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Human Digital Twins for pervasive healthcare: A scoping review

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Abstract

Background: Human Digital Twins (HDTs) have recently emerged, especially in the context of healthcare. With the growing emphasis on preventive healthcare beyond diagnosis, pervasive sensing has become essential which enables continuous monitoring through real-world data captured from wearables and/or mobile devices. **Objective:** This scoping review investigates how pervasive sensing technologies have been utilized in the implementation of HDTs for healthcare, with a focus on understanding the twinning methods, identifying their advantages and limitations, and uncovering key challenges encountered in real-world applications. **Methods:** We proposed an analytical framework to examine how pervasive sensing technologies are utilized in the implementation of HDTs for personal health management. Using this framework, we conducted a comprehensive literature search across PubMed, Scopus, IEEE Xplore, Web of Science, and Google Scholar. **Results:** A total of 39 eligible papers were reviewed. We present an analysis of these studies and provide a discussion on the potential and limitations of HDTs in the context of pervasive healthcare. **Conclusions:** The key takeaway is that the integration of HDTs and pervasive sensing

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provides a foundation for realizing pervasive healthcare by enabling not one-time digital replication, but continuous and comprehensive monitoring of individuals, including their surrounding environments and behavioral changes.

Keywords
human digital twin, data-driven modeling, patient-centric treatment, pervasive health

Introduction

Pervasive healthcare refers to a healthcare paradigm that utilizes ubiquitous sensing and computing technologies to enable continuous, real-time monitoring and personalized interventions across daily life contexts, beyond traditional clinical environments.[1,2] Since health is influenced by a wide range of factors including genetic, behavioral, socioeconomic, and environmental elements,[3] continuous and context-aware monitoring is essential. In particular, tracking individuals in their daily environments allows for a more comprehensive understanding of how social and environmental contexts affect the users' health outcomes.[4] For the pervasive healthcare, recent studies have leveraged sensors, such as smartphones and wearables, and artificial intelligence (AI) models to passively capture behavioral and environmental factors in everyday life contexts to detect and forecast specific diseases.

In this context, Human Digital Twins (HDTs) have also been explored as a promising approach to enable pervasive healthcare. As a broader concept, A Digital Twin (DT) refers to a digital or virtual representation of a physical entity and its underlying processes, designed to support visualization, simulation, and prediction.[5] In healthcare, physical entities typically represent individuals, or components of individuals such as specific organs or body parts, along with their environments. Such DTs are often referred to as HDTs or medical DTs. The DT concept is closely aligned with entity- or service-centric modeling approaches in context-aware computing and ambient intelligence,[6,7] which integrate diverse data sources to model user states and deliver intelligent, context-sensitive services. This perspective positions HDTs as a foundation for pervasive healthcare systems that continuously monitor individuals, detect emerging risks, and deliver timely, personalized interventions in everyday contexts.[8–23]

Recently, a number of reviews have been published to introduce what HDTs are and how they can be applied in the healthcare domain (see Table 1). The previous reviews primarily offered conceptual overview of HDTs[24,25] and explore their current applications in healthcare settings[26,27,28] Also, the studies identified technical challenges in their implementation across healthcare systems[26,27,29,30] A subset of these works also explores human-centered applications, particularly in the context of personalized medicine and behavior change.[25,28,29,30] For example, Lauer-Schmaltz et al. proposed a user-centered design methodology (ETHICA) that accounts for human factors such as behavior, cognition, and ethical considerations.[30] This study presents a design framework that overcomes the limitations of conventional digital twin development and provides a flexible approach to managing the complexity of human factors, including behavior, psychological states, and environmental dynamics. As such, recent studies have increasingly explored how HDTs can be applied to prevention, diagnosis, and rehabilitation in the healthcare domain, based on data that captures human behavior and environmental factors.

However, most prior reviews offer limited insights how HDTs are actually implemented in *real-world, pervasive healthcare environments* that require continuous and context-aware sensing. The

Table 1. Comparison of HDT Review Studies in Healthcare Domains: (1) Pervasive Sensing Coverage (2) Human-Centered Perspective (Focused, Moderate, and Not Focused) and (3) Implementation (Conceptual Focus vs Implemented: Covering Implemented HDT Work).

Ref No.	Title	Scope/Key Focus	Pervasive sensing	Human-centered perspective	Implementation
24	Katsoulakis et al. (2024)	General healthcare applications Scoping review across domains	Not focused	Moderate	Implemented
26	Xames & Topcu (2024)	Healthcare systems System architecture and challenges	Not focused	Not focused	Implemented
27	Sun et al. (2023)	Medicine and healthcare Overview of updates and challenges	Not focused	Not focused	Implemented
29	Barresi et al. (2023)	Human-centered HDTs Opportunity and ethical issues of using HDTs	Not focused	Focused	Conceptual Focus
25	Lauer-Schmaltz et al. (2024)	Conceptual definition of HDTs Theoretical framework	Not focused	Focused	Implemented
30	Lauer-Schmaltz et al. (2024)	HDT design methodology Systematic methodology for HDT design	Moderate	Focused	Conceptual Focus
28	Lauer-Schmaltz et al. (2022)	Therapy and rehabilitation Behavior change design	Not focused	Focused	Implemented
Our paper		Pervasive healthcare HDT systems implementation using pervasive sensing	Focused	Focused	Implemented

existing reviews have primarily focused on disease-specific or organ-level applications, often treating digital twinning as a *one-time representation* of the physical state. However, to enable dynamic and responsive HDTs that reflect changes over time and context, pervasive sensing is essential for continuously capturing physical, behavioral, and environmental data. To address this gap, this article focuses on studies with *"HDT systems implementation"* for pervasive healthcare by mapping physical entities to the digital world using real-world data, and that have developed example applications demonstrating their practical use in everyday contexts. Building on these studies, we propose a framework that structurally outlines the step-by-step process of implementing HDTs, aiming to support the broader adoption of HDT systems in healthcare domains where they have not yet been applied.

