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Viewpoint

Bringing the Public Health Informatics and Technology Workforce Together: The PHIAT Conference

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Abstract

The field of public health informatics has undergone significant evolution in recent years, and advancements in technology and its applications are imperative to address emerging public health challenges. Interdisciplinary approaches and training can assist with these challenges. In 2023, the inaugural Public Health Informatics and Technology (PHIAT) Conference was established as a hybrid 3-day conference at the University of California, San Diego, and online. The conference's goal was to establish a forum for academics and public health organizations to discuss and tackle new opportunities and challenges in public health informatics and technology. This paper provides an overview of the quest for interest, speakers and topics, evaluations from the attendees, and lessons learned to be implemented in future conferences.

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KEYWORDS

public health informatics; health informatics; technology; health technology; digital health; digital intervention; digital interventions; conference; health conference; health conferences; public health workforce; public health worker; public health workers; PHIAT Conference; PHIAT; public health; health surveillance

Introduction

In recent decades, the field of public health informatics has undergone significant evolution, propelled by advancements in technology and the imperative to address emerging public health challenges. From its early beginnings in manual data collection to the widespread adoption of electronic health records and sophisticated data analytics, public health informatics has played a pivotal role in revolutionizing health care data management and surveillance systems. This historical trajectory underscores the continuous efforts to leverage technology and data-driven approaches to enhance public health outcomes and address the complex needs of populations worldwide. As the field continues to grow and adapt, understanding its historical context provides valuable insights into its current state and future directions. Especially after the COVID-19 pandemic, public health informatics has continued to grow as a field, and as expected, workforce needs have and will continue to expand for health information fields [1].

According to the US Bureau of Labor Statistics, health information technologists and medical registrars have a job growth outlook of 16% over the next 10 years, with an average of 3100 position openings per year [2]. This includes specialized positions in public health informatics and technology. However, growing and expanding does not come without workforce issues, such as recruitment, diversity, retention, burnout, and posttraumatic stress disorder among public health, public health informatics, and technology workers, which was especially exacerbated by COVID-19 [3-5]. In addition to these challenges, although there is rising enrollment in public health programs, there are fewer graduates entering public health agencies [6,7].

There are US-based conferences, such as the American Public Health (APHA) Association Annual Meeting [8], AcademyHealth [9], and other public health conferences [10-13], as well as a range of technology conferences, such as the Associates of Computing Machinery (ACM) [14] and Institute of Electrical and Electronics Engineers (IEEE) [15] conferences; there is also the American Medical Informatics Association (AMIA) [16] conference for biomedical and clinical informatics. Nevertheless, few conferences are available to address the bridge between public health, informatics, and technology.

In 2023, the inaugural Public Health Informatics and Technology (PHIAT) Conference was held as a 3-day hybrid conference. The PHIAT Conference occurred with an in-person option on the third day at the University of California, San Diego. The aim of the conference was to create an environment for academia and public health organizations to discuss and address emerging public health challenges and opportunities specifically in and with informatics and technology [17].

Preliminary Research: Gathering Interest

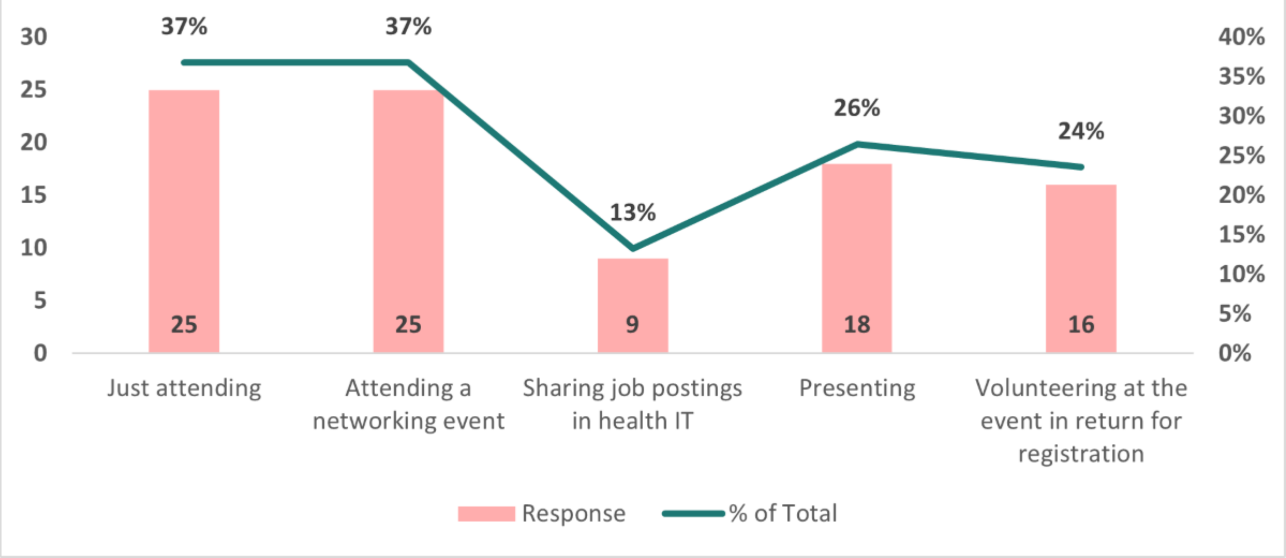
At the time of the first PHIAT Conference, we had not identified any public-facing events directly focused on public health informatics and technology. To gather interest and ideas on how and where to announce the conference, we designed a preliminary survey to understand the feasibility of a conference dedicated specifically to public health informatics and technology. The survey was shared with the AMIA Public Health Informatics Working Group [18], the APHA LinkedIn group [19], and the Chronic Disease Geographic Information Systems Basecamp group of public health agency practitioners [20].

The preliminary survey included both closed- and open-ended questions related to interest in the idea of a public health IT conference, likelihood of attending a conference in June of the same year, rating of specific public health topics, preferred conference format, likelihood of attending the conference in person, and preferred level of participation. The brief survey was fielded from February 2 to 6, 2023, with most responses in the first 2 days.

This initial survey resulted in 46 responses and indicated a strong interest in the conference. Most of the participants had general positive reactions and indicated a willingness to pay for and attend the hybrid conference. The response rates for each question varied because not all respondents answered every question, some of the questions allowed respondents to answer with more than 1 choice, and all questions were optional.

The data presented in Figure 1 use a scale of 1 to 5 to denote interest level (where 5 signifies high interest and 1 signifies low interest) in a public health IT conference. Most of the respondents (23/42, 55%) noted a high level of interest. Additionally, 40% (17/42) of respondents were moderately interested. Importantly, none of the respondents expressed a lack of interest in the public health IT conference. These statistics underscore a substantial demand for hosting more public health IT conferences in the future.

Figure 1. Interest in attending a public health IT conference.



Conclusions regarding the likelihood of attending a conference months after this survey can be drawn from the data displayed in Figure 2. Using a scale of 1 to 5 to indicate interest levels (where 5 denotes strong interest and 1 denotes low interest), 34% of total responses showed a moderate degree of interest in attending the public health IT conference (11/32; n=14 missing values). In addition, 31% (10/32) gave the conference a rating of either 5 or 4 on the scale, demonstrating a strong level of interest. The significant relevance and interest respondents have expressed in attending the public health IT conference are illustrated in Figure 2, which supports the earlier findings.

Figure 2. Likelihood of attending the conference in June 2023.

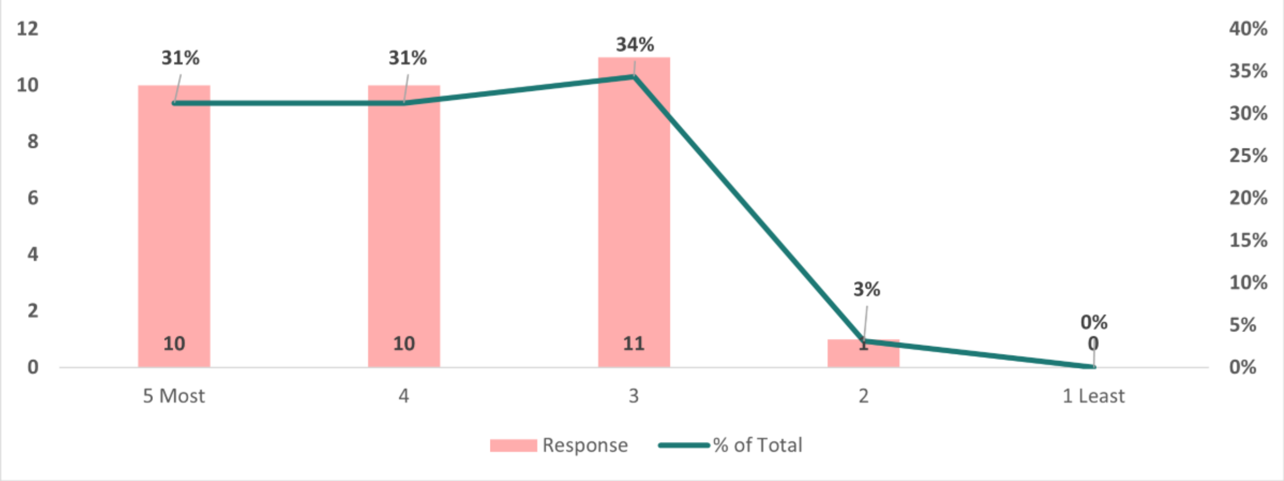
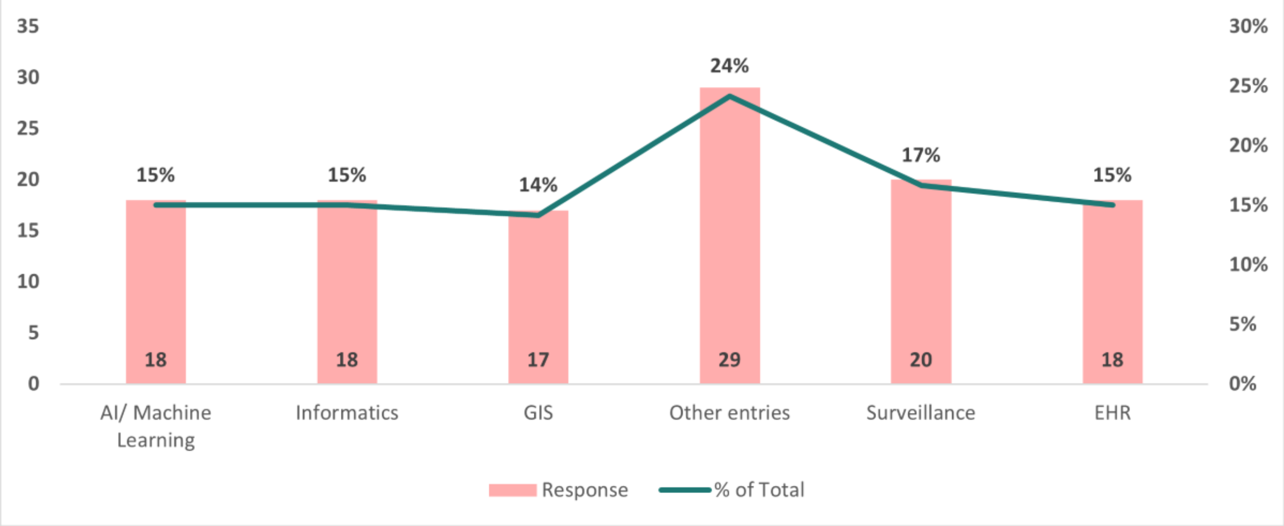


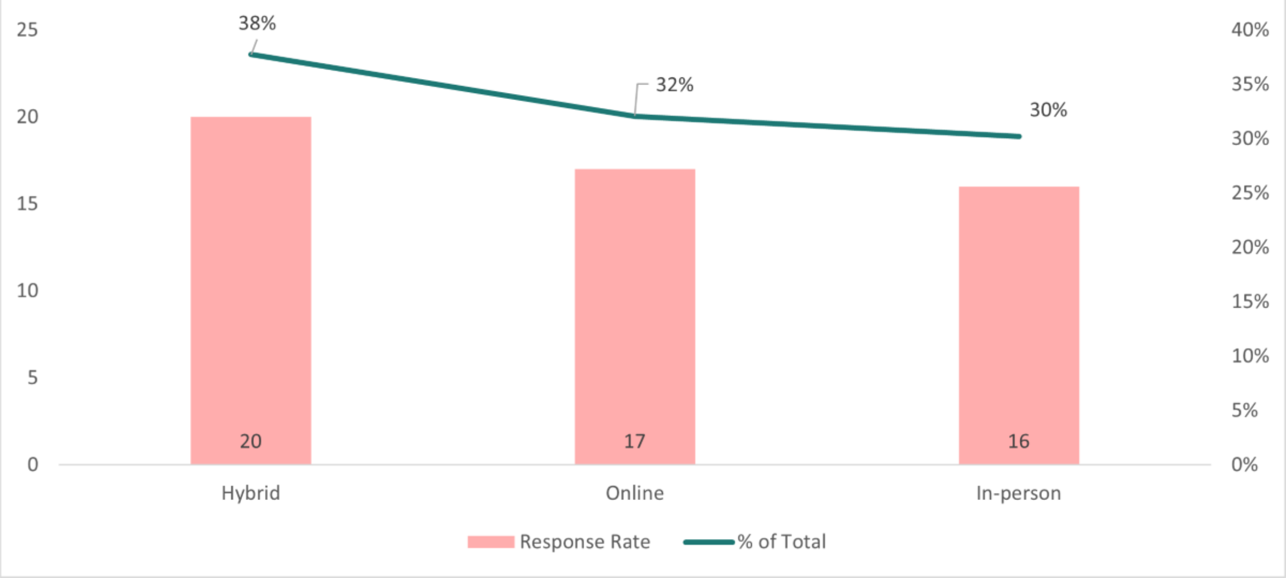
Figure 3 provides insights into the public health IT topics that piqued the interest of the respondents. These findings were valuable for this and future conference planning. The results indicated the following trends: the highest area of interest is categorized as “other entries,” such as public safety, alternatives to certain software, health information exchange and data sharing, and standards and guidance. Additionally, topics related to surveillance garnered significant attention, with 20 of 120 (17%) responses showing interest. The remaining topics garnered comparable levels of interest among respondents. Specifically, artificial intelligence (AI) and machine learning, electronic health records (EHRs), informatics, and geographic information systems (GISs) attracted similar levels of interest, each capturing 15% of the responses (18/120). Lastly, GISs received interest in 17 of 120 responses. These insights provide a comprehensive view of the preferences among the respondents for various public health IT topics.

Figure 3. Preferred public health IT conference topics.



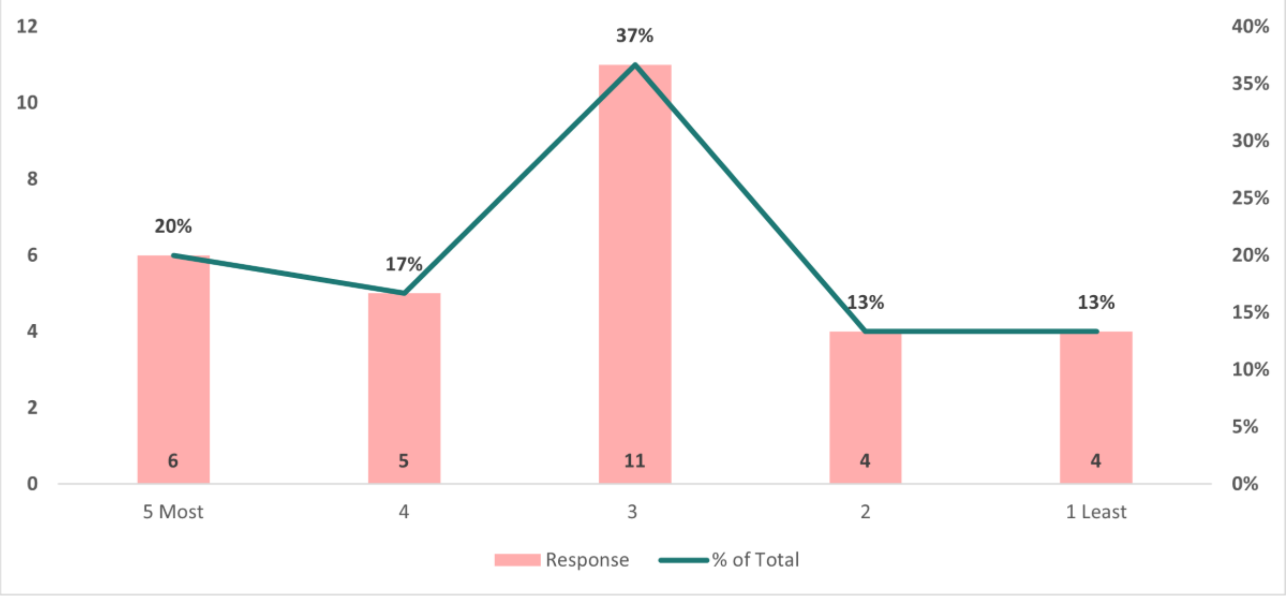
Based on the data presented in Figure 4, valuable insights can be gleaned regarding the potential formats for future public health IT events after the COVID-19 pandemic. These insights could be instrumental in guiding decisions on how to attract a greater number of participants while maintaining optimal learning effectiveness and efficiently budgeting the conference costs. Among the 53 responses, the preferred formats for a public health IT conference were as follows: 20 responses (38%) indicated a preference for a hybrid format; 17 responses (32%) expressed a preference for a web-based format; and 16 responses (30%) favored an in-person format. These findings provided a clearer understanding of the preferences of respondents regarding the format of the public health IT conference, thereby informing future planning and decision-making processes.

