take initiatives in online healthcare communities. Ind Manag Data Syst 2020 Jun 30;120(7):1401-1420. [doi: 10.1108/imds-12-2019-0684]
32. Bitner MJ, Booms BH, Mohr LA. Critical service encounters: the employee's viewpoint. J Mark 1994 Oct;58(4):95-106. [doi: 10.2307/1251919]
33. Caruana A. Service loyalty. Eur J Mark 2002 Aug;36(7/8):811-828. [doi: 10.1108/03090560210430818]
34. Borucki CC, Burke MJ. An examination of service-related antecedents to retail store performance. J Organiz Behav 1999 Nov;20(6):943-962. [doi: 10.1002/(sici)1099-1379(199911)20:6<943::aid-job976>3.0.co;2-9]
35. Petrovčič A, Petrič G, Manfreda KL. The effect of email invitation elements on response rate in a web survey within an online community. Comput Human Behav 2016 Mar;56:320-329. [doi: 10.1016/j.chb.2015.11.025]
36. Ye Q, Law R, Gu B, Chen W. The influence of user-generated content on traveler behavior: an empirical investigation on the effects of e-word-of-mouth to hotel online bookings. Comput Human Behav 2011 Mar;27(2):634-639. [doi: 10.1016/j.chb.2010.04.014]
37. Gretzel U, Yoo KH. Use and impact of online travel reviews. Inf Commun Technol Tour 2008:35-46. [doi: 10.1007/978-3-211-77280-5_4]
38. Yang J, Mai E. Experiential goods with network externalities effects: an empirical study of online rating system. J Bus Res 2010 Sep;63(9-10):1050-1057. [doi: 10.1016/j.jbusres.2009.04.029]
39. Zhang Z, Ye Q, Law R, Li Y. The impact of e-word-of-mouth on the online popularity of restaurants: a comparison of consumer reviews and editor reviews. Int J Hosp Manag 2010 Dec;29(4):694-700. [doi: 10.1016/j.ijhm.2010.02.002]
40. Gao G, Greenwood BN, McCullough J, Agarwal R. A digital soapbox? The information value of online physician ratings. In: Proceedings of the Academy of Management Annual Meeting. 2012 Presented at: Academy of Management Annual Meeting; August 3-7, 2012; Boston, MA, USA p. 16354. [doi: 10.5465/AMBPP.2012.16354abstract]
41. Sillence E, Briggs P, Harris PR, Fishwick L. How do patients evaluate and make use of online health information? Soc Sci Med 2007 May;64(9):1853-1862. [doi: 10.1016/j.socscimed.2007.01.012] [Medline: 17328998]
42. Guo S, Guo X, Fang Y, Vogel D. How doctors gain social and economic returns in online health-care communities: a professional capital perspective. J Manag Inf Syst 2017 Aug 17;34(2):487-519. [doi: 10.1080/07421222.2017.1334480]
43. Bresnahan TF, Brynjolfsson E, Hitt LM. Information technology, workplace organization, and the demand for skilled labor: firm-level evidence. Q J Econ 2002 Feb 01;117(1):339-376. [doi: 10.1162/003355302753399526]

Abbreviations

OHC: online health community

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Review

Application of the eHealth Literacy Model in Digital Health Interventions: Scoping Review

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Abstract

Background: Digital health interventions (DHIs) are increasingly being adopted globally to address various public health issues. DHIs can be categorized according to four main types of technology: mobile based, web based, telehealth, and electronic health records. In 2006, Norman and Skinner introduced the *eHealth literacy model*, encompassing six domains of skills and abilities (basic, health, information, scientific, media, and computer) needed to effectively understand, process, and act on health-related information. Little is known about whether these domains are assessed or accounted for in DHIs.

Objective: This study aims to explore how DHIs assess and evaluate the eHealth literacy model, describe which health conditions are addressed, and which technologies are used.

Methods: We conducted a scoping review of the literature on DHIs, based on randomized controlled trial design and reporting the assessment of any domain of the eHealth literacy model. MEDLINE, CINAHL, Embase, and Cochrane Library were searched. A duplicate selection and data extraction process was performed; we charted the results according to the country of origin, health condition, technology used, and eHealth literacy domain.

Results: We identified 131 unique DHIs conducted in 26 different countries between 2001 and 2020. Most DHIs were conducted in English-speaking countries (n=81, 61.8%), delivered via the web (n=68, 51.9%), and addressed issues related to noncommunicable diseases (n=57, 43.5%) or mental health (n=26, 19.8%). None of the interventions assessed all six domains of the eHealth literacy model. Most studies focused on the domain of health literacy (n=96, 73.2%), followed by digital (n=19, 14.5%), basic and media (n=4, 3%), and information and scientific literacy (n=1, 0.7%). Of the 131 studies, 7 (5.3%) studies covered both health and digital literacy.

Conclusions: Although many selected DHIs assessed health or digital literacy, no studies comprehensively evaluated all domains of the eHealth literacy model; this evidence might be overlooking important factors that can mediate or moderate the effects of these interventions. Future DHIs should comprehensively assess the eHealth literacy model while developing or evaluating interventions to understand how and why interventions can be effective.

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KEYWORDS

eHealth literacy; digital health interventions; consumer health information; scoping review; mHealth; mobile phone

Introduction

Digital Health Interventions

In the last 20 years, digital health or eHealth has emerged as an important research field. At the intersection of medical informatics, public health, and business, eHealth refers to the use of "health services and information delivered or enhanced through the Internet and related technologies" [1]. Technologies such as web based, mobile based, telehealth, and electronic health records (EHRs) have become widely adopted in the so-called *digital health interventions* (DHIs). DHIs can be defined as "health services delivered electronically through formal or informal care. DHIs can range from electronic medical records used by providers to mobile health (mHealth) apps used by consumers" [2]. The World Health Organization has recently produced a classification of DHIs, identifying four main types: clients, health care providers, health systems, and data services [3]. On PubMed, as of August 3, 2020, the number of records mentioning *eHealth* or *DHIs* in their title or abstract has consistently increased over the past 20 years, starting from 65 in 2000 to 11,395 in 2019, reaching a total of 6720.

Some systematic reviews and meta-analyses have described the effectiveness of DHIs in addressing various public health problems, such as somatic diseases [4], or health literacy and health outcomes [5]. Nevertheless, it is still unclear what makes DHIs superior to nondigital interventions or what components of these interventions facilitate positive outcomes reported [6]. In addition, it is unclear whether DHIs are effective because of their content or the manner in which they are delivered. Regarding the content of interventions, some systematic reviews have focused on exploring the way people process and understand information available on the internet [7,8]. In fact, with so many resources and information available on the internet, patients and users enrolled in DHIs may face challenges in understanding and making sense of the information they receive. Some research has focused on problems related to the ability to process information derived from web-based sources or delivered through technologies.

The eHealth Literacy Model

In 2006, Norman and Skinner [9] proposed a conceptual model that encompasses six different domains of literacy required to process information from technology sources: traditional literacy, health literacy, information literacy, scientific literacy, media literacy, and computer literacy. According to Norman and Skinner [9], traditional or basic functional literacy includes simple and primitive literacy skills, including the ability to read and understand text and the ability to speak and write in a certain language. Information literacy includes the ability to know how knowledge is structured and how information can be used in a certain way that informs other people. Media literacy is the capability to critique a media subject and place information in different contexts. Health literacy, coined in the 1970s, can be generally defined as "the degree to which individuals can obtain, process, understand, and communicate about health-related information needed to make informed health decisions" (as reported by Berkman et al [10]). According to Norman and Skinner [9], health literacy is the ability to perform basic reading and numerical tasks required to function in the health care environment; patients with adequate health literacy can read, understand, and act on health care information. More recent evolutions of the concept include a variety of competencies and skills, including knowledge, motivation, and competencies related to accessing, understanding, appraising, and applying health-related information in health care, disease prevention, and health promotion settings [11]. Several systematic reviews have analyzed the relationship between health literacy and a variety of health outcomes, indicating that a good level of health literacy is generally associated with positive health outcomes in various health domains, such as vaccination [12], noncommunicable diseases (NCDs) such as chronic kidney disease or coronary artery disease, heart failure [13-15], oral health [16], quality of life [17], and excess body weight [18]. Some other review evidence has shown how interventions promoting critical health literacy [19] could be very beneficial for the community [20] or among specific segments of the population, such as adolescents [21] or older adults [22].

Strictly related to the concept of eHealth is computer or technology literacy, which is the capability to use new technologies and software and the ability to access electronic health information [9]. Recent conceptualizations expand this domain to look at the ability to process information, to engage with patients' own health, at the motivation and ability to engage with digital devices, at feeling safe and in control, at having access to health care and technological systems that work, and at meeting digital services that suit individuals' needs [23]. Norman and Skinner [24] have developed a scale to assess eHealth literacy, called *eHealth literacy scale* (*eHEALS*), which has been one of the most adopted and cited, with 449 citations on the *Journal of Medical Internet Research* page and more than 1320 results on Google Scholar (as of August 3, 2020). The last domain of the eHealth literacy model, scientific literacy, involves the ability to allocate health-related findings in the right context by systematically understanding the "nature, aims, methods, applications, limitations, and politics" of building knowledge [9]. Several systematic reviews have analyzed the relationship between health literacy in mHealth apps and interventions [5,7,8,25,26], generally reporting positive associations among health literacy, digital literacy, and health outcomes. Other reviews have specifically examined how technology can affect health literacy in health programs [27-29].

According to the developers of the eHealth literacy model, the six domains can be grouped into two main categories: analytic (traditional, media, and information) and context-specific (health, scientific, and computer). The analytical category refers to a set of competencies that can be applied to a wide range of information sources, whereas context-specific categories include competencies that can only be applied to a specific problem in a specific context [9]. For example, the ability of a person living with type 2 diabetes to process information related to diabetes is different from their ability to process information related to vaccines, mental health, or other chronic conditions. Similarly, the ability to use a mobile phone to call someone does not necessarily translate into the ability to use a mobile app, navigate a website, or evaluate the information retrieved while searching on the internet.

Related Work and Study Aims

Arguably, researchers developing DHIs should always take into account the domains of computer or technology literacy and health literacy, as these are potential pathways for more effective and equitable interventions [30]. Health literacy can be viewed as both an outcome and a mediator in interventions intended to improve health outcomes [31]. Technologies or delivery modes can also be seen as interacting or moderating factors [32], depending on the type of technology used to deliver an intervention on a specific health topic. DHIs can be developed to improve health literacy (outcome) or they can be developed to improve clinical outcomes in which one or more dimensions of the eHealth literacy model are considered as mediators or moderators of the effects of the intervention. Researchers developing DHIs could then assume that people enrolling in these interventions should have good levels of functional, scientific, media, and information literacy to understand how to write or read information they are exposed to.

However, to what extent are these assumptions tenable? In other words, is the eHealth literacy model purely conceptual or does it find a concrete application in DHIs? To the best of our knowledge, there are no systematic reviews that specifically discuss the application of the complete eHealth literacy model in DHIs. When we were developing the search strategies for this project, we searched for existing systematic reviews in PubMed and PROSPERO databases with the keyword *eHealth literacy* and identified only four systematic reviews [33-36]. However, all these reviews have focused on the domain of digital literacy, looking at specific health outcomes in specific segments of the population, such as people living with HIV [33], underserved populations in the United States [34], older adults [35], or college students [36]. Therefore, this scoping review aims to identify and describe DHIs that assess any domain of the eHealth literacy model and to identify which domains are assessed and evaluated the most. We considered DHIs that were developed to improve clinical outcomes or that were aimed at different literacies, according to the eHealth literacy model. In other words, we considered interventions that looked at eHealth literacy either as an outcome or as a mediator of intervention effects, as long as the domains of the eHealth literacy model were assessed.

Methods

Overview

We followed the scoping review framework by Arksey and O'Malley [37], which encompasses five stages: (1) identification of the initial research questions; (2) identification of relevant studies; (3) study selection; (4) charting the data; and (5) collating, summarizing, and reporting the results. The stages are described further in the following sections.

Stage 1: Identifying the Research Question

The main review question, based on the eHealth literacy model, was "To what extent are DHIs assessing the 6 domains of the eHealth literacy model?" More specifically, we wanted to answer the following research questions: What domains of the eHealth literacy model (ie, computer, health, traditional, media, information, and science literacy) are assessed and reported in the literature? What health conditions have been investigated? What technologies are used?

Stage 2: Identifying Relevant Studies

We searched four electronic databases that cover most of the medical and public health literature: MEDLINE, CINAHL, Embase, and Cochrane Library.