For this, we conducted a scoping review[31] on HDT technologies by answering the following questions: (1) What are the main objectives of HDT applications that enable pervasive, continuous, and personalized services? (2) Which entities and processes should be digitally modeled to reflect users' health states in everyday life contexts? and (3) How we can support the real-time sensing and dynamic updates required for pervasive healthcare? By synthesizing the major findings from the reviewed articles, we aim to clarify how DT technologies have been leveraged to support personalized and context-aware health services in pervasive healthcare settings. Based on this analysis, we identify two core elements that characterize implemented HDT systems enabling pervasive healthcare: (1) the types of physical entities being modeled, which encompass personal, social, and environmental factors associated with health conditions, and (2) the framework which typically consists of three interconnected stages, sensing (collecting real-world data), mapping (transforming low-level sensor data into high-level health-related features), and acting (providing timely interventions).

The key takeaway of this review is that HDTs can serve as a key role in pervasive healthcare by enabling continuous monitoring, personalized interpretation, and context-aware intervention. By integrating multimodal data and contextual information, HDTs can generate personalized insights (e.g., when and why certain events occur). Furthermore, predictive modeling and simulation support timely, data-driven actions (e.g., what action to take and how), making HDTs effective for just-in-time intervention in everyday health management.

Textbox 1. Inclusion and Exclusion Criteria for Reviewed Articles stages

Eligibility criteria for the scoping review.

- Inclusion criteria
  - Document types: journal article or proceeding paper
  - Study types: any type of original peer reviewed research
  - Language: English
  - Period: published since January 2010
  - Study content:
    - Studies that developed and evaluated DT system prototype for individual's health management
- Exclusion criteria
  - Document types: No journal article or proceeding paper (e.g., standards, editorials, etc.)
  - Study types: survey, review, or perspective articles
  - Language: any other language
  - Study content:
    - Studies that only presented DT architecture without a real DT system prototype
    - Studies where the physical entity of a DT is not a person
    - Studies that proposed a new DT modeling algorithm or its performance improvement

Methods

Overview

This section illustrates the review methods and characteristics of the HDT definition and key components used for the scoping review of recent studies that present case studies with working prototypes. This paper complies with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for scoping reviews to ensure the reliability of the search results[32] (see Figure 1).

Search strategy

A comprehensive search was conducted from major electronic databases (i.e., PubMed, IEEE, Scopus, Web of Science, and Google Scholar) to find relevant studies. A search was performed on 24 Feb 2025 from four electronic databases, including all articles published since January 2010.

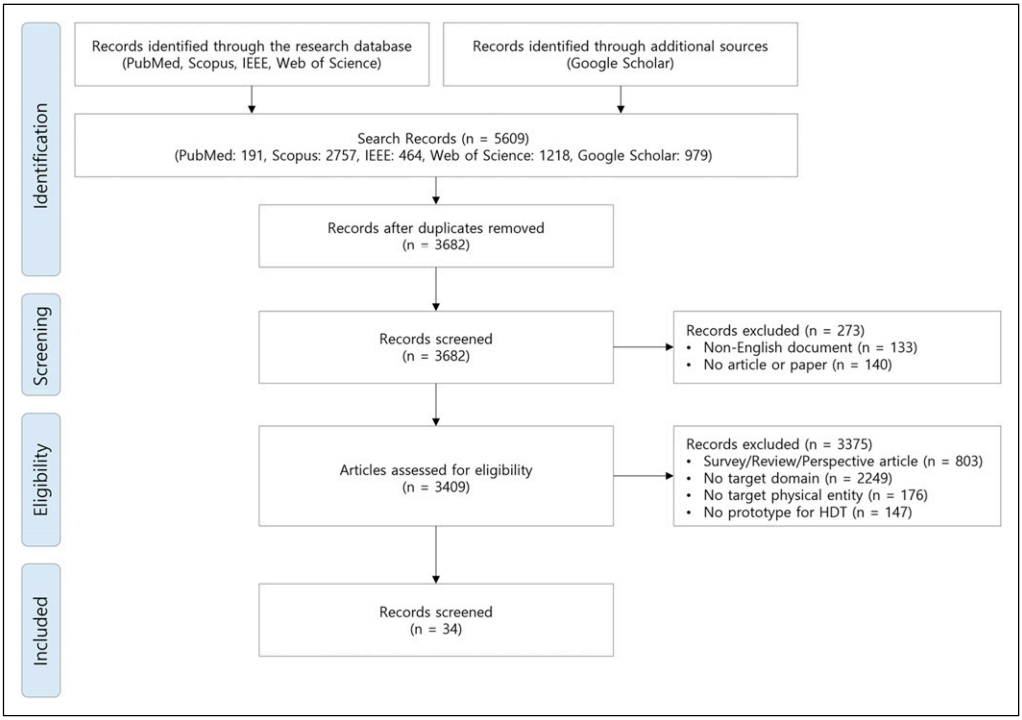

Figure 1. The flow description of PRISMA process.

Three authors skilled in information retrieval developed search strategies for four electronic citation databases. Search terms were designed to comprehensively capture research publications utilizing DTs for human health management in the healthcare or medical fields. As a result, combinations of the following terms were used to search for target articles: ("digital twin" AND "medical") OR ("digital twin" AND "human") OR ("digital twin" AND "health"). All authors performed peer review to ensure the accuracy and consistency of search results. Multimedia Appendix 1 provides the complete search strategy.

Eligibility criteria

Inclusion and exclusion criteria were established based on a literature review and discussion of the research questions, as shown in Textbox 1. Articles were required to meet all inclusion criteria to be included in the final review.

Primary inclusion criteria were any original peer-reviewed research article published in the healthcare or medical field using qualitative, quantitative, or mixed methodologies. All articles were written in English and were not limited by publication period. Among the articles that met these inclusion criteria, those that implemented and evaluated a HDT system prototype for patient health management were finally selected. HDT system prototype is not simply a conceptual presentation of the definition or utilization method of DT, but a visible system that senses actual physical entities through sensors, extracts features from the sensed data (i.e., mapping), and performs simulation, intervention, or visualization through modeling. We reviewed only papers that developed prototypes to analyze how DT is actually utilized in the pervasive healthcare field.

Exclusion criteria were documents not written in English or the following types: systematic reviews, survey papers, perspective articles, conference papers, protocols, case studies, comments and editorial letters, and unpublished works. Regarding research content, studies using HDTs in domains other than healthcare or medical fields were excluded. In addition, articles that utilized DTs in the healthcare or medical field but the physical entity was not a person (e.g., DT of an operating room), articles that only proposed a conceptual architecture or framework without building a DT system prototype, or articles that suggested a new DT modeling algorithm or focused on performance improvement were also excluded.

