Integration of digital twins to simulate community health scenarios and evaluate the effectiveness of public health interventions led by pharmacists

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KEYWORDS

Digital twins, Public Health Interventions, Community Health, Pharmacists, Precision Medicine, Healthcare, Patient

ABSTRACT

Public health emergencies such as the 2019 coronavirus disease (COVID-19) have increased the focus on digital technology. A digital twin (DT) is a cybernetic representation of a physical object (e.g., a person or a community) that helps us comprehend the complexity of the real thing and makes it easier to foresee, avoid, track, and improve its actual performance. To prepare for a new age of reliable and precise public health and medical care, DT technology can propel a much-needed radical transformation of conventional electronic health and medical records, which centre on individuals and their aggregates covering populations. Hence, this paper presents the Digital Twin-based Public Health Intervention Model (DT-PHIM) to simulate community health led by pharmacists. The use of digital twins in healthcare has the potential to revolutionize workflow analysis and resource allocation, ultimately resulting in better patient care and more efficient operations. In addition, healthcare providers may hone their abilities and rehearse intricate treatments in a secure and realistic environment with the help of digital twins. There is great promise for digital twin technology to revolutionize healthcare by boosting innovation, patient safety, and overall patient outcomes. On top of that, DTs may help doctors and other medical staff, such as hospital pharmacists, make decisions by simulating how therapy would affect these patients. The experimental outcomes demonstrate that the suggested DT-PHIM model increases the patient data access ratio by 97.4%, the monitoring efficiency ratio by 96.2% and the decision-making ratio by 98.2% compared to other existing models.

1. Introduction

A Digital Twin is a digital representation of a real object or system. Community Health utilizes a virtual representation of a population, health system, or individual health behaviours and diseases [1]. Modern healthcare relies on digital technologies and services to aid patients and physicians with data collecting, clinical communications, and disease management decision assistance [2]. Crucial activities, such as data analytics and modelling, are propelled by technology in medical research that aims to enhance diagnoses, medication efficacy, and treatment delivery [3]. It is believed that the new digital twin technology, mostly used by engineering and industrial companies, may enhance clinical and public health outcomes, speed up medical discovery efforts, and open up new avenues for scientific inquiry [17]. For instance, by facilitating the development of more accurate public health treatments, digital twins can serve as a social equalizer and bring substantial societal advantages [4]. In addition, when the technology is used in clinical practice, it is imperative that all healthcare personnel, such as clinicians, nurses, pharmacists, and pharmacy technicians, have complete proficiency with the technology and feel at ease when advising and teaching patients on how to utilize the digital intervention [5] properly.

Better decision-making, stronger support for public health initiatives, and the ability to implement more personalized and efficient interventions for population health management are all possible outcomes of adopting certain strategies, such as conducting process/asset-wise and comprehensive data privacy validation, providing good governance, and executing coordinated multinational efforts [18]. Expertise in medication management, patient education, and coordinated treatment makes pharmacists valuable in improving public health. Their management and involvement in public health activities help improve critical health issues and enhance community health outcomes [7]. For better health intervention planning, implementation, and evaluation, digital twins are being developed in public health [9]. These include digital representations of people, healthcare systems, or health settings [20]. Data collected from electronic health records, wearable devices, and environmental sensors allows these computer models to simulate various health scenarios, such as treating chronic diseases, allocating resources, and disease outbreaks [8]. This type of technology makes predictive analysis, real-time monitoring, enhanced response plans, and personalized therapy possible [19]. For instance, during the COVID-19 pandemic, digital twins improved disease transmission forecasts and resource allocation [6]. Despite their potential, improving their use in public health will need resolving data privacy issues, model complexity, and multidisciplinary collaboration [10].

Related works

Angie Luna Pinzon et al. [11] recommended the Assessment of Programmes in Complex Adaptive Systems (ENCOMPASS) model for analyzing public health programs. To determine which features were crucial for evaluating the LIKE program, the author superimposed them on top of the discovered ones and placed them in the context of the program. The practical applied emphasis and incorporation of important features from previous systems assessment studies make ENCOMPASS valuable. It has applications in the assessment of public health programs in systems that are complex and adaptable.

M. N. Mohd Tariq et al. [12] suggested the single-blind cluster randomized controlled trials (SBCRCT) for analyzing the efficiency of health education-based intervention (HEBI) in enhancing flood disaster preparedness among the community. Participants will be asked to participate in the research when randomly chosen and meet the inclusion criteria. Through health lectures and videos, liaison officers will manage the delivery of health literacy modules based on the Health belief theory. There can be three data collection periods: immediately after the intervention, three months later, and at baseline. Participants' demographic information, level of education, experience, and attitude toward disaster preparation will be evaluated using a standardized questionnaire.