We used a predefined search strategy, encompassing keywords and medical subject headings to cover three main concepts: *eHealth literacy model*, *digital health*, and the *study design* for interventions. The *eHealth literacy model* concept entailed terms such as health literacy, literacy, computer literacy, information literacy, basic, functional, scientific, media, information, computer, health, eHealth, literacy, literate, illiteracy, and illiterate. The second concept, *digital health*, expanded on the above and entailed keywords, such as *telemedicine*, *internet*, *mobile*, *phone*, *digital*, *medium* or *media*, *mHealth*, *eHealth*, *telemedicine*, and *computer*, based on other systematic reviews recently conducted by one of the authors [6,38,39]. The third concept, that is, the research design, entailed a predefined set of keywords and operands that Cochrane has developed to identify randomized controlled trials (RCTs); this is because we wanted to identify the best level of evidence available [40]. The search strategy used for MEDLINE is provided in Multimedia Appendix 1. Database searches were completed, and references were retrieved on January 24, 2020.

In addition, we used the reference list of identified systematic reviews on the topic to identify other potentially relevant studies.

Stage 3: Study Selection

We followed the Joanna Briggs' Institute's PCC (Population-Concept-Context) framework [41,42] to define our inclusion criteria, as it applies to scoping reviews. We included studies that discussed DHIs (concepts) and reported the assessment of at least one domain of the eHealth literacy model (context). In this context, we conceived the dimensions of the eHealth literacy model as either outcomes or mediators of DHIs. The assessment of the different types of literacy was considered a sufficient indicator for DHIs considering such dimensions as outcomes or mediators of intervention effects. We did not restrict the results to any population, with the idea of inductively categorizing the results according to health condition, hence defining the population of reference in the analytical phase.

The screening process consisted of two stages: title and abstract as well as full-text screening. The first stage involved 2 reviewers (MEB and MB) and one research assistant, who independently screened all records identified by the searches. This task was completed using a web-based application for systematic reviews, Rayyan [43]. The interrater reliability was excellent (agreement 96%; Cohen κ=0.834; Gwet AC1=0.950). All records with disagreement among the 3 reviewers were automatically included in the full-text screening stage. The full-text screening stage was completed by the first author with the help of a research assistant and verified by the fourth author. All disagreements were resolved through discussion.

Stage 4: Charting the Data

For each retrieved record, 2 authors (MEB and MB) extracted the following information into a Microsoft Excel spreadsheet: first author name, year of publication, article title, journal, and number of trial registry (if available), principal investigator name (if available), country of the first author or of the principal investigator (if available). This information was used to identify and map articles pertaining to the same study. In the full-text stage, we also extracted text to verify whether the record included a digital component, was based on a randomized controlled design, focused on specific health conditions, and measured and reported results related to one of the domains of the eHealth literacy model (health, computer, basic or functional, information, media, and scientific literacy).

When multiple records were available for one study, we chose the country of origin of the first author or of the principal investigator listed in the study protocol; we chose the year of publication of the first published article available.

On the basis of the information extracted, we categorized studies according to the domains of the eHealth literacy model (ie, health, computer, basic or functional, information, media, and scientific literacy). We also inductively categorized the studies according to the health conditions described. When multiple conditions were reported, we categorized the study as having multiple conditions. Finally, we inductively categorized the interventions according to four main types of technology: (1) *mobile-based*, including mobile apps, text messages, and interactive voice response, exclusively designed for mobile or other handheld devices; (2) *web-based*, including those designed for being accessed via computer, explicitly labeled as *web- or internet-based*, *online*, and *e-learning*, delivered through bespoke websites or social media outlets, such as social networking sites (eg, Facebook or Twitter)—social media are web-based apps that can be accessed via different devices connected to the internet, including smartphones [39,44,45]; (3) *telehealth*, comprising telerehabilitation, telemedicine, or other interventions focused on distributing services and information via electronic information and telecommunication devices [46]; (4) *EHRs*, focusing on EHRs that are defined as "a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users" [47]. Telehealth and EHR interventions use the internet to connect various devices, including tablets and mobile phones, yet they represent a different type of delivery mode and format: EHRs. We labeled interventions using a combination of the modes described earlier, as reported in other studies [6,48]. When studies reported a combination of the abovementioned categories, we categorized the study as a *hybrid*.

The first author and a research assistant independently completed the classifications; in case of inconsistencies or disagreements between the classifications, the fourth author acted as a third reviewer and resolved the disagreements through discussion. All the authors agreed with the final categorization.

Stage 5: Collating, Summarizing, and Reporting the Results

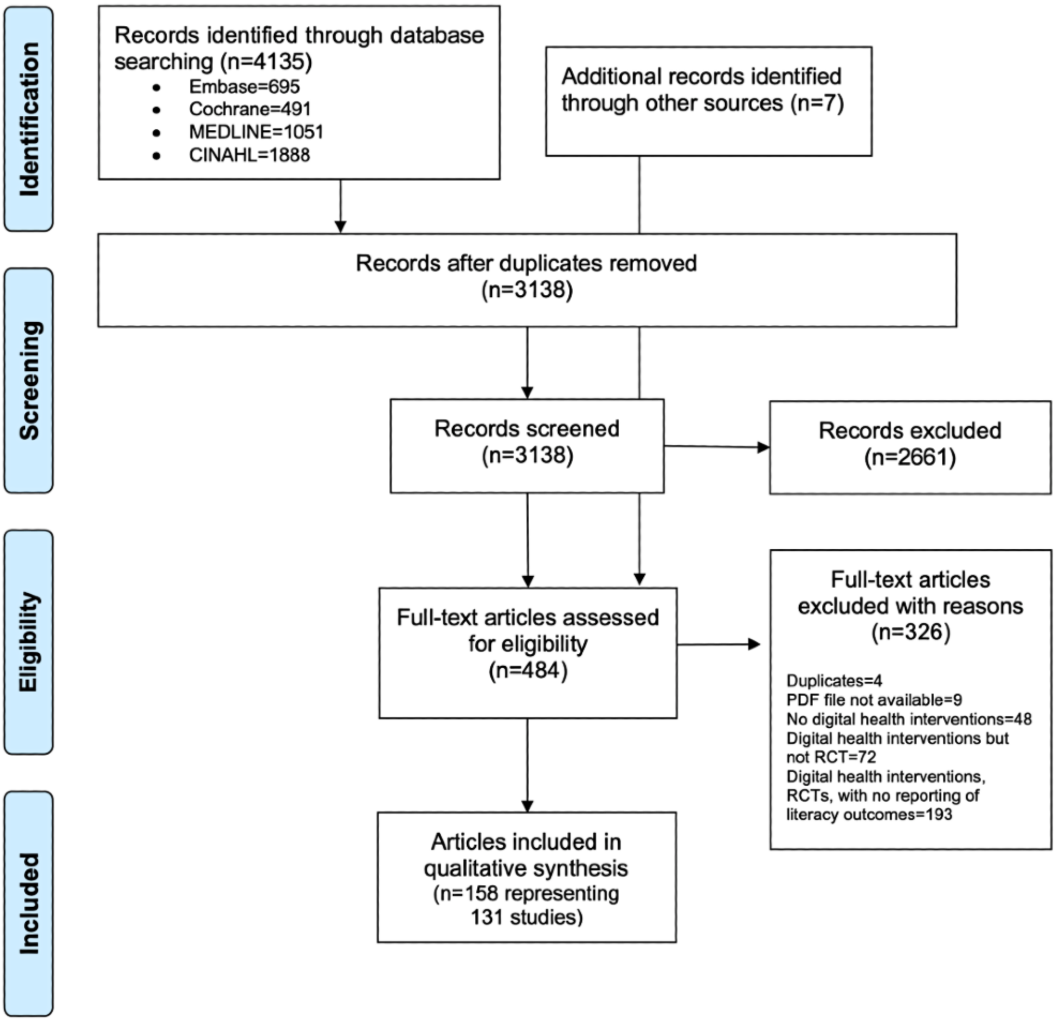
We performed a descriptive analysis of the characteristics of the included papers and reported the results by year of publication, the country of origin of the study authors, eHealth literacy domain, health condition, and type of technology used.

Results

Search Results

The electronic database search yielded 4135 records. The selection process is summarized in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram shown in Figure 1. Briefly, after removing duplicates, the titles and abstracts of 3138 records were independently screened by 3 reviewers. During the title and abstract screening, we excluded 2661 records that were deemed irrelevant. The remaining 477 records were assessed for eligibility in the full text. Scanning the reference lists of two relevant systematic reviews [5,49] allowed us to identify seven other eligible records. We evaluated the eligibility of 484 records that were screened in full text. Of these, 326 records were excluded for the following reasons: 48 did not discuss DHIs (wrong context); 72 reported on digital interventions but did not use an RCT or randomized clinical trial design (wrong study design); 193 records discussed DHIs but did not report any type of literacy (no relevant outcome assessed or reported); 4 were duplicate records; and for the remaining 9 records, we could not retrieve a PDF file. The list of excluded references is provided in Multimedia Appendix 2. Overall, we included 158 records: 79 records reported concluded interventions and 79 records reported protocols of ongoing studies, without reporting results. These were included because they described the assessment of some domains of the eHealth literacy model. The 158 records described a total of 131 unique studies.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram. RCT: randomized controlled trial.



Characteristics of the Included Studies

Publication Year and Geographic Distribution

As shown in Figure 2, most of the selected studies were conducted in the last 4 years (86/131, 65.6%), followed by an exponential trend, peaking in 2019 (30/131, 22.9%) and ranging from 2001 to 2020.

The studies were conducted in 26 countries (Table 1). Most studies were conducted across 3 countries (81/131, 61.8%), including the United States (43/131, 32.8%), Australia (28/131, 21.3%), and the United Kingdom (10/131, 7.6%). Approximately one-third of the studies (38/131, 29%) were conducted in European countries such as the United Kingdom (10/38, 26%); Germany (8/38, 21%); Denmark (5/38, 13%); Sweden (4/38, 11%); the Netherlands (3/38, 8%); Norway (2/38, 5%); and Belgium, Finland, Luxemburg, Ireland, Slovakia, and Switzerland (1/38, 3% each). Asian countries were represented by Iran (4/16, 25%); Turkey (3/16, 19%); Hong Kong (2/16, 13%); Singapore (2/16, 13%); Japan (2/16, 13%); and Jordan, Malaysia, and Pakistan (1/16, 6% each). Overall, only 0.8% (1/131) of studies were conducted in Africa (South Africa) and 22.1% (29/131) in Oceania (New Zealand: 1/29, 3%; Australia: 28/29, 97%).

In the following sections, we have reported the results according to our research objectives, whereas a table with the detailed characteristics of the selected studies is provided in Multimedia Appendix 3.

Figure 2. Distribution of selected studies (N=131) by year of publication.

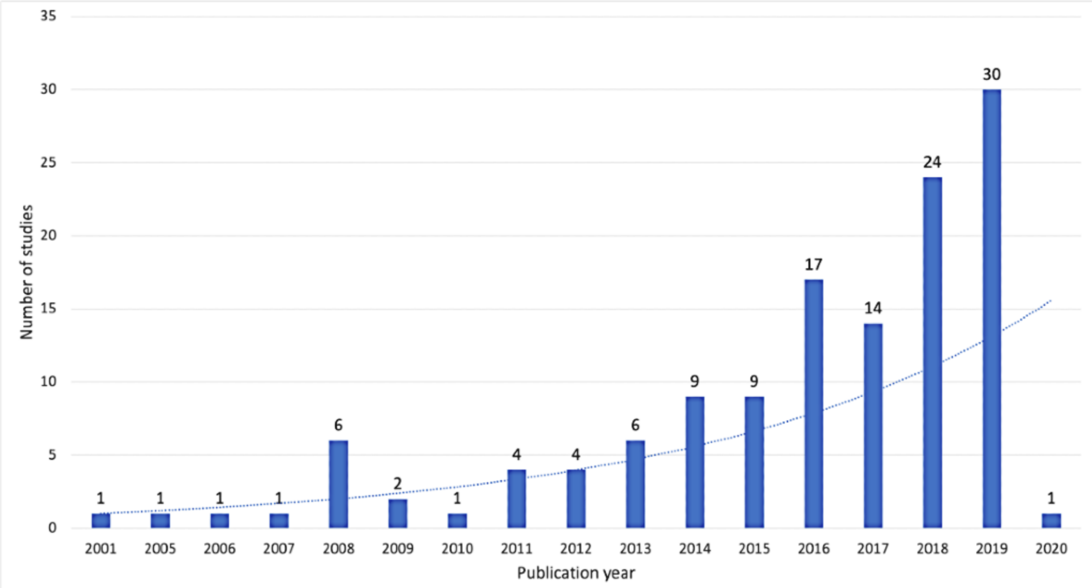


Table 1. Distribution of included studies by country (N=131).