To ensure consistency and reproducibility of study selection, the content of each paper was independently reviewed by three authors based on inclusion and exclusion criteria to assess eligibility. The authors independently reviewed the abstract of each paper and, when necessary, downloaded the full paper to ensure it met the criteria. During this process, the authors followed the PRISMA procedure[33] to ensure a review process.

After each author's review was completed, the final eligible papers were discussed in an inter-author meeting. Papers that were unanimously assessed as eligible by all authors were included in the final list. For papers where there was disagreement on eligibility, the remaining co-authors reviewed the papers and made a final decision.

Data extraction

Three reviewers independently extracted descriptive data on the characteristics of selected publications. The extracted characteristics included the purpose of utilizing HDT, the physical entity targeted by the HDT, the environment surrounding the physical entity, and the underlying process that refers to a set of steps performed by that physical entity. In addition, information on the sensing-mapping- acting process performed through the HDT system was extracted from each publication.

Synthesis of results

We summarized the extracted data results from selected articles. Each study was analyzed according to multiple key dimensions that reflect how HDT systems are implemented and utilized in pervasive healthcare contexts. The summary of each article are presented in Appendix 2.

- The "*Purpose/Benefit*" column indicates the primary goal of each HDT system, such as health monitoring, disease tracking, or rehabilitation support.
- The "*Physical Entity*" refers to what is being digitally twinned. This includes not only specific individuals (e.g., patients with diabetes, nurses) and body parts (e.g., heart, joints), but also aspects of human behavior (e.g., gait, medication intake, emotional expression).

We include human behavior as part of the physical entity because behavior often represents the most observable and actionable manifestation of an individual's internal state. In many HDT systems, behavioral signals serve as primary input for both sensing and modeling, enabling real-time tracking of physical or cognitive conditions. The "*Environment*" describes where the HDT system was deployed or simulated, ranging from hospital-based settings to home environments and rehabilitation spaces.

- The "*Underlying Process*" refers to the physiological or behavioral functions modeled in the system, such as insulin infusion, gait pattern, or inflammatory response.
- The "*Sensing*" column lists the types of sensors or input data used to collect information from the physical entity, including biosignals (e.g., heart rate), medical sensors, camera-based imaging, or annotated logs.
- The "*Mapping*" columns (Low-level and High-level) describe how raw sensor data are transformed into higher-level representations. Low-level mapping includes features like facial landmarks or blood oxygen levels, while high-level mapping involves abstractions such as insulin intake, gait sequences, or diagnostic scores.
- The "*Acting*" column explains how the system responds to the interpreted data. These responses were categorized into simulation (e.g., prediction of disease progression), visualization (e.g., display of vital signs), and intervention (e.g., gait correction).

Results

Study selection

Of the 5648 articles identified in the search results, 1927 duplicates (34.12% of 5648) were removed. An initial eligibility assessment was performed on the titles and abstracts of 3721 articles, excluding 273 articles (4.83%); 133 articles (2.35%) were excluded because they were not written in English, and 140 articles (2.48%) were not conference papers or journal format papers (e.g., Editorial, presentation or standards materials).

In the second round of eligibility assessment, the full text of 3448 articles (61.05%) was assessed according to the eligibility criteria, and 3223 papers (57.06%) were excluded; 1884 articles (33.36%) were excluded because they were the document type in the exclusion criteria (e.g., survey or review article) and 1339 articles (23.71%) were excluded because they were not studies in a healthcare target domain (i.e., healthcare or medical).

225 articles (3.98%) met the inclusion criteria as studies utilizing DTs in the target domain. Of the 225 articles, 112 articles were excluded because they were studies on DT modeling algorithms or lacked specific system prototyping, and 74 articles were excluded because the target physical entity of the DT was not a human. Finally, 39 studies were selected based on inclusion and exclusion criteria. Figure 1 shows the PRISMA-ScR flow diagram for details of screening and eligible articles.

Purpose of DT in healthcare and medical study

We reviewed a total of 39 papers related to health and DTs. As shown in Figure 2, the number of publications peaked in 2021, with China and the USA leading the contributions. Based on the framework we proposed, we organized our analysis of the reviewed papers. First, we summarized how each paper performed sensing a certain physical entity in the real world and *mapping* it into digital data. Additionally, we provided a summary of how these *mapped data* were used to design *acting*, such as simulation or intervention, in the real world. From the perspective of the *physical entity*, out of the total 39 papers, 19 papers were related to physical diseases, 6 papers to mental diseases, 3 papers to behavior, and 10 papers to the shape and movement of the body (see Figure 3(b)). In terms of *sensing* and mapping, each entity was mapped into digital representations such as organ status, mental state, movement status, and body models using sensor data, medical records, and image data captured by cameras. Regarding *acting*, based on the mapped data,

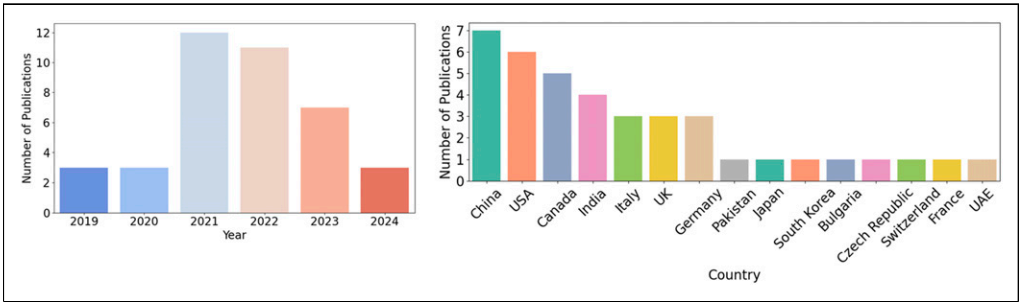

Figure 2. Publications of HDT papers for pervasive healthcare by year and country.

23 papers provided information to users in the form of simulations, 15 papers through interventions, and 14 papers through visualization (see Figure 3(b)).