Shannon McCarley et al. [21] proposed the Community-Based Participatory Mixed Methods Research (CBPMMR) for analyzing the Nutrition Intervention. In this manuscript, the four stages of CBPR are outlined: (1) linking and diagnosing, (2) prescribing-employing, (3) assessing, and (4) distributing and cleansing interventions. The intervention encouraged Latino parent (mostly Central American in the US) to give their toddlers and infants filtered tap water instead of sugary drinks. By facilitating collaborative learning, CBPMMR improved the intervention's design, execution, and assessment while revealing early behavioural results and new information about the processes that may cause behaviour change [13].

Phyllis Dako-Gyeke et al. [14] discussed the qualitative research approach (QRA) for piloting community health advocacy teams to enhance the efficiency of long-lasting insecticide net dissemination. Using a QRA, 43 members of CHAT from six different communities in Ghana's Eastern and Volta areas were surveyed. The CHAT includes important community members whose responsibilities revolve around capacity development, social and behavioural change communication (SBCC) tactics, and community/social mobilization. All of the study cities had the CHATs installed for four months as a pilot program, during which time we noted any problems or possibilities. Members of CHAT took part in six focus groups that were recorded, verbatim transcribed, and subjected to thematic analysis using NVivo 13.

Do Hwa Byun et al. [15] deliberated the Analytic Hierarchy Process (AHP) for Prioritizing Community-Based Intervention Programs for Enhancing Treatment Compliance of Patients with Chronic Illnesses. The author observed that enhancing treatment adherence of patients with chronic illnesses must be considerably more essential than upgrading healthcare systems, based on our survey of 185 community health physicians in Korea using this AHP questionnaire. Proper implementation of this AHP paradigm requires more studies to broaden survey participants to include primary care providers and possibly federal lawmakers

2. Methodology

There is a growing reliance on complicated, high-volume data from many sources in public health. The promise of more accurate public health in the digital age necessitates new forms of infrastructure to support operations. Public health interventions can greatly enhance the health and welfare of communities and populations, and digital technologies can make this happen. A growing area of study known as "digital public health" has emerged from the public health sector's interest in using digital technology in health care, building on the work of digital health professionals. Public health interventions in the digital realm may cover a wide range of topics, from disease prevention to population health surveillance, and they evolve at a much faster rate than their analogue counterparts, making it difficult to evaluate them. Numerous people with long-term health conditions, such as persistent breathing problems or lung disease, are often seen in classical community health programs. Nevertheless, for a doctor to make therapeutic decisions, they need intricate phenotyping procedures that can consistently be matched to prescription and medication for a patient. Modern medical technology has made it possible to address the more complex issues that traditional approaches to chronic disease management sometimes neglect. Figure 1 shows the Advanced technologies for Public Health Intervention.

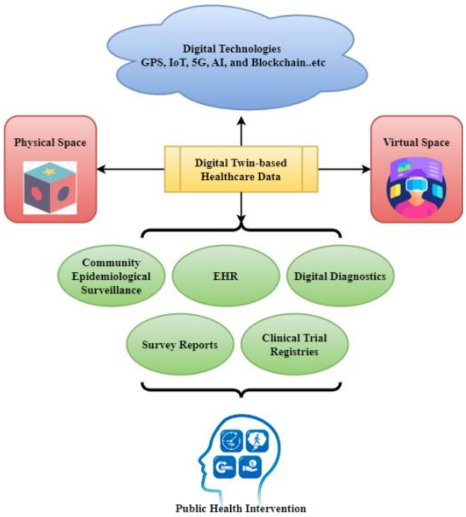

Figure 1. Advanced Technologies for Public Health Intervention

The advanced technologies include IoT, AI, blockchain, cloud computing, DT and 5G networks. This paper presents a hospital management framework within the context of COVID-19. The framework allows for adding all relevant dimensions to the DT model and includes a real-time or near-real-time feedback loop to maintain an acceptable quality of experience (QoE). This study presents a patient-centric conceptual framework for COVID-19 hospital administration focused on the quality of experience (QoE) of the healthcare provider, the user. It is based on the frameworks that have been discussed. Equation (1) shows the expansion of the five-dimensional design to m-dimensions.

$$DT\ Model = f(VE, PE, DD, SS, CN, YY1, YY2, \dots YYm) \quad (1)$$

As shown in Equation (1), where VE denotes the virtual equivalents, PE indicates the physical entities, SS are the services for PE and VE, DD is the DT data, and CN are the connections. Additional dimensions $(YY1, YY2, \dots YYm)$ can be added based on a particular application (e.g., number of available beds, number of infected patients, etc) in the community health scenarios. All DT agents in a group may stay at varying distances from each other. Our approach creates every conceivable combination of a group's members. Each pair is assigned a number value, which denotes its proximity, from 10 predetermined ranges. Every range meets the relation $0 \leq A_{low} < A_{high} \leq 1$, where A_{low} and A_{high} are upper and lower bounds of the range, correspondingly. Only when an infected individual is in the infectious stage of the illness may the behaviours that cause infection in another person be considered significant. Equation (2) determines the infection value of an at-risk person due to the harmful effects caused by an infected agent's activities.

$$infection = (1 - protection\ level) \times E \times proximity \quad (2)$$

Here, $0 \leq P_{min} \leq E \leq P_{max} \leq 1$; P_{min} and P_{max} correspondingly, the upper and lower bounds of the influences of an diseased person’s activities on others. Instead, Equation (3) computes the infection values owing to the positive effect of activities, i.e., sanitizing.

$$infection = (-1) \times (1 - protection\ level) \times E \quad (3)$$

Here, $-1 \leq W_{min} \leq E \leq W_{max} \leq 0$; W_{min} and W_{max} are, correspondingly, the lower and upper bounds of the influences of an activity on oneself.

The next step is to compare this infection value to a predetermined action infection threshold. If this barrier is crossed, the vulnerable person's infection level will be increased (or decreased, in the case of good-impacting activities) by an amount equivalent to the contamination value computed above. In conclusion, this infection level will confirm or deny an individual's infection status according to a predetermined threshold. Evidence that an action will affect others is still lacking, even after the fact. An activity could have repercussions without necessarily aiding in disease transmission.

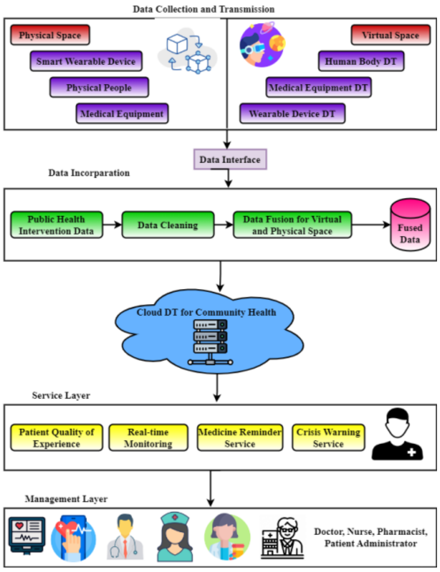

Figure 2. Proposed DT-PHIM model

Figure 2 shows the proposed DT-PHIM model. The data are taken from the COVID-19 outcomes by vaccination status Kaggle dataset [16]. Virtual objects, physical objects, services, and data about their fusion comprise digital twin healthcare data (DTH data). The first step is gathering information from real and virtual individuals and sending it to the middleware or database via adapters or data interfaces. The term physical people data refers to a wide variety of sources, including yet not limited to medical records, images, and results from medical examinations conducted in hospitals; health data collected by smart healthcare devices used by users outside of hospitals, such as blood pressure, heart rate, body fat percentage, and glucose levels; and data sourced from third parties, such as information about medical insurance and consultations. Model data, simulation data, assessment data of the human body, medical equipment, and wearable device digital twin models are all part of virtual people data. The second step in ensuring data integrity and consistency is merging physical and virtual data using data fusion and cleaning techniques. Some examples of such algorithms include the Kalman filter, neural networks, and others. Third, the cloud medical service platform's data centre holds the fused data in a uniform format. Through intelligent perception and virtualized access, medical institutions may augment their cloud healthcare platform with the resources and skills of other healthcare providers, including hospitals, clinics, community health centres, and third-party agencies. The platform may receive services from patients through personal health records (PHR) and wearable devices. The resource management layer supplies the medical resources, healthcare capabilities, and data that are part of health and public health service operations.

A location-based service (LBS) offers healthcare services by sensing the user's location information using location-aware technology. In this research, the data was retrieved via the route planning service of the Location-based Service (LBS) provider after the DT agent-specific schedules were generated for community health scenarios. This study obtained the optimized route that complies with road networks and accessibility by inputting details such as starting and ending points, method of transportation, and anticipated departure time. This research regarded driving as a separate method of transportation as there is almost no risk of infection when travelling. Each group pattern was given a different driving preference rate. At the same time, the transportation distance influenced the likelihood of driving. Here is how the chance of driving was calculated for each trip:

$$q(d) = \frac{2}{1+e^{-\beta qu\frac{d}{D}}} - 1 \quad (4)$$

As inferred from equation (4), where the probability functions q(d) received the distance d between the origin and destination as inputs. D is the distance threshold, which this study sets to 5000 m. qu is the driving preference parameter set in the group patterns. β had values of 0.4, making the likelihood of driving close to 100% when qu equivalents 10. Along with driving, other forms of mobility, including walking, cycling, and public transit, were evaluated for their infection possibilities. The likelihood of using the bus, train, bike, walking, etc., is calculated in Equation (4) (with a different D) and enumerates the possible adoption of favourable results in the community health scenario with the help of goal-oriented planning and directed public health interventions.

3. Results and discussion

This paper presents the Digital Twin-based Public Health Intervention Model (DT-PHIM) to simulate community health led by pharmacists. The data are taken from the COVID-19 outcomes by vaccination status Kaggle dataset [16]. Beginning with the week ending April 3, 2021, when COVID-19 vaccinations were widely accessible in Chicago, the rates for completely vaccinated and unvaccinated individuals are calculated. Rates for booster shots will start the week ending October 23, 2021, after the CDC suggested them for adults 65 and up, as well as adults in specific populations, high-risk institutional and occupational environments, and anyone who received the Pfizer or Moderna vaccine as part of their primary series, or the Johnson & Johnson vaccine.

Patient Data Access Ratio

Through intelligent perception and virtualized access, medical institutions may augment their cloud healthcare platform with the resources and skills of other healthcare providers, including hospitals, clinics, community health centres, and third-party agencies. The platform may receive services from patients through personal health records (PHR) and wearable devices. Additionally, medical institutions should have their model developers or service providers upload their digital twin healthcare models to a cloud-based system. These models should include information about patients, capabilities, and available resources. Figure 3 shows the patient data access ratio.

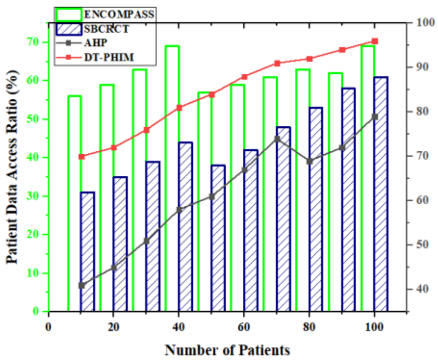

Figure 3. Patient Data Access Ratio.

Monitoring Efficiency Ratio

Digital twins enable remote monitoring and improved patient engagement. Patients can actively engage with their digital twin to learn about their health, track progress, and make informed decisions, leading to enhanced adherence to treatment procedures and better health results. Digital twins can monitor physiological parameters, vital signs, and other real-time health-related data to identify abnormalities or early warning indications. This makes intervening proactively, avoiding difficulties, and improving treatment programs possible. Digital Twin helps detect chronic disease early by analyzing physiological and behavioural data to manage chronic disease in a large population. Figure 4 shows the monitoring efficiency ratio.

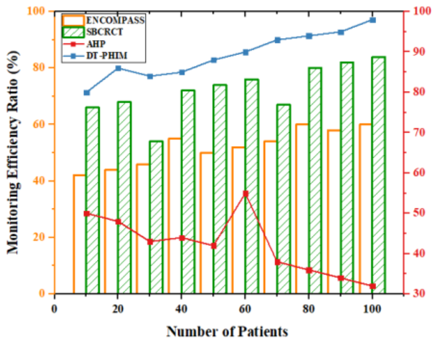

Figure 4. Monitoring Efficiency Ratio

Decision-Making Ratio

Digital twins have the potential to revolutionize healthcare by bringing patients and doctors together in real-time, allowing for more patient-centred treatment and jointly making decisions. Many facets, including health management, decision-making, and prediction, are included in digital twin intervention. It brings new ideas and technology to conventional community health intervention. Model establishment and prediction description are the primary uses of digital twins in precision health, with limited deployment in multi-centre settings. A more solid and comprehensive database is suggested to be established to enhance clinical decision-making and decrease the probability of inaccurate treatments. Figure 5 shows the decision-making ratio.

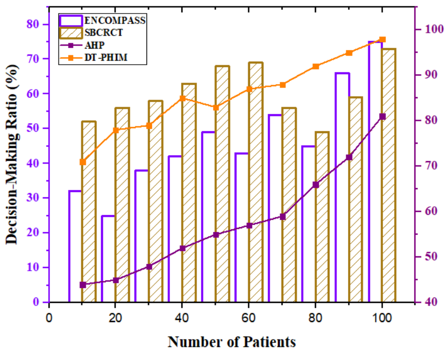

Figure 5. Decision-Making Ratio.

4. Conclusion and future scope

This paper presents the Digital Twin-based Public Health Intervention Model (DT-PHIM) to simulate community health led by pharmacists. This study proposes an established user-centred design process to be included in developing DT-based public health interventions. The social determinants of health include health education, community and participation in society, intersectoral collaboration, interventions to reduce risk factors for behaviour (such as alcohol, tobacco, poor nutrition, and lack of exercise), and so on. Better health decision-making at the national and subnational levels may be facilitated by sharing data collected by community health workers through digital health systems, allowing for more efficient diagnosis and treatment of people across all health domains. This community health worker envisioned a digital tool to enhance access to high-quality health data so that community health officers could make evidence-based choices on disease awareness programs.

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