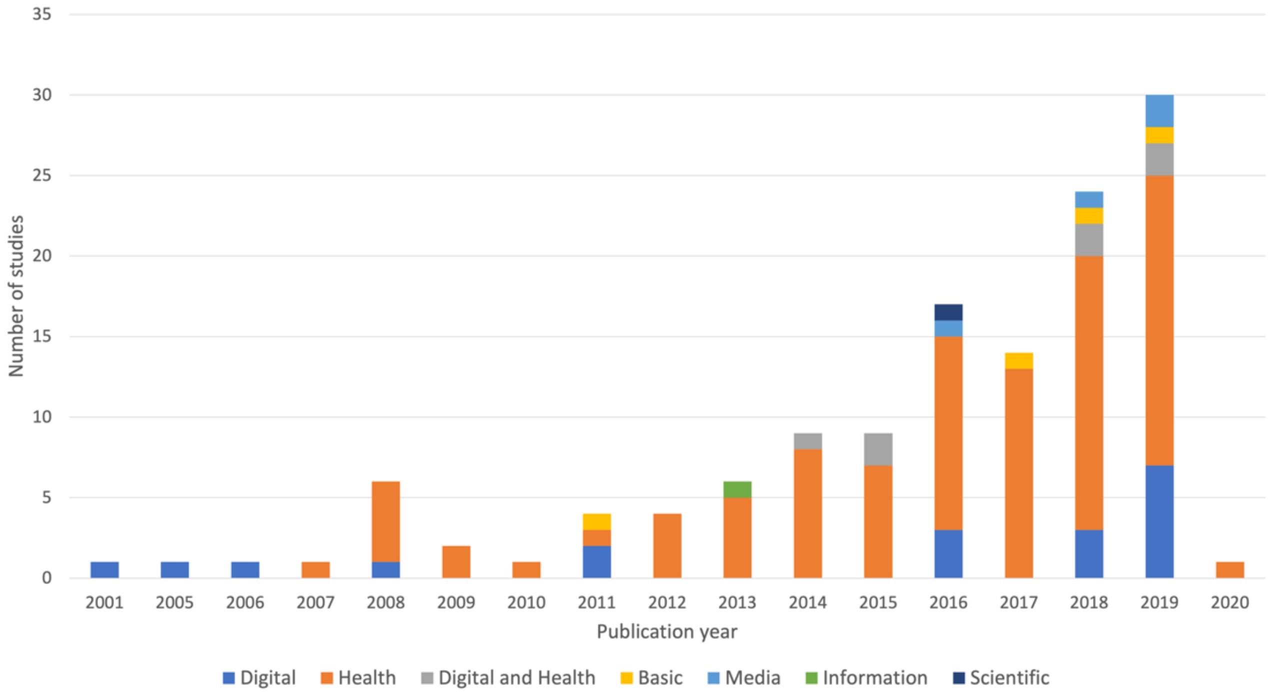
Country	Studies, n (%)
United States	43 (32.8)
Australia	28 (21.3)
United Kingdom	10 (7.6)
Germany	8 (6.1)
Denmark	5 (3.8)
Sweden	4 (3.1)
Iran	4 (3.1)
Netherlands	3 (2.2)
Turkey	3 (2.2)
Brazil	2 (1.5)
Canada	2 (1.5)
Hong Kong	2 (1.5)
Japan	2 (1.5)
Norway	2 (1.5)
Singapore	2 (1.5)
Belgium	1 (0.7)
Finland	1 (0.7)
Ireland	1 (0.7)
Jordan	1 (0.7)
Luxemburg	1 (0.7)
Malaysia	1 (0.7)
New Zealand	1 (0.7)
Pakistan	1 (0.7)
Slovakia	1 (0.7)
South Africa	1 (0.7)
Switzerland	1 (0.7)

Domains of the eHealth Literacy Model Assessed

Figure 3 presents the years of publication of the included studies grouped by domain of the eHealth literacy model. In total, 2.2% (3/131) of the included studies were published before 2006, when the seminal publications of the eHealth literacy model appeared [9,24]. These studies included an assessment of computer literacy. Studies published in 2008 mostly reported assessments of health literacy.

Of the 131 studies included, none assessed or measured all six domains of the eHealth literacy model. Most of the studies (124/131, 94.6%) focused on one of the six domains of the eHealth literacy model; only 5.3% (7/131) of studies reported the assessment of two domains, namely health literacy and digital or computer literacy. Most of the studies that reported on one literacy domain (124/131, 94.7%) focused on health literacy (95/124, 76.6%), followed by digital or computer literacy (19/124, 15.3%), basic or functional literacy (4/124, 3.2%), media literacy (4/124, 3.2%), information literacy (1/124, 0.8%), and scientific literacy (1/124, 0.8%).

Figure 3. Distribution of studies (N=131) by eHealth literacy model domain.



Health Conditions Addressed and Technologies Used

Table 2 provides a summary of the selected studies grouped by technology category and health condition category.

A large number of studies (61/131, 46.5%) discussed interventions addressing NCDs, such as hypertension, obesity, end-stage kidney disease, type 2 diabetes, chronic kidney disease, heart disease (vascular disease, cerebrovascular disorders, ischemic heart disease, coronary artery disease, and heart failure), fibromyalgia syndrome, and asthma. Of these 61 NCD-focused studies, 3 (5%) also discussed mental health topics, and 1 (2%) covered sexual and reproductive health. The second most covered category of health conditions was mental health (26/131, 19.8%), including depression, eating disorders, mental and behavioral disorders, anxiety, and suicide prevention. Other topics included health education (16/131, 12.2%), such as health promotion, health communication, patient provider communication and literacy, aging and maternal and infant health (4/131, 3.0% of studies), sexual and reproductive health, and substance use (3/131, 2.2% of studies each). The remaining 11.4% (15/131) studies covered a variety of health topics.

Table 2. Number of studies by health condition category and type of technology used.

Health condition and technology used	Web based (n=68), n (%)	Mobile based (n=40), n (%)	Telehealth (n=10), n (%)	EHRs[a] (n=5), n (%)	Hybrid (n=8), n (%)	Total (N=131), n (%)
NCDs[b]	22 (32.4)	19 (47.5)	6 (60)	3 (60)	6 (75)	56 (42.7)
NCDs—mental health	1 (1.5)	2 (5)	0 (0)	0 (0)	0 (0)	3 (2.3)
NCDs—sexual and reproductive health	0 (0)	0 (0)	0 (0)	0 (0)	1 (12.5)	1 (0.8)
Mental health	21 (30.9)	4 (10)	1 (10)	0 (0)	0 (0)	26 (19.8)
Aging	2 (2.9)	1 (2.5)	1 (10)	0 (0)	0 (0)	4 (3.1)
Health education topics	9 (13.2)	4 (10)	1 (10)	2 (40)	0 (0)	16 (12.2)
Maternal and infant health	2 (2.9)	2 (5)	0 (0)	0 (0)	0 (0)	4 (3.1)
Sexual and reproductive health	2 (2.9)	1 (2.5)	0 (0)	0 (0)	0 (0)	3 (2.3)
Substance use	2 (2.9)	1 (2.5)	0 (0)	0 (0)	0 (0)	3 (2.3)
Other health topics	7 (10.3)	6 (15)	1 (10)	0 (0)	1 (12.5)	15 (11.5)

[a]EHR: electronic health record.

[b]NCD: noncommunicable disease.

With regard to the technologies used, most studies included web-based interventions (68/131, 51.9%), followed by mobile-based (40/131, 30.5%), telehealth (10/131, 7.6%) EHRs (5/131, 3.8%), and hybrid interventions (8/131, 6.1%). Examples of web-based technology included e-learning portals for specialized training [50,51], experimental websites, and social media platforms [52-54], which are used to deliver motivational or informational campaigns. Mobile-based interventions included health apps [55-57], SMS text messaging or WhatsApp [58], games [59,60], and interactive voice response [61,62]. Telehealth interventions included rehabilitation programs [63,64] or remote counseling [65]. Hybrid interventions included combinations of mobile apps and EHRs [55-57], SMS text messaging and EHRs [66], or a mix of web- and mobile-based technologies [67].

Among web-based interventions (n=68), most focused on NCDs (22/68, 32%), mental health (21/68, 31%), and health education topics (9/68, 13%). Mobile-based interventions (n=40) followed a similar pattern, with approximately half of the studies focusing on NCDs (19/40, 48%) or other health topics (6/40, 15%). Most telehealth (6/10, 60%), EHR (3/5, 60%), and hybrid (6/8, 75%) interventions focused on NCDs.

Discussion

Principal Findings

This is the first scoping review examining the extent to which DHIs have assessed, accounted for, and reported any of the six domains of the eHealth literacy model by Norman and Skinner [9]. We identified a sizable literature discussing DHIs developed in 26 countries, spanning two decades. The eHealth literacy model [9] and eHEALS [24] date back to 2006, but we included 3 studies that were published before that year and all assessed computer literacy. This might indicate that attention toward the ability to use technology was a research interest in the early 2000s. However, this interest has not grown exponentially and concomitantly with the growth of DHIs. It is interesting to observe that the assessment of digital literacy has grown only after 2015, but it has remained below the assessment of health literacy, which was the domain assessed the most over time. There is no clear explanation for these trends. A bibliometric analysis of the studies cited in the seminal papers mentioned above could reveal the connections between publications and demonstrate when the eHealth literacy model has received more citations.

Most of the evidence comes from the *Global North*, that is, from English-speaking countries including the United States, Australia, and the United Kingdom. A few studies have been conducted in countries of the *Global South*, such as Africa, Latin America, or South East Asia. This finding is consistent with that reported in a recent scoping review on digital health innovations [68] and in a recent bibliometric analysis of research on mHealth apps [69], which showed a predominance of articles published in the United States, the United Kingdom, Australia, and Canada. Publication bias and limited evidence from developing countries or the *Global South* has been previously reported in the literature [70-72], yet there seems to be a lack of evidence on DHIs from Africa, the Middle East, South America, or Southeast Asia. There may be various reasons for this absence of evidence. First, research on digital technologies might not have reached an advanced stage to produce interventions with the highest level of evidence (ie, RCTs). Second, the existing digital divide might persist in many countries, both low- and high-income countries [30]; however, mobile phones and telemedicine are becoming more widely adopted [46,73]. Third, researchers based in low- and middle-income countries (LMICs) may be published in languages other than English or might have limited English language proficiency, but this latter assumption does not seem to be grounded in evidence [74,75]. Another reason might be that researchers in LMICs might choose to publish in journals that are not indexed in the databases we searched. Alternatively, researchers in LMICs might not have the possibility to publish their results because of a lack of funding for open access publications or because editors demonstrate publication bias [72]. Regardless of the reasons, we call for digital health researchers based in countries of the Global South to publish more study protocols and diffuse intervention results; we also call the international community of editors and publishing houses to incentivize or support research published from these underrepresented countries, so that stronger conclusions can be drawn from a truly global evidence base.

Domains of the eHealth Literacy Model Assessed

Our findings showed that none of the 131 selected DHIs conducted in the last 20 years accounted for or assessed all six domains of the eHealth literacy model. Although these interventions were included because they assessed at least one domain of the model, only 5.3% (7/131) of studies included the assessment of more than one domain. These 7 studies assessed only digital and health literacy. Our study also shows that most DHIs have assessed and evaluated health literacy [19] among intervention participants, which is an important factor that can determine the health outcomes of a study [21,31,32]. Although the focus on health literacy in DHIs is consistent with some literature reviews combining the study of health literacy identified through our searches [5,22,26,34,35,49], it is somewhat surprising that none of the other four domains of the eHealth literacy model were concomitantly addressed.

There are numerous explanations for these findings. First, researchers specialized in DHIs might not be familiar with or might have ignored the original model, even though the seminal paper by Norman and Skinner [9] and the paper describing the eHEALS [24] are highly cited (as of October 17, 2020, Google Scholar showed 1128 and 1450 citations, respectively). Second, researchers might have decided to focus on other domains of the model while making implicit or explicit assumptions about the levels of literacy in other domains. For example, the limited evidence related to the assessment of the domains of scientific, information, media, and functional literacy might be based on the assumption that digital literacy instruments, such as the popular eHEALS [24], include questions related to the use of information on the internet as a medium of search information; hence, these could be associated with media and information literacy domains. However, there exist several instruments that specifically assess media literacy [76,77], scientific literacy [78,79], and information literacy [80,81]. Moreover, Norman and Skinner [9] did not consider overlapping elements when they developed the eHealth literacy model, which considers the six domains as distinct and separate.

