Human Digital Twins for Pervasive Healthcare: A Scoping Review

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Abstract

Human digital twins replicate humans in virtual worlds with real-time sensing and machine learning, enabling various services such as visualization, simulation, and prediction. The concept of human digital twins has recently been applied in diverse domains such as manufacturing and healthcare. However, there is a lack of systematic reviews and discussions on the key components of human digital twins and their applications in mental healthcare contexts. This article first offers a scoping review of the purposes of human digital twins and their models and thereafter charts how human digital twins with sensing, mapping, and acting capabilities can serve as an enabling technology for a data-driven, patient-centric, systems approach to pervasive mental healthcare. This article used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) for selecting 24 papers from the last 10 years in PubMed, Web of Science, Scopus, and Google Scholar.

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Human Digital Twins for Pervasive Healthcare: A Scoping Review

Abstract

Background: A digital twin (DT) represents a digital copy or virtual entity, replicating a physical entity and its underlying processes to enable visualization, simulation, and prediction. Studies using DT in the healthcare field show the potential of a system approach for patient-centered treatment that comprehensively predicts and diagnoses an individual's health status by collecting, contextualizing, and interpreting various individual data sources. However, there is currently no published evidence synthesis on how to utilize DT to approach data-driven, patient- centered systems in healthcare; Uncertainty still remains as to how to best exploit the potential of DT technology for patient-centric care in new fields of healthcare.

Objective: This scoping review aimed to identify the extent and breadth of existing literature on how DT is utilized for patient-centric treatment in healthcare and provide insights into how DT can be applied and expanded into new healthcare fields.

Methods: A comprehensive literature search on utilizing DT for personal health management was conducted in the following databases: PubMed, Scopus, IEEE Xplore, Web of Science, and Google Scholar, without any restrictions. A search was performed on 4 August 2023 from the above electronic databases, including all articles. Search terms were designed to comprehensively capture research publications utilizing digital twins 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"). Three reviewers reviewed the papers' title, abstract, and full text. Reviewers independently extracted and analyzed data to map the available evidence and performed peer-review validation of their work.

Results: 34 papers selected based on eligibility assessment were reviewed and synthesized according to the proposed framework. Among the 34 papers, 15 papers dealt with physical diseases as the target physical entity, 14 papers on body pose and behavior, and 5 papers on mental diseases. In terms of sensing and mapping, previous studies used various data resources such as sensor data, medical records, and image data captured by cameras to map an individual's physical/mental state and behavior into digital representations. Regarding acting, 18 papers performed simulations related to individual health and disease states based on mapped data, 12 papers provided personalized intervention (i.e., treatment), and 12 supported health monitoring through visualization.

Conclusions: The key takeaway of this review and outlook is that human digital twins can offer a data-driven, patient-centric systems approach for enabling pervasive healthcare. Data integration and contextualization help gain personalized insights about health issues (when and why that happens), and predictive modeling enables context-aware health intervention to manage everyday challenges (what and how to do by leveraging data visualization for simulation and just-in-time intervention).

Keywords: Human Digital Twin; Data-driven modeling; Patient-centric treatment; Pervasive health

Introduction

Many elements affect one's health, including genetic, behavioral, socioeconomic, and environmental factors [24]. For healthcare, it is beneficial to conduct pervasive tracking beyond personal levels, as health is largely affected by social and environmental levels [1]. Thus, recent studies on healthcare 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 or forecast specific diseases. These pervasive sensing studies highlight that health diagnosis and treatment require a patient-centric, systems approach because health problems can be demystified by analyzing sensor data related to individuals' personal, social, and environmental contexts. Beyond disease-specific AI modeling, which only detects or forecasts specific diseases, a patient-centric, systems approach helps comprehensively understand an individual's health by systematically collecting, contextualizing, and interpreting multiple data sources.