Figure 4. Preferred format for the conference.



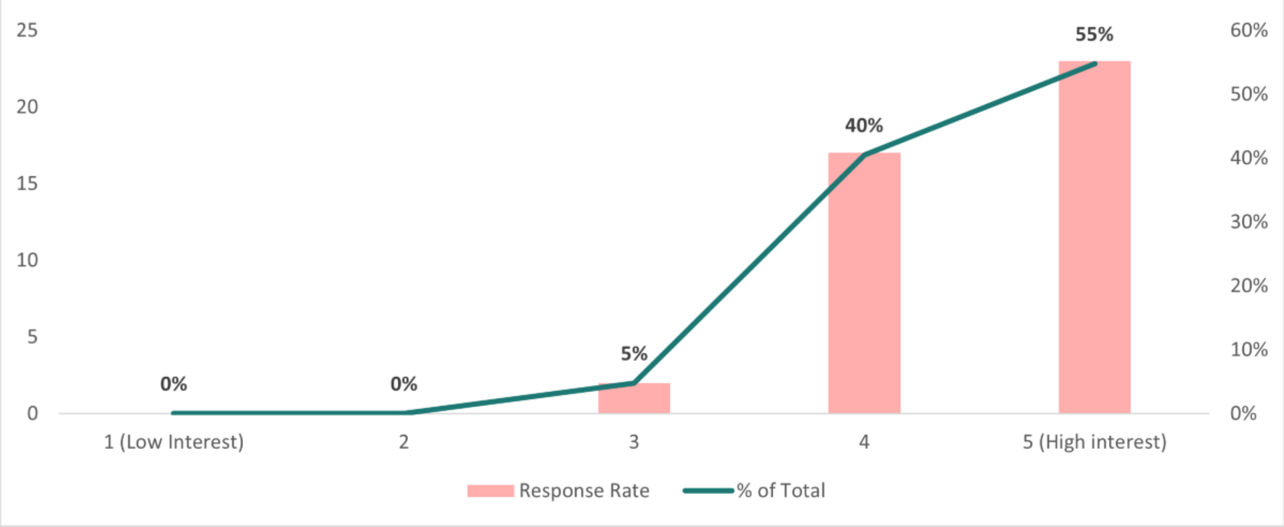
We extended our inquiry by posing a follow-up question based on the previous questions. Figure 5 offers valuable insights into the anticipated participation levels in public health IT events after COVID-19. Over time, this information will facilitate the observation of growth trends in the public health informatics IT conference landscape. Among the 30 total respondents, a majority, 11 individuals (37%), expressed their intention to participate in the conference. Notably, 6 respondents (20%) displayed a high likelihood of joining the conference in person in San Diego, California. Based on the groups that were selected to have access to the survey, these results provide a view of respondents' intentions to participate, aiding in gauging interest and contributing to future conference planning endeavors.

Figure 5. Likelihood of in-person attendance in San Diego, CA.



We polled various public health and technology interest groups to learn about their preferences and interests to further increase the value of a public health IT conference. Five different categories were clarified by the insights (Figure 6). These insights are crucial for tailoring the conference to meet the preferences of the participants. The survey outcomes highlighted the following preferences among the 68 responses: the most popular choice, preferred by 20 individuals (29%), was attending a networking event. Attending the conference exclusively was favored by 16 respondents (24%); 13 respondents (19%) expressed their interest in volunteering at the event in exchange for registration. Additionally, 12 individuals (18%) indicated their desire to present at the conference. Lastly, 7 respondents (10%) expressed interest in sharing job postings during the conference. These findings offer a comprehensive understanding of the attendees' preferences and aspirations, which will contribute to creating a well-rounded and engaging public health IT conference.

Figure 6. Preferred levels of participation.



Description of the Conference

Cross-Sector Collaborations

The PHIAT Conference was designed to include the latest academic research on public health informatics and technology. The event featured public health department representatives, academic researchers, and businesses sharing their innovative approaches to improving public health. We enjoyed providing this space for interaction and communication across these various sectors and look forward to continuing to cultivate these discussions to share public health informatics and technology best practices, policy implementations, case studies, and the latest innovative developments in the field.

Structure of the Conference

The hybrid nature of the conference allowed for academics, organization professionals, and students to attend either via video conferencing or in-person for the day 3 workshops during Pacific Standard Time. We found that this maximized the opportunity for individuals to be able to attend across demographic, socioeconomic, and geographic spaces where time, location, or cost were potentially constraining factors. The option of meeting either online or in person provided more opportunities for internationally based individuals to attend our conference. For example, speakers from other continents were able to present, sleep, and watch the rest of the event online without having to travel. Some were able to share prerecorded presentations and to participate online at a time-zone appropriate time, watch the recording, connect with other speakers, and submit their event feedback later. Additionally, students were able to register at a discounted rate and attend the event remotely if travel funding was a concern. Finally, attendees with logistical challenges were able to attend live for a short period of time, leave, and then return without the need to travel to the event.

Some presenters, such as the national coordinator for health IT and the presenters from Esri Health and Human Services and the Department of Biomedical Informatics of the University of California, San Diego, were personally invited to speak, due to their known expertise and our familiarity with their work. Additionally, many of the presenters were selected through their abstract submissions, quality of presentation, and suitability for the theme of the conference. A team of 5 individuals selected the abstracts, and talks were scheduled based on the theme of the day and time availability of speakers. In cases where the time zones were many hours apart, such as in Australia, presenters were given the opportunity to prerecord their sessions.

Event Overview

The first day of the event included a range of discussions, such as community solutions, AI, machine learning, data sharing, and health equity. There were a variety of organizations and teams represented, such as universities, health centers, community-based agencies, and researchers.

We began the event (Multimedia Appendix 1 includes a link to the agenda) with a presentation led by KSW on the status of the public health informatics workforce and workforce needs now and in the near future. We continued the event with many of our featured invited presenters. The national coordinator for health IT, Micky Tripathi, PhD, MPP, discussed the US federal health IT strategy and goals for interoperable infrastructure under TEFCA (Trusted Exchange Framework and Common Agreement), emphasizing further collaborations with qualified health information networks (QHINs).

As Nanette Star, MPH, of Esri's health and human services team mentioned on day 2 in her keynote speech, "pictures are worth a thousand words and maps are worth a thousand pictures." Her keynote speech was focused on understanding health GISs to answer questions, in addition to sharing some use cases for GISs in public health. Additionally, on day 2 AMA provided a talk on developing strategy for GIS leadership, including important points such as understanding why the map is made, who it is made for, and what is seen and remains unseen in the data provided.

The event provided space for discussion on emerging themes of blockchain technology for public health data security, presented by Tsung-ting Tim Kuo, PhD, of the University of California, San Diego, biomedical informatics department, who shared some of his National Institutes of Health–funded research on blockchain models for health. Findings from opioid-related disorder research through natural language processing for social media and GISs for health were presented by Anthony Corso, PhD, of California Baptist University.

A broader discussion on technology and innovation for public health was provided by Azizi Seixas, PhD, of the University of Miami Media Innovation Lab. The organizers also led a discussion on public health big data, AI, and ethical challenges, with great insight from attendees. We were very aware that many of our speakers did not have specific backgrounds in public health. Their topics were intentionally welcomed due to their importance and relevance for the possibilities of public health innovation, collaboration, adaptation, and framework development. They were also invited because public health professionals often have not yet been working with these topics.

On the final day of the event, we met in person at the campus of the University of California, San Diego, where we provided 2 workshops that were also available via video conferencing. One workshop was hosted by Ming Hsiang Tsou, PhD, of San Diego State University on big data and GISs for precision public health. This was followed by a workshop on artifact evaluation by Gondy Leroy, PhD, of the University of Arizona, followed by health informatics presentations from researchers at the University of California, San Diego, and a networking reception where participants had the opportunity to discuss their conference reflections, build new partnerships, and share their interest in the future conference next year.

Postconference Feedback

We conducted a postconference survey to gather insights from attendees' experience and feedback, aiming to better understand their preferences and optimize our marketing strategies for the PHIAT Conference in the future. Most of the respondents learned about this conference via email and word of mouth and from the Public Health Podcast Network [21] newsletters and monthly events. Attendees of this inaugural conference were drawn to it for the opportunity to advance their professional development.

The postconference survey asked why participants were interested in attending; their comments, with our responses, are shown in Table 1.

Table 1. Postconference survey comments from participants and our responses.

Comment	Response
"I'm a public health informatics epidemiologist and I am really interested to learn more about how we can make our informatics program more advanced and efficient."	PHIAT was designed with the public health workforce and academia in mind. With innovation and corporate development and academic partnerships, the goal was to improve the quality of public health data processes while fueling innovative ideas for research and development for positive public health implications.
"My position is focused on chronic disease informatics, and I was hoping to see examples of informatics methods and case studies using electronic health records or clinical data."	Developing workflows for electronic health data and building health information exchange infrastructure are continuing goals for public health, and another goal with the PHIAT Conference is to cultivate better processes for building public health informatics infrastructures. The use of informatics is still relatively new for public health departments, and this is often beyond the scope of departmental epidemiological methods. We hope to include more public health informatics professionals to speak at our conferences as the event becomes more established.
"I was very interested in hearing from guest speakers experienced in the IT side of public health and knew there would be a great variety in professionals sharing their knowledge."	There is a small percentage of public health professionals who have been trained in foundational IT skills, such as database development, the software development life cycle, and informatics frameworks, and we were excited to invite and bring these individuals together through the conference. We also intended to welcome new professionals and researchers into this field, either for their own research or professional development interests or to increase institutional knowledge at their public health departments.
"The main reasons for attending this conference were to foster and enhance professional growth and development. This public health informatics conference provides educational sessions (what tools can be used by combining machine learning and GIS), training workshops (how to develop a research question), and tutorials that focus on enhancing technical skills, understanding policy frameworks, and mastering health information technologies. Attending these meetings has allowed me to extend my horizons and keep ahead of the curve in my career."	The decision not to focus on one specific public health technological topic, such as epidemiological surveillance, and to focus on a broad range of topics in informatics and technology for public health professionals provided the opportunity for professionals to learn from a breadth and depth of knowledge. We hope that professionals had the opportunity to learn about ideas, topics, and developments that they had not heard of before. We also hope that attendees left the event with new ideas, approaches, and concepts to advance the quality of their work and their career development.

Respondents indicated an interest in a variety of educational seminars, training workshops, and tutorials at the conference with the goal of improving their personal technical proficiency, comprehending policy frameworks, and mastering health information technologies. They expressed a desire to learn more about developing research questions, using electronic health records and clinical data in informatics approaches and case studies, and merging machine learning and GIS technologies, which were topics covered in our conference sessions. One of the respondents said, "Attending these meetings helped me stay at the forefront of the field as a public health informatics epidemiologist with a focus on chronic illness informatics." In order to progress and refine their organization's informatics program for increased efficiency and effectiveness, attending meaningful conferences has been crucial. One participant indicated that they learned about the conference from other guest speakers well-versed in the IT side of public health, which is driven by an insatiable need for information. They excitedly embraced the chance to receive insightful knowledge and immerse themselves in a wide range of skills.

Attendee feedback highlighted several key aspects of their experience at the public health informatics conference. They commended Nanette Star’s presentation and the use of QR codes in the slides to enhance interactivity. The suggestion to include more presentations of this nature for future events was well received. Additionally, attendees expressed interest in hearing from major health care organizations regarding their use of community health care data and the impact of IT developments on care improvements. In relation to the timing of the conference, we received suggestions that the length of the conference remain 1-3 days with 4-5 hours a day of presentations and 3 hours for practice, questions, and discussions.

In terms of cost, based on the 3 day–long conference in San Diego, which included a valuable networking reception, participants suggested an average registration fee of US $400 per person. In addition, based on the financial considerations that some attendees might have, participants also sought opportunities for a discounted student rate and a reduced rate for professionals currently experiencing unemployment. Further suggestions included hiring professional teams to run the event, which would help us focus on moderating the panels. In order to enhance the conference experience, attendees also suggested adding interactive sessions with explicit discussion questions or expert panels. They observed that several themes appeared to be more concerned with public health than public health informatics, which suggests that the conference’s thematic substance can move toward becoming more focused on public health informatics technologies. Partnering with recognized public health informatics leaders or organizations, like the US Centers for Disease Control and Prevention’s Office of Informatics and Information Resources Management, was also advised.

Overall, there was general interest in the various topics of public health technology and precision public health and enthusiasm in the discussions.

Conclusion

The inaugural PHIAT Conference was an engaging, informative, and much-needed event providing public health professionals with information that many in the field were not previously familiar with. The technological side of public health is a crucial part of the future of health, yet many professionals are still new to the concepts of how AI, machine learning, and other technologies of precision public health can contribute to their organizations’ data and infrastructure capabilities.

Lessons Learned

We found a high level of interest in the topics presented and are looking forward to continuing these discussions to further build, support, and develop public health technological infrastructure. In addition, most attendees appreciated the interactive sessions with discussion questions and expert panels, suggesting that more such sessions be included in future events.

When asked in the postevent survey about their feedback for improvement, attendees provided their feedback, including the statements in Table 1.

We plan to continue the PHIAT Conference yearly and collaborate with additional institutions who work in public health informatics. At this time, we will continue to host the event in the San Diego or southern California area.

Future Plans

For the time being, the conference will be presented in 2 formats in alternate years. For 2024 and even-numbered years, the event will be a 1-day PHIAT summit event to continue with updates in the field by selected leaders in health IT, GISs, machine learning, modeling and simulation, and more to provide interim updates from policy and innovation perspectives. The event will return in odd-numbered years in the 3-day abstract submission format, highlighting new developments in various public health IT and informatics topics with discussion from academics, public health practitioners, and enterprises. To support event accessibility, we will likely continue to use an in-person, 3-day format for the next event, with the option to participate online as well for those who are unable to travel due to logistical or financial concerns. With the expansion of fellowships and programs in public health informatics and technology, we would like to collaborate and partner for a larger discussion on workforce preparedness. Additionally, we are seeking sponsorships to create a space for greater impact and reach in public health informatics and technology.

Acknowledgments

We would like to thank Gerardo Arellano, PhD, and the University of California, San Diego, Raza Resource Centro for providing space for the 2023 Public Health Informatics and Technology Conference (PHIAT) Conference, as well as our student volunteers Diana Carrillo, Joshua Chola, Valeria Vallejo-Montoya, and Rainaclare Sibal for assisting with the event.

Conflicts of Interest

AMA is the founder of the Public Health Media Network, which sponsored this event. The authors have no other conflicts to disclose.

Multimedia Appendix 1
The 2023 Public Health Informatics and Technology Conference Agenda Booklet.

[PDF File (Adobe PDF File), 5268 KB - ojphi_v16i1e55377_app1.pdf]

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Abbreviations

AI: artificial intelligence
EHR: electronic health record
GIS: geographic information system
ML: machine learning
PHIAT: Public Health Informatics and Technology
QHIN: qualified health information network
TEFCA: Trusted Exchange Framework and Common Agreement

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

A comparative review is presented of available technologies suitable for automatic reading of patient identification bracelet tags. Existing technologies' backgrounds, characteristics, advantages and disadvantages, are described in relation to their possible use by public health care centers with budgetary limitations. A comparative assessment is presented of suitable automatic identification systems based on graphic codes, both one- (1D) and two-dimensional (2D), printed on labels, as well as those based on radio frequency identification (RFID) tags. The analysis looks at the tradeoffs of these technologies to provide guidance to hospital administrator looking to deploy patient identification technology. The results suggest that affordable automatic patient identification systems can be easily and inexpensively implemented using 2D code printed on low cost bracelet labels, which can then be read and automatically decoded by ordinary mobile smart phones. Because of mobile smart phones' present versatility and ubiquity, the implantation and operation of 2D code, and especially Quick Response® (QR) Code, technology emerges as a very attractive alternative to automate the patients" identification processes in low-budget situations. Keywords— Patient identification, Automatic identification, 2D Codes, RFID, ID tags, EHR.

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Abstract

Health care consumers increasingly obtain health information from the Internet to inform their health care; the health care consumer, who also has the role of patient, maintains the right to access information from sources of their choosing for this purpose. However, noteworthy considerations exist including information appraisal skills, health literacy and the patient-provider relationship. Awareness and education are warranted to assist the health care consumer in achieving proficiency as they turn to the Internet for health information.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

The aim of this study was to examine the association between the local food environment and obesity proportions among 3- to 4-year-old children who were participants in the WIC program in Los Angeles County using spatial analyses techniques. Spatial analysis software, ArcGIS and Geoda, were used to compute the retail food environment index (RFEI) per ZIP code, to check for spatial autocorrelation and to control for permeability of the boundaries. Linear regression and ANOVA were used to examine the impact of the food environment on childhood obesity. Fast-food restaurants represented 30% and convenience stores represented 40% of the sum of food outlets in areas where WIC participants reside. Although there was no statistically significant association between RFEI and 3- to 4-year-old obesity proportions among WIC children, analysis of variance (ANOVA) tests demonstrated statistically significant positive associations between obesity and the number of convenience stores and the number of supermarkets. Our findings suggest that RFEI, as currently constructed, may not be the optimal way to capture the food environment. This study suggests that convenience stores and supermarkets are a likely source of excess calories for children in low-income households. Given the ubiquity of convenience stores in low-income neighborhoods, interventions to improve availability of healthy food in these stores should be part of the many approaches to addressing childhood obesity. This study adds to the literature by examining the validity of the RFEI and by demonstrating the need and illustrating the use of spatial analyses, using GeoDA, in the environment/obesity studies.