Although intervention designers should aim to develop content that is understood by people with low functional literacy [82,83], this fact should be proven or verified by the same intervention designers. One way to do so is to assess functional literacy or to report the level of literacy rather than to just develop the content of the intervention through formal readability and usability testing. The fact that other domains of the eHealth literacy model were not always conducted raises concerns about the generalizability of such interventions across the eHealth literacy spectrum. DHIs tend to attract tech-savvy, healthy volunteers who have access to technology and who might have different sociodemographic and psychological profiles compared with people who belong to vulnerable segments of the population and do not have access to technology [30].

Another important finding was that few identified DHIs assessed digital literacy (n=26). Not assessing digital literacy is based on the assumption that all participants are equally able to use technology and are able to make sense of the information delivered. This assumption might not be tenable in all contexts, and it does not allow researchers to understand whether participants appropriately received the intervention. In other words, health literacy is context-specific and varies according to different situations and topics. Arguably, health and digital literacy might act as moderators of intervention effects and not including these factors might underestimate or overestimate intervention effects [84].

The limited assessment of digital literacy in DHIs also raises some ethical considerations in terms of equity and social justice, as these interventions tend to attract highly educated, healthy, and digitally literate individuals who have easy access to technology, leaving out less-educated and poorer segments of the population, who may be most in need of the interventions themselves [30,85]. This selection bias isolates segments of the population that are traditionally difficult to reach [86,87], yet it is important to acknowledge that the results of DHIs might be less generalizable than interventions that do not use technology.

Another reason for the absence of a comprehensive and accurate assessment of the six domains of the eHealth literacy model might be due to the fact that this assessment will be unfeasible and daunting for the participants. Holding constant the basic or functional literacy (ie, numeracy and ability to read), assessing all six domains using existing scales for media, scientific, health, digital, and information literacy would require longer questionnaires that will take more time to complete, which might discourage participation in these studies. For example, one of the most used instruments to assess digital literacy is the relatively short (8 items) eHEALS [24]. However, for context-specific domains such as health literacy [9], there are many more instruments available, which vary in length and complexity [25,88]. A recent review identified 43 different instruments [89], and the Health Literacy Toolshed database included 200 measures [90]. Similar issues of measurement pertain to the assessment of literacy in a digital world [91], including media literacy [92]. Nevertheless, we urge digital health researchers to find ways to assess and evaluate the different domains of the eHealth literacy model, so that they can gain a better understanding of the study participants' characteristics, abilities, and needs. If measuring all domains might appear unfeasible, we suggest that DHI researchers prioritize the assessment of digital literacy—using the short eHEALS [24]—and health literacy, which is context specific, according to the model by Norman and Skinner [9]. Once the health topic or context is defined (mental health, breast cancer, etc), the choice of a short, yet valid instrument to assess health literacy in that context would become easier. As digital health and health literacy can change due to the intervention itself, we recommend assessing these constructs before and after the intervention. Finally, media, scientific, and traditional literacy are analytical skills that are not specific to any context; it would be easier for researchers to routinely assess these domains before the start of any intervention.

Health Conditions Addressed and Technologies Used

This scoping review showed that the selected DHIs published in the last 20 years focused mostly on NCDs, delivered via web- or mobile-based platforms. This is consistent with the findings of a few recent scoping reviews focusing on research on DHIs for behavior change [93,94] or in a recent bibliometric analysis of mHealth apps [69]. Although most DHIs have covered NCDs and mental health, there are many avenues for digital health. Further systematic reviews could be developed to specifically qualify and quantify the effectiveness of DHIs delivered via web or mobile phones in reducing NCDs and mental health issues. These systematic reviews could also anticipate sensitivity analyses based on the modes of delivery, length of the interventions, or the assessment of eHealth literacy model domains. This scoping review provides a valuable map of the evidence and sets the research agenda for DHIs in the coming years.

Strengths and Limitations

To the best of our knowledge, this is the first scoping review that systematically examined evidence pertaining to the application of the eHealth literacy model by Norman and Skinner [9] in DHIs. We looked at the highest quality of evidence, following a predetermined search strategy and a systematic approach to appraise the literature, without restricting our searches to specific periods, populations, countries, or health conditions. Nevertheless, this study has some limitations that are common to many other systematic or scoping reviews. These limitations include the fact that we looked only at peer-reviewed articles available in English. It is possible that some evidence on the use of the eHealth literacy model could have been reported in non–peer-reviewed or gray literature. Another limitation is related to the use of an RCT filter and focus on the RCT study design. Although RCTs provide the highest level of evidence, according to Grading of Recommendations Assessment, Development and Evaluation standards [40], it might be possible that some relevant research entailed the use of other types of study designs.

Conclusions

This review suggests that future DHIs should focus more on the assessment of the eHealth literacy domains when developing a DHI, especially the domains that are assessed the least, such as scientific, media, basic, and information literacy. Even though assessing all domains of the eHealth literacy model might be unfeasible, it would allow researchers to account for factors that might moderate or mediate the effects of the interventions on the targeted health outcomes.

Future systematic reviews should be conducted to examine the effects of DHIs on various health outcomes identified in this review by anticipating subgroup or sensitivity analyses comparing different types of intervention, delivery modes, and most importantly different levels of health literacy or digital literacy.

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Authors' Contributions

This study is the result of the Integrative Learning Experience carried out by MEB as a partial fulfillment of the Master of Public Health, offered by the Faculty of Health Sciences, American University of Beirut, Lebanon. TKK and FEJ acted as advisors and second readers of the project, respectively; MB acted as the project's preceptor and supervisor. MB and MEB conceived and designed the review and MB coordinated it. TKK and FEJ provided intellectual feedback in the development of the study. MEB and MB were involved in developing the search strategy, extracted the data, completed the analyses, and interpreted the data. MEB and MB drafted the manuscript. All authors have reviewed and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

MEDLINE search strategy.
[DOCX File , 25 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Records excluded during the full-text screening phase with full citations.
[DOCX File , 74 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Characteristics of included studies with references.
[DOCX File , 265 KB-Multimedia Appendix 3]

References

1. Eysenbach G. What is e-health? J Med Internet Res 2001;3(2):E20 [FREE Full text] [doi: 10.2196/jmir.3.2.e20] [Medline: 11720962]
2. Soobiah C, Cooper M, Kishimoto V, Bhatia RS, Scott T, Maloney S, et al. Identifying optimal frameworks to implement or evaluate digital health interventions: a scoping review protocol. BMJ Open 2020 Aug 13;10(8):e037643 [FREE Full text] [doi: 10.1136/bmjopen-2020-037643] [Medline: 32792444]
3. Classification of digital health interventions v1.0 : a shared language to describe the uses of digital technology for health. World Health Organization. 2018. URL: https://tinyurl.com/ybd4kedp [accessed 2021-05-17]
4. Elbert NJ, van Os-Medendorp H, van Renselaar W, Ekeland AG, van Roijen LH, Raat H, et al. Effectiveness and cost-effectiveness of ehealth interventions in somatic diseases: a systematic review of systematic reviews and meta-analyses. J Med Internet Res 2014 Apr 16;16(4):e110 [FREE Full text] [doi: 10.2196/jmir.2790] [Medline: 24739471]
5. Jacobs RJ, Lou JQ, Ownby RL, Caballero J. A systematic review of eHealth interventions to improve health literacy. Health Informatics J 2016 Jun;22(2):81-98 [FREE Full text] [doi: 10.1177/1460458214534092] [Medline: 24916567]
6. Bardus M, Smith JR, Samaha L, Abraham C. Mobile phone and web 2.0 technologies for weight management: a systematic scoping review. J Med Internet Res 2015 Nov 16;17(11):e259 [FREE Full text] [doi: 10.2196/jmir.5129] [Medline: 26573984]
7. Car J, Lang B, Colledge A, Ung C, Majeed A. Interventions for enhancing consumers' online health literacy. Cochrane Database Syst Rev 2011 Jun 15(6):CD007092 [FREE Full text] [doi: 10.1002/14651858.CD007092.pub2] [Medline: 21678364]
8. Diviani N, van den Putte B, Giani S, van Weert JC. Low health literacy and evaluation of online health information: a systematic review of the literature. J Med Internet Res 2015 May 07;17(5):e112 [FREE Full text] [doi: 10.2196/jmir.4018] [Medline: 25953147]
9. Norman CD, Skinner HA. eHealth literacy: essential skills for consumer health in a networked world. J Med Internet Res 2006 Jun 16;8(2):e9 [FREE Full text] [doi: 10.2196/jmir.8.2.e9] [Medline: 16867972]
10. Berkman ND, Davis TC, McCormack L. Health literacy: what is it? J Health Commun 2010;15 Suppl 2:9-19. [doi: 10.1080/10810730.2010.499985] [Medline: 20845189]
11. Sørensen K, Van den Broucke S, Fullam J, Doyle G, Pelikan J, Slonska Z, (HLS-EU) Consortium Health Literacy Project European. Health literacy and public health: a systematic review and integration of definitions and models. BMC Public Health 2012 Jan 25;12:80 [FREE Full text] [doi: 10.1186/1471-2458-12-80] [Medline: 22276600]
12. Lorini C, Santomauro F, Donzellini M, Capecchi L, Bechini A, Boccalini S, et al. Health literacy and vaccination: a systematic review. Hum Vaccin Immunother 2018 Feb 01;14(2):478-488 [FREE Full text] [doi: 10.1080/21645515.2017.1392423] [Medline: 29048987]
13. Cajita MI, Cajita TR, Han H. Health literacy and heart failure: a systematic review. J Cardiovasc Nurs 2016;31(2):121-130 [FREE Full text] [doi: 10.1097/JCN.0000000000000229] [Medline: 25569150]
14. Taylor DM, Fraser S, Dudley C, Oniscu GC, Tomson C, Ravanan R, ATTOM investigators. Health literacy and patient outcomes in chronic kidney disease: a systematic review. Nephrol Dial Transplant 2018 Sep 01;33(9):1545-1558. [doi: 10.1093/ndt/gfx293] [Medline: 29165627]
15. Ghisi GL, Chaves GS, Britto RR, Oh P. Health literacy and coronary artery disease: a systematic review. Patient Educ Couns 2018 Feb;101(2):177-184. [doi: 10.1016/j.pec.2017.09.002] [Medline: 28899710]
16. Firmino RT, Ferreira FM, Paiva SM, Granville-Garcia AF, Fraiz FC, Martins CC. Oral health literacy and associated oral conditions: a systematic review. J Am Dent Assoc 2017 Aug;148(8):604-613. [doi: 10.1016/j.adaj.2017.04.012] [Medline: 28477838]
17. Zheng M, Jin H, Shi N, Duan C, Wang D, Yu X, et al. The relationship between health literacy and quality of life: a systematic review and meta-analysis. Health Qual Life Outcomes 2018 Oct 16;16(1):201 [FREE Full text] [doi: 10.1186/s12955-018-1031-7] [Medline: 30326903]
18. Michou M, Panagiotakos DB, Costarelli V. Low health literacy and excess body weight: a systematic review. Cent Eur J Public Health 2018 Sep;26(3):234-241 [FREE Full text] [doi: 10.21101/cejph.a5172] [Medline: 30419628]
19. Chinn D. Critical health literacy: a review and critical analysis. Soc Sci Med 2011 Jul;73(1):60-67. [doi: 10.1016/j.socscimed.2011.04.004] [Medline: 21640456]
20. de Wit L, Fenenga C, Giammarchi C, di Furia L, Hutter I, de Winter A, et al. Community-based initiatives improving critical health literacy: a systematic review and meta-synthesis of qualitative evidence. BMC Public Health 2017 Jul 20;18(1):40 [FREE Full text] [doi: 10.1186/s12889-017-4570-7] [Medline: 28728547]
21. Fleary SA, Paasche-Orlow MK, Joseph P, Freund KM. The relationship between health literacy, cancer prevention beliefs, and cancer prevention behaviors. J Cancer Educ 2019 Oct;34(5):958-965 [FREE Full text] [doi: 10.1007/s13187-018-1400-2] [Medline: 30022378]
22. Chesser AK, Woods NK, Smothers K, Rogers N. Health literacy and older adults: a systematic review. Gerontol Geriatr Med 2016;2:A [FREE Full text] [doi: 10.1177/2333721416630492] [Medline: 28138488]