This article discusses the possibility of leveraging digital twins in such an endeavor. A digital twin represents a digital copy or virtual entity, replicating a physical entity and its underlying processes to enable visualization, simulation, and prediction [4]. Physical entities in the healthcare domain represent (parts of) individuals and their environments; thus, digital twins are generally referred to as human digital twins or medical digital twins. The digital twin concept resembles entity- or service-centric modeling approaches in context-aware computing and ambient intelligence [2], [33], where various data sources are integrated to systematically understand users and their needs to offer context-aware, intelligent services. This provides an opportunity for human digital twins, as it enables a data-driven, patient-centric, systems approach for enabling pervasive healthcare by systematically understanding when and why problematic situations occur and offering timely health interventions in everyday contexts.

Hence, this article reviews recent studies on human digital twins (HDTs) providing case studies and prototypes. Understanding existing use cases and key components of human digital twins helps us better envision pervasive health services with human digital twin technologies. This article begins with a scoping review [28] on human digital twin technologies by answering the following questions: What are the major purposes of HDT applications in healthcare studies? What physical entities and their underlying processes are modeled for digital twinning? What are the typical system workflows of an HDT?
Synthesizing the reviewed articles' major findings and critical reflection on recent data-driven health research helps us envision how digital twin technologies can enable a patient-centric, systems approach to pervasive healthcare. The core elements of human digital twins for pervasive healthcare include: (1) target physical entities for replication, encompassing personal, social, and environmental factors associated with health issues, and (2) systems modeling with sensing, mapping, and acting stages that represent what types of sensor data (sensing) are used to contextualize health issues (mapping) for timely diagnosis and treatment (acting)

This study aims to identify how DT has been defined and utilized in the field of healthcare for personal health management by analyzing existing research.
Based on the comprehensive survey, this article emphasizes the need for shifting the focus of digital twins research from the current diagnosis-oriented direction to the prevention-oriented direction for the pervasive healthcare. Then, it further discusses the potential of the utilization of patient-generated health data (PGHD) in the latter direction. The key takeaway of this review is that by collecting PGHD in real-time, digital twin technology will provide adaptive intervention that enables the prevention and management of individual diseases or health conditions in advance beyond simply diagnosing them.

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 [40].

Search Strategy

A comprehensive search was conducted from major electronic databases such as PubMed, IEEE, Scopus, Web of Science, and Google Scholar to find relevant studies. A search was performed on 4 August 2023 from the above electronic databases, including all articles, without any search period restriction.

Three authors skilled in information retrieval developed search strategies for four electronic citation databases. Search terms were designed to comprehensively capture research publications utilizing digital twins 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

Textbox 1. Articles inclusion and exclusion criteria

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

Eligibility criteria for the systematic scoping review

- Inclusion criteria
  - Document types: journal article or proceeding paper
  - Study types: any type of original peer-reviewed research
  - Language: English
  - Period: All
  - Study content:
    - Studies that developed and evaluated a DT system prototype for individuals’ 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

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 digital twin system prototype for patient health management were finally selected.

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 digital twins in domains other than healthcare or medical fields were excluded. In addition, articles that utilized digital twins in the healthcare or medical field but the physical entity was not a person (e.g., digital twin of an operating room), articles that only proposed a conceptual architecture or framework without building a digital twin system prototype, or articles that suggested a new digital twin 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 [26] to ensure a systematic review process.