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Original Paper

The Association of Broadband Internet Use With Drug Overdose Mortality Rates in the United States: Cross-Sectional Analysis

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Abstract

Background: The availability and use of broadband internet play an increasingly important role in health care and public health.

Objective: This study examined the associations between broadband internet availability and use with drug overdose deaths in the United States.

Methods: We linked 2019 county-level drug overdose death data in restricted-access multiple causes of death files from the National Vital Statistics System at the US Centers for Disease Control and Prevention with the 2019 county-level broadband internet rollout data from the Federal Communications Commission and the 2019 county-level broadband usage data available from Microsoft's Airband Initiative. Cross-sectional analysis was performed with the fixed-effects regression method to assess the association of broadband internet availability and usage with opioid overdose deaths. Our model also controlled for county-level socioeconomic characteristics and county-level health policy variables.

Results: Overall, a 1% increase in broadband internet use was linked with a 1.2% increase in overall drug overdose deaths. No significant association was observed for broadband internet availability. Although similar positive associations were found for both male and female populations, the association varied across different age subgroups. The positive association on overall drug overdose deaths was the greatest among Hispanic and Non-Hispanic White populations.

Conclusions: Broadband internet use was positively associated with increased drug overdose deaths among the overall US population and some subpopulations, even after controlling for broadband availability, sociodemographic characteristics, unemployment, and median household income.

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KEYWORDS

opioids; broadband internet; mortality; public health; digital divide; access; availability; causal; association; correlation; overdose; drug abuse; addiction; substance abuse; demographic; United States; population

Introduction

Over 900,000 individuals have died from drug overdoses within the last 2 decades, posing a significant public health concern in the United States [1,2]. Opioids, either obtained illicitly or as a prescription, accounted for approximately 75% of the total drug overdose deaths in 2020 [1,2]. Recent numbers suggest an acceleration of both drug and opioid overdose deaths during the COVID-19 pandemic, with the United States experiencing the largest number of drug overdose deaths during this period (93,300 deaths) compared to that reported in any given year within the last 2 decades.

Internet access alongside digital literacy in general have been increasingly recognized as a “super” social determinant of health [3,4]. Access to broadband internet has been identified as a crucial public health issue (including its effect on the domain of access to credible information [5]) and a critical infrastructure for equitable access to health care, especially for underserved communities [6,7]. More specifically, the widening availability of broadband internet could potentially worsen the health inequalities in the United States, as it disproportionately impacts already marginalized groups such as racial/ethnic minorities, the older population, individuals with lower incomes, those with less education, and residents of rural areas [5]. According to the Federal Communications Commission (FCC), approximately 19 million individuals in the United States do not have access to a reliable broadband service, often referred to as reliable high-speed internet. This issue, termed the digital divide, primarily targets rural regions but also encompasses “segments of segregated urban areas that remain disconnected” [4]. Individuals with reduced income and less formal education are less inclined to possess a home broadband service or a mobile data plan subscription, necessitating their reliance on limited cell plan data or local public Wi-Fi hot spots [8,9].

Broadband internet access has been linked with disparities in various health outcomes, ranging from health information–seeking and health communication [10] to access to care during public health emergencies requiring remote care [11]. A recent US study demonstrated an association between lack of broadband coverage and adverse mental health outcomes [12]. In addition, access to broadband internet could affect drug and substance use through several channels. For instance, purchase of drugs via the internet is faster, anonymous, and less risky, which makes overall access to drugs easier; accordingly, the internet has been deemed a “pipeline for narcotics” [13]. Existing research indicates that in instances where drugs are easily accessible on the internet, there is a notable surge in the number of new and first-time users regardless of socioeconomic status [13]. Although, theoretically, increases in knowledge and information should lead to more optimal consumer choices, substantial networking opportunities may result in peers having a significant influence over health behaviors [14]. This raises the possibility that the marked growth in US drug abuse may have partially stemmed from the wider availability of illicit drugs on the internet [15].

The availability of telehealth through broadband internet is likely to reduce health disparities by connecting providers with individuals living in remote areas [6,7,16]. Telehealth brings specialized health care to communities where it was previously unavailable [17,18]. Thus, having access to and the ability to use broadband internet services can affect major public health outcomes such as drug overdose deaths.

Furthermore, access and usage data sets are critically important in building a full and accurate broadband internet map. Access data show current and future plans, while usage data help to understand how access translates into consumption. The aim of our study was to explore how broadband access and usage intersect with drug abuse by using access and usage data to elucidate the association of broadband internet with drug overdose mortality rates. In addition, given that in this time and age almost all counties have internet/mobile data plans in place, our study aimed to explore whether the emphasis should shift from broadband availability to actual usage, which is potentially the more relevant metric from a public health perspective.

Methods

Data Sources

Primary data for the study were obtained from three main sources: (1) 2019 county-level drug overdose death data from restricted-access multiple causes of death files available from the National Vital Statistics System (NVSS) at the US Centers for Disease Control and Prevention (CDC); (2) 2019 county-level broadband internet rollout data from the FCC; and (3) 2019 county-level broadband usage data available from Microsoft’s Airband Initiative. In addition, county-level socioeconomic and demographic characteristics were gathered from the US Census Bureau and US Bureau of Labor Statistics.

All drug overdose deaths were measured per 10,000 persons per year by county. Following the CDC and NVSS guidelines, we used the Tenth Revision of the *International Classification of Diseases Clinical Modification* codes X40-X44 (unintentional), X60-X64 (intentional), X85 (homicide), and Y10-Y14 (undetermined) to identify all drug overdose deaths.

Ethical Considerations

As this was a secondary data analysis, there was no requirement of approval from an institutional review board.

Statistical Analysis

Data analysis was performed using descriptive analysis and a cross-sectional regression analysis. In addition to examining the effects of broadband availability and usage on drug overdose deaths, we investigated how these effects vary based on different subpopulations and location characteristics.

The one-way fixed-effects regression equation used for this analysis was:

$$Y_j = \alpha_0 + \partial BB_j + \beta X_j + \delta_s + \varepsilon_s$$

where Y_j is the outcome variable for county j. The BB_j vector indicates the broadband internet availability and usage in a given county during 2019. Internet availability was measured as the percentage of people per county with access to fixed terrestrial broadband at minimum speeds of 25 Mbps/3 Mbps. Internet usage was measured as the percentage of people per county that use the internet at broadband speeds based on the methodology provided by Microsoft.

Microsoft estimates broadband usage by combining data from multiple Microsoft services. These data are combined with the number of households per county and zip code. While Microsoft suppresses any location with less than 20 devices in zip code–level data, this is not an issue for the county-level data used in our study. Every time a device receives an update or connects to a Microsoft service, Microsoft estimates the throughput speed of a machine. To calculate the broadband speed, they use the size of the package sent to the computer and the total time of the download. They determine the zip code–level location data via the reverse IP. Therefore, they can count the number of devices that have connected to the internet at broadband speed for each zip code based on the FCC's definition of broadband, which is 25 Mbps per download. The zip code–level data were then aggregated to the county level. Microsoft's data might be more representative in regions where its products are more widely used and less representative in regions where its products have lower penetration rates. Since Microsoft's data primarily come from devices running Windows operating systems and services such as Bing, Edge browser, and Xbox, this might skew the data toward certain types of devices and services and may not capture the full spectrum of internet-connected devices or platforms.

The coefficient on these variables (∂) captures the direct effect of broadband availability and usage on the outcome. X_j is a vector of observed socioeconomic and demographic characteristics of county j and ε_s is the error term. State fixed effects eliminate the omitted variable bias that may result from the time-invariant differences between states. The analysis was performed using robust Huber-White standard errors to capture arbitrary within-county heteroscedasticity.

Results

The descriptive statistics showed that 1.71 drug overdose deaths occurred per 10,000 county population in 2019 in the United States. Although approximately 76.6% of people in a given county had access to broadband internet in 2019, only approximately 28% of people were using the internet at broadband speeds (Table 1).

Table 1. Summary statistics.

Variable	Counties, n	Mean (SD)
Outcome variables		
Drug overdose deaths[a]	3104	1.71 (1.48)
Internet availability (% of county population with access to broadband internet)	3104	76.627 (23.88)
Internet usage (% of county population using internet at broadband speeds)	3104	28.133 (19.027)
Kidney deaths[a]	3103	2.179 (1.721)
Non-Hispanic White deaths[a]	3104	1.917 (1.739)
Non-Hispanic Black deaths[a]	3093	2.718 (45.691)
Non-Hispanic other deaths[a]	3104	8.354 (35.53)
Hispanic deaths[a]	3104	0.844 (3.17)
Deaths for those with less than high school education[a]	3104	2.889 (4.101)
Deaths for those with some college education[a]	3104	4.173 (4.033)
Deaths for those with college education or higher[a]	3103	0.486 (1.446)
Male deaths[a]	3104	2.165 (2.138)
Female deaths[a]	3104	1.264 (1.446)
Deaths among those aged ≤19 years[a]	3103	0.1 (0.447)
Deaths among those aged 20-29 years[a]	3103	2.205 (3.554)
Deaths among those aged 30-39 years[a]	3104	3.796 (5.117)
Deaths among those age 40-49 years[a]	3104	3.244 (4.866)
Deaths among those aged 50-64 years[a]	3104	2.39 (3.048)
Deaths among those aged ≥65 years[a]	3104	3.108 (12.245)
Control variables		
Percent county poverty	3103	14.429 (5.772)
Percent population with no health insurance	3103	11.903 (5.108)
Net migration (the number of immigrants minus the number of emigrants in the county)	3104	192.543 (2937.949)
Percent of county population with a college degree or higher	3104	22.018 (9.566)
Median household income (US $)	3103	55,707.34 (14,456.62)
Percent of county population that is unemployed	3103	3.977 (1.41)
Share of population aged 20-34 years	3104	0.18 (0.037)
Share of population aged 35-49 years	3104	0.175 (0.019)
Share of population aged 50-64 years	3104	0.203 (0.024)
Share of population aged ≥65 years	3104	0.198 (0.047)
Share of the female population	3104	0.499 (0.022)
Share of the Black population	3104	0.094 (0.144)
Share of the Hispanic population	3104	0.097 (0.138)
Share of the Asian population	3104	0.015 (0.028)
Counties with population of ≥50,000 (dummy variable)	3104	0.319 (0.466)
Metro counties (dummy variable)	3104	0.374 (0.484)
Adjacent to an urban area (dummy variable)	3104	0.424 (0.494)
Rural county (dummy variable)	3104	0.201 (0.401)

[a] Measured per 10,000 of the total or specific subpopulation indicated.

The regression analysis results in Table 2 show that a 1% increase in broadband internet usage is significantly associated with a 1.2% increase in overall drug overdose deaths among the general population.

Table 2. Associations between broadband internet usage and drug overdose deaths.[a]

Variables	Drug overdose (full sample)	Drug overdose in counties with a population over 50,000	Drug overdose in counties with a population less than 50,000	Kidney disease–related deaths (full sample)
Internet usage, coefficient (robust SE)	0.012 (0.002)[b]	0.008 (0.004)[c]	0.008 (0.003)[d]	0.004 (0.003)[e]
Internet availability	Yes[f]	Yes	Yes	Yes
Socioeconomic variables	Yes	Yes	Yes	Yes
Demographic variables	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes
Robust standard errors	Yes	Yes	Yes	Yes
Number of observations	3103	990	2113	3103
Adjusted R^2	0.296	0.456	0.232	0.214

[a] The regression analysis includes the set of full control variables shown in Table 1.

[b] *P*<.001.

[c] *P*=.05.

[d] *P*=.007.

[e] *P*=.18.

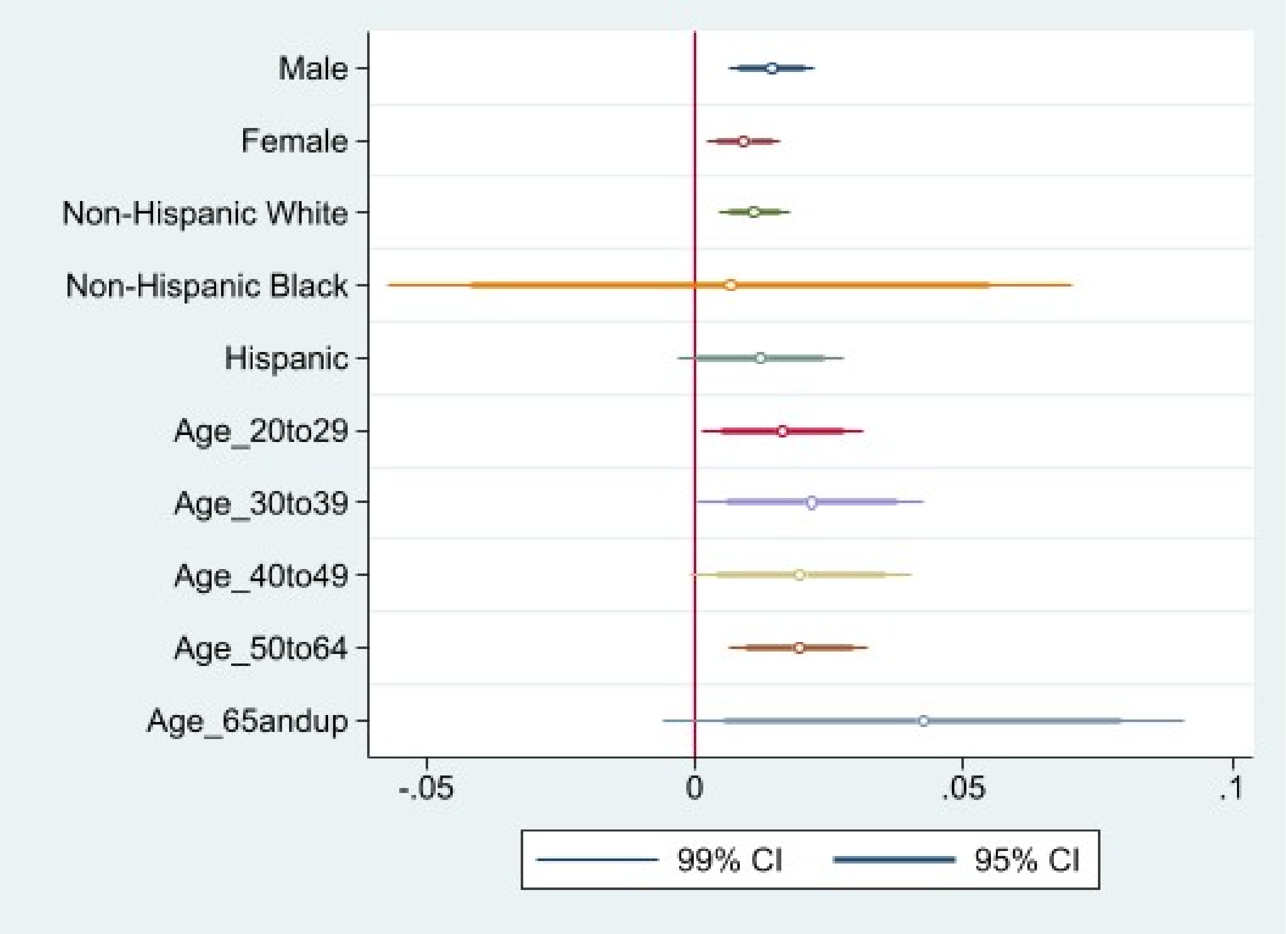
[f] Indicates inclusion of the variable as a control in the regression model; coefficients for subpopulations and the full set of controls are provided in Multimedia Appendix 1.

Splitting the sample into counties with a population more and less than 50,000 showed that the association result was primarily driven by the relationship between these variables in the less populated counties.

This association could result from the fact that the internet encourages greater consumption of drugs by making illegal drugs more accessible. Internet purchasing is more convenient and less risky because of anonymity. Furthermore, online drug sales could also be less risky for suppliers than offline sales. Thus, it is reasonable to expect broadband internet usage to improve market liquidity and spur both the demand and supply of illicit drugs. If this is the case, we would expect no significant association between broadband internet and mortality rates from chronic conditions. To test our assumption, we considered mortality rates associated with kidney disease, which is a chronic condition and should not be associated with internet availability. There was no association between internet availability/usage rates and kidney disease–related mortality rates (Table 2).

Further analysis revealed that different subpopulations are disproportionately affected by the associations between internet usage and drug-related deaths (see Figure 1). More specifically, Figure 1 shows that a 1% increase in internet usage is associated with a 1.1% increase in drug overdose deaths among the non-Hispanic White population, a 1.2% increase among the Hispanic population, a 1.4% increase among the male population, and a 1% increase among the female population. There appears to be no statistically significant association for the Non-Hispanic Black population, although the coefficient's SE is wide for this population because of the small sample size. Additionally, a 1% increase in broadband internet usage was significantly associated with a 1.7% increase in drug overdose deaths among those aged 20-29 years, a 2.2% increase among those aged 30-39 years, a 2% increase among those aged 40-49 years, a 1.9% increase among those aged 50-64 years, and a 4.3% increase among those 65 years and older compared with those 19 years and younger.

Figure 1. Associations between broadband internet usage and drug overdose deaths for different subpopulations. The figure presents the estimates of regression analysis where each variable is the dependent variable and the estimate shown is the coefficient of internet use as a dummy variable. Each regression includes the full controls shown in Table 1.



Discussion

Principal Findings

The findings of this study show that increased usage of broadband internet is positively and significantly associated with increased drug overdose deaths in the general US population as well as in several subpopulation categories, with the largest increase observed among the population 65 years and older compared with those 19 years and younger.