23. Norgaard O, Furstrand D, Klokker L, Karnoe A, Batterham R, Kayser L, et al. The e-health literacy framework: a conceptual framework for characterizing e-health users and their interaction with e-health systems. Knowl Manage E-Learn Int J 2015;7(4):540. [doi: 10.34105/j.kmel.2015.07.035]
24. Norman CD, Skinner HA. eHeals: the eHealth literacy scale. J Med Internet Res 2006 Nov 14;8(4):e27 [FREE Full text] [doi: 10.2196/jmir.8.4.e27] [Medline: 17213046]
25. Collins SA, Currie LM, Bakken S, Vawdrey DK, Stone PW. Health literacy screening instruments for eHealth applications: a systematic review. J Biomed Inform 2012 Jun;45(3):598-607 [FREE Full text] [doi: 10.1016/j.jbi.2012.04.001] [Medline: 22521719]
26. Kim H, Xie B. Health literacy in the eHealth era: a systematic review of the literature. Patient Educ Couns 2017 Jun;100(6):1073-1082. [doi: 10.1016/j.pec.2017.01.015] [Medline: 28174067]
27. Dominick G, Friedman D, Hoffman-Goetz L. Do we need to understand the technology to get to the science? A systematic review of the concept of computer literacy in preventive health programs. Health Edu J 2010 Mar 15;68(4):296-313. [doi: 10.1177/0017896909349289]
28. Hur I, Lee R, Schmidt J. How healthcare technology shapes health literacy? A systematic review. Healthcare Information Systems and Technology (Sighealth). 2015. URL: https://aisel.aisnet.org/amcis2015/HealthIS/GeneralPresentations/3/ [accessed 2021-05-17]
29. Hæsum LK, Ehlers L, Hejlesen O. Influence of health literacy on outcomes using telehomecare technology: a systematic review. Health Edu J 2015 Jan 09;75(1):72-83. [doi: 10.1177/0017896914565489]
30. Azzopardi-Muscat N, Sørensen K. Towards an equitable digital public health era: promoting equity through a health literacy perspective. Eur J Public Health 2019 Oct 01;29(Supplement_3):13-17 [FREE Full text] [doi: 10.1093/eurpub/ckz166] [Medline: 31738443]
31. Paasche-Orlow MK, Wolf MS. The causal pathways linking health literacy to health outcomes. Am J Health Behav 2007;31 Suppl 1:19-26. [doi: 10.5555/ajhb.2007.31.supp.S19] [Medline: 17931132]
32. Neter E, Brainin E. Association between health literacy, ehealth literacy, and health outcomes among patients with long-term conditions. Eur Psychol 2019 Jan;24(1):68-81. [doi: 10.1027/1016-9040/a000350]
33. Han H, Hong H, Starbird LE, Ge S, Ford AD, Renda S, et al. Ehealth literacy in people living with HIV: systematic review. JMIR Public Health Surveill 2018 Sep 10;4(3):e64 [FREE Full text] [doi: 10.2196/publichealth.9687] [Medline: 30201600]
34. Chesser A, Burke A, Reyes J, Rohrberg T. Navigating the digital divide: a systematic review of eHealth literacy in underserved populations in the United States. Inform Health Soc Care 2016;41(1):1-19. [doi: 10.3109/17538157.2014.948171] [Medline: 25710808]
35. Watkins I, Xie B. eHealth literacy interventions for older adults: a systematic review of the literature. J Med Internet Res 2014 Nov 10;16(11):e225 [FREE Full text] [doi: 10.2196/jmir.3318] [Medline: 25386719]
36. Stellefson M, Hanik B, Chaney B, Chaney D, Tennant B, Chavarria EA. eHealth literacy among college students: a systematic review with implications for eHealth education. J Med Internet Res 2011 Dec 01;13(4):e102 [FREE Full text] [doi: 10.2196/jmir.1703] [Medline: 22155629]
37. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol 2005 Feb;8(1):19-32. [doi: 10.1080/1364557032000119616]
38. Bardus M, Smith JR, Samaha L, Abraham C. Mobile and Web 2.0 interventions for weight management: an overview of review evidence and its methodological quality. Eur J Public Health 2016 Aug;26(4):602-610 [FREE Full text] [doi: 10.1093/eurpub/ckw090] [Medline: 27335330]
39. Bardus M, Rassi RE, Chahrour M, Akl EW, Raslan AS, Meho LI, et al. The use of social media to increase the impact of health research: systematic review. J Med Internet Res 2020 Jul 06;22(7):e15607 [FREE Full text] [doi: 10.2196/15607] [Medline: 32628113]
40. Burns PB, Rohrich RJ, Chung KC. The levels of evidence and their role in evidence-based medicine. Plast Reconstr Surg 2011 Jul;128(1):305-310 [FREE Full text] [doi: 10.1097/PRS.0b013e318219c171] [Medline: 21701348]
41. Aromataris E, Munn Z, editors. JBI manual for evidence synthesis. In: Joanna Briggs Institute Reviewer's Manual. Australia: JBI - The University of Adelaide; 2020.
42. Munn Z, Peters MD, Stern C, Tufanaru C, McArthur A, Aromataris E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. BMC Med Res Methodol 2018 Nov 19;18(1):143 [FREE Full text] [doi: 10.1186/s12874-018-0611-x] [Medline: 30453902]
43. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. Syst Rev 2016 Dec 05;5(1):210 [FREE Full text] [doi: 10.1186/s13643-016-0384-4] [Medline: 27919275]
44. Constantinides E, Fountain SJ. Web 2.0: Conceptual foundations and marketing issues. J Direct Data Digit Mark Pract 2008 Jan 4;9(3):231-244. [doi: 10.1057/palgrave.dddmp.4350098]
45. Bardus M. The web 2.0 and social media technologies for pervasive health communication: are they effec. Stud Commun Sci 2011;11(1):119-136. [doi: 10.5169/seals-791189]
46. Zobair K, Sanzogni L, Sandhu K, Islam M. Telemedicine adoption opportunities and challenges in the developing world. Eval Chall Opport Healthcare Ref 2020:193. [doi: 10.4018/978-1-7998-2949-2.ch008]

47. Häyrinen K, Saranto K, Nykänen P. Definition, structure, content, use and impacts of electronic health records: a review of the research literature. Int J Med Inform 2008 May;77(5):291-304. [doi: 10.1016/j.ijmedinf.2007.09.001] [Medline: 17951106]
48. Brørs G, Pettersen TR, Hansen TB, Fridlund B, Hølvold LB, Lund H, et al. Modes of e-Health delivery in secondary prevention programmes for patients with coronary artery disease: a systematic review. BMC Health Serv Res 2019 Jun 10;19(1):364 [FREE Full text] [doi: 10.1186/s12913-019-4106-1] [Medline: 31182100]
49. Carter MC, Burley VJ, Cade JE. Handheld electronic technology for weight loss in overweight/obese adults. Curr Obes Rep 2014 Sep;3(3):307-315. [doi: 10.1007/s13679-014-0112-0] [Medline: 26626760]
50. Taylor-Rodgers E, Batterham PJ. Evaluation of an online psychoeducation intervention to promote mental health help seeking attitudes and intentions among young adults: randomised controlled trial. J Affect Disord 2014 Oct 15;168:65-71. [doi: 10.1016/j.jad.2014.06.047] [Medline: 25038293]
51. Jorm AF, Kitchener BA, Fischer J, Cvetkovski S. Mental health first aid training by e-learning: a randomized controlled trial. Aust N Z J Psychiatry 2010 Dec;44(12):1072-1081. [doi: 10.3109/00048674.2010.516426] [Medline: 21070103]
52. Tse CK, Bridges SM, Srinivasan DP, Cheng BS. Social media in adolescent health literacy education: a pilot study. JMIR Res Protoc 2015 Mar 09;4(1):e18 [FREE Full text] [doi: 10.2196/resprot.3285] [Medline: 25757670]
53. Feinkohl I, Flemming D, Cress U, Kimmerle J. The impact of personality factors and preceding user comments on the processing of research findings on deep brain stimulation: a randomized controlled experiment in a simulated online forum. J Med Internet Res 2016 Mar 03;18(3):e59 [FREE Full text] [doi: 10.2196/jmir.4382] [Medline: 26940848]
54. Hui A, Wong PW, Fu K. Evaluation of an online campaign for promoting help-seeking attitudes for depression using a facebook advertisement: an online randomized controlled experiment. JMIR Ment Health 2015;2(1):e5 [FREE Full text] [doi: 10.2196/mental.3649] [Medline: 26543911]
55. Schougaard LM, Mejdahl CT, Petersen KH, Jessen A, de Thurah A, Sidenius P, et al. Effect of patient-initiated versus fixed-interval telePRO-based outpatient follow-up: study protocol for a pragmatic randomised controlled study. BMC Health Serv Res 2017 Jan 26;17(1):83 [FREE Full text] [doi: 10.1186/s12913-017-2015-8] [Medline: 28122609]
56. Navaneethan SD, Jolly SE, Schold JD, Arrigain S, Nakhoul G, Konig V, et al. Pragmatic randomized, controlled trial of patient navigators and enhanced personal health records in CKD. Clin J Am Soc Nephrol 2017 Sep 07;12(9):1418-1427 [FREE Full text] [doi: 10.2215/CJN.02100217] [Medline: 28778854]
57. Redfern J, Usherwood T, Harris MF, Rodgers A, Hayman N, Panaretto K, et al. A randomised controlled trial of a consumer-focused e-health strategy for cardiovascular risk management in primary care: the Consumer Navigation of Electronic Cardiovascular Tools (CONNECT) study protocol. BMJ Open 2014 Jan 31;4(2):e004523 [FREE Full text] [doi: 10.1136/bmjopen-2013-004523] [Medline: 24486732]
58. Khaleghi M, Shokravi FA, Peyman N, Moridi M. Evaluating the effect of educational interventions on health literacy through social networking services to promote students' quality of life. Korean J Fam Med 2019 May;40(3):188-193 [FREE Full text] [doi: 10.4082/kjfm.18.0060] [Medline: 30997783]
59. Parisod H, Pakarinen A, Axelin A, Löyttyniemi E, Smed J, Salanterä S. Feasibility of mobile health game "Fume" in supporting tobacco-related health literacy among early adolescents: a three-armed cluster randomized design. Int J Med Inform 2018 May;113:26-37. [doi: 10.1016/j.ijmedinf.2018.02.013] [Medline: 29602430]
60. Sanchez R, Brown E, Kocher K, DeRosier M. Improving children's mental health with a digital social skills development game: a randomized controlled efficacy trial of adventures aboard the S.S. GRIN. Games Health J 2017 Feb;6(1):19-27. [doi: 10.1089/g4h.2015.0108] [Medline: 28051877]
61. Cyan R, Hussain H, Shehki I, Ishaq Z, Khan T, Rothenberg R. Affordable technology for saving maternal and infant lives: moving on with solutions. Ann Glob Health 2016;82(3):382. [doi: 10.1016/j.aogh.2016.04.620]
62. Kamal AK, Muqeet A, Farhat K, Khalid W, Jamil A, Gowani A, et al. Using a tailored health information technology-driven intervention to improve health literacy and medication adherence in a Pakistani population with vascular disease (Talking Rx) - study protocol for a randomized controlled trial. Trials 2016 Mar 05;17(1):121 [FREE Full text] [doi: 10.1186/s13063-016-1244-1] [Medline: 26944938]
63. Rezvani F, Härter M, Dirmaier J. Promoting a home-based walking exercise using telephone-based health coaching and activity monitoring for patients with intermittent claudication (TeGeCoach): protocol for a randomized controlled trial. Psychother Psych Med 2018 Aug 06;68(08):e43. [doi: 10.1055/s-0038-1667988]
64. Dinesen B, Dittmann L, Gade JD, Jørgensen CK, Hollingdal M, Leth S, et al. "Future Patient" telerehabilitation for patients with heart failure: protocol for a randomized controlled trial. JMIR Res Protoc 2019 Sep 19;8(9):e14517 [FREE Full text] [doi: 10.2196/14517] [Medline: 31538944]
65. Mudiyanselage SB, Stevens J, Watts JJ, Toscano J, Kotowicz MA, Steinfort CL, et al. Personalised telehealth intervention for chronic disease management: a pilot randomised controlled trial. J Telemed Telecare 2019 Jul;25(6):343-352. [doi: 10.1177/1357633X18775850] [Medline: 29793387]
66. Sexual Health Empowerment for Women's Health. Clinical Trials. 2019. URL: https://clinicaltrials.gov/ct2/show/NCT03984695 [accessed 2021-05-17]
67. Duncan M, Vandelanotte C, Kolt GS, Rosenkranz RR, Caperchione CM, George ES, et al. Effectiveness of a web- and mobile phone-based intervention to promote physical activity and healthy eating in middle-aged males: randomized controlled