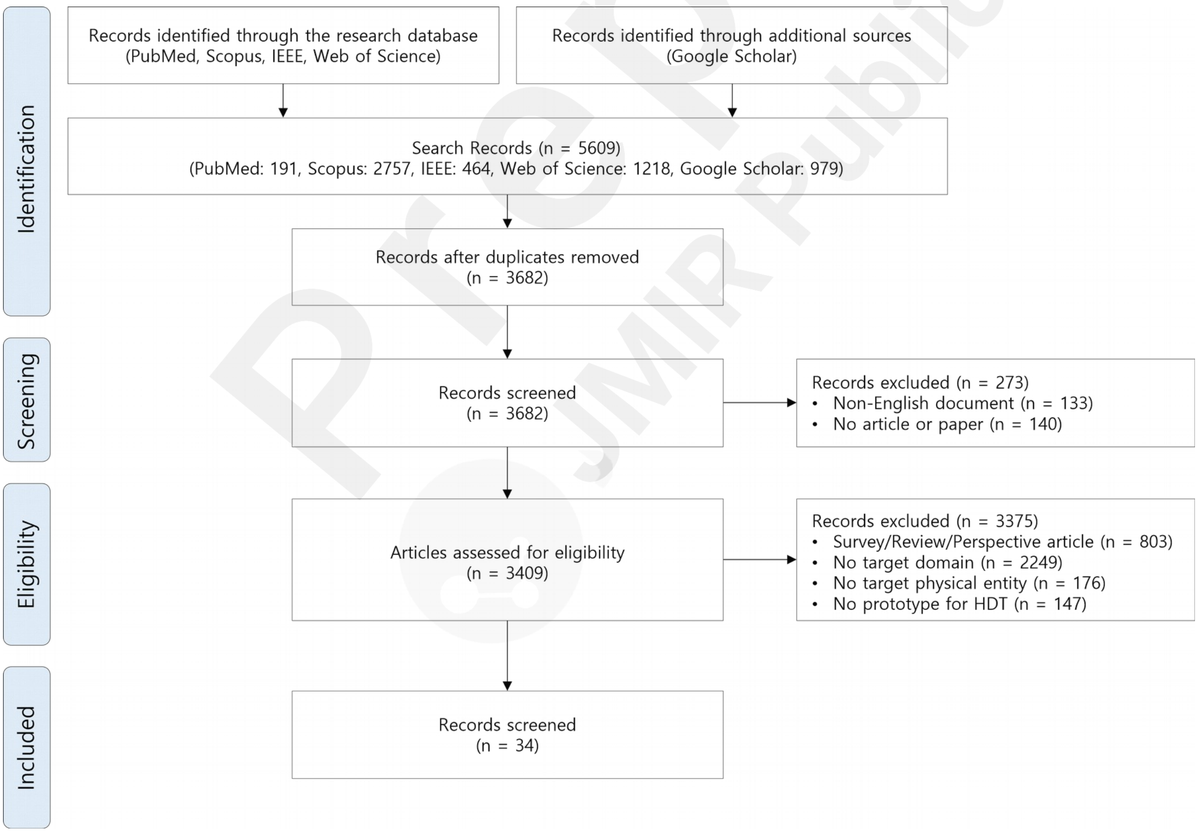

Figure 1. The flow description of PRISMA process

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 together 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 DT, the physical entity targeted by the DT, 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 DT system was extracted from each publication.

Synthesis of Results

Data results extracted from selected articles were descriptively summarized. Descriptions of *Acting* items were grouped into clusters according to *Acting* type (e.g., Intervention or Simulation). A new cluster was created whenever an *Acting* type appeared that could not be classified into an existing cluster. Finally, all characteristics summarized from each article are presented in Appendix 2.

Results

Study Selection

As a result of the eligibility assessment conducted by three authors, 3,665 (99.5%) of the 3,682 papers were assessed for eligibility without further discussion. On the other hand, 17 articles (0.5%) underwent further discussion to agree on eligibility. For the 17 papers, the authors went through iterative discussions and made the final decision on eligibility.

Of the 5,609 articles identified in the search results, 1,927 duplicates (59.20%) were removed. An initial eligibility assessment was performed on the titles and abstracts of 3,682 articles, excluding 273 articles (4.86%); 133 articles (2.37%) were excluded because they were not written in English, and 140 articles (2.50%) 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 3,409 articles (60.78%) was assessed according to the eligibility criteria, and 3,375 papers (60.17%) were excluded; 508 articles (9.06%) were excluded because they were the document type in the exclusion criteria (e.g., survey or review article) and 1,339 articles (23.87%) were excluded because they were not studies in a healthcare target domain (i.e., healthcare or medical).