Our approach is novel in carefully distinguishing two different existing definitions of “broadband internet access” that are critical for studying its equity and potential impact on individual and community health outcomes: (1) its physical availability to individuals and communities (broadband availability) and (2) its adoption and effective use by those individuals and communities (broadband usage) [7,19,20]. Although no previous studies have examined the link between broadband internet usage and drug overdose deaths to our knowledge, there have been a few studies examining the link between drug abuse and the internet using the rollout of Craigslist [15], broadband internet subscription rates and opioid prescribing via telemedicine during COVID-19 [21], broadband internet and youth mental health [22], and broadband internet access and treatment admissions to substance use programs [23]. Specifically, one of the earliest studies examining the link between broadband internet access and drug abuse found that every 10% increase in the number of residential high-speed internet lines per capita at the state level was associated with a 1% increase in admissions to treatment programs for substance abuse [23]. Another study, using the phased rollout of Craigslist, a major web-based platform, found that Craigslist’s entry was associated with a 14.9% increase in drug abuse treatment admissions, a 5.7% increase in drug abuse violations, and a 6.0% increase in drug overdose deaths in the United States [15]. Although different in magnitude, these previous findings are in line with the results of this study, especially in terms of the direction of the effects of the internet on the health outcomes examined. Other researchers examining the link between broadband internet and youth mental health found similar directional effects of internet access. In particular, access to high-speed internet resulted in an increase in diagnoses of depression, anxiety, drug abuse, and personality disorders for the younger cohorts of both males and females but not for the older cohort [22]. In contrast, Oyler et al [21] found that broadband subscription rates (low and high) did not affect opioid prescriptions dispensed in Kentucky counties during the time period of Executive Order 2020-243 issued by the state’s governor on March 22, 2020, which limited nonurgent medical procedures in Kentucky to conserve personal protective equipment and medical supplies for patients with COVID-19.

These findings suggest that access to broadband internet may not affect legal prescriptions of opioids. Despite the heterogeneity, if taken together with previous research, our findings suggest that broadband internet usage may be contributing to the drug epidemic in the United States.

Strengths and Limitations

We should acknowledge that our measure of broadband internet availability does not include internet access via mobile phones. Unfortunately, these data are currently not available; thus, our estimation of the effect of broadband availability would be an underestimation. To obtain information on internet access via mobile use, we downloaded the American Community Survey (ACS) census data for 2021 and 2022, which were the two most recent years (along with 2016) with data available on two relevant questions. The first question was whether or not someone in the household uses or connects to the internet, regardless of whether or not they pay for the service. The second was whether or not anyone in the household has a data plan for a smartphone or other mobile device. Since the ACS does not provide the county Federal Information Processing Standard (FIPS) code for all observations, we could only identify the county FIPS codes for a subset of the respondents and only data for 2022 included FIPS codes for rural counties. Using the Economic Research Service–US Department of Agriculture rural-urban continuum codes [24] to classify rural counties, we found that 94.30% (n=21,733) of households in rural counties and 95.37% (n=1,897,961) in metro and urban counties had a household member with a data plan. Using the same sample and definition of rural, we also found that 97.22% (n=22,657) of households in rural counties and 96.71% (n=1,999,196) of households in metro and urban counties had a household member that uses or connects to the internet. Thus, the use of data plans and internet connection in rural areas is very similar to those in metro and urban areas. Another limitation is that we do not have data for a longitudinal study that could provide opportunities for examining causal relationships.

These limitations notwithstanding, the findings of this study underscore the importance of curbing illegal drug sales via web-based pharmacies and social networks. In addition, it is important for the Food and Drug Administration to monitor the shipping of medications to the United States from other countries. The results of this study emphasize the importance of tracking prescription drug use and sales on web-based platforms to better understand the amount and the types of transactions of prescription drugs taking place on these platforms and the role these platforms play in prescription drug abuse in the United States.

Finally, we have included controls in the regression model that mediate the association between internet connectivity and overdose rates, such as the percentage of uninsured population in a county, which, as expected, was negatively associated with overdose rates although not significantly. Even though determining the mediating effects of such variables was not within the scope of this study, research on the mediating effects of insurance availability, distance from medical resources, and other factors may be an important area for future research.

Conclusions

Broadband internet usage is positively associated with increased drug overdose deaths among the overall US population and some subpopulations, even after controlling for broadband availability, sociodemographic characteristics, unemployment, and median household income. These findings merit further investigation and can assist in policy shaping and thoughtful resource allocation to susceptible populations, especially in areas with recently improved broadband internet access.

Authors' Contributions

GK and VZH had full access to all the data in the study. These authors take full responsibility for the accuracy and integrity of the data and the analysis. IK and KT contributed substantially in writing the manuscript and interpreting the findings. All authors contributed to study concept and design; acquisition, analysis, or interpretation of data; and drafting of the manuscript. IK and KT critically reviewed the manuscript for important intellectual content. GK and VZH performed the statistical analysis.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Table S1: Associations between broadband internet usage and drug and overdose deaths; Table S2: Associations between broadband internet usage and drug and overdose deaths with coefficients for the full set of controls; Table S3: Associations between broadband internet usage and drug overdose deaths for different subpopulations with coefficients for the full set of controls.
[DOCX File , 34 KB - ojphi_v16i1e52686_app1.docx]

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Abbreviations

ACS: American Community Survey
CDC: Centers for Disease Control and Prevention
FCC: Federal Communications Commission
FIPS: Federal Information Processing Standard

NVSS: National Vital Statistics System

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

This paper describes the software architecture of a system designed in response to the health development potential of two concomitant trends in poor countries: i) The rapid expansion of community health worker deployment, now estimated to involve over a million workers in Africa and Asia, and ii) the global proliferation of mobile technology coverage and use. Known as the Mobile Technology for Community Health (MoTeCH) Initiative, our system adapts and integrates existing software applications for mobile data collection, electronic medical records, and interactive voice response to bridge health information gaps in rural Africa. MoTeCH calculates the upcoming schedule of care for each client and, when care is due, notifies the client and community health workers responsible for that client. MoTeCH also automates the aggregation of health status and health service delivery information for routine reports. The paper concludes with a summary of lessons learned and future system development needs.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

In this article the author outlines the key issues in the development of a regional health information infrastructure suitable for public health data collections. A set of 10 basic design and development principles as used and validated in the development of the successful New Zealand National Health Information Infrastructure in 1993 are put forward as a basis for future developments. The article emphasises the importance of securing clinical input into any health data that is collected, and suggests strategies whereby this may be achieved, including creating an information economy alongside the care economy. It is suggested that the role of government in such developments is to demonstrate leadership, to work with the sector to develop data, messaging and security standards, to establish key online indexes, to develop data warehouses and to create financial incentives for adoption of the infrastructure and the services it delivers to users. However experience suggests that government should refrain from getting involved in local care services data infrastructure, technology and management issues.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

Since taking office, President Obama has made substantial investments in promoting the diffusion of health information technology. The objective of the national health IT program is, generally, to enable health care providers to better manage patient care through secure use and sharing of health information. Through the use of technologies including electronic health records, providers can better maintain patient care information and facilitate communication, often improving care outcomes. The recent tornado in Joplin, MO highlights the importance of health information technology in the health center context, and illustrates the importance of secure electronic health information systems as a crucial element of disaster and business continuity planning. This article examines the experience of a community health center in the aftermath of the major tornado that swept through the American midwest in the spring of 2011, and provides insight into the planning for disaster survival and recovery as it relates to patient records and health center data.

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Original Paper

Acceptability of a Digital Adherence Tool Among Patients With Tuberculosis and Tuberculosis Care Providers in Kilimanjaro Region, Tanzania: Mixed Methods Study

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Abstract

Background: The World Health Organization has recommended digital adherence tools (DATs) as a promising intervention to improve antituberculosis drug adherence. However, the acceptability of DATs in resource-limited settings is not adequately studied.

Objective: We investigated the acceptability of a DAT among patients with tuberculosis (TB) and TB care providers in Kilimanjaro, Tanzania.

Methods: We conducted a convergent parallel mixed methods study among patients with TB and TB care providers participating in our 2-arm cluster randomized trial (REMIND-TB). The trial aimed to investigate whether the evriMED pillbox with reminder cues and adherence feedback effectively improves adherence to anti-TB treatment among patients with TB in Kilimanjaro, Tanzania. We conducted exit and in-depth interviews among patients as well as in-depth interviews among TB care providers in the intervention arm. We conducted a descriptive analysis of the quantitative data from exit interviews. Translated transcripts and memos were organized using NVivo software. We employed inductive and deductive thematic framework analysis, guided by Sekhon’s theoretical framework of acceptability.

Results: Out of the 245 patients who completed treatment, 100 (40.8%) were interviewed during exit interviews, and 18 patients and 15 TB care providers were interviewed in-depth. Our findings showed that the DAT was highly accepted: 83% (83/100) expressed satisfaction, 98% (98/100) reported positive experiences with DAT use, 78% (78/100) understood how the intervention works, and 92% (92/100) successfully used the pillbox. Good perceived effectiveness was reported by 84% (84/100) of the participants who noticed improved adherence, and many preferred continuing receiving reminders through SMS text messages, indicating high levels of self-efficacy. Ethical concerns were minimal, as 85 (85%) participants did not worry about remote monitoring. However, some participants felt burdened using DATs; 9 (9%) faced difficulties keeping the device at home, 12 (12%) were not pleased with receiving daily reminder SMS text messages, and 30 (30%) reported challenges related to mobile network connectivity issues. TB care providers accepted the intervention due to its perceived impact on treatment outcomes and behavior change in adherence counseling, and they demonstrated high level of intervention coherence.

Conclusions: DATs are highly acceptable in Tanzania. However, some barriers such as TB-related stigma and mobile network connectivity issues may limit acceptance.

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KEYWORDS

acceptability; digital adherence tool; medication reminder monitors; patients with tuberculosis; TB; adherence; TB care provider

Introduction

Tuberculosis (TB) is a significant public health problem and the second leading infectious killer after COVID-19 [1]. The World Health Organization has set a target in its “end TB strategy” to reduce TB deaths by 75% in 2025 and 90% in 2030 [2]. Tanzania is among the 30 countries with high TB burden and is estimated to have had a TB incidence of 208 per 100,000 persons and 1.3% of multidrug-resistant TB cases in 2021 [1]. In 2020, Tanzania reported that about 26,800 people died from TB [3]. TB is a curable disease if adequate treatment is implemented [4]. However, treatment adherence is a major challenge that hinders TB treatment efforts [5]. Insufficient adherence to TB medication is contributed by multiple factors such as the social context, health system, economic factors, patient-related factors (forgetfulness, low knowledge), health service accessibility, and drug-related factors such as drug side effects [6,7].

The World Health Organization has recommended digital adherence tools (DATs) that include SMS text messages, medication event monitoring devices, and video-observed treatment as promising interventions for improving TB adherence [8]. DATs can remind patients to take their medications, offer dose information, alert health care practitioners to risky behavior patterns, and allow health care practitioners to intervene when treatment is interrupted [9]. Furthermore, digital devices provide baseline information for health care providers during adherence counseling, patient motivation, replacement of interrupted medication, and scheduling clinic visits [8].

DATs have proven feasible in high- and low-resource settings [9-11]. Further, studies have shown that these devices have relatively high acceptability in Tanzania among people living with HIV, in Uganda and China among patients with drug-susceptible TB, and in South Africa among patients with multidrug-resistant TB [12-15]. However, literature indicates that the wide implementation of DATs in China has shown challenges, such that 11.3% refused to use DATs at enrollment and 8.2% refused to use DATs during treatment [16]. Another study in Vietnam showed that participants could not use the pillbox as required because they could not carry it to their workplace [17]. More evidence on the acceptability of DATs is needed to inform its large-scale implementation in resource-limited settings.

Investigating implementation research outcomes such as acceptability, feasibility, sustainability, and adoption is essential for identifying implementation bottlenecks that may hamper intervention effectiveness in a real-world setting [18]. In addition, when a health care intervention is not considered acceptable, it may affect health care providers’ perception and treatment delivery [19]. In this study, we aimed to investigate the acceptability of DATs among patients and TB care providers for improving adherence to anti-TB drugs among patients with TB in Kilimanjaro, Tanzania.

Methods

Study Design

We conducted a convergent parallel mixed methods study, which was embedded in our cluster randomized trial (REMIND-TB), among patients with TB and TB care providers.

Ethics Approval

This study was approved by the Kilimanjaro Christian Medical College research ethics and review committee (approval 1157, dated December 10, 2018) and the National Health Research ethics subcommittee (ref NIMR/HQ/R.8a/VolIX/2992, dated January 14, 2019). We registered the trial at the Pan African Clinical Trials Registry under PACTR201811755733759 on November 8, 2018.

REMIND-TB Trial

From 2019 to 2021, we conducted a 2-arm cluster randomized trial to investigate whether the evriMED pillbox with reminder cues and adherence feedback effectively improved adherence to anti-TB treatment among patients with TB in Kilimanjaro region in Tanzania. Study sites were randomized into 12 clusters: 6 intervention arms and 6 control arms. The inclusion criteria for the trial were patients’ diagnosis with presumptive sensitive TB, aged 18-65 years, attending care at any of the TB centers in the Kilimanjaro region of Tanzania, willing to use the evriMED pillbox, able to read and understand SMS text messages, and able to understand and willing to sign informed consent. Exclusion criteria were hospitalized patients and those who previously participated in similar studies. We provided each participant in the intervention arm with an evriMED1000 pillbox for their medication storage and intake. In the control arm, participants followed the standard of care procedures. In both arms, we followed participants for 6 months of treatment. In the evriMED arm, participants received a reminder SMS text message every day 30 minutes before their set time of taking medication. Detailed information about the REMIND-TB trial and the DAT can be found elsewhere [20].

evriMED Pillbox

The evriMED1000 is a type of tablet dispenser with a SIM card produced by Wisepill, based in South Africa. The pillbox records the opening of the box and stores the so-called medication events on a chip, along with the date and time whenever it is opened. This information is transmitted to a centralized server when one opens the device. Additionally, the evriMED1000 delivers a daily heartbeat event that includes information about the device’s identification, battery life, and signal quality. If the pillbox is not opened on a particular day, any pending events will be transmitted during the next heartbeat.

The evriMED1000 sends a reminder SMS text message to an individual’s mobile phone 30 minutes before intake time. If the individual does not take the medication within 1 hour of the intake period, a second reminder SMS text message is generated and sent. The patient does not require internet connectivity to receive the reminder SMS text message. The Wisepill pillbox uses a global roaming SIM chip that will connect to the best available mobile network in the area. These devices are designed to work in low-network resource settings (see Multimedia Appendix 1).

As the trial was an implementation study, TB care providers took full responsibility for participant care within their regular duties. They had to explain and demonstrate the use of the evriMED device to patients, provide medication through the device, and discuss adherence reports generated by the device during follow-up clinics. Participants were trained on device usage upon enrollment and were required to stay with it for the entire 6-month treatment period. Any challenges related to device functionality or misunderstandings were addressed through ongoing discussions between patients and care providers during follow-up visits.

Mixed Methods Study on Acceptability of DATs

Study Procedures

Enrolled participants from the intervention arm of the REMIND-TB trial who completed 6 months of treatment were called for a phone interview. One inclusion criterion for this study was that participants had to be randomized into the intervention arm, while we excluded all the participants randomized into the control arm. The other inclusion and exclusion criteria were the same as in the trial. In addition, we purposively selected 18 patients with TB for an in-depth interview. Considering that this was an implementation study in which all the activities were performed by TB care providers, we purposively selected 15 TB care providers to understand the acceptability pattern of evriMED. We aimed at a heterogenic sample for both patients and health care workers by considering patients with good and poor adherence as well as diverse professional experiences among TB care providers. We obtained written informed consent from all individuals who participated in the acceptability study. After completing the follow-up of all participants in the REMIND-TB trial, we purposively selected TB treatment centers with their respective care providers in each cluster, who were called for an in-depth interview. Interviews were performed by trained research assistants using a topic guide in the Swahili language. Audio recordings of the interviews were transcribed and translated by experienced research assistants.

Theoretical Framework of Acceptability

The theoretical framework of acceptability (TFA) is a theoretical framework that helps to evaluate the intervention acceptability based on the lived or perceived experiences of individuals who deliver or receive an intervention [19]. The TFA has 7 constructs that can evaluate acceptability before, during, and after implementation performance (Table 1). In this study, we used TFA to investigate the acceptability of DATs among patients with TB and TB care providers. We believe that this theoretical framework is the best to use for this study due to its robustness in integrating the comprehensive concept of acceptability derived from diverse theories in health psychology and behavior change. To our knowledge, this inherent strength makes TFA the best theory of acceptability when compared to other theories. In addition to that, several studies have employed this theory to evaluate the acceptability of health care interventions [15,21-23].

Table 1. Constructs and description of the theoretical framework of acceptability.

Constructs	Description
Affective attitude	How an individual feels about the intervention
Burden	The perceived amount of effort that was required to participate in the intervention
Ethicality	The extent to which the intervention has a good fit with an individual’s value system
Intervention coherence	The extent to which the participant understands the intervention and how it works
Opportunity costs	The extent to which benefits, profits, or values were given up to engage in the intervention
Perceived effectiveness	The extent to which the intervention is perceived to have achieved its intended purpose
Self-efficacy	The participant’s confidence that they can perform the behavior(s) required to participate in the intervention

Data Collection Tools

Exit Survey

We conducted an exit survey after a participant completed the treatment. The survey was conducted by phone by trained research assistants. We performed the survey by using a semistructured questionnaire that we developed using the 7 constructs of the acceptability framework (affective attitude, perceived burden, ethicality, perceived effectiveness, intervention coherence, self-efficacy, and opportunity cost).