trial of the ManUp study. J Med Internet Res 2014 Jun 12;16(6):e136 [FREE Full text] [doi: 10.2196/jmir.3107] [Medline: 24927299]
68. Iyawa G, Herselman M, Botha A. A scoping review of digital health innovation ecosystems in developed and developing countries. In: Proceedings of the IST-Africa Week Conference (IST-Africa). 2017 Presented at: IST-Africa Week Conference (IST-Africa); May 30- June 2, 2017; Windhoek, Namibia. [doi: 10.23919/istafrica.2017.8102325]
69. Peng C, He M, Cutrona SL, Kiefe CI, Liu F, Wang Z. Theme trends and knowledge structure on mobile health apps: bibliometric analysis. JMIR Mhealth Uhealth 2020 Jul 27;8(7):e18212 [FREE Full text] [doi: 10.2196/18212] [Medline: 32716312]
70. Singh D. Publication bias - a reason for the decreased research output in developing countries. Afr J Psych 2006 Oct 02;9(3):153-155. [doi: 10.4314/ajpsy.v9i3.30216]
71. Mulimani P. Publication bias towards Western populations harms humanity. Nat Hum Behav 2019 Oct 10;3(10):1026-1027. [doi: 10.1038/s41562-019-0720-5] [Medline: 31602030]
72. Yousefi-Nooraie R, Shakiba B, Mortaz-Hejri S. Country development and manuscript selection bias: a review of published studies. BMC Med Res Methodol 2006 Aug 01;6:37 [FREE Full text] [doi: 10.1186/1471-2288-6-37] [Medline: 16879753]
73. Adelakun O, Garcia R. Technical factors in telemedicine adoption in extreme resource-poor countries. In: Global Health and Volunteering Beyond Borders. Switzerland: Springer; 2019:83-101.
74. Hyland K. Academic publishing and the myth of linguistic injustice. J Second Lang Writ 2016 Mar;31:58-69. [doi: 10.1016/j.jslw.2016.01.005]
75. Hyland K. Participation in publishing: the demoralizing discourse of disadvantage. In: Habibie P, Hyland K, editors. Novice Writers and Scholarly Publication. Switzerland: Palgrave Macmillan; 2018:13-33.
76. Ashley S, Maksl A, Craft S. Developing a news media literacy scale. Journal Mass Commun Educ 2013 Jan 02;68(1):7-21. [doi: 10.1177/1077695812469802]
77. Eristi B, Erdem C. Development of a media literacy skills scale. Contemp Educ Technol 2017;8(3):A. [doi: 10.30935/cedtech/6199]
78. Bybee R, McCrae B, Laurie R. PISA 2006: an assessment of scientific literacy. J Res Sci Teach 2009 Oct;46(8):865-883. [doi: 10.1002/tea.20333]
79. Harlen W. The assessment of scientific literacy in the OECD/PISA project. Stud Sci Educ 2001 Jan;36(1):79-103. [doi: 10.1080/03057260108560168]
80. Kurbanoglu SS, Akkoyunlu B, Umay A. Developing the information literacy self‐efficacy scale. J Doc 2006 Nov;62(6):730-743. [doi: 10.1108/00220410610714949]
81. Çoklar AN, Yaman ND, Yurdakul IK. Information literacy and digital nativity as determinants of online information search strategies. Comp Hum Behav 2017 May;70:1-9. [doi: 10.1016/j.chb.2016.12.050]
82. Mackert M, Kahlor L, Tyler D, Gustafson J. Designing e-health interventions for low-health-literate culturally diverse parents: addressing the obesity epidemic. Telemed J E Health 2009 Sep;15(7):672-677 [FREE Full text] [doi: 10.1089/tmj.2009.0012] [Medline: 19694596]
83. Mackert M, Champlin SE, Holton A, Muñoz II, Damásio MJ. eHealth and health literacy: a research methodology review. J Comput-Mediat Comm 2014 Apr 12;19(3):516-528. [doi: 10.1111/jcc4.12044]
84. Pelikan JM, Ganahl K, Roethlin F. Health literacy as a determinant, mediator and/or moderator of health: empirical models using the European Health Literacy Survey dataset. Glob Health Promot 2018 Nov 14:57-66. [doi: 10.1177/1757975918788300] [Medline: 30427258]
85. Bardus M, Hassan FA. eHealth for obesity prevention among low-income populations: is research is promoting health for all? Marco Bardus. Eur J Public Health 2016;26(1):77. [doi: 10.1093/eurpub/ckw166.010]
86. Glasgow RE. eHealth evaluation and dissemination research. Am J Prev Med 2007 May;32(5 Suppl):119-126. [doi: 10.1016/j.amepre.2007.01.023] [Medline: 17466816]
87. Atienza AA, Hesse BW, Baker TB, Abrams DB, Rimer BK, Croyle RT, et al. Critical issues in eHealth research. Am J Prev Med 2007 May;32(5 Suppl):71-74 [FREE Full text] [doi: 10.1016/j.amepre.2007.02.013] [Medline: 17466821]
88. Haun J, Luther S, Dodd V, Donaldson P. Measurement variation across health literacy assessments: implications for assessment selection in research and practice. J Health Commun 2012;17 Suppl 3:141-159. [doi: 10.1080/10810730.2012.712615] [Medline: 23030567]
89. Duell P, Wright D, Renzaho AM, Bhattacharya D. Optimal health literacy measurement for the clinical setting: a systematic review. Patient Educ Couns 2015 Nov;98(11):1295-1307. [doi: 10.1016/j.pec.2015.04.003] [Medline: 26162954]
90. Health Literacy Tool Shed. URL: https://healthliteracy.bu.edu/ [accessed 2021-05-17]
91. Jones-Kavalier BR, Flannigan SL. Connecting the digital dots : literacy of the 21st century. Educause Q. 2006. URL: https://er.educause.edu/-/media/files/articles/2006/4/eqm0621.pdf?la=en&hash=072FD518E173153E68975F73DA646847D9736291 [accessed 2021-05-17]
92. Ptaszek G. Media literacy outcomes, measurement. In: The International Encyclopedia of Media Literacy. Hoboken, New Jersey, United States: Wiley; 2019.

93. Joseph-Shehu EM, Ncama BP, Mooi N, Mashamba-Thompson TP. The use of information and communication technologies to promote healthy lifestyle behaviour: a systematic scoping review. BMJ Open 2019 Oct 28;9(10):e029872 [FREE Full text] [doi: 10.1136/bmjopen-2019-029872] [Medline: 31662364]
94. Taj F, Klein MC, van Halteren A. Digital health behavior change technology: bibliometric and scoping review of two decades of research. JMIR Mhealth Uhealth 2019 Dec 13;7(12):e13311 [FREE Full text] [doi: 10.2196/13311] [Medline: 31833836]

Abbreviations

DHI: digital health intervention
eHEALS: eHealth literacy scale
EHR: electronic health record
LMIC: low- and middle-income country
mHealth: mobile health
NCD: noncommunicable disease
PCC: Population-Concept-Context
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT: randomized controlled trial

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Original Paper

Validation of Visual and Auditory Digital Markers of Suicidality in Acutely Suicidal Psychiatric Inpatients: Proof-of-Concept Study

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Abstract

Background: Multiple symptoms of suicide risk have been assessed based on visual and auditory information, including flattened affect, reduced movement, and slowed speech. Objective quantification of such symptomatology from novel data sources can increase the sensitivity, scalability, and timeliness of suicide risk assessment.

Objective: We aimed to examine measurements extracted from video interviews using open-source deep learning algorithms to quantify facial, vocal, and movement behaviors in relation to suicide risk severity in recently admitted patients following a suicide attempt.

Methods: We utilized video to quantify facial, vocal, and movement markers associated with mood, emotion, and motor functioning from a structured clinical conversation in 20 patients admitted to a psychiatric hospital following a suicide risk attempt. Measures were calculated using open-source deep learning algorithms for processing facial expressivity, head movement, and vocal characteristics. Derived digital measures of flattened affect, reduced movement, and slowed speech were compared to suicide risk with the Beck Scale for Suicide Ideation controlling for age and sex, using multiple linear regression.

Results: Suicide severity was associated with multiple visual and auditory markers, including *speech prevalence* ($\beta=-0.68$, $P=.02$, $r^2=0.40$), *overall expressivity* ($\beta=-0.46$, $P=.10$, $r^2=0.27$), and head movement measured as *head pitch variability* ($\beta=-1.24$, $P=.006$, $r^2=0.48$) and *head yaw variability* ($\beta=-0.54$, $P=.06$, $r^2=0.32$).

Conclusions: Digital measurements of facial affect, movement, and speech prevalence demonstrated strong effect sizes and linear associations with the severity of suicidal ideation.

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KEYWORDS

digital phenotyping; digital biomarkers; digital health; depression; suicidal ideation; digital markers; digital; facial; suicide; suicide risk; visual; auditory

Introduction

Timely, efficient, sensitive, and noninvasive measurement approaches are required to improve suicide risk assessment [1]. One promising avenue is the use of remote digital monitoring methodologies that utilize smart devices, such as phones and wearables, in conjunction with deep learning algorithms to infer behavioral and physiological states associated with suicide risk [2,3].

While suicide risk is often comorbid with other mental disorders, in particular, major depressive disorder (MDD) and schizophrenia, suicidal behavior is increasingly recognized as unique in presentation and risk profile [4-7]. Based on prior knowledge, visual and auditory data sources represent a compelling direction in the objective measurement of behavior associated with suicide risk. Emil Kraepelin first observed that suicide risk was associated with melancholic states characterized by slowed speech, where patients appeared to "become mute in the middle of a sentence," and further observed how "the facial expression and the general attitude are sleepy and languid, the speech is low…" [8]. More contemporarily, reduced facial expressivity and movement measured using standardized coding schemes based on videos of patient interviews differentiated depressed patients with and without suicide risk [9], and altered vocal characteristics have been observed in acutely suicidal patients [5].

A number of visual and auditory characteristics can be directly quantified, including gross motor activity [10], head movement variability [11-13], facial activity [14], and properties of speech [15]. The automated measurement of these clinical features introduces the possibility of objective digital assessment of visual and auditory markers of suicide risk. Given that audio and video data sources can be captured remotely, this further introduces the possibility of greatly scaling the reach and frequency of assessment. Increased scale and objectivity can facilitate increased accuracy and accessibility of clinical risk and treatment response assessment.

Visual and auditory biomarkers were selected based on a mechanistic theory that reduced serotonin, a key risk factor for suicidal behavior and a primary biological target for treatment of MDD, will affect behavioral characteristics, including an individual's speech, head movement, and facial activity. Serotonergic tone is known to mechanistically impact motor functioning directly and via interactions with dopamine and norepinephrine signaling [16-18]. Depleted serotonin has been observed in the postmortem brains of individuals with MDD [19] and those who have committed suicide [20]. Furthermore, direct pharmacological manipulation of serotonin using selective serotonin reuptake inhibitors (SSRIs) increases suicide risk [21,22].

While novel measurements are promising, validation is required before such metrics can be interpreted clinically. Key steps for validation include comparison to traditional clinical measures, both cross-sectionally and as they change alongside treatment and disease course [23]. Such measures should strive to be easy to collect, should have increased sensitivity to facilitate frequent and accurate assessment, and should be validated in relationship to narrower biological phenotypes and treatment targets than traditional endpoints offer. This will lead to improved dynamic treatment research and clinical decision making based on modulation of underlying neurobiological deficits [24,25].

In this study, we examined measurements extracted from video interviews using open-source deep learning algorithms to quantify facial, vocal, and movement behaviors in relation to suicide risk severity in patients interviewed soon after admission to a psychiatric hospital following a suicide attempt.

Methods

Study Participants

Participants were recruited from the Psychiatric University Hospital, Zurich, Switzerland, as part of the "SIMON–Suicide Ideation MONitoring" study. The SIMON study has been funded by the Digital Lives initiative of the Swiss National Science Foundation (SNSF) and was approved by the ethics committee of the Faculty of Philosophy, University of Zurich (approval number: 19.2.1). The study aims to develop a digital protocol to monitor and predict suicidal ideation and hospital readmission in high-risk psychiatric patients. Digital markers of psychopathology are set to be derived from smartphone-based experience sampling, mobile passive sensing, and video recordings of patient free speech.

Patients were included in the study if they met the following criteria: (1) admission to the hospital after a suicide attempt or in the context of suicidal ideation, and suicidal ideation was identified in the first diagnostic intake interview, (2) sufficient knowledge of the German language, (3) being a smartphone user, and (4) discharge from the clinic after identification of suicidal ideation, with established outpatient care contact with a physician or psychologist. Patients were excluded if they met the following criteria: (1) planning to leave the greater Zurich area within the study period, (2) sharing a smartphone with another person, and (3) being active military personnel. Researchers kept track of all patients admitted to the hospital and contacted the treating psychologist or physician in case of eligibility. Patients who met the inclusion criteria and for whom an approval from the psychologist or physician was granted were informed about the study. If patients agreed to participate in the study, they were invited for a baseline assessment appointment that entailed the following: (1) detailed information about the study, (2) collection of informed consent signed by the patient, (3) assessment of current mental disorders with the Mini International Neuropsychiatric Interview (MINI; version 6), (4) a short videotaped semistructured qualitative interview (for which additional informed consent signed by the patient was obtained) upon agreement, (5) electronic/pen and paper questionnaires evaluating relevant psychological variables, and (6) smartphone app installation. Participants were reimbursed with up to CHF 120 (US $127).

At the time of the video assessment, all patients had an inpatient status at the Psychiatric University Hospital Zurich. We recruited patients admitted to the psychiatric hospital to ensure an appropriate reach and a sufficient sample size of the high-risk psychiatric patient group. For practical reasons and because of the format of the semistructured interviews (ie, questions asked by the researcher and video recordings with a tablet), we obtained video recordings during the baseline interview, when patients were still inpatients. However, the remaining parts of the study (ie, remote patient monitoring using smartphones) commenced after patients were discharged from the hospital. In that way, we assessed patient well-being and behavior in an ecologically valid manner outside the hospital. However, this study only focused on the video recordings from the time patients were inpatients.

Participants were recruited for the study on a rolling basis. At the time of the analysis, 30 patients agreed to participate in the videotaped interview, of whom 20 completed the necessary baseline questionnaires. Ultimately, the analysis was conducted on a sample of 20 patients.

Clinical Assessment of Suicidality

Assessment of suicide risk was completed at baseline. The Beck Scale for Suicide Ideation (BSS) questionnaire (German validated version) [26] was administered to evaluate patients' current intensity of attitudes, plans, and behaviors to commit suicide. Patients' history of nonsuicidal self-injury and suicide attempts was assessed using the following two self-report items from the Self-Injurious Thoughts and Behaviors Interview (SITBI): (1) "In your life, have you purposefully hurt yourself without wanting to die?" and (2) "How many times in your lifetime have you made an attempt to kill yourself during which you had at least some intent to die?" [27,28].

Collection of Video and Audio Data

At baseline, patients were given the choice of additionally participating in a video-recorded interview. Upon agreement, patients signed an informed consent form specific to this part of the study. A short videotaped semistructured qualitative interview was performed. A laptop was placed on the table in front of the patient, and 1-minute video and audio samples were recorded. During the qualitative video interview, participants answered introductory questions assessing their current state, as well as questions about experiences with different valences (ie, neutral, positive, and negative) and temporal dimensions (ie, past, present, and future). Overall, the following six video and audio samples, each at 1 minute, were recorded per participant: introduction (neutral present), neutral, positive past, positive future, negative past, and negative future. Multimedia Appendix 1 displays exemplary questions asked for each category. The conversation for each category starts with the central question (first in order) asked by the researcher, followed by additional questions to keep the participant involved and talking during the 1-minute recordings.

Machine Learning Computer Vision and Voice Analysis

All analyses were conducted in a Python environment using open-source tools. No novel machine learning models were trained for the purposes of this study, rather existing tools for the measurement of facial expressivity [29], vocal acoustics [30], and patterns of movement [31] were utilized. The code used to calculate the biomarkers has been compiled into its own open-source package, which allows for other researchers to replicate the methods used in this manuscript [32]. The videos were segmented to only include the participants' responses to the questionnaires, with behaviors during free speech cropped out and then concatenated for analysis of digital markers.

Facial Activity Analysis

Initially, all videos were segmented into frames, resulting in a minimum of 33 image frames per second. Thereafter, OpenCV, an open-source computer vision software package [33], was used to segment each image into three matrices consisting of red, blue, and green spectrum pixels. Subsequently, each frame was analyzed using OpenFace [29], an open source software package that has demonstrated validity next to expert human ratings of Facial Action Coding Scheme (FACS) [34], a standardized methodology to measure facial movements that reflect activity in the underlying human facial musculature utilized in the production of basic emotions. Specifically, for each frame, OpenFace outputs (1) a binary value indicating the presence of an action unit and (2) a continuous value indicating the intensity with which the action unit is being expressed. Action unit intensities were used to derive measures of individual emotional expressivity (ie, *happiness expressivity*, *sadness expressivity*, *fear expressivity*, *anger expressivity*, *surprise expressivity*, and *disgust expressivity*). Action unit intensities were also used to calculate *overall expressivity* regardless of emotion.

Movement Analysis

The angle of the head's pitch (up and down movement) and yaw (side to side movement) was acquired for each video frame using OpenFace. The standard deviations of the frame-wise pitch and yaw measurements were used as indicators of head movement (ie, *head pitch variability* and *head yaw variability*).

Voice Analysis

Recordings were segmented into speech and nonspeech parts using Parselmouth, an open-source software package utilized for vocal analysis [30]. The percentage of the audio file where speech was recorded as opposed to no speech (ie, *speech prevalence*) was calculated to represent how much the participant was talking given the length of the recording.

Data Analysis

Initially, BSS scores were regressed on all movement, facial, and audio markers controlling for age and sex using separate multiple linear regressions. Facial activity, movement, and voice are all behavioral characteristics that are influenced by both age and sex. Hence, it was important to conduct a multiple linear regression controlling for age and sex in order to remove the influence of those factors on the final comparisons between digital measures and BSS scores. In addition to significance testing, unique variance accounted for in BSS scores by the digital measures was assessed using Cohen *d* [35]. Following analysis of *overall expressivity*, the BSS was regressed on expressivity of each emotion correcting for multiple comparisons using false discovery rate adjustment to reduce *P*-value inflation due to chance.

Results

Suicide Severity

Suicidal ideation severity on the BSS across subjects was, on average, above the clinical cutoff of 9, indicating severe suicide risk (μ=10.9, σ=10.2, range 0-31) and an average count of three past suicide attempts (σ=6.9, range 0-30).

Facial Activity

Controlling for age and sex, *overall expressivity* demonstrated a significant negative linear association with BSS scores, indicating that decreased facial activity is associated with greater suicide risk (β=−0.46, *P*=.01, r^2=0.27). This indicates that facial activity decreases as suicide severity increases, with the strongest evidence in the context of facial expressions without emotional expressions.

To better understand if particular emotions contributed to the observation of *composite expressivity*, we regressed BSS scores with individual emotional expressivity, sex, and age. *P* values were adjusted using false discovery rate adjustment. Post-hoc analyses demonstrated significance using Benjamini-Hochberg adjusted *P* values for *sadness expressivity* (β=−0.68, *P*=.01, r^2=.43), *surprise expressivity* (β=−0.74, *P*=.002, r^2=0.53), and *disgust expressivity* (β=−0.64, *P*=.04, r^2=0.35), but not for *fear*, *anger*, and *happiness expressivity* (Table 1).

Table 1. Results from multiple linear regression between Beck Scale for Suicide Ideation questionnaire scores and digital measurements of facial expressivity, vocal behavior, and head movement, controlling for age and sex.

Predictor	Coefficient	Standard error	*t* (df)	*P* value	*F* (df)	R^2	Adjusted R^2	*P* value
Regression 1					0.9013 (1)	0.153	−0.017	.46
Constant	0.2020	0.380	0.531 (18)	.60				
Anger expressivity	−0.2456	0.322	−0.762 (18)	.46				
Age	0.0068	0.007	0.960 (18)	.35				
Sex	0.1167	0.172	0.680 (18)	.51				
Regression 2					2.6930 (1)	0.350	0.220	.08
Constant	0.1213	0.240	0.506 (18)	.62				
Disgust expressivity	−0.6401	0.278	−2.305 (18)	.04				
Age	0.0120	0.006	1.980 (18)	.07				
Sex	0.1422	0.146	0.972 (18)	.35				
Regression 3					1.0430 (1)	0.173	0.007	.40
Constant	0.2628	0.380	0.692 (18)	.50				
Fear expressivity	−0.3210	0.328	−0.978 (18)	.34				
Age	0.0060	0.007	0.842 (18)	.41				
Sex	0.1056	0.170	0.620 (18)	.54				
Regression 4					0.6834 (1)	0.120	−0.056	.58
Constant	0.0051	0.292	0.018 (18)	.99				
Happiness expressivity	−0.0228	0.255	−0.089 (18)	.93				
Age	0.0083	0.007	1.194 (18)	.25				
Sex	0.1517	0.178	0.852 (18)	.41				
Regression 5					3.7140 (1)	0.426	0.311	.04
Constant	0.4394	0.270	1.629 (18)	.12				
Sadness expressivity	−0.6785	0.240	−2.830 (18)	.01				
Age	0.0082	0.006	1.480 (18)	.16				
Sex	0.0345	0.152	−0.228 (18)	.82				
Regression 6					5.7130 (1)	0.533	0.440	.008
Constant	−0.0441	0.198	−0.223 (18)	.83				
Surprise expressivity	−0.7437	0.204	−3.645 (18)	.002				
Age	0.0143	0.005	2.734 (18)	.02				
Sex	0.2421	0.127	1.912 (18)	.08				
Regression 7					1.8200 (1)	0.267	0.120	.19
Constant	0.2881	0.300	0.961 (18)	.35				
Overall expressivity	−0.4585	0.264	−1.734 (18)	.10				
Age	0.0054	0.006	0.833 (18)	.42				
Sex	0.1947	0.158	1.234 (18)	.24				
Regression 8					3.3890 (1)	0.404	0.285	.046
Constant	0.3291	0.256	1.285 (18)	.22				
Speech prevalence	−0.6808	0.255	−2.674 (18)	.02				
Age	0.0057	0.006	0.991 (18)	.34				
Sex	0.3429	0.158	2.170 (18)	.047				
Regression 9					4.5330 (1)	0.476	0.371	.02

Predictor	Coefficient	Standard error	*t* (df)	*P* value	*F* (df)	R^2	Adjusted R^2	*P* value
Constant	0.4192	0.248	1.689 (18)	.11				
Head pitch variability	−1.2465	0.391	−3.189 (18)	.006				
Age	0.0124	0.005	2.294 (18)	.04				
Sex	−0.0342	0.143	−0.239 (18)	.81				
Regression 10					0.1170 (1)	0.317	0.181	.12
Constant	0.1006	0.245	0.411 (18)	.69				
Head yaw variability	−0.5408	0.260	−2.081 (18)	.06				
Age	0.0125	0.006	1.979 (18)	.07				
Sex	0.1723	0.150	1.146 (18)	.27				

Voice Analysis

Controlling for age and sex, *speech prevalence* demonstrated a significant negative linear association with BSS scores, indicating that suicide severity scores increased as speech decreased (β=−0.68; *P*=.02, r^2=0.40; Table 1).

Movement Analysis

Controlling for age and sex, both *head pitch variability* and *head yaw variability* demonstrated significant negative linear relationships with suicide severity (β_{pitch}=−1.24, *P*=.006, r^2=0.48; β_{yaw}=−0.54, *P*=.055, r^2=0.32), indicating that lower levels of head movement were associated with greater suicide severity scores (Table 1).

Discussion

We examined visual and auditory measures of facial activity, head movement, and speech production, which were all calculated using deep learning algorithms applied to open-ended clinical interviews with psychiatric patients following a suicide attempt. The goal of this work was to determine if key indicators of suicide severity could be measured in an objective and automated manner using video data captured during clinical interviews that provided structured questions, but were otherwise kept deliberately open to mimic psychiatric interviewing in routine care. Achieving this goal provides a proof of concept that suicide risk can be assessed through analysis of unstructured video interview data in conjunction with deep learning algorithms designed to measure clinical/behavioral characteristics.

Objective measurements of visual and auditory markers of suicidality calculated from videos of patient behavior can be useful in the context of psychiatric care and clinical research, in particular, if the measurements can be acquired without specialized hardware using video or audio from regular patient-clinician interactions, as has been demonstrated in this study. Such tools have applications in clinical practice as they can allow for remote measurement of symptomatology. For example, virtual clinic visits through video calls can involve digital measurements to assess mental health if such measurements are integrated into the technology utilized. Existing smartphone-based platforms allow for the collection of video and audio data and subsequent calculation of digital measures, and can be applied in out-patient settings to remotely acquire these measurements without adding further burden on the clinical staff [36-38]. Of course, such technologies face a great deal of challenges before they can be deployed in patient care, starting with further validation of methodologies, passage through regulatory review as dependable clinical measures, and adoption by health care professionals into their day-to-day clinical workflows [39]. Ultimately, methods that can provide remote, objective, and passive measurement of clinical functioning can greatly increase the reach of treatment development, dissemination, and personalization [25,40].

Finally, the studied markers were selected based on a mechanistic theory that reduced serotonin in the brain, a key risk factor for suicidal behavior, will manifest in behavioral characteristics, including those involving a patient's speech, head movement, and facial activity. These primary hypotheses were confirmed. Overall facial expressivity, speech activity, and head movement during spontaneous behavior, which are all downstream effects of motor slowing, were correlated with BSS scores. This work provides a proof of concept that proxy markers of underlying neurobiological functioning can be used to measure clinical risk. Demonstrating this indicates that there is potential to remotely measure more specific neurobiological phenotypes to determine risk or examine the response to treatment. For example, owing to suicide risk associated with SSRIs, there is a need for close clinical monitoring during the initiation of treatment. Similarly, such models may be useful to determine who would benefit from treatments that affect serotonergic tone. Ultimately, by measuring a more specific biologically based phenotype, there is greatly increased opportunity to improve sensitivity of measurement and specificity of treatment [24].

The work has key limitations. First, this work represents a proof of concept. The indicated markers for risk assessment or measurement of clinical severity should only be used in an exploratory manner until such markers can be validated in larger and more diverse clinical populations and settings. We need to directly determine the amount of video data needed and the clinically meaningful cutoffs to determine clinical functioning. It is likely that like traditional suicide risk assessment, multiple characteristics together are needed to determine risk or severity. Multiple digital measures can be combined to produce a more robust metric, but like traditional scale development, this requires larger samples from diverse populations. Importantly, the current work uses open-source software, and additionally, we have published our software methods. As such, there is no access barrier for researchers to implement identical methods to test and extend the current approach. An open-source approach lends itself to rapid replication, extension, and implementation.

Ultimately, this proof-of-concept study demonstrates that theoretically grounded visual and auditory digital measurements are valid as markers of suicide severity. This effort provided a digital approach akin to traditional clinical assessment whereby a skilled clinician listens to a patient and applies internal working models developed through years of experience to assess clinical functioning.

Conflicts of Interest

AA, VK, and VY are employed by and hold stock options in AiCure, LLC. The other authors have no conflicts to declare.

Multimedia Appendix 1

Exemplary questions for the six categories of the videotaped semistructured qualitative interview.
[DOCX File , 21 KB-Multimedia Appendix 1]

References

1. Claassen CA, National Action Alliance for Suicide Prevention Research Prioritization Task. The agenda development process of the United States' National Action Alliance for Suicide Prevention Research Prioritization Task Force. Crisis 2013 May;34(3):147-155. [doi: 10.1027/0227-5910/a000208] [Medline: 23628664]
2. Torous J, Walker R. Leveraging Digital Health and Machine Learning Toward Reducing Suicide-From Panacea to Practical Tool. JAMA Psychiatry 2019 Oct 01;76(10):999-1000 [FREE Full text] [doi: 10.1001/jamapsychiatry.2019.1231] [Medline: 31290952]
3. Vahabzadeh A, Sahin N, Kalali A. Digital Suicide Prevention: Can Technology Become a Game-changer? Innov Clin Neurosci 2016;13(5-6):16-20 [FREE Full text] [Medline: 27800282]
4. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders, 5th Edition. Washington, DC: American Psychiatric Association; 2013.
5. Cummins N, Scherer S, Krajewski J, Schnieder S, Epps J, Quatieri TF. A review of depression and suicide risk assessment using speech analysis. Speech Communication 2015 Jul;71:10-49. [doi: 10.1016/j.specom.2015.03.004]
6. Pompili M, Amador XF, Girardi P, Harkavy-Friedman J, Harrow M, Kaplan K, et al. Suicide risk in schizophrenia: learning from the past to change the future. Ann Gen Psychiatry 2007 Mar 16;6(1):1-22. [doi: 10.1186/1744-859x-6-10]
7. Sisti D, Mann JJ, Oquendo MA. Toward a Distinct Mental Disorder-Suicidal Behavior. JAMA Psychiatry 2020 Jul 01;77(7):661-662. [doi: 10.1001/jamapsychiatry.2020.0111] [Medline: 32186693]
8. Diefendorf AR, Kraepelin E. Clinical psychiatry: A textbook for students and physicians, abstracted and adapted from the 7th German edition of Kraepelin's Lehrbuch der Psychiatrie. New York, NY: MacMillan Co; 1907.
9. Heller M, Haynal V. Depression and Suicide Faces. In: Ekman P, Rosenberg EL, editors. What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS). Oxford, United Kingdom: Oxford University Press; 2005.
10. Buyukdura JS, McClintock SM, Croarkin PE. Psychomotor retardation in depression: biological underpinnings, measurement, and treatment. Prog Neuropsychopharmacol Biol Psychiatry 2011 Mar 30;35(2):395-409 [FREE Full text] [doi: 10.1016/j.pnpbp.2010.10.019] [Medline: 21044654]
11. Alghowinem S, Goecke R, Wagner M, Parkerx G, Breakspear M. Head Pose and Movement Analysis as an Indicator of Depression. 2013 Presented at: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction; September 2-5, 2013; Geneva, Switzerland. [doi: 10.1109/acii.2013.53]
12. Dibeklioglu H, Hammal Z, Cohn JF. Dynamic Multimodal Measurement of Depression Severity Using Deep Autoencoding. IEEE J. Biomed. Health Inform 2018 Mar;22(2):525-536. [doi: 10.1109/jbhi.2017.2676878]
13. Kim Y, Cheon S, Youm C, Son M, Kim JW. Depression and posture in patients with Parkinson's disease. Gait Posture 2018 Mar;61:81-85. [doi: 10.1016/j.gaitpost.2017.12.026] [Medline: 29306811]
14. Girard J, Cohn J, Mahoor M, Mavadati S, Rosenwald D. Social Risk and Depression: Evidence from Manual and Automatic Facial Expression Analysis. Proc Int Conf Autom Face Gesture Recognit 2013:1-8 [FREE Full text] [doi: 10.1109/FG.2013.6553748] [Medline: 24598859]
15. Garcia-Toro M, Talavera JA, Saiz-Ruiz J, Gonzalez A. Prosody impairment in depression measured through acoustic analysis. J Nerv Ment Dis 2000 Dec;188(12):824-829. [doi: 10.1097/00005053-200012000-00006] [Medline: 11191583]
16. El Mansari M, Guiard BP, Chernoloz O, Ghanbari R, Katz N, Blier P. Relevance of norepinephrine-dopamine interactions in the treatment of major depressive disorder. CNS Neurosci Ther 2010 Jul;16(3):e1-17 [FREE Full text] [doi: 10.1111/j.1755-5949.2010.00146.x] [Medline: 20406250]
17. Herrera-Guzmán I, Gudayol-Ferré E, Herrera-Guzmán D, Guàrdia-Olmos J, Hinojosa-Calvo E, Herrera-Abarca JE. Effects of selective serotonin reuptake and dual serotonergic-noradrenergic reuptake treatments on memory and mental processing

speed in patients with major depressive disorder. J Psychiatr Res 2009 Jul;43(9):855-863. [doi: 10.1016/j.jpsychires.2008.10.015] [Medline: 19128810]
18. Morrissette DA, Stahl SM. Modulating the serotonin system in the treatment of major depressive disorder. CNS Spectr 2014 Dec;19 Suppl 1:57-67; quiz 54. [doi: 10.1017/S1092852914000613] [Medline: 25544378]
19. Stockmeier CA. Involvement of serotonin in depression: evidence from postmortem and imaging studies of serotonin receptors and the serotonin transporter. Journal of Psychiatric Research 2003 Sep;37(5):357-373. [doi: 10.1016/s0022-3956(03)00050-5] [Medline: 12849929]
20. Stockmeier CA, Shapiro LA, Dilley GE, Kolli TN, Friedman L, Rajkowska G. Increase in serotonin-1A autoreceptors in the midbrain of suicide victims with major depression-postmortem evidence for decreased serotonin activity. J Neurosci 1998 Oct 15;18(18):7394-7401 [FREE Full text] [Medline: 9736659]
21. The Lancet. SSRIs: suicide risk and withdrawal. The Lancet 2003 Jun 14;361(9374):1999. [doi: 10.1016/S0140-6736(03)13671-9] [Medline: 12814704]
22. Wessely S, Kerwin R. Suicide risk and the SSRIs. JAMA 2004 Jul 21;292(3):379-381. [doi: 10.1001/jama.292.3.379] [Medline: 15265855]
23. Coravos A, Khozin S, Mandl KD. Developing and adopting safe and effective digital biomarkers to improve patient outcomes. npj Digit. Med 2019 Mar 11;2(1):40 [FREE Full text] [doi: 10.1038/s41746-019-0090-4] [Medline: 31304386]
24. Torous J, Onnela J, Keshavan M. New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. Transl Psychiatry 2017 Mar 07;7(3):e1053 [FREE Full text] [doi: 10.1038/tp.2017.25] [Medline: 28267146]
25. Lenze EJ, Rodebaugh TL, Nicol GE. A Framework for Advancing Precision Medicine in Clinical Trials for Mental Disorders. JAMA Psychiatry 2020 Jul 01;77(7):663-664. [doi: 10.1001/jamapsychiatry.2020.0114] [Medline: 32211837]
26. Kliem S, Lohmann A, Mößle T, Brähler E. German Beck Scale for Suicide Ideation (BSS): psychometric properties from a representative population survey. BMC Psychiatry 2017 Dec 04;17(1):389 [FREE Full text] [doi: 10.1186/s12888-017-1559-9] [Medline: 29202737]
27. Nock MK, Holmberg EB, Photos VI, Michel BD. Self-Injurious Thoughts and Behaviors Interview: development, reliability, and validity in an adolescent sample. Psychol Assess 2007 Oct;19(3):309-317. [doi: 10.1037/1040-3590.19.3.309] [Medline: 17845122]
28. Chu C, Hom MA, Stanley IH, Gai AR, Nock MK, Gutierrez PM, et al. Non-suicidal self-injury and suicidal thoughts and behaviors: A study of the explanatory roles of the interpersonal theory variables among military service members and veterans. J Consult Clin Psychol 2018 Jan;86(1):56-68 [FREE Full text] [doi: 10.1037/ccp0000262] [Medline: 29172592]
29. Brahmbhatt S. Introduction to Computer Vision and OpenCV. In: Practical OpenCV. Berkeley, CA: Apress; 2013:3-5.
30. Baltrusaitis T, Robinson P, Morency L. OpenFace: An open source facial behavior analysis toolkit. 2016 Presented at: 2016 IEEE Winter Conference on Applications of Computer Vision (WACV); March 7-10, 2016; Lake Placid, NY. [doi: 10.1109/wacv.2016.7477553]
31. Ekman P, Rosenberg E. What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS). Oxford, United Kingdom: Oxford University Press; 2005.
32. Jadoul Y, Thompson B, de Boer B. Introducing Parselmouth: A Python interface to Praat. Journal of Phonetics 2018 Nov;71:1-15. [doi: 10.1016/j.wocn.2018.07.001]
33. Cohen ML. An Adaptive R-Estimate. Fort Belvoir, VA: Defense Technical Information Center; 1980.
34. Insel TR. Digital phenotyping: a global tool for psychiatry. World Psychiatry 2018 Oct;17(3):276-277 [FREE Full text] [doi: 10.1002/wps.20550] [Medline: 30192103]
35. Abbas A. anzarabbas/ms_dbms_mdd_suicidality. GitHub, Inc. URL: https://github.com/anzarabbas/ms_dbms_mdd_suicidality [accessed 2021-01-15]
36. Galatzer-Levy I, Abbas A, Yadav V, Koesmahargyo V, Aghjayan A, Marecki S, et al. Remote digital measurement of visual and auditory markers of Major Depressive Disorder severity and treatment response. medRxiv Preprint posted online August 26, 2020. [doi: 10.1101/2020.08.24.20178004]
37. Galatzer-Levy IR, Abbas A, Koesmahargyo V, Yadav V, Perez-Rodriguez MM, Rosenfield P, et al. Facial and vocal markers of schizophrenia measured using remote smartphone assessments. medRxiv Preprint posted online December 4, 2020. [doi: 10.1101/2020.12.02.20219741]
38. Abbas A, Yadav V, Smith E, Ramjas E, Rutter SB, Benavides C, et al. Computer vision-based assessment of motor functioning in schizophrenia: Use of smartphones for remote measurement of schizophrenia symptomatology. medRxiv Preprint posted online July 25, 2020. [doi: 10.1101/2020.07.20.20158287]
39. Abbas A, Schultebraucks K, Galatzer-Levy I. Digital Measurement of Mental Health: Challenges, Promises, and Future Directions. Psychiatric Annals 2021 Jan 01;51(1):14-20. [doi: 10.3928/00485713-20201207-01]
40. Insel TR. Digital phenotyping: a global tool for psychiatry. World Psychiatry 2018 Oct;17(3):276-277 [FREE Full text] [doi: 10.1002/wps.20550] [Medline: 30192103]

Abbreviations

BSS: Beck Scale for Suicide Ideation
MDD: major depressive disorder
SSRI: selective serotonin reuptake inhibitor

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