In the reviewed studies, HDT systems in pervasive healthcare were applied for five main purposes (see Figure 3(a)). First, several systems focused on *health monitoring*. Those systems continuously track users' physical or cognitive states such as vital signs, posture[34] sudden falls[35] or cognitive decline[36] to support early detection and intervention. Second, HDTs were used for *disease tracking and diagnosis*, modeling physiological processes (e.g., heart or knee function[37]) to diagnose conditions like Crohn's disease[38] cancer[39] or diabetes, and to estimate future health risks such as fracture likelihood[40] Third, some studies employed HDT for *rehabilitation and physical therapy*, supporting telerehabilitation programs or assisting physiotherapists by modeling joint or limb movement trajectories.[41] Fourth, HDTs were utilized in *treatment planning and optimization*, enabling systems to monitor drug concentration (e.g., fentanyl[42]), manage glycemic variability, or guide trauma response strategies. Lastly, *simulation and prediction* functionalities were integrated to generate personalized physiological estimates (e.g., patient height during CT scans[43]) and to simulate treatment outcomes using biomechanical models. Together, these approaches illustrate the diverse ways HDTs can support personalized and context-aware services in pervasive healthcare.

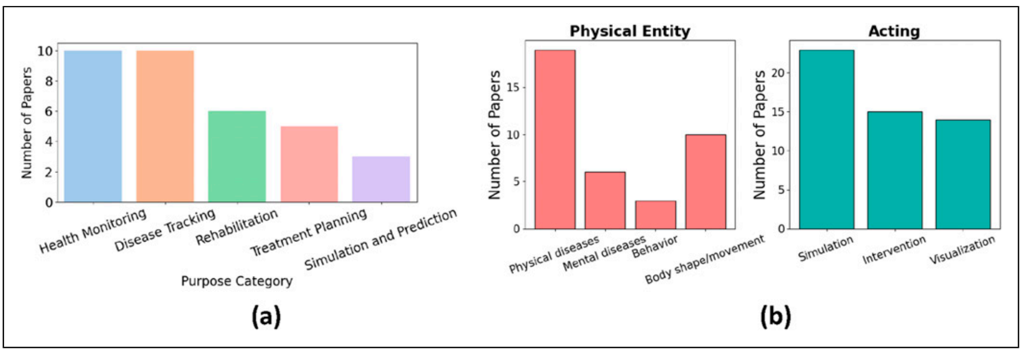

Figure 3. (a) Purposes of HDT System in Pervasive Healthcare and (b) Distribution of the physical entity twinned and the types of acting.

Physical entity, environment, and process modeling

In the studies reviewed, physical entities represented in HDT systems were categorized into six major groups (see Figure 4). First, a number of studies focused on *disease-specific patients*, such as those with Crohn's disease,[38] cancer,[40] diabetes,[44] or cardiovascular conditions.[45] As shown in Figure 5, among the papers addressing specific diseases, cancer and cardiovascular conditions were the most frequently studied. These cases typically involved modeling disease progression, treatment response, or physiological measurements related to specific conditions. Second, HDTs were designed to simulate or monitor specific *organs or body parts*, including the heart,[46] joints and knees,[37,47] or the spine,[48] often for the purposes of diagnosis, motion analysis, or biomechanical simulation. Third, several studies concentrated on *general human subjects* without a specific clinical diagnosis, focusing on broader representations of the human body[41] or physiological mechanisms.[49]. Fourth, some HDTs were tailored for *elderly individuals*, addressing age-related health issues such as cognitive decline,[36] fall detection,[35] or diabetes management in older adults.[50] Fifth, studies in *clinical or professional contexts* included not only patients but also healthcare professionals such as nurses,[51] doctors,[52] caregivers,[50] therapists,[41,53] and health coaches.[54] These roles were often part of the HDT's social interaction model. Lastly, several systems focused on *assistive or rehabilitation contexts*, where HDTs were applied to support telerehabilitation,[41] exercise training,[55] or the use of assistive exoskeletons.[53]

In addition to modeling physical entities themselves, many HDT systems also captured the deployment environments in which those entities operated. These environments were broadly categorized into seven types (see Figure 6). The most frequently represented were hospital-based settings, including intensive care units, operating rooms,[37] and inpatient beds,[51] where continuous physiological monitoring or acute condition management was required. Home-based environments were also common, supporting long-term monitoring and personalized care for elderly or chronically ill patients.[36,44,56] Rehabilitation-specific settings included clinics or assisted environments with support from assistive robots or physiotherapists,[41] while professional-involved settings involved active roles of caregivers, nurses, and health coaches.[50,52,54] A small number of studies focused on fitness-related environments, such as treadmill-based gait training[49] or athletic performance modeling,[55] and lab or simulated

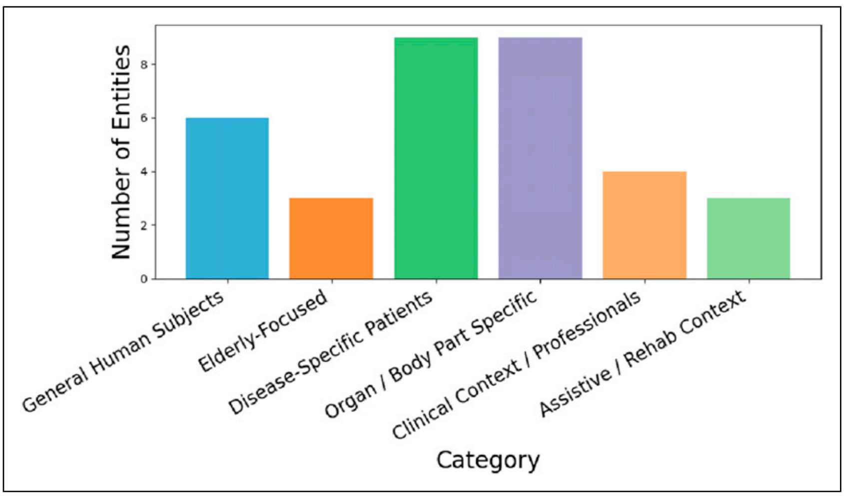

Figure 4. Categorization of physical entities in HDT papers for pervasive healthcare.