In-Depth Interviews

We conducted in-depth interviews with patients and TB care providers from the intervention clusters. Patients and TB care providers were interviewed at their respective health facilities at the agreed time. All interviews were conducted by 2 experienced researchers led by the first author (AEM). We used different topic guides for in-depth interviews with patients and care providers, respectively. We used the Sekhon framework for acceptability to define the guide [19]. Questions mainly focused on the 7 constructs of TFA. The questionnaires were adapted if new topics came up during interviews.

Data Analyses

To answer the objective regarding the acceptability of evriMED among patients with TB and TB care providers, we conducted a descriptive analysis of the exit survey responses using STATA (version 15; Stata Corp LLC). The results of the exit survey provided an overview of the frequency and percentages of each element of acceptability. In addition, we analyzed the qualitative responses of participants and TB care providers inductively and deductively by using thematic framework analyses. Three researchers independently read the transcripts (AEM, MSdB, and RAM). We developed memos and subthemes inductively based on the narratives and deductively by adopting preidentified themes from the theoretical framework constructs. We uploaded transcripts and memos in NVivo software (Lumivero) for coding and data organization. Narratives from the transcripts were then coded based on the predefined subthemes.

Results

Description of the Patients

We enrolled 280 patients in the intervention arm; of these, 21 (7.5%) died before study completion, and 14 (5%) were excluded due to either being transferred to other regions or lost to follow-up. Of the 245 (87.5%) patients who completed treatment, 145 (59.2%) were not interviewed because their phone numbers were unreachable. We interviewed 100 (40.8%) patients. The details of the demographic characteristics of the patients with TB are shown below in Table 2.

In addition, we in-depth interviewed 18 patients and 15 TB care providers or directly observed therapy, and we reached data saturation in these interviews. Among the 18 patients, 12 (67%) were males and 6 (33%) were females. Detailed demographic characteristic are shown in Table 3. Of the 15 TB care providers who were interviewed, 3 (20%) were males and 12 (80%) were females, of whom 4 (27%) were clinicians, 1 (6%) was a pharmacist, 4 (27%) were medical attendants, and 6 (40%) were registered nurses.

Table 2. Demographic characteristics and treatment outcomes of the patients with tuberculosis (N=280).

Characteristics	Values, n (%)
Sex	
Male	207 (73.9)
Female	73 (26.1)
Inclusion clusters	
Moshi rural district hospital	21 (7.5)
Moshi rural health center	115 (41)
Moshi urban district hospital	3 (1.1)
Moshi urban health center	42 (15)
Same and Mwanga health facilities	49 (17.5)
Kibongoto National Infectious Disease hospital	50 (17.9)
Age (years)	
<20	2 (0.7)
20-29	50 (17.9)
30-29	57 (20.4)
40-49	89 (31.8)
50-59	52 (18.6)
≥60	30 (10.7)
Education level	
None	9 (3.2)
Primary	213 (76.1)
Secondary	56 (20)
Tertiary	2 (0.7)
Marital status	
Married	155 (55.4)
Single	79 (28.2)
Separated or divorced	35 (12.5)
Widowed	11 (3.9)
Treatment outcome	
Cured/completed treatment	245 (87.5)
Transferred and lost	14 (5)
Dead	21 (7.5)

Table 3. Demographic and adherence characteristics of the in-depth interviews with individuals diagnosed with tuberculosis.

	Sex	Age (years)	Education	Marital status	Participant's adherence as shown by DAT[a] (%)[b]
1	Female	30	Secondary	Married	10
2	Male	40	Primary	Married	24
3	Male	58	Primary	Married	21
4	Male	55	Primary	Married	38
5	Female	53	Primary	Single	99
6	Male	48	Primary	Married	99
7	Male	56	Primary	Married	21
8	Female	38	Primary	Single	0
9	Female	49	Primary	Married	100
10	Male	63	Secondary	Married	100
11	Female	45	Primary	Separated	68
12	Male	52	Primary	Married	90
14	Male	59	Primary	Married	99
14	Male	41	Primary	Married	99
15	Female	45	Primary	Divorced	41
16	Male	52	Primary	Married	93
17	Male	40	Primary	Married	96
18	Male	60	Secondary	Married	98

[a] DAT: digital adherence tool.

[b] Absolute values of the percentages are not provided because the adherence score in the evriMED monitor is automatically generated by the pillbox based on the patient's daily medication intake behavior.

Patients' and TB Care Providers' Acceptability of DAT

The table summarizing the quantitative survey findings can be found in Multimedia Appendix 2.

Affective Attitude

Many participants described positive views concerning the use of the intervention. In the exit interview, 98% (98/100) of the participants indicated their general experience with the pillbox was either good or very good, 83% (83/100) reported that the intervention was satisfactory, and 85% (85/100) had either a good or very good attitude toward the content of the reminder SMS text messages. Of the 20 people who saw their adherence graphs, 18 (90%) had a good or very good attitude toward graphs.

In the in-depth interviews, participants expressed positive opinions about the appearance and attractiveness of the pillboxes. They were particularly impressed with the white color of the pillbox. TB care providers and patients acknowledged the appropriateness of the pillbox's size, stating that it allowed for hygienic medication storage. However, some TB care providers suggested increasing the pillbox size to accommodate patients' cards. Furthermore, some participants appreciated the pillbox's size as it matched the size of TB drug blisters. Additionally, participants with comorbidities (TB-HIV) found the large size of the pillbox advantageous for storing drugs for other diseases. This is illustrated in the following quotes.

> *…From my point of view, the device is good. Even from looking at it. Even the color itself is not bad.* [Patient, 42-year-old male]

> *…it reminds him. Even though he doesn't have his phone, it helps him think he should take medication. The second thing I see is that drugs stay safe. Thirdly, it helped patients to be alert. They were swallowing the medicine on time, and if they forgot, it reminded them.* [TB directly observed therapy, registered nurse]

Participants and TB care providers highlighted the benefits they experienced from using the intervention, particularly regarding medication reminders and storage. TB care providers expressed satisfaction with attending to patients utilizing the intervention, as it enabled them to monitor progress through adherence reports. However, a few participants expressed negative sentiments. One participant suggested that having pillboxes in different colors would be more attractive, as the white color could quickly get dirty. Another participant felt the pillbox size was too large to carry and recommended reducing its size by half, as also mentioned by some other participants.

> *…It alerted us that why this guy/patient has this problem. Let us call him and sit to talk with him about what the problem is.* [TB directly observed therapy, medical attendant]

> *…The first advantage is to be reminded. You understand me. It reminds you. I have been reminded many times because I also like to sleep; if I do not go*

> *out, I always like to sleep at home. Also, drug storage.* [Patient, 30-year-old female]
>
> *…It's good, but when it's new. If it is new, it is very attractive. Now, it shows it has been used. It is clean, but not attractive anymore.* [Patient, 56-year-old male]
>
> *…I don't know…the size should be reduced to half! I see it is big.* [Patient, 30-year-old female]

Perceived Burden

We examined the perceived effort involved in using the intervention. During the exit interview, some participants (n=100) faced challenges when using the intervention. Specifically, 10 (10%) respondents mentioned experiencing TB-related stigma, 12 (12%) expressed discomfort with receiving daily SMS text message reminders, 7 (7%) found it challenging to use the device, 9 (9%) encountered difficulties keeping it at home, and 3 (3%) reported issues with charging the device. Additionally, 30 (30%) reported experiencing challenges with mobile network connections.

In-depth interviews revealed a few aspects that participants and TB care providers were experiencing in using the intervention. Few participants expressed challenges in travelling with the pillbox. TB care providers mentioned that the intervention increased their workload, as it required extensive discussions with patients about various aspects of adherence. Moreover, mobile network–related issues caused delays in the system's signal transmission when the pillbox was opened, leading to poor adherence reports for some patients and incorrect SMS text message notifications. Some participants suggested that the system should not send reminder SMS text messages to treatment supporters, as the device occasionally failed to detect events due to network problems. This can be seen from the following quotes.

> *…I did not feel comfortable going with it because others would suspect me [of being sick].* [Patient, 56-year-old male]
>
> *…But the time was insufficient according to the working environment. So, once you get a patient in this environment, it is a bit of a challenge to sit with them. You must be brief because the time is insufficient, and you might need to work in the OPD wards simultaneously. So, if you sit with that patient for a long time, you will cause a jam in another unit.* [TB directly observed therapy, medical attendant]
>
> *…If the network is fine, the adherence is good. But, if he goes to a place without a network, the device is not communicating even if he has taken the medicine.* [TB directly observed therapy, medical attendant]

Ethicality

Many participants and care providers described the intervention as fitting well with their value system. Exit interviews with participants revealed that 85% (85/100) did not worry about being monitored remotely, and 77% (77/100) said they did not experience any form of stigma. Similar findings were observed in the in-depth interviews. Many participants considered the pillbox morally acceptable and appreciated how it helped maintain their confidentiality. TB care providers also found the content of the reminder SMS text messages to be beneficial for their patients, as illustrated in the quotes below.

> *…I saw the benefits of hiding the secret of my illness. The device is acceptable for my side. I do not know for others.* [Patient, 56-year-old male]
>
> *…It is morally right to use the device.* [Patient, 42-year-old male]
>
> *…I think the SMS contents were fine.* [TB directly observed therapy, medical attendant]

Furthermore, participants emphasized that the pillbox and SMS text messages aligned with their social values within their families. They highlighted that the intervention facilitated ongoing support from their families throughout the medication period, as described by the following participants.

> *…even my wife told me: "The time to take the medicine is near. Go and take the medicine." Even if the hours have not arrived, she remembers.* [Patient, 42-year-old male]
>
> *…They supported me well. For example, giving me milk food. Even, sometimes, when they do cleaning, they wipe the device.* [Patient, 48-year-old female]

Intervention Coherence

Most participants and TB care providers claimed to understand the intervention and how it works. The findings from the exit interview revealed that 78% (78/100) of the respondents indicated they understood the intervention, 92% (92/100) mentioned they could use the intervention without any challenge, and 84% (84/100) could charge the device without problems. However, only 20% (20/100) of the participants were shown their adherence graphs during their counseling sessions with care providers.

Similar findings emerged during the in-depth interviews, where many participants and TB care providers effectively communicated the purpose of the intervention and its operational processes. During the interview, we asked health care providers to show how they had informed participants about intervention objectives and how it worked. The in-depth interviews revealed that health care workers understood the intervention's objectives and were adept at conveying this information to their patients. Furthermore, participants and care providers were able to explain how different components of the pillbox, such as the alarm, lights, charging system, and reminder system, communicate with the server. However, the interviews revealed that most participants did not remember the name of the pillbox. Instead, they used to call it by their local name, kiboksi, which means "the box." This is demonstrated in the following quotes.

> *…It reminds you to swallow the medicine, so when you open it, it indicates someone has opened the device and swallowed it. When you do not open it, it means you have not swallowed it. So, you will be sent a reminder message.* [TB directly observed therapy, registered nurse]
>
> *…This device, first, is the one we use to store medicine. Second, when you open this device, it turns*

> *on the lights and gives an alarm. Once you have taken out the medicine inside and used the one you need, the other ones you must put back in. When you put them back inside the device, you close this device. If you close it properly, the lights turn off. One thing I have noticed is that it gets to the point where you open it, and then the lights turn on and off. The moment it turns on and off, it does not show the indicator again.* [Patient, 63-year-old male]

> *…Honestly, the graph has never been shown to me.* [Patient, 30-year-old female]

Perceived Effectiveness

Participants and TB care providers expressed that the intervention successfully achieved its intended goal. In the exit interviews, 84% (84/100) of the respondents acknowledged that the intervention improved their treatment adherence. Similar findings were observed in the in-depth interviews with both participants and TB care providers. Participants mentioned that the intervention facilitated adherence by providing timely reminders, enabling them to stick to their scheduled intake times. They found the SMS text message reminders especially helpful when occupied with other activities and when prone to forgetfulness. Furthermore, TB care providers reported that the intervention significantly improved the treatment outcomes for patients compared to those who did not use the pillbox, as described in the following quotations.

> *…Receiving the message that says "the time of intake is near." That has helped me a lot because you are probably far from home. So, you will estimate I have 20 minutes or half an hour to be home.* [Patient, 63-year-old male]

> *…I thank God, to be honest, no patients could stop medication or even die.* [TB directly observed therapy, medical attendant]

> *…Honestly, I have been successful because many patients have recovered; they didn't get resistance.* [TB directly observed therapy, clinician]

Health care providers expressed that the intervention improved their rapport with patients by providing feedback on adherence counseling, fostering a sense of compassion and love. They found the adherence report valuable in effectively monitoring the patients' progress. Moreover, the intervention resulted in positive behavioral changes among TB care providers. Many providers mentioned that the feedback in adherence counseling sessions helped them refine their approach when attending to patients with TB, and they gained a better understanding of the significance of adherence in time of medication, which had previously been given less attention, as described in the following quotations.

> *…It helps to keep the closeness…among the patients…You even get time to talk to him and discover what's happening with him. Many positive patients have come out completely healed.* [TB directly observed therapy, registered nurse]

> *…For us care providers, it was helpful because we are not doing one work, but also doing other work. So, once we get the patient's information for reference from the devices, it helps us to know if the patients are in good care compared to those who are not using the devices.* [TB directly observed therapy, medical attendant]

> *…in the past, we were giving drugs, but we did not emphasize that if a patient should swallow medicine at 8 AM, it should be taken at 8 AM every day. We used to tell them to take drugs in the morning regardless of the time. For this study, we dispensed and told them to choose whether it was 8 or 9 o'clock. He will choose and should take the drug at the same time every day. And we have seen that it has brought great success.* [TB directly observed therapy, clinician]

Opportunity Costs

Few participants mentioned that they had to give up something valuable to participate in this study. Exit interview results show that 6% (6/100) of the respondents incurred extra costs while using the intervention. From the in-depth interviews, 1 participant expressed that he incurred higher costs because he received a reminder when he was away from home and did not want to ruin his intake report. Therefore, he decided to take a quick transport to get home on time. Another participant mentioned working fewer hours than usual to get home early to take medication on time.

> *…There was a period when I was receiving messages, but if I went somewhere and became late, I had to take a quick motorcycle.* [Patient, 63-year-old male]

> *…That happens once in a while because you may find that you are working somewhere, and then you still have time, but you have to leave early.* [Patient, 42-year-old male]

Self-Efficacy

Many participants and TB care providers said they were confident to engage in the intervention. In the exit interviews with participants, 84% (84/100) of the respondents said they were comfortable to continue receiving reminder SMS text messages every day. The same was reported in the in-depth interviews, in which some of the participants expressed that they preferred the device to be given to many patients and not to a few just for research. Others mentioned that they were confident in explaining the pillbox to their families and relatives. TB care providers expressed that the intervention would be suitable to be adopted in their care and, if possible, include patients experiencing other diseases such as HIV, as illustrated in the quotations below.

> *…For my part, I advise this research project to continue. Not just for research purposes only and end there. It should continue because it is a good thing, and the scope should be expanded to get more people to use this device.* [TB directly observed therapy, registered nurse]

> *…This device is so good to the extent that I liked it and wished I could remain with it.* [Patient, 53-year-old male]

Discussion

Principal Findings

This study aims to evaluate the acceptability of a DAT (evriMED1000 pillbox) among patients and TB care providers to improve adherence to anti-TB drugs in Kilimanjaro, Tanzania. The overall findings of this study indicate high acceptance of DAT among patients with TB and TB care providers. We found that the high acceptance of DATs was based on the positive attitude toward using the DAT (affective attitude), wherein 83% (83/100) of the participants were satisfied with the intervention, 98% (98/100) expressed good experiences, 78% (78/100) understood how the intervention works, and 92% (92/100) could use the pillbox, such as opening the device, refilling the pills, and recharging the box (intervention coherence). Of the 100 participants, 84 reported improved adherence (perceived effectiveness), and they preferred to continue receiving reminder SMS text messages (self-efficacy). A few participants reported experiencing difficulties while using DATs. Some participants reported experiencing TB-related stigma; 12% (12/100) were not happy being reminded daily, and 9% (9/100) reported experiencing difficulties keeping the device at home. Additionally, 30% (30/100) reported experiencing challenges with mobile network connectivity issues.

Comparison With Prior Work

Our findings support similar studies reporting on the acceptability of DATs among patients and health care providers [12,13,15,24]. The potential benefit of DAT, such as its ability to monitor medication adherence or ease of use, was deemed valuable by patients and TB care providers. A study done in South Africa reported that the acceptability of DAT was highly associated with its ease of use among patients [12]. The real-time medication monitoring reports and feedback on adherence helped patients understand their health conditions and led to improved patient and health care provider relationships [12,24,25]. In addition, it led to improved care practice and behavior change among TB care providers. Many health care providers reported feeling more accountable for patient follow-up and motivating patients to adhere to the time of medication intake. Feedback on adherence counseling also generated a sense of care among patients, which had an impact on the psychosocial life of the patients.

However, participants reported several challenges with DATs, such as incorrect sending of SMS text messages due to network failure, large size of the pillbox, and existence of the reminder alarm, which led to fear of disclosure and, consequently, nonuse of the device during travelling. Similar challenges have been reported in other studies [14,26], which, if not well addressed, might contribute significantly to the nonuse of DATs and less uptake of DATs [24]. TB care providers reported increased workload during the use of DATs. Similar findings were reported in a study done in China, where health care providers reported a moderate workload increase during DAT implementation [16]. However, this contradicts a study in India, which reported a decreased health care workload [24]. We found that the increased workload by health care workers was reported as a major concern in settings with shortage of care staff—mainly dispensaries and health centers. Larger facilities such as hospitals reported a slight increase in the workload. In addition, 48% (48/100) of the participants stated that adherence reports from the device were not shown nor utilized in their conversations with health care workers. The health care provider was likely to have little knowledge of the value of adherence reports as a tool for counseling. Regular training should be conducted to reinforce their understanding of the intervention for effective scale-up. Fear of TB stigma and unwanted disclosure should be considered for effective intervention scale-up.

Limitations and Strengths

This study had certain limitations. One significant limitation was that because of the COVID-19 pandemic, all exit interviews were conducted via phone calls, which posed challenges related to network connectivity and potential interruptions during the questioning process. Mitigation strategies were employed, such as recapping participant responses to ensure accurate information capture. Another limitation was the small sample size in the exit survey compared to the total number of enrolled participants in the trial. The small sample size can be attributed to the public policy implemented in July 2021, wherein unregistered SIM cards were blocked, making it difficult to reach most participants. Nonetheless, we found that the demographic characteristics of the participants who were interviewed (100/245) did not differ from those of the participants who were not interviewed due to the change in the government policy, indicating that the interviewed participants were likely representative of those who were not interviewed. Additionally, 59.2% (145/245) of the participants who were not reached due to the change in the government policy were not affected during the medication period. The change in the government policy regarding SIM card registration occurred when many of our participants had already completed the treatment follow-up and were waiting for the exit survey. In this case, the change in the government policy impacted the exit survey process rather than the intervention itself.

This study has notable strengths that enhance its significance and scope. First, we enrolled participants from all TB-providing facilities in the Kilimanjaro region, thereby offering a comprehensive understanding of acceptability from a broader perspective. Notably, our research pioneers the investigation of the evriMED reminder pillbox's acceptability among patients with TB in East Africa, providing valuable insights on the acceptance. Additionally, using the TFA facilitated a robust understanding of the acceptability of the evriMED reminder pillbox among patients with TB.

Conclusion

Our study demonstrates the positive acceptance of a DAT (evriMED) among patients and TB care providers for improving anti-TB drug adherence in Kilimanjaro, Tanzania. Although the potential acceptability of DATs is evident, addressing concerns related to mobile network connectivity and participants' preferences regarding the number of reminder SMS text messages, and providing adequate training and technical support to health care providers are critical for successful implementation. Future research should explore the impact of evriMED on large-scale implementation in different settings.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
EvriMED monitor and its associated intervention.
[PDF File (Adobe PDF File), 188 KB - ojphi_v16i1e51662_app1.pdf]

Multimedia Appendix 2
Exit survey findings.
[PDF File (Adobe PDF File), 87 KB - ojphi_v16i1e51662_app2.pdf]

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Abbreviations

DAT: digital adherence tool
TB: tuberculosis
TFA: theoretical framework of acceptability

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Original Paper

Inferring Population HIV Viral Load From a Single HIV Clinic's Electronic Health Record: Simulation Study With a Real-World Example

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Abstract

Background: Population viral load (VL), the most comprehensive measure of the HIV transmission potential, cannot be directly measured due to lack of complete sampling of all people with HIV.

Objective: A given HIV clinic's electronic health record (EHR), a biased sample of this population, may be used to attempt to impute this measure.

Methods: We simulated a population of 10,000 individuals with VL calibrated to surveillance data with a geometric mean of 4449 copies/mL. We sampled 3 hypothetical EHRs from (A) the source population, (B) those diagnosed, and (C) those retained in care. Our analysis imputed population VL from each EHR using sampling weights followed by Bayesian adjustment. These methods were then tested using EHR data from an HIV clinic in Delaware.

Results: Following weighting, the estimates moved in the direction of the population value with correspondingly wider 95% intervals as follows: clinic A: 4364 (95% interval 1963-11,132) copies/mL; clinic B: 4420 (95% interval 1913-10,199) copies/mL; and clinic C: 242 (95% interval 113-563) copies/mL. Bayesian-adjusted weighting further improved the estimate.

Conclusions: These findings suggest that methodological adjustments are ineffective for estimating population VL from a single clinic's EHR without the resource-intensive elucidation of an informative prior.

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KEYWORDS

HIV; human immunodeficiency virus; viral load; population viral load; electronic health record; EHR; electronic health records; EHRs; electric medical record; EMR; electric medical records; EMRs; patient record; patient record; health record; health records; personal health record; PHR; selection weights; sampling; sampling bias; Bayes

Introduction

There has been increasing interest in using electronic health record (EHR) data as part of public health surveillance efforts [1]. In an interview conducted among local health departments, Comer et al [2] reported 23 such uses, including incidence or prevalence of infectious and chronic diseases, such as diabetes, hepatitis B and C, asthma, and depression, and uptake of disease prevention programs, including vaccination and HIV testing. Uptake of HIV testing is especially relevant and timely given the 2019 US Department of Health and Human Services' "Ending the HIV Epidemic: A Plan for America" initiative [3]. The plan calls for a 75% reduction in the number of new HIV diagnoses within 5 years and a 90% reduction within 10 years.

To realize this ambitious goal, health departments monitor data on HIV in their jurisdictions. There are a variety of metrics for doing so, including incidence, prevalence, late diagnoses, and viral load (VL), a marker for the success of HIV testing programs and connection to care and treatment. Undetectable VL is the desired outcome in the HIV care continuum because an undetectable VL equates to zero transmission risk, the foundation of treatment as prevention [4]. A hierarchy of aggregated VL measures exist and relate to the natural sampling process that occurs from the source population when individuals are diagnosed (community VL), are connected to care (in-care VL), and have VL measures obtained (monitored VL) [5]. The broadest categorization, population VL, is the most comprehensive measure of the HIV transmission potential. However, population VL cannot be directly measured due to lack of complete sampling of the population of people living with HIV as well as lack of complete or recent VL data among those diagnosed [5]. Despite its utility and appeal, the measure has notable challenges, including population selection, varying definitions and calculations, and complete and accurate surveillance [6]. These issues may have led to the decline in its use following its introduction in 2009. Nevertheless, population VL—if quantifiable—is a useful latent measure of transmission potential and quality of HIV care and treatment in a specific geographic area. Even a biased measure can be useful if it can be calibrated to a less biased or an unbiased measure. For example, one contemporary paper using data from the 2010s investigated community VL and HIV incidence in South Carolina and found that community VL disparities mirrored disparities in HIV access to care for nonprioritized groups including women, rural populations, and heterosexual transmission [7].

Absent complete (or a representative random) sampling of a population of people living with HIV, one may turn to EHRs from various clinics to estimate population VL. A given health department might wish to know the distribution of VL among people living with HIV in its jurisdiction but only have a single HIV care program that serves the community. As such, the ability to estimate population VL from a single EHR may be of value. In fact, researchers have previously demonstrated how EHR data can improve the accuracy of HIV surveillance programs [8]. However, use of EHRs for these purposes faces methodological challenges, including ambiguous catchment [9]. A given EHR can be expected to over- or under-sample with respect to characteristics of people living with HIV (eg, health, income, race, age, distance to clinic). We sought to investigate the feasibility of imputing population VL from a single EHR and under what conditions this may be possible.

Methods

Creation of the Synthetic Data Set and Clinics

To establish the feasibility of recovering the true population VL from a single clinic's EHR, we would need both clinic-level VL EHR data as well as the VL from the source population, data which are difficult to obtain as this would require measuring VL among those unaware of their HIV status as well as those not engaged in care. In lieu of this, we created a hypothetical synthetic source population: This population can be considered a large urban area in the United States with a population size of 1,000,000 people and 1% HIV seropositivity, or 10,000 people living with HIV. We defined 3 demographic strata for the population, as follows: age: <35 years, 35-44 years, 45-54 years, >54 years; gender: male, female; race/ethnicity: non-Hispanic White, non-Hispanic Black or African American, Hispanic or Latino. These categories were not meant to be inclusive of all risk groups but rather commonly reported groups for calibrating VL.

The demography of people living with HIV was randomly sampled from a uniform distribution with probabilities informed from the Centers for Disease Control and Prevention (CDC) 2020 HIV Surveillance Report [10]. Specifically, approximately 75% of the population was set to male, and 25% was set to female. Age distributions were as follows: 18% <35 years, 19% 35-44 years, 24% 45-54 years, and 39% >54 years. Race/ethnicity distributions were as follows: 33% White, 45% Black or African American, and 23% Hispanic or Latino. VL was randomly sampled from a log-normal distribution with a $\log_{10}$ geometric mean of 3.65 (4449 copies/mL) and a $\log_{10}$ SD of 1.2. The mean was informed from the measured community VL from the San Francisco, CA HIV/AIDS Case Surveillance System for 2005-2008 [11], and the SD was informed from the CDC's guidance document on community VL [5]. VL was adjusted jointly across the demographic strata by multiplying the VL by a randomly sampled probability obtained from a normal distribution with the following means and accompanying SD of 10%: –1% male and +18% female; +21% <35 years, –10% 35-44 years, –26% 45-54 years, and –26% >54 years; –10% White, +13% Black or African American, and +15% Hispanic or Latino. These adjustments were informed from differences observed in VL in the San Francisco surveillance data [11].

To simulate the HIV care continuum from this source population, we set approximately 10% of the population as unaware of their HIV status. This group was more likely to be younger, male, and Black or African American based on a study of concurrent HIV and AIDS diagnosis in San Francisco [12]. Among those aware of their status, we created an "in care" group in which approximately 72% of those in care would be virally suppressed (<200 copies/mL), mirroring the 2021 San Francisco HIV epidemiology annual report [13], although we stress that our primary intention is not to replicate San Francisco surveillance data but rather create a hypothetical urban population. Sampling the "in care" group in this manner resulted in an average 20% of the aware group also being in care.

Finally, to isolate the effects of various sampling mechanisms, we created 3 HIV clinics with differing catchments. Clinic A was sampled directly from the source population, Clinic B was sampled from those aware of their HIV status, and Clinic C was sampled from those in care. Each clinic contained 250 active patients oversampled by male sex, White race, and age ≥45 years. The demographic composition of each clinic was set to reflect observed patterns of retention in HIV care [14] and to yield an EHR in which the mean VL differed from the source population. We created 1000 versions of each clinic to account for random variability.

Creation of the Catchment Sampling Weights and Weighted Analysis

Let K be the size of the source population, V be the number of people aware of their HIV status, N be the number of people in care, and S be the number of patients in care at a clinic. We can estimate the catchment sampling weight using equation 1:

$$W = 1 / Beta((S + 1), (N + 1 - S)) \quad \textbf{(1)}$$

In this equation, N arises from $Binomial(N/K, K)$, where N/K is the prevalence of people living with HIV and in care in the source population. Weights are calculated per the demographic strata enumerated earlier that related to a clinic's catchment (ie, race, age, and gender) such that V, N, S, and W are all calculated separately for each stratum. The final sample weight is obtained for each person by multiplying the corresponding stratum-specific weights.

To allow for the possibility of weight misspecification when they are not estimated appropriately, for example due to an ambiguous catchment, we transformed W as outlined in equation 2:

$$P_{biased} = \log(P/(1-P)) + b*\log(VL) \quad \textbf{(2)}$$

In this equation, P is the inverse of W, that is, the individual selection probability of being in the clinic, and consequently, the inverse of P_{biased} is the misspecified (biased) weights. The coefficient "b" is the bias factor and was set to 0.1, a conservative starting point that would still meaningfully shift the weights. Under equation 2, a positive bias factor demonstrates the scenario whereby individuals with higher VLs are less likely to be sampled in the clinic, but, unbeknownst to the researchers, the catchment model does not identify them as such. Consequently, this bias factor down-weighted their contribution in the weighted analysis by a factor of 0.1, when they should have been up-weighted. Larger bias factors would create greater weight misspecification, albeit with the same conclusions.

We simulated 1000 of the unbiased and biased weights per participant, then calculated the population geometric mean (GM) VL for each clinic, where $GM=\exp(\text{mean}(\log_{10}(VL)))$. We also calculated the unweighted GM and took the root mean squared error (RMSE) between the weighted and unweighted measures. The final calculations are thus based on the 1000 weights for each of the 1000 clinic As, 1000 clinic Bs, and 1000 clinic Cs. Our target estimand was the median and 95% interval of each clinic's GM distribution.

Postweighting Bayesian Adjustment

Following the weighted analysis, we conducted a Bayesian analysis with the expectation that this would further improve our ability to impute the population VL from a given clinic. This approach is analogous to that taken by others who treated weighted observations as "data" that enter the likelihood part of the Bayesian computation [15]. For this analysis, we assumed the true mean and variance were unknown and specified a Normal-Gamma conjugate prior, although, since our focus was only on the posterior mean, the calculations became simplified. The prior mean (μ_0) was informed by the San Francisco HIV/AIDS Case Surveillance System, namely $\log_{10}$ GM VL of 3.65. As a starting point for the prior sample size (n_0), we took the perspective of a clinic's population's VL measured at a previous time point (ie, available before the observed VL data used in the weighted analysis). For example, one might posit that such data were collected immediately upon diagnosis as opposed to routine monitoring during antiretroviral therapy. Following our weighted analysis, these observed measurements have a logarithmic mean of and effective sample size, $n_w=\Sigma W$ for each of the 1000 clinic samples. The posterior logarithmic mean of the population VL (μ_n) conditional on posterior variance is specified in equation 3.

$$\mu_n = ((n_0 \times \mu_0) + n_w \times) / (n_0 + n_w) \quad \textbf{(3)}$$

To examine the influence of the prior sample size, we operationalized n_0 in 3 ways: $0.25 \times n_w$, $0.5 \times n_w$, and $2 \times n_w$. Additionally, to reflect the earlier scenario of the prior data collected upon diagnosis, we conducted a final analysis for clinic C where μ_0 was informed from clinic B's weighted mean and the more conservative $n_0=0.25*n_w$. As before, these calculations were performed for each of the 1000 clinic weights for each of the 1000 clinics.

Real-World Clinic Data Set

As an applied demonstration of our methods, we obtained the most recently available VL on active patients retained in care for HIV at the Holloway Community Program at ChristianaCare (Wilmington, DE). Patients' age, race, and gender were coded using the same categories defined earlier for our synthetic population. Denominators needed for the catchment model were obtained from the US Census Bureau 2021 American Community Survey [16] population sizes for Delaware (the presumed catchment of the Holloway program) and the Delaware Integrated HIV Prevention and Care Plan for 2022-2026 that includes statewide surveillance data as of 2019 [17]. Using the procedures outlined earlier, we estimated the population VL from the clinic data; however, as we did not have access to historic unbiased estimates of VL for this jurisdiction, we used the prior as described in our synthetic analysis. To further acknowledge uncertainty in the prior mean (μ_0), we conducted a sensitivity analysis with μ_0 modified in 3 ways ($0.25 \times \mu_0$, $0.5 \times \mu_0$, and $2 \times \mu_0$) and repeated the Bayesian adjustment across the 3 prior sample sizes.

All analyses were performed in R version 3.6.3 (R Foundation for Statistical Computing). Analytic codes are available for download from [18]. HIV VL point estimates and 95% intervals are presented on a linear scale in the main text and a logarithmic scale in Multimedia Appendices 1-5.

Results

Synthetic Population and Clinics

Each clinic was approximately 93% male; 4% <35 years, 5% 35-44 years, 40% 45-54 years, and 51% >54 years; and 81% White, 13% Black or African American, and 6% Hispanic or Latino (Table 1).

Table 1. Characteristics of the synthetic population and clinics as well as the real-world cohort from the Holloway Community Program at ChristianaCare (Wilmington, DE).

Characteristic	Synthetic EHRs[a,b]				Real-world EHR
	Population[c] (n=10,000)	Clinic A[d] (n=250)	Clinic B[e] (n=250)	Clinic C[f] (n=250)	Holloway (n=1807)
Age (years), n (%)					
<35	1817 (18.2)	12 (4.8)	10 (4)	10 (4)	278 (15.4)
35-44	1819 (18.2)	12 (4.8)	12 (4.8)	15 (6)	299 (16.5)
45-54	2727 (27.3)	97 (38.8)	98 (38.2)	96 (38.4)	332 (18.4)
>54	3634 (36.3)	129 (51.6)	130 (52)	129 (51.6)	898 (49.7)
Gender, n (%)					
Female	2497 (25)	17 (6.8)	17 (6.8)	19 (7.6)	558 (30.9)
Male	7503 (75)	233 (93.2)	233 (93.2)	213 (92.4)	1249 (69.1)
Race/ethnicity, n (%)					
Non-Hispanic Black or African American	4446 (44.5)	30 (12)	27 (10.8)	32.5 (13)	1128 (62.4)
Non-Hispanic White	3332 (33.3)	205 (82)	207 (82.8)	200 (80)	514 (28.4)
Hispanic or Latino	2220 (22.2)	15 (6)	15 (6)	18 (7.2)	165 (9.1)
Viral load (copies/mL), geometric mean	3996	3147	3108	173	41
Viral load, $\log_{10}$ geometric mean	3.60	3.50	3.49	2.24	1.61

[a] EHR: electronic health record.

[b] The 3 synthetic clinic electronic health records (n=250 per clinic) were sampled from a source population of people living with HIV (n=10,000) and were oversampled by male sex, White race, and age ≥45 years.

[c] Synthetic population results given as the median values from 1000 hypothetical clinics.

[d] Sampled directly from the source population.

[e] Sampled from a subset of the source population based on diagnosed HIV.