220 articles (3.92%) met the inclusion criteria as studies utilizing digital twins in the target domain. Of the 220 articles, 99 articles (17.65%) were excluded because they were studies on digital twin modeling algorithms or lacked specific system prototyping, and 74 articles (13.19%) were excluded because the target physical entity of the digital twin was not a human. Finally, 34 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

Thirty-four studies examined the purpose of DT use. In these studies, DT was mainly utilized for the simulation of body organs or tissues (e.g., [44]) and monitoring to provide personalized treatment (e.g., [9]). Simulation studies using DT have modeled the structure, function, and mechanisms of body tissues or organs, such as the heart or knee [30], to diagnose specific disease states [43] or predict changes in risk [46]. Studies using DT for monitoring track human abnormal behavior (e.g., sudden falling [31]), posture [9], or mental health condition (e.g., cognitive disorder [17], stress/emotion status [11]) to provide timely customized treatment (or intervention). In addition, DT was also used to support patients' rehabilitation treatment [44] and provide personalized optimal exercise training [5].

Physical entity, environment, and process modeling

In the studies examined, physical entities were broadly categorized into patients (e.g., [16]), cohorts (e.g., people with diabetes [38]), individual behavior [39], and some organs/tissues of the human body (e.g., heart [23], an arm [41]). Individuals included patients, nurses, and specific target groups such as the elderly [20]. Personal behavior included the patient's gait [44] and athlete's exercise/activity [5], and organs/tissues/organs included the heart [10], colon [43], knees/joints [7], [30], etc. In addition, there were studies on twinning cancer [46]. The environment surrounding a physical entity is largely classified into social environment and physical environment. Social environment refers to the people or organizations that influence a physical entity. In the studies examined, the social environment includes doctors [8], [20], caregivers [20], therapists [41], [42], and health coaches [34]. In studies using DT for rehabilitation treatment [44], assistive robots act as social entities and interact with patients. The physical environment refers to the external or spatial environment surrounding a physical entity. This review included the patient's home [11], [17], [20], [38], hospital [46], operating room [30], sickbed [16],
and treadmill [32] as physical environments.

Physical entities have underlying processes that refer to a set of steps performed by that physical entity. The processes are replicated in the HDT to track the behavior of the physical entity or measure its state (or condition). Examples of behavioral tracking included monitoring patient medication behavior [17], gait [44], bedside patient posture [16], and exercise posture [9]. Status measures included trauma severity [8], heart rate [3], and vital sign measurements for diagnosing health conditions [46], as well as mental health measures of cognition [29], stress [11], and emotional state [37].

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. Physiological sensing was related to human or tissue function, for example, heartbeats (e.g., [23]) and skin conductance data (e.g., [27]). Behavioral sensing was used for human behavior tracking, including motion sensor signals (e.g., [13]). Environmental sensing was classified into social and physical sensing. Physical sensing was used for the spatial environment, such as room temperature (e.g., [27]), while social sensing was related to activities such as social media (e.g., [23]).

In addition, general medical records such as Personal Health Records (PHR) [20], [23] or Computed Tomography (CT) scanned images (e.g., Cross-sectional images) [30] 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 [6].

Acting: Mapping enables action in HDT. The acting types were divided into three main categories: intervention, simulation, and visualization. The intervention provided necessary treatment and measures to people through the modeling results. For example, in healthcare, interventions were actuated by alerting the caregiver [20] or calling an ambulance [23]. The simulation provided prediction results for the future behavior or state of a physical entity. Examples include simulations of human safety checks [15] and treatment selections [8]. Visualization was mainly used as an act that supports the interaction between a physical entity and its environment. In a rehabilitation treatment scenario [42], 3D muscle activity visualization helped the patient and physician collaborate in treatment.