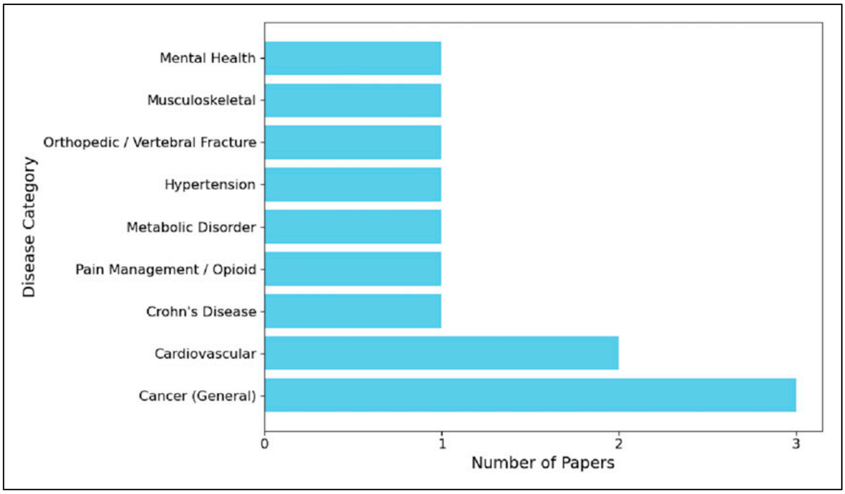

Figure 5. Distribution of disease types in HDT papers for pervasive healthcare. (12 out of 39 papers addressed specific diseases).

environments were used for prototyping and stress-testing HDT systems under controlled conditions. Finally, virtual platforms such as web-based dialogue system[57] or metaverse-based healthcare services[35] emerged as novel contexts for HDT deployment.

To support the replication of underlying processes, HDT systems employed a wide range of *sensing technologies* to capture users' physical, physiological, and behavioral states in pervasive healthcare settings. Since many studies employed multiple sensing modalities, a single paper is categorized under multiple sensing categories. For example, Tianze Sun et al.[58] which utilized CT/

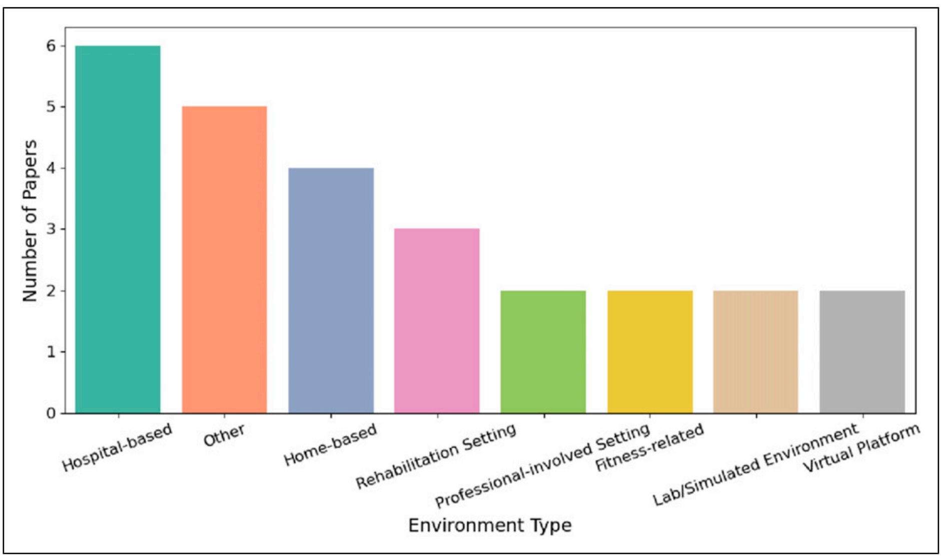

Figure 6. Categorization of HDT Deployment Environments (Excluding not specified cases).

MRI scans and wearable sensors is categorized as 'Wearable Sensors' and 'Camera-based Imaging'. As illustrated in Figure 7, the most commonly used category was wearable sensors, which enabled continuous and unobtrusive tracking of vital signs, movement, and physical activity. Camera-based imaging was used to capture body pose, movement trajectories, or facial expressions, often in combination with environmental and behavioral data such as GPS signals, food intake, or daily routines. Microphones/Voice Capture were used in mental health studies to infer stress or emotions via dialog or vocal tone. Environmental Sensors and Smartphones/Mobile Sensing facilitated the passive monitoring of context, such as location, ambient conditions, or daily routines. Meanwhile, a portion of studies relied solely on Clinical or Laboratory Data, such as EMRs, genetic profiles, or lab test results, without incorporating sensing devices. These sensing technologies enabled HDTs to model a variety of underlying processes, including medication behavior,[36] gait and posture,[41] rehabilitation activity,[34] and physiological responses such as trauma severity[52] or heart function.[59] Furthermore, mental health states such as cognition,[60] stress,[56] and emotion[61] were inferred through a combination of biosignals, behavioral patterns, and dialog data.

Overall system workflow of DT

Prior studies were analyzed according to the workflow of the HDT, i.e., sensing, mapping, and acting. We summarized the analysis results of all the surveyed papers in Appendix 2.

Sensing. Three types of sensing modalities have been reported in previous studies: physiological, behavioral, and environmental sensing.[39,44,56] Physiological sensing was related to human or tissue function, for example, heartbeats (e.g.[46]) and skin conductance data (e.g.[62]). Behavioral sensing was used for human behavior tracking, including motion sensor signals (e.g.[63]). Environmental sensing was classified into social and physical sensing. Physical sensing was used for the spatial environment, such as room temperature (e.g.[62]), while social sensing was related to activities such as social media (e.g.[46]).

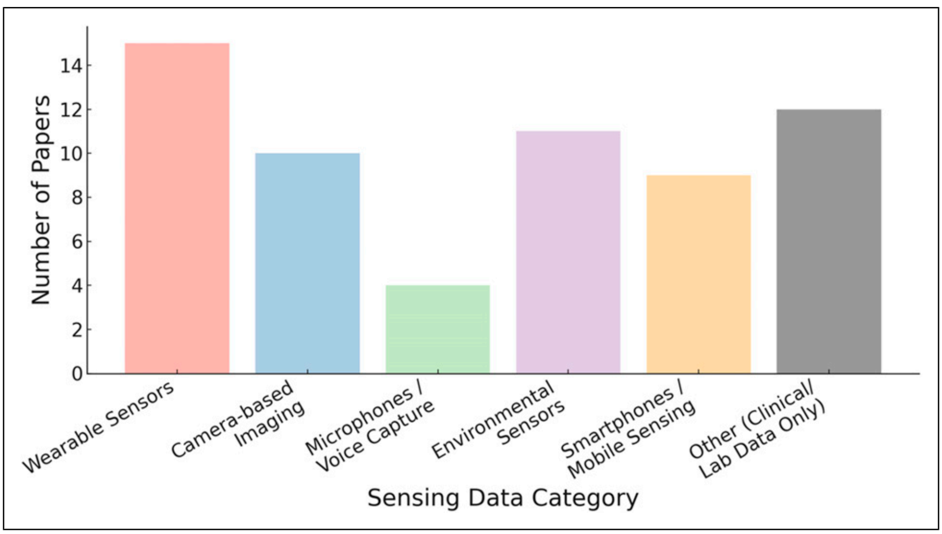

Figure 7. Sensing technologies in HDT systems for pervasive healthcare.