[f] Sampled from a subset of the source population based on retention in care.

Figure 1 contrasts the observed, weighted, and Bayesian adjusted VLs comparing the clinics to the population (see Multimedia Appendix 1 for logarithmic results). Across the 1000 simulations, the median GM population VL was 3996 (95% interval 3780-4214) copies/mL. For each clinic A, B, and C, the median GM VL point estimates and 95% intervals were 3147 (95% interval 2294-4301), 3108 (95% interval 2216-4383), and 173 (95% interval 123-240) copies/mL, respectively. Following weighting, the estimates moved in the direction of the population value with correspondingly wider 95% intervals as follows: clinic A: 4364 (95% interval 1963-11,132) copies/mL; clinic B: 4420 (95% interval 1913-10,199) copies/mL; clinic C: 242 (95% interval 113-563) copies/mL. Bayesian adjustment resulted in a shrinking of intervals, depending on the prior sample size, where the large sample size resulted in tighter intervals, and clinic C had a notable shift in point estimates toward the population mean. With a 25% of the clinic prior sample size, the posterior estimates were 433 (95% interval 236-851) copies/mL; with a 50% of the clinic prior sample size, the posterior estimates were 639 (95% interval 384-1120) copies/mL; and with a 200% of the clinic prior sample size, the posterior estimates were 1685 (95% interval 1307-2231) copies/mL. When using the weighted clinic B estimates to inform the prior for clinic C, we also noted an improvement in estimating the population mean, with posterior estimates of 432 (95% interval 230-889) copies/mL.

Figure 1. Comparison of the distribution of the geometric mean HIV viral load for 3 clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000), with results representing 1000 hypothetical clinicals each with 1000 sampling weight adjustments based on sampling from the source population (A) directly, (B) based on diagnosed HIV, or (C) based on retention in care (all 3 oversampled by male sex, White race, age ≥45 years). Bayesian 1: prior sample size of 25% of the weighted clinic sample size; Bayesian 2: prior sample size of 50% of the weighted clinic sample size; Bayesian 3: prior sample size of 200% of the weighted clinic sample size; Bayesian 4: prior mean informed from weighted clinic B estimates.

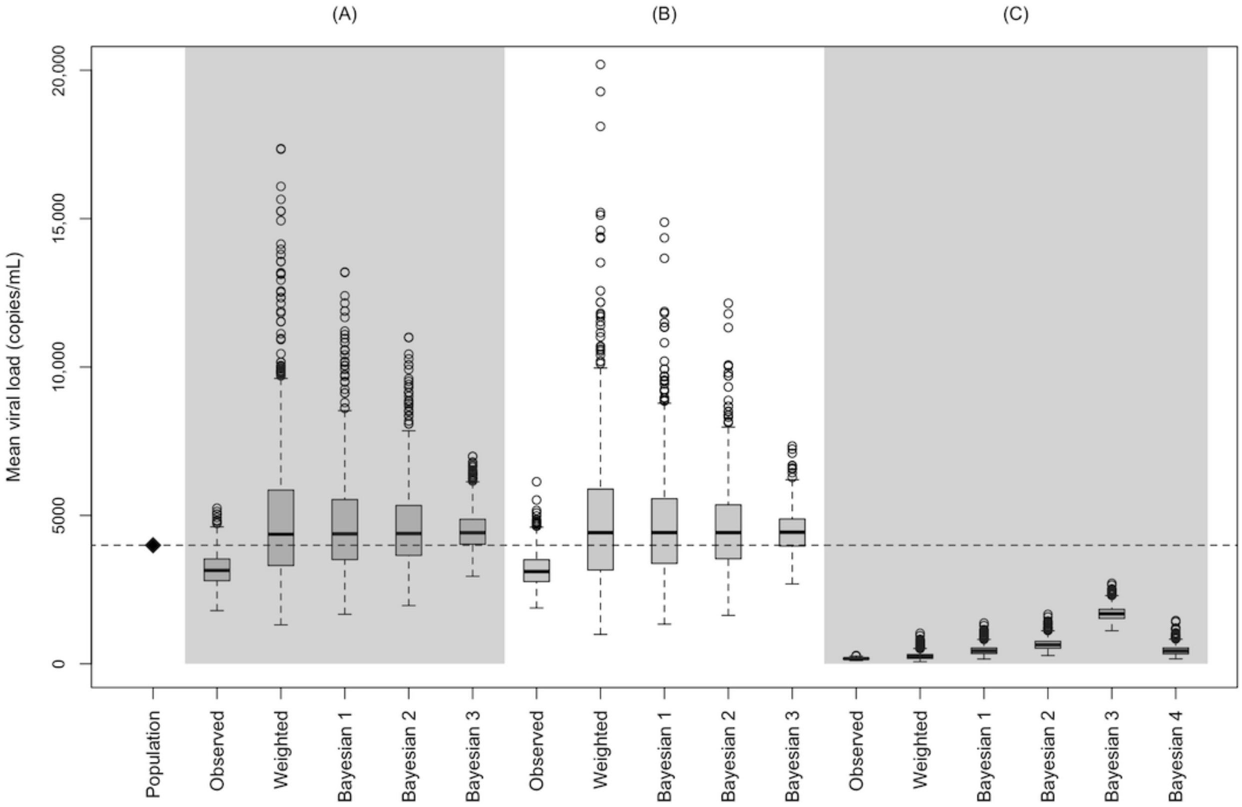


Figure 2 depicts the averaged RMSE for each clinic for each weighting strategy (see Multimedia Appendix 2 for logarithmic results). RMSE was greatest in the purely weighted analyses, with median errors and 95% intervals for each clinic as follows: clinic A: 1174 (95% interval 288-7261) copies/mL; clinic B: 1265 (95% interval 261-6369) copies/mL; and clinic C: 3745 (3385-4018) copies/mL. RMSE was lowest in the Bayesian analysis that followed weighting with the larger prior sample size, as follows: clinic A: 490 (95% interval 92-2026) copies/mL; clinic B: 528 (95% interval 96-1884) copies/mL; and clinic C: 2319 (95% interval 1773-2747) copies/mL. Figure 3 shows the impact of the weight misspecifications (see Multimedia Appendix 3 for logarithmic results). As expected, the biased weight systematically down-weighted higher VL individuals when they should have been up-weighted, as might occur based on an inaccurate catchment model where individuals with higher VLs were less likely to be sampled in the clinic.

Figure 2. Comparison of the root mean squared error (RMSE) of the geometric mean HIV viral load for 3 clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000), with results representing 1000 hypothetical clinicals each with 1000 sampling weight adjustments based on sampling from the source population (A) directly, (B) based on diagnosed HIV, or (C) based on retention in care (all 3 oversampled by male sex, White race, age ≥45 years). Bayesian 1: prior sample size of 25% of the weighted clinic sample size; Bayesian 2: prior sample size of 50% of the weighted clinic sample size; Bayesian 3: prior sample size of 200% of the weighted clinic sample size; Bayesian 4: prior mean informed from weighted clinic B estimates.

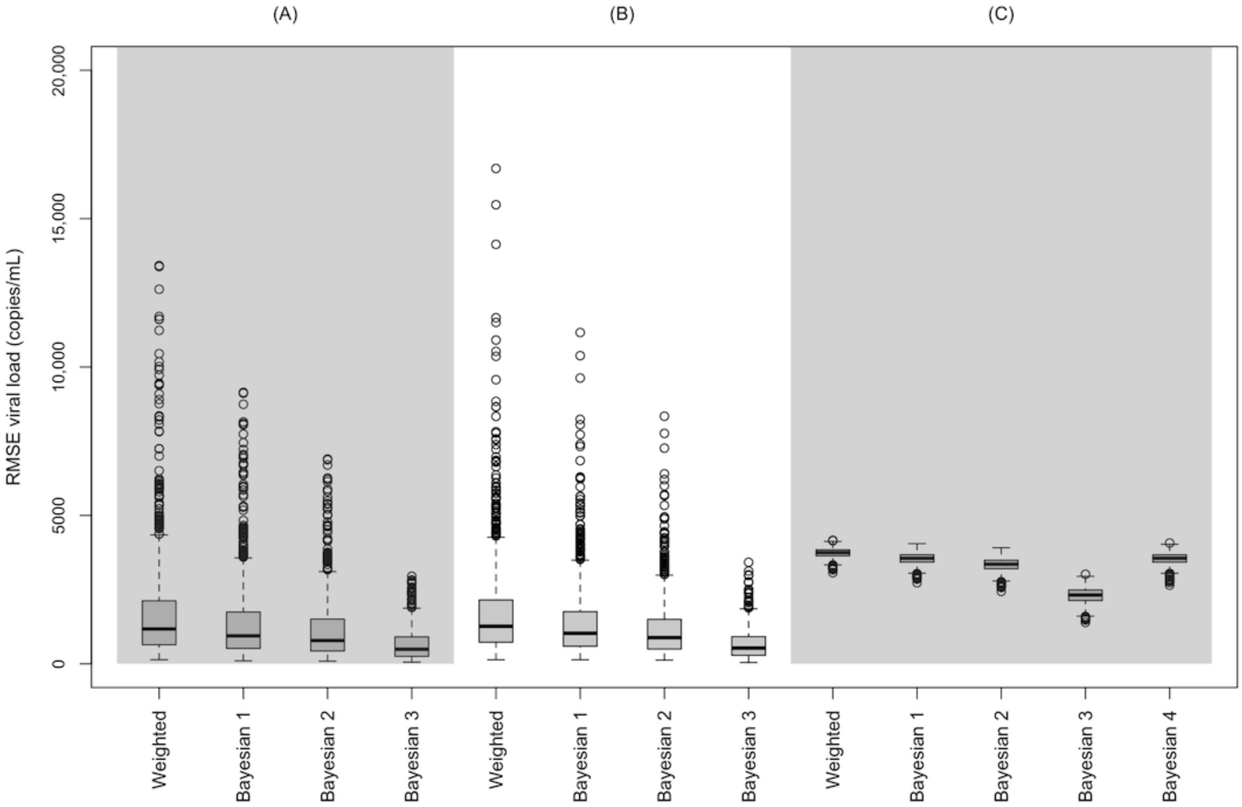
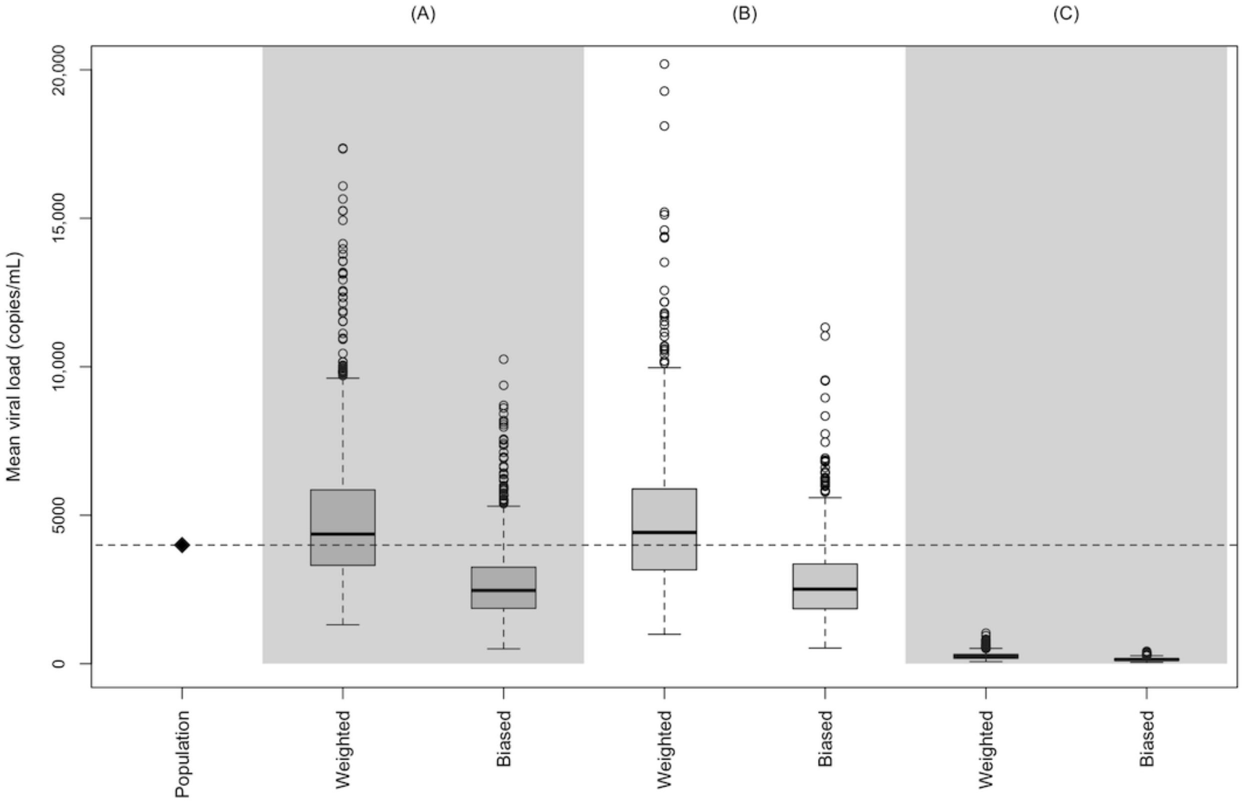


Figure 3. Comparison of weight misspecification in the weighted geometric mean HIV viral load for 3 clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000), with results representing 1000 hypothetical clinicals each with 1000 sampling weight adjustments based on sampling from the source population (A) directly, (B) based on diagnosed HIV, or (C) based on retention in care (all 3 oversampled by male sex, White race, age ≥45 years).



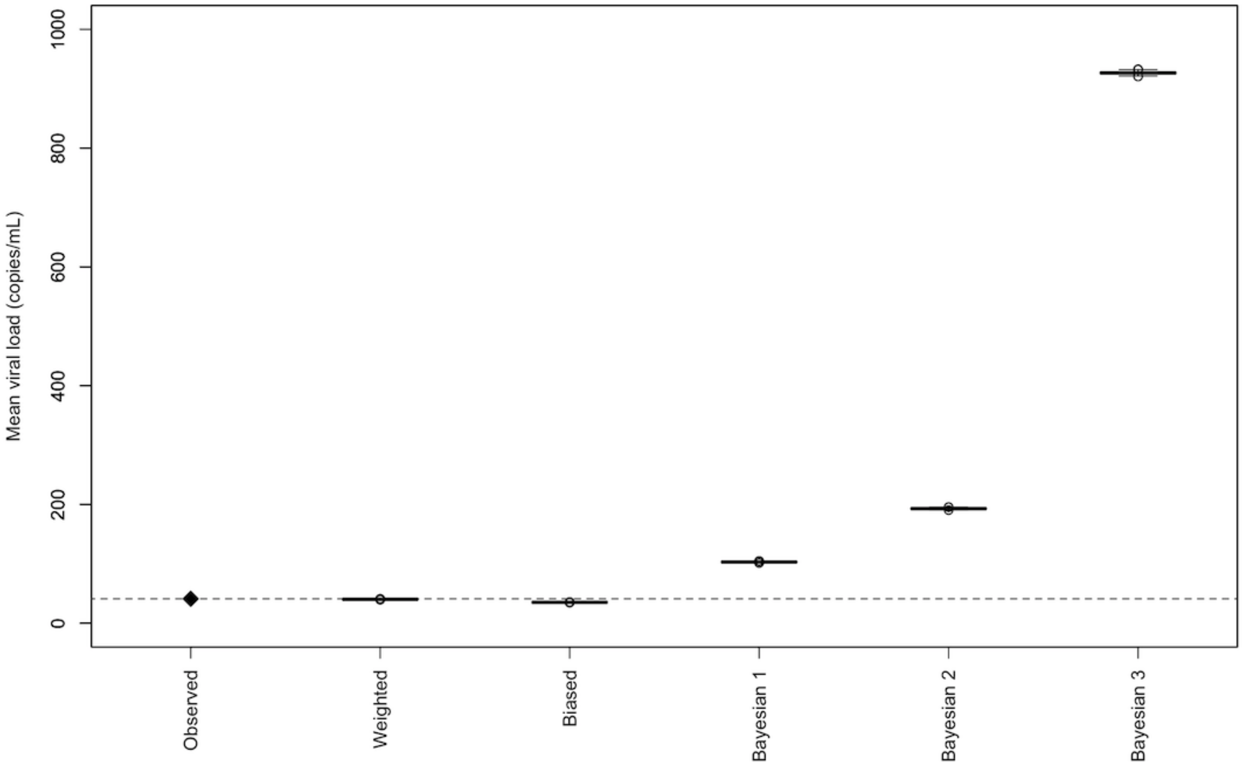
Holloway Community Program Clinic

The 2021 population in Delaware was 1,003,384. For each demographic stratum, the populations had the following characteristics: age (<35 years: 420,844; 35-44 years: 122,088; 45-54 years: 115,300; >54 years: 345,152), gender (male: 485,908; female: 517,476), and race/ethnicity (non-Hispanic White: 595,212; non-Hispanic Black or African American: 205,217; Hispanic or Latino: 101,213; other: 101,742). As of 2019, there were an estimated 3841 people living with HIV; 2984 were in care, and 857 were not in care. For each demographic stratum among those in care, the populations had the following characteristics: age (<35 years: 394; 35-44 years: 432; 45-54 years: 703; >54 years: 1455), gender (male: 2125; female: 859), and race/ethnicity (non-Hispanic White: 958; non-Hispanic Black or African American: 1725; Hispanic or Latino: 222; other: 79).

There were 1807 active patients in the Holloway Community Program with a resulted VL test as of the date of EHR data extraction. The GM VL of the clinic was 41, and the geometric SD was 190,261 copies/mL; 1656 of the 1807 (91.6%) patients were virally suppressed (<200 copies/mL). Additional characteristics may be found in Table 1.

Figure 4 presents the inferred population VL measure from the clinic's EHR (see Multimedia Appendix 4 for logarithmic results). The weighting-only adjustment had negligible impact compared with the unweighted estimate, while the biased weights shifted the estimates slightly lower to a median of 35 copies/mL. The biased weight systematically down-weighted higher VL individuals when they should have been up-weighted, as might occur based on an inaccurate catchment model where individuals with higher VLs were less likely to be sampled in the clinic. Meanwhile, the Bayesian adjustment moved the weighted estimate from 40 copies/mL to a median of 103 copies/mL with the 25% prior sample size, to 193 copies/mL with the 50% prior sample size, and to 926 copies/mL with the 200% prior sample size. Results were sensitive to the assumption about the informative prior's mean (Multimedia Appendix 5).

Figure 4. Inferred population geometric mean HIV viral load for Delaware based on active patients retained in care at the Holloway Community Program at ChristianaCare (Wilmington, DE), with results representing 1000 sampling weight adjustments. Bayesian 1: prior sample size of 25% of the weighted clinic sample size; Bayesian 2: prior sample size of 50% of the weighted clinic sample size; Bayesian 3: prior sample size of 200% of the weighted clinic sample size.



Discussion

Using a synthetic population, we observed that recovery of population VL from a single center's monitored VL was hampered when a historic measurement or informed guess at the prior population VL was unavailable. In other words, good VL data are preferred to methodological adjustments of incomplete data.

Community VL, calculated from individuals who have been diagnosed with HIV, has been used to generalize risk of HIV transmission and evaluate retention in care and viral suppression [6]. However, as mentioned in the Introduction, this measure has several shortcomings. First, it will almost always result in underestimated VL, as individuals who are unaware of their HIV status will likely have higher VLs. Relatedly, timing of the individual VL measure may also impact the community estimate, as VL will fluctuate over time (eg, acute vs chronic infection). Second, there may be issues with defining the specific geographic area of the community and whether this population is "closed." Although closed communities would allow for a more accurate community VL measurement, the applicability and feasibility are hindered in the real world by population migration. Third, sampling bias may be present when there is a high prevalence of undiagnosed people living with HIV [6]. In these situations, the use of the population VL may be more appropriate for reflecting transmission potential should we be able to impute data for those undiagnosed or not retained in care. To address these limitations, alternate metrics have been proposed, such as the prevalence of viremia based on viral suppression [19]. As such, researchers have adopted alternative community-level VL measures that reflect the prevalence of HIV in the community as well as distinguishing between those who are virally suppressed and those who have a high VL and are more likely to contribute to community spread [6,19]. The methods we have demonstrated can readily be adapted to other HIV measures where a weighted mean may be desired, such as CD4 cell counts among people living with HIV for a given jurisdiction. Regardless of the metric used, there is still risk of ecologic fallacy at the aggregate level wherein a higher population VL may not correspond to higher individual transmission risk when prophylaxis is common.

Others have acknowledged the important challenge of the use of EHR data for population inference when health care–seeking behavior and access to care impact representativeness. EHR-based studies are susceptible to issues of confounding, information bias, and selection bias [9]. Bower et al [20] demonstrated how selection into an EHR is not random and recommended techniques such as sampling (poststratification) weights and propensity scoring and inverse probability weighting (IPW) to adjust estimates, in their case, of cardiovascular disease risk. Flood et al [21] used EHR data to estimate childhood obesity and found that the application of sampling weights to their data allowed estimates to be comparable to a nationally representative survey. Goldstein et al [22] used IPW to adjust for presumed selection bias in a single-center EHR-based study when exposure and outcome relate to catchment. It is worth delineating how these 2 complementary strategies—sampling/poststratification weighting versus propensity scoring/IPW—differ in EHR research.

The IPW approach requires specification of a probability model (ie, the propensity score) for selection into the EHR from the source population, conditioned on measured characteristics related to this process. However, this demands the EHR capture relevant details on the catchment process, or those data can be readily linked, and EHRs are well-known to lack data on epidemiological determinants [23]. On the other hand, using a sampling weight assumes we have access to the denominators from which the EHR data are sampled. One such source of data we have used are census estimates, which can be stratified by factors relating to catchment and tuned to the local environment. The challenge with this approach is that, in practice, we may not know all the characteristics defining catchment process, the census might not capture those characteristics, or there may be ambiguous geography. Indeed, catchment is a multifactorial and sometimes nebulous process related to health care availability, accessibility, affordability, accommodation, and acceptability [24]. One potential way to gain insight into catchment is to compare EHR data with census data to see which characteristics are over- or under-represented for a given geographic area defined by the clinic. If the census lacks data on catchment-relevant factors but the EHR captures these details (eg, sexual orientation), this may favor the IPW approach.

Another important limitation of our approach was our construction of the sampling weights. We assumed a simple random sample within each catchment stratum to calculate the sampling weights. In our synthetic population, this was known with certainty, although we blinded ourselves to this oracle view by not retaining the selection probabilities during the data generation process but rather relying on our catchment model. However, as exemplified in our biased weighted analysis and the real-world clinic data set, the catchment stratum may be uncertain and, in our case, presumably underestimated population VL. Many extensions exist to improve weighting approaches, such as raking, which we did not evaluate herein [25]. We also observed a decrease in precision—widening of intervals—when comparing the weighted versus unweighted results. This has been termed the bias-variance tradeoff, where improved accuracy may be accompanied by worsened precision [26].

A particular strength to our approach is the straightforward implementation and Bayesian adjustment that can be carried out with minimal programming ability. The included source code [18] can serve as a starting point. More complicated cluster survey designs may also benefit from Bayesian methods [27,28]. Bayesian analysis requires careful deliberation over which priors may be most appropriate. Informative priors are useful and straightforward, but obtaining unbiased estimates of VL can be prohibitively expensive for some jurisdictions, and measures obtained in one jurisdiction may not be exchangeable with another. Indeed, we observed that our real-world application was sensitive to the choice of prior. Nonetheless, even a small unbiased survey can dramatically reduce RMSE and thus may be justified. This would have to be done only once to seed Bayesian prospective surveillance of population VL. These methods can be adapted to other aggregated measures of disease prevalence, for both research and practice purposes, especially if an historic prior estimate is available.

Health departments have expressed interest in using EHR data for many community health measures that can help inform resource allocation and public health decision-making in different contexts. Comer et al [2] identified 23 of these; hepatitis B and C infection was a high priority measure and one in which previous surveys such as the National Health and Nutrition Examination Survey [29,30] can serve as an informative prior. If, for example, a focal outbreak of hepatitis C is detected from an EHR, this could suggest targeted treatment and prevention efforts to cure infection and reduce future transmission.

In short, we observed that methodological adjustments were ineffective to recover the true population VL in our data without prior knowledge of what this value may be. Further validation using real-world EHR data from diverse clinical settings is needed to confirm this finding. Should such prior data be available, then it may be possible to infer population characteristics from a biased clinic sample in the EHR. Moving forward, we encourage those with access to population-based surveys of community health metrics—especially at subnational levels—to continue to disseminate these data to enable epidemiologic methods such as ours.

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Authors' Contributions

The study was conceived by NDG and IB. NDG obtained the funding. NDG and IB conducted the analyses. All authors interpreted the findings, drafted the initial manuscript, and approved the final submission.

Conflicts of Interest

NDG consults for ChristianaCare, unrelated to this work. All other authors report no financial conflicts of interest.

Multimedia Appendix 1

Comparison of the distribution of the logarithmic geometric mean HIV viral load (VL) for three clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000). Clinic A was sampled directly from the source population, whereas clinics B and C were sampled from a subset of the source population based on diagnosed HIV (clinic B) or retention in care (clinic C). All synthetic clinics oversampled by male sex, White race, and 45 years of age or older. Results represent 1,000 hypothetical clinics each with 1,000 sampling weight adjustments. 1 Prior sample size of 25% of the weighted clinic sample size. 2 Prior sample size of 50% of the weighted clinic sample size. 3 Prior sample size of 200% of the weighted clinic sample size. 4 Prior mean informed from weighted clinic B estimates.

[PNG File , 189 KB - ojphi_v16i1e58058_app1.png]

Multimedia Appendix 2

Comparison of the root mean squared error (RMSE) of the logarithmic geometric mean HIV viral load (VL) for three clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000). Clinic A was sampled directly from the source population, whereas clinics B and C were sampled from a subset of the source population based on diagnosed HIV (clinic B) or retention in care (clinic C). All synthetic clinics oversampled by male sex, White race, and 45 years of age or older. Results represent 1,000 hypothetical clinics each with 1,000 sampling weight adjustments. 1 Prior sample size of 25% of the weighted clinic sample size. 2 Prior sample size of 50% of the weighted clinic sample size. 3 Prior sample size of 200% of the weighted clinic sample size. 4 Prior mean informed from weighted clinic B estimates.

[PNG File , 151 KB - ojphi_v16i1e58058_app2.png]

Multimedia Appendix 3

Comparison of weight misspecification in the weighted logarithmic geometric mean HIV viral load (VL) for three clinic electronic health records (n=250 per clinic) sampled from a synthetic source population of people living with HIV (n=10,000). Clinic A was sampled directly from the source population, whereas clinics B and C were sampled from a subset of the source population based on diagnosed HIV (clinic B) or retention in care (clinic C). All synthetic clinics oversampled by male sex, White race, and 45 years of age or older. Results represent 1,000 hypothetical clinics each with 1,000 sampling weight adjustments. The biased weight systematically down-weighted higher VL individuals when they should have been up-weighted, as might occur based on an inaccurate catchment model where individuals with higher VLs were less likely to be sampled in the clinic.

[PNG File , 147 KB - ojphi_v16i1e58058_app3.png]

Multimedia Appendix 4

Inferred population geometric mean HIV viral load (VL) for Delaware based on active patients retained in care at the Holloway Community Program at ChristianaCare (Wilmington, DE). Results represent 1,000 sampling weight adjustments. The biased weight systematically down-weighted higher VL individuals when they should have been up-weighted, as might occur based on an inaccurate catchment model where individuals with higher VLs were less likely to be sampled in the clinic. 1 Prior sample size of 25% of the weighted clinic sample size. 2 Prior sample size of 50% of the weighted clinic sample size. 3 Prior sample size of 200% of the weighted clinic sample size.

[PNG File , 110 KB - ojphi_v16i1e58058_app4.png]

Multimedia Appendix 5

Sensitivity analysis of inferred population geometric mean HIV viral load (VL) for Delaware based on active patients retained in care at the Holloway Community Program at ChristianaCare (Wilmington, DE). Results represent 1,000 Bayesian sampling weight adjustments. Sensitivity analysis compared three alternate specifications of the prior mean for VL: 25%, 50%, and 200% of the original specification (m0). Prior sample size was varied three ways: 25%, 50%, and 200% of the weighted clinic sample size.

[PNG File , 118 KB - ojphi_v16i1e58058_app5.png]

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Abbreviations

CDC: Centers for Disease Control and Prevention
EHR: electronic health record
GM: geometric mean
IPW: inverse probability weighting
PLWH: people living with HIV
RMSE: root mean squared error
VL: viral load

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

Background: Human immunodeficiency virus and acquired immunodeficiency syndrome (HIV/AIDS) remains a significant international public health challenge. The Statewide HIV/AIDS Information Network (SHINE) Project was created to improve HIV/AIDS health information use and access for health care professionals, patients, and affected communities in Indiana. Objective: Our objective was to assess the information-seeking behaviors of health care professionals and consumers who seek information on the testing, treatment, and management of HIV/AIDS and the usability of the SHINE Project's resources in meeting end user needs. The feedback was designed to help SHINE Project members improve and expand the SHINE Project's online resources. Methods: A convenience sample of health care professionals and consumers participated in a usability study. Participants were asked to complete typical HIV/AIDS information-seeking tasks using the SHINE Project website. Feedback was provided in the form of standardized questionnaire and usability "think-aloud" responses. Results: Thirteen participants took part in the usability study. Clinicians generally reported the site to be "very good," while consumers generally found it to be "good." Health care professionals commented that they lack access to comprehensive resources for treating patients with HIV/AIDS. They requested new electronic resources that could be integrated in clinical practice and existing information technology infrastructures. Consumers found the SHINE website and its collected information resources overwhelming and difficult to navigate. They requested simpler, multimedia-content rich resources to deliver information on HIV/AIDS testing, treatment, and disease management. Conclusions: Accessibility, usability, and user education remain important challenges that public health and information specialists must address when developing and deploying interventions intended to empower consumers and support coordinated, patient-centric care.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

Unlike traditional approaches to sexuality and HIV education which can be constrained by the sensitive nature of the subject, Information Technology (IT) can be an innovative teaching tool that can be used to educate people about HIV. This is especially relevant to interventions targeting young people; the population group fond of using IT, and the same group that is more vulnerable to HIV/AIDS. Yet, there are significantly few empirical studies that rigorously evaluated computer-assisted school-based HIV/AIDS interventions in developing countries. The modest studies conducted in this area have largely been conducted in developed countries, leaving little known about the effectiveness of such interventions in low resource settings, which moreover host the majority of HIV/AIDS infections. This research addresses this gap by conducting a controlled before-after intervention evaluation of the impacts of the World Starts With Me (WSWM), a computer-assisted HIV/AIDS intervention implemented in schools in Uganda. The research question was: did the WSWM intervention significantly influence students' sexual behaviours, HIV/AIDS knowledge, attitudes and self-efficacy? To address this question, questionnaires were simultaneously administering to 146 students in an intervention group (the group receiving the WSWM intervention) and 146 students in a comparison group (the group who did not receive the WSWM intervention), before (February 2009) and after the intervention (December 2009). Findings indicate that the intervention significantly improved students' HIV/AIDS knowledge, attitudes self-efficacy, sex abstinence and fidelity, but had no significant impact on condom use. The major reason for non-use of condoms was lack of knowledge about condom use which can be attributed to teachers' failure and inabilities to demonstrate condom use in class. To address this challenge, intervention teachers should be continuously trained in skills-based and interactive sexuality education. This training will equip them with self-confidence and interactive teaching skills, including tactics for emphasing building students' skills through role plays and interactive assignments. In addition, the HIV interventions themselves should include interactive virtual condom use demonstrations that can be accessed by students themselves. Key words: ICT for HIV/AIDS; WSWM; HIV/AIDS behaviours, knowledge and attitudes; students.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

Background Spatial outbreak detection algorithms using routinely collected healthcare data have been developed since the late 90s to identify and locate disease outbreaks. However, current well-received spatial algorithms assume only one outbreak cluster present at the same point of time which may not be valid during a pandemic when several clusters of geographic areas concurrently occur. Based on a retrospective evaluation on time-series and spatial algorithms, this paper suggests that time series analysis in detection of pandemics is still a desirable process, which may achieve more sensitive performance with better timeliness. Methods In this paper, we first prove in theory that two existing spatial models, the likelihood ratio and the Bayesian spatial scan statistics, are not useful if multiple clusters occur at the same point of time in different geographic regions. Then we conduct a comparison between a spatial algorithm, the Bayesian Spatial Scan Statistic (BSS), and a time series algorithm, the wavelet anomaly detector (WAD), on the performance of detecting the increase of the over-the-counter (OTC) medicine sales during 2009 H1N1 pandemic. Results The experiments demonstrated that the Bayesian spatial algorithm responded to the increase of thermometer sales about 3 days later than the time series algorithm. Conclusion Time-series algorithms demonstrated an advantage for early outbreak detection, especially when multiple clusters occur at the same time in different geographic regions. Given spatial-temporal algorithms for outbreak detection are widely used, this paper suggests that epidemiologists or public health officials would benefit by applying time series algorithms as a complement to spatial algorithms for public health surveillance.

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Roles of Health Literacy in Relation to Social Determinants of Health and Recommendations for Informatics-Based Interventions: Systematic Review

Abstract

Strengthening the capacity of public health systems to protect and promote the health of the global population continues to be essential. Leveraging informatics practices and principles is beneficial for improving global health response capacity. A critical step is to develop an informatics agenda for global health. With the aim of building a foundation for this agenda, the authors developed a workshop to examine the evidence in this domain, recognize the gaps, and document evidence-based recommendations. On 21 August 2011, at the 2011 Public Health Informatics Conference in Atlanta, GA, USA, a four-hour interactive workshop was conducted with 85 participants from 15 countries. Participants represented governmental organizations, private sector companies, academia, and non-governmental organizations. The workshop discussion followed an agenda of a plenary session - Planning and Agenda Setting - and four tracks:; Policy and Governance; Knowledge Management, Collaborative Networks and Global Partnerships; Capacity Building; and Globally Reusable Resources: Metrics, Tools, Processes, Templates, and Digital Assets. Track discussions created a rich environment to examine the evidence base and the participants' experience to gather information about the current status, compelling benefits, challenges, barriers, and gaps for global health informatics as well as articulate opportunities and recommendations. This report provides a summary of the discussions and key recommendations as a first step towards building an informatics agenda for global health. Attention to the identified issues is expected to lead to measurable improvements in health equity, health outcomes, and impacts on population health. We propose the workshop report be used as a foundation for the development of the full agenda and a detailed roadmap for global health informatics activities based on further contribution from key stakeholders. The global health informatics agenda and roadmap can provide guidance to countries for developing and enhancing their individual and regional agendas.

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