Discussion

Principal Results and Comparison with Prior Work

In this review, we comprehensively introduce how digital twins are being utilized in the field of healthcare, based on the concepts of physical entity, sensing, mapping, and acting. Previous research reviewing digital twins in the healthcare domain has primarily focused on research related to specific diseases, where sensing specific parts of the body and mapping data have been the primary objectives [56, 57]. On the other hand, some of the other previous works were limited to introducing potential applications of digital twin technology in the field of medicine [58, 59]. While these disease-specific reviews have provided valuable insights into the use of digital twins in those particular areas, they have not offered a broader understanding of how digital twins can be applied in various other healthcare cases. Focusing on this issue, we introduce how digital twins have been comprehensively utilized across the entire field of healthcare, including body, behavior, and disease. Furthermore, we provided a framework categorizing research into physical entities, sensing, mapping, and acting, which can serve as a foundational tool for future digital twin research. By using this framework, researchers can plan their work more structurally when aiming to apply digital twins to new problems. They can determine which entity to target (physical entity), how to measure it (sensing), how to convert the data (mapping), and how to provide information to stakeholders (acting). As a result, we offer insights into how digital twins can be applied and extended to new healthcare domains.

This paper reviewed a total of 34 papers related to health and digital twins, based on the framework we proposed. 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 34 papers, 15 papers were related to physical diseases [23, 52, 6, 42, 41, 3, 54, 38, 43, 48, 46, 49, 50, 30, 34], 5 papers to mental diseases [8, 17, 11, 37, 29], 4 papers to behavior [20, 44 , 31, 5], and 10 papers to the shape and movement of the body [53, 55, 7, 10, 9, 16, 39, 51, 32, 47]. 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, 18 papers provided information to users in the form of simulations, 12 papers through interventions, and 12 papers through visualization (See Acting column in Appendix 2).

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 digital twins to model the health status of specific parts of an individual’s body (tissues, organs). For that, the previous studies 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 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 aimed at predicting risks and conducting causal analysis of risk factors. 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 of patients.

Until now, physical disease has been aimed at ‘diagnosis’ using discrete information that can be obtained at a specific time, such as medical records or images taken at a specific time [52, 6, 54, 43, 10, 29, 50, 31], it is also possible to aim for disease ‘prevention’ and ‘management’ through the observation of everyday behavior. Depending on the objectives and targets for utilizing digital twins, different technologies may be involved in the sensing process. Thus, beyond the data widely used in previous research, such as medical records and images, there is potential to apply a variety of sensing methods that can monitor everyday life activities in the context of digital twins.

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 [35]. The digital twin 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, the addition of technologies that support holistic and full-cycle data collection and health management for an individual’s disease or health condition can enhance the fidelity of digital twin models. For example, for individual disease prediction, prevention, and treatment, a new mapping method is needed that can link an individual’s environment, genetics, and biological characteristics with a specific disease or risk level.

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, Patient Generated Health Data (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, digital twin technology can provide just-in-time adaptive interventions for proactive prevention and response to diseases and health conditions.

Limitations

Our scoping review has several limitations. To make the review more feasible, we were only able to include studies collected from four databases. As this does not include all existing HDT studies and literature, the generalizability of the review results is limited. Our research categorization is based on the frameworks of context-aware computing and ambient intelligence [4], [62], but further fine-grained analyses can be performed to understand the technology backgrounds. The current literature search only included papers that were published before September 2023. Since the field has been rapidly growing, there should be follow-up studies on surveying the latest progress in digital twin technologies.

Conclusions

This scoping review reviewed literature utilizing digital twins for patient-centric treatment in the existing healthcare field. 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 34 papers selected based on eligibility criteria and summarized each paper according to the framework (i.e., sensing-mapping-acting) presented in this paper. The key takeaway message of this review is that DT, which has been mainly used for existing diagnosis-oriented treatment, can also be used to predict a wider range of disease types and risks through collecting data on patients' daily lives. To this end, this paper emphasizes that it is necessary to collect and utilize context-aware data through mobile and wearable devices to collect daily life data.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors did not use generative AI and AI-assisted technologies.

Conflicts of Interest

We have no conflicts of interest to disclose.
All authors declare that they have no conflicts of interest.

Author Contribution

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.

Data availability

The data sets generated and analyzed during this study are available at the URL link; https://rb.gy/ijb6w2

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

Multimedia Appendix 1

Search Strategy

Multimedia Appendix 2

Survey results summary

Multimedia Appendix 3

PRISMA ScR Checklist

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Supplementary Files

Multimedia Appendixes

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