In addition, general medical records such as Personal Health Records (PHR)[46,50] or Computed Tomography (CT) scanned images (e.g., Cross-sectional images)[37] were used as indirect sensing data to capture various biometric signals related to the body in the medical field.

Mapping. The collected sensing data were mapped to various features according to the purpose of the HDT twinning. The mapping process can be stratified into low- and high-level layers. Low-level layers used the features directly mapped from raw sensor data, and the high-level layers used the features synthesized from low-level layers. For example, a blood pressure waveform collected through sensing is parameterized to calculate the abdominal aortic aneurysm (AAA) diameter (i.e., low-level feature), and the AAA severity level (i.e., high-level feature) is then determined based on the AAA diameter.[64]

Acting. Mapping enables action in HDT. We defined Acting as the system's responsive function based on mapped health data, and categorized it into three subtypes: (1) Simulation, which refers to generating predictive outcomes using computational models; (2) Visualization, which involves representing internal states or simulation results in a human-interpretable format; and (3) Intervention, which entails real-world feedback such as notifications or treatment adjustments.

The intervention provided necessary treatment and measures to people through the modeling results. For example, in healthcare, interventions were actuated by alerting the caregiver[50] or calling an ambulance.[46] The simulation provided prediction results for the future behavior or state of a physical entity. Examples include simulations of human safety checks[65] and treatment selections.[52] Visualization was mainly used as an act that supports the interaction between a physical entity and its environment. In a rehabilitation treatment scenario,[53] 3D muscle activity visualization helped the patient and physician collaborate in treatment.

We also noted that the three types of acting can operate dependently and independently depending on the use case: (1) Simulation only: In backend systems, predictive models may run simulations (e.g., risk of heart attack based on ECG and activity data) to support doctor's clinical decisions without displaying the simulation to users or triggering direct interventions, (2) Visualization only: Wearable applications may visualize real-time data (e.g., step counts or heart rate) to promote user awareness without any predictive modeling or automated suggestions (i.e., intervention), and (3) Intervention only: Simple rule-based systems may trigger actions (e.g., a reminder to take a break after long sedentary periods) to users without simulating future health status or visualizing current status. However, in most cases, the three types of acting are utilized simultaneously because those are closely related.

The representative example of the case is Just-In-Time Adaptive Intervention (JITAI).[66,67,68,69,70,71,72] The integration of those acting components enables the implementation of JITAI which decides 'when and what to help' (Just-in-time) and 'how to help (Adaptive intervention). The *simulation* is used to monitor user's health status change using sensors and predict optimal intervention timing, *visualization* supports user awareness that enables self-regulation, and *intervention* facilitates real-time behavior change. Therefore, we note that all of the three components of acting are closely engaged with users with different purposes.

Shifting the focus of digital twins: From diagnosis-oriented to prevention-oriented

In recent times, there has been an increase in research focusing on mental diseases and everyday behaviors. However, the majority of research is still primarily centered on physical diseases. Existing research that emphasizes physical diseases has traditionally utilized DTs to model the health status of specific parts of an individual's body (tissues, organs, organs). For that, the previous studies[37,38,58,73,74] have used data such as records of diseases or images and visuals captured at specific moments in time of the organs or tissues. The goal of existing research[38,40,58,73,74,75] has been to map such data into high-level information, such as the risk of specific diseases, and extract additional insights. The mapping results are used to visualize the state of organs/tissues and for simulations[38,40,58,73,74,75] aimed at predicting risks and conducting causal analysis of risk factors.[39,58,74,75] These types of data have been utilized to support the medical activities of doctors and healthcare professionals or to provide additional explanations during the treatment process to patients.[37,38,39,40,58,73,75]

Until recently, the diagnosis of physical diseases relied primarily on discrete snapshots of health data, such as medical records or imaging results. In contrast, the continuous observation of daily behaviors using sensors now enables a shift toward more preventive and longitudinal approaches to disease management. Depending on the objectives and targets for utilizing HDTs, different technologies may be involved in the sensing process. For instance, while traditional HDT systems often rely on structured data such as electronic medical records or diagnostic images, as shown in Figure 7, more recent approaches incorporate wearable devices (e.g., smartwatches for heart rate and sleep tracking), camera-based systems (e.g., posture or gait monitoring via depth sensors), and mobile sensing (e.g., GPS and app usage data for behavioral analysis). These technologies enable the monitoring of daily activities, environmental contexts, and physiological changes in real time, expanding the applicability of DTs from clinical settings to everyday life (see Figure 8).

In particular, digital healthcare has emerged as a significant issue in recent times, and the importance of Patient-Generated Health Data (PGHD) has also come to the forefront. PGHD refers to the results of monitoring an individual's or patient's daily life, collected outside of traditional care settings, and contains clinically relevant data.[48] The HDT models developed and utilized in previous research have primarily targeted specific organs or tissues, making it challenging to extend them to other diseases or health conditions. However, incorporating technologies that support holistic and full-cycle data collection and health management can significantly enhance the fidelity of HDT models. To enable personalized disease prediction, prevention, and treatment, it is essential to adopt new mapping methods that integrate an individual's environment, genetic profile, and biological characteristics with specific diseases or risk levels. For instance, in predicting the risk of Type 2 diabetes,[76] such mapping may involve a multi-omics approach that integrates lifestyle patterns (e.g., physical inactivity detected by wearables), genetic variations linked to insulin resistance,

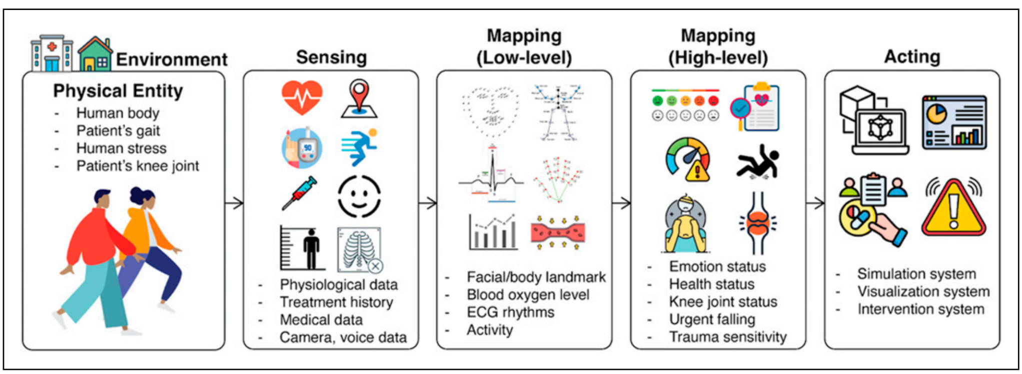

Figure 8. Workflow of human digital twin (HDT) implementation in healthcare.

transcriptomic or proteomic markers, and clinical measures such as blood glucose levels to more accurately model disease onset and progression. This multimodal integration across behavioral, omics, and clinical modalities allows HDTs to offer highly personalized and context-aware prevention and treatment plans.

This requires expanded considerations for data collection types, scope, methods, and modeling. From a sensing perspective, real-time sensing of physiological data collected from individuals or patients can be employed in addition to clinical data such as Electronic Health Records, images, and visuals. Diagnostic and treatment decisions typically need to consider various factors beyond disease-related symptoms, including environmental factors and lifestyle habits. In this context, PGHD voluntarily collected and generated by individuals or patients in their everyday lives can be utilized, not just relying on records from specialized institutions (e.g., hospitals). On the mapping front, mapping technologies are needed to understand disease/health states at a fine-grained level based on sensed data. For instance, using PGHD, models related to an individual's disease and associated mechanisms or symptoms can be created. Regarding acting, it is essential to consider a broader range of target audiences and methods for providing actions. The scope of the target audience for acting should extend beyond just doctors and patients to include their surrounding environments (e.g., caregivers, family, etc.). Moreover, the focus can shift from short-term diagnosis to the management of diseases and health conditions throughout the entire lifecycle (continuous and periodic), including prevention and intervention. For example, proactive prevention can be made possible by monitoring and tracking an individual's daily life and leveraging collected PGHD. Many diseases progress over several years before symptoms and diagnosis occur, and treatment can fail due to irreversible tissue damage, making early diagnosis and intervention crucial. By collecting PGHD in real-time, DT technology can provide just-in-time adaptive interventions for proactive prevention and response to diseases and health conditions.

Discussion

Principal results and comparison with prior work

In this review, we examined how HDTs have been practically implemented to support *pervasive healthcare*, focusing on the components of physical entity, sensing, mapping, and acting. Although previous reviews have offered valuable conceptual insights into HDTs,[24,25,27,28,29,30] there has been limited research on the practical applications of HDTs in pervasive healthcare. Specifically, the role of HDTs in enabling continuous, personalized, and context-sensitive health management in everyday settings has remained underexplored.

To address this gap, we reviewed studies that collected real-world data from daily environments, mapped the data into meaningful health-related features, and implemented applications such as simulations, visualizations, or interventions. Based on this analysis, we proposed a generalized framework that captures the structures and processes essential to pervasive healthcare HDTs.

Our framework categorizes implementation practices according to four core components (i.e., physical entities, sensing, mapping, and acting) providing a structured guide for future research. Researchers can use this framework to identify the target of replication (physical entity), choose appropriate sensing technologies to capture real-life data, define how to transform raw inputs into contextual insights (mapping), and design appropriate outputs for real-time feedback or decision-making (acting). Through this, we offer a practical lens for extending HDT applications beyond clinical settings and into the broader spectrum of pervasive healthcare.

Challenges in the implementation of Human Digital Twins for pervasive healthcare

While HDT in healthcare service has significant potential value, multiple critical challenges should be addressed for real-world applications. First, various technical mechanisms are required to mitigate the ethical concerns associated with *handling sensitive personal information*.[77] HDT for healthcare services involves complex processes of collecting, storing, and processing sensitive personal health data, exposing it to risks such as data leakage and identity theft, and making it subject to greater impacts, such as manipulation of a patient's HDT leading to incorrect diagnoses or treatments or even targeted cyberattacks based on inferred health vulnerabilities. Therefore, HDT must incorporate security measures (e.g., encryption) that ensure the safe processing of data at every stage.

Another critical challenge from a data collection perspective is securing high-quality and reliable data.[24] While the quality of sensor-acquired data itself is important, it is equally essential to verify whether the collected data is truly useful for disease diagnosis. Because poor data quality can compromise the reliability of HDT and fundamentally threaten the system's usability.[77] Thus, methods to ensure the quality of collected data must be carefully considered (e.g., a visualization tool to monitor the collected data quality[78]).

Preventing the misuse of high-quality data is also a significant issue.[79] AI technologies in HDT can be leveraged to infer personal health information beyond the intended scope of the service. To prevent unintended inferences by service providers, legal and institutional frameworks must be established. Moreover, users must be provided with sufficient information to accurately understand these complex data processing procedures, ensuring informed consent.

In addition to general concerns around data collection, wearable sensing which is commonly employed in HDT systems to enable real-time, context-aware monitoring presents its own set of practical and ethical challenges. These devices require sustained *physical contact* with the user, and long-term wearability can be hindered by discomfort, inconvenience, or stigmatization, particularly in older adults or individuals with chronic conditions. Such usability issues may lead to inconsistent data streams or reduced compliance,[80,81,82] undermining the continuity and completeness of HDT models.

Moreover, wearable sensors often capture highly sensitive and granular information, such as location, movement patterns, and physiological signals, intensifying concerns around data privacy and surveillance. Users may be hesitant to adopt such systems without clear transparency about what data are collected, how they are processed, and who has access to them. As a result, HDT systems that incorporate wearable sensing must carefully consider privacy-preserving strategies, such as on-device data processing, anonymization, or user-controlled data sharing, and clearly communicate their data practices to foster user trust.

Another challenge lies in integrating heterogeneous datasets collected from various data sources.[83] Prior studies have highlighted the integration of multiple data sources for inference and the complexities of data harmonization as key challenges to implement DT.[24,26,77] In practice, implementing DT requires research on standardized protocols and data structures that can facilitate interoperability by integrating sensor-derived data. Along with data harmonization, systematic frameworks must be established to determine where the integrated data will be stored, who will retain ownership, and who will bear overall management responsibility. Even if a trustworthy DT system is successfully developed, integrating it into existing healthcare systems remains a separate concern.[84] Further societal discussions are necessary to decide whether DT-provided information should be used for everyday health management or should be formally integrated into physician-mandated medical systems. Without addressing these challenges, the potential of DT will inevitably remain constrained. Resolving these complex legal, institutional, and technical uncertainties surrounding DT for healthcare services is a prerequisite for its practical implementation.

Towards context-aware implementation of HDTs in pervasive healthcare

To further advance HDTs toward achieving proactive, personalized, and context-aware pervasive healthcare, we suggest the following research directions.

- Expand targets beyond physical diseases and address underrepresented disease and populations: Most HDT implementations focus on modeling physiological organs (e.g., heart, joints) and physical disease states. Future work should explore more about how HDTs can represent behavioral patterns and mental health indicators in a continuous and context-aware manner. In addition, the current literature focuses mostly on musculoskeletal, cardiovascular, and cancer-related applications. Areas such as metabolic conditions (e.g., diabetes), neurodegenerative diseases (e.g., Alzheimer's), or mental health (e.g., depression) are less explored and present opportunities for new HDT applications.
- Broaden the scope of sensing modalities and advance mapping methods for real-life health data: Current HDTs rely heavily on wearable and imaging-based sensors. To support pervasive healthcare, researchers should integrate ambient, interactional, and environmental sensing (e.g., voice, smart home devices, contextual sensors) that can capture everyday activities and social interactions without increasing user burden. In addition, mapping processes are often simplistic (e.g., rule-based or statistical). There is a need for advanced multimodal fusion techniques, such as deep learning, transformer-based integration, or graph-based modeling, that can learn representations from complex, asynchronous sensor data. However, as these fusion models grow in complexity, they often suffer from reduced interpretability, making it essential to incorporate explainable AI (XAI) approaches to ensure clinical trust, transparency, and accountability in decision-making. Furthermore, as HDT systems rely on heterogeneous data sources for sensor fusion, there should be standardization of data protocols and model components by proposing unified data schemas, feature representations, and interface protocols to improve interoperability across platforms.
- Development of unobtrusive, privacy-preserving, and user-friendly sensing technologies: Addressing long-term usability and wearability concerns is critical for sustained data collection in daily life settings, especially for older adults and chronic disease patients. In addition, research is needed to develop on-device processing, anonymization, or user-controlled data sharing methods to improve user trust while ensuring rich and secure data for HDT models.
- Evaluation of HDTs in longitudinal and diverse real-world settings: Most existing studies reviewed in our survey focus primarily on demonstrating the feasibility of HDTs. There should be further research on long-term field studies to validate HDT effectiveness in real-life healthcare scenarios and to investigate how system performance varies across user populations and environments. In addition, further investigation is required into how HDT systems can be harmonized with existing medical workflows and what roles patients, caregivers, and clinicians should play in interacting with these systems.

Limitations

Our scoping review has several limitations. First, because we filtered studies based on strict criteria—specifically, studies that collected real-world data, extracted both low- and high-level features, and implemented actual applications—the number of papers included in our review was relatively small, totaling 39. Nevertheless, through an in-depth analysis of these 39 studies, we found that most HDT-related research in healthcare has primarily focused on physical diseases, rather than mental health conditions or behavioral aspects. We also observed that HDT is predominantly used for simulation purposes. Since the field is rapidly evolving, follow-up studies are needed to capture the latest developments in DT technologies. Our literature search only included studies published before December 2024, so it will be important to continue tracking newly published HDT case studies in the future. Additionally, to make the review process more manageable, we limited our search to four databases. As a result, not all existing HDT studies were included, which may limit the generalizability of our findings. Lastly, our research categorization was guided by the frameworks of context-aware computing and ambient intelligence.[5,26] However, more fine-grained analyses—focusing on the technological aspects of HDT modeling, such as feature extraction methods and types of AI models used—could further enhance our understanding of the technical foundations behind HDT implementations. In particular, a deeper investigation into how different sensor modalities, data fusion strategies, and real-time processing techniques are employed across HDT systems would provide valuable insights for advancing practical applications. Moreover, exploring the relationship between model complexity and application domains (e.g., acute care vs long-term monitoring) could help identify best practices and design principles tailored to specific healthcare contexts. As HDT research continues to diversify, developing a standardized taxonomy for HDT components and functions may also support more systematic comparisons across studies (Supplemental material 1).

Conclusions

This scoping review examined HDTs that have been practically implemented in pervasive healthcare. We searched the literature from several databases (e.g., PubMed, Scopus, IEEE Xplore, Web of Science, and Google Scholar). As a result, this paper reviewed a total of 39 papers selected based on eligibility criteria, and we identified how HDTs are used across four key components (i.e., physical entity, sensing, mapping, and acting) to support real-world applications such as monitoring, diagnosis, rehabilitation, and simulation. The key takeaway message of this review is that HDTs can also be used to predict a wider range of disease types and risks through collecting diverse PGHD data on patients' daily lives. To this end, this paper emphasizes that it is necessary to collect and utilize context-aware data through mobile, wearable, and IoT devices to collect daily life data (Supplemental material 2).

Author note

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Author's Contributions

Joonyoung Park (JYP) developed the software necessary to conduct the survey and analyzed and synthesized the collected data. JYP performed activities to annotate the surveyed data, scrub data and maintain research data for initial use and later re-use. Uichin Lee (UCL) conceptualized ideas and formulated of overarching research goals and aims. UCL oversighted of the planning and execution of research activities, including mentoring and funding acquisition. JYP, Eunji Park (EJP), and Soowon Kang initially cross-checked the survey results based on the inclusion criteria, and all authors conducted discussions and verification to reach consensus on the results. JYP and EJP wrote the original draft and final manuscript. All authors reviewed the draft and final manuscript.

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The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Supplemental Material

Supplemental material is available online.

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Appendix

Multimedia Appendix 1

Search Strategy

Multimedia Appendix 2

PRISMA ScR Checklist

Abbreviations

HDT	Human Digital Twin
DT	Digital Twin
AI	Artificial Intelligent
PGHD	Patient Generated Health Data
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses.