Preprints.org

Review

Not peer-reviewed version

# Intelligent Healthcare: A Systematic Review of Digital Twins in Healthcare Systems

Zhenhong Hu , Akshith Ullal , Divya Vellanki , Yingbo Ma , Andrea E. Davidson , Anina Pillai , Gabriel Suvajdzic , Rushi Patel , Ceyhun Haziroglu , Joseph Kurrasch , Yuanfang Ren , Tezcan Ozrazgat-Baslanti , Benjamin Shickel , Azra Bihorac *

Posted Date: 6 November 2026

Keywords: digital twin; healthcare; AR/VR/MR/XR; artificial intelligence

Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC, OpenAlex.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

*Review*

# Intelligent Healthcare: A Systematic Review of Digital Twins in Healthcare Systems

**Zhenhong Hu [1,2], Akshith Ullal [1,2], Divya Vellanki [1,2], Yingbo Ma [3], Andrea E. Davidson [1,2], Anina Pillai [1], Gabriel Suvajdzic [1], Rushi Patel [1,2], Ceyhun Haziroglu [1,2], Joseph Kurrasch [4], Yuanfang Ren [1,2], Tezcan Ozrazgat-Baslanti [1,2], Benjamin Shickel [1,2] and Azra Bihorac [1,2,*]**

[1] AI for Health Institute, University of Florida, 1889 Museum Road, Suite 2410, Gainesville, FL 32611, USA

[2] Division of Nephrology, Hypertension, and Renal Transplantation, Department of Medicine, University of Florida, Gainesville, FL, USA

[3] University of Tennessee at Knoxville, School of Information Sciences, Tennessee, USA

[4] College of Medicine, University of Florida, Gainesville, FL, USA

* Correspondence: abihorac@ufl.edu; Tel: +(352)-294-8580; Fax: +(352)-392-5465

**Abstract**

Digital twins (DTs) have emerged as a transformative technology across various industries, and their potential in healthcare is garnering significant attention. DTs represent digital replicas of physical objects, systems, processes, and environments, offering unprecedented opportunities for personalized, precision, and intelligent healthcare. This paper systematically reviews the current applications of DTs in healthcare, focusing on how these technologies can enhance healthcare, improve patient and provider experiences, and deliver intelligent and personalized care. By leveraging immersive virtual worlds, healthcare practitioners can simulate complex medical situations, refine treatment strategies, and engage patients in more tailored, interactive ways. However, the integration of DTs into healthcare systems also presents technical, regulatory, and ethical challenges, such as data privacy concerns, the need for standardized protocols, and issues of accessibility. Addressing these challenges is crucial for the successful adoption and implementation of DTs in healthcare. This review aims to provide a comprehensive overview of the transformative potential of DTs in intelligent healthcare, while also highlighting the need for continued research and development in this rapidly evolving field. Through this systematic review, we seek to encourage further innovation and collaboration, paving the way for a future where DTs play a central role in intelligent healthcare delivery.

**Keywords:** digital twin; healthcare; AR/VR/MR/XR; artificial intelligence

## 1. Introduction

The concept of digital twins (DTs) traces its origins back to the early development of simulation and modeling techniques in the 1960s and 1970s, when digital models were initially employed in aerospace and automotive industries to simulate physical systems under various conditions (e.g., during the Apollo missions) [1,2]. This period marked a foundational phase where virtual replicas were utilized for testing and analysis, laying the groundwork for what would eventually be recognized as the Digital Twin concept. By the 1980s and 1990s, advancements in virtual prototyping further solidified this approach, allowing for the simulation and testing of product designs prior to their physical realization and effectively bridging the gap between digital models and physical prototypes [3].

The formalization of the DT concept is credited to Dr. Michael Grieves, who introduced the idea in 2003 [4,5]. Grieves defined the DT as a virtual counterpart to the physical product, emphasizing the connection between physical and virtual worlds. NASA's subsequent adoption of the DT concept for spacecraft simulations further underscored its potential in high-stakes environments, where real-

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



time digital models were leveraged to enhance mission planning and execution [6]. As the concept evolved, it rapidly gained traction across various industries, particularly with the emergence of Industry 4.0 in the early 2010s. This era saw the integration of the Internet of Things (IoT), big data, and advanced analytics, enabling more sophisticated DTs capable of real-time interaction with their physical counterparts [7]. As DTs matured, their applications expanded beyond individual products to encompass complex systems and entire infrastructures. By the late 2010s, DTs were increasingly employed in fields like urban planning, healthcare, and smart manufacturing, reflecting a broadening scope and enhanced capabilities [8].

In recent years, the intersection of DTs with emerging technologies has paved the way for the development of interconnected virtual and physical worlds [9–12]. The impetus for the development of such immersive digital environments lies in its capacity to fundamentally alter the dynamics between physical and digital realms. Initially conceived by Neal Stephenson in his novel Snow Crash, this digital ecosystem (called the "Metaverse") has transitioned from a speculative concept to a burgeoning reality with advancements in augmented reality (AR), virtual reality (VR), artificial intelligence (AI), and blockchain technologies. Within this framework, blockchain technology plays a critical role in ensuring the security and authenticity of digital identities and transactions, thereby enhancing trust and reliability in virtual interactions [13]. By offering experiences that seamlessly bridge these domains, these technologies have the potential to revolutionize various industries, including healthcare.

In healthcare, DTs have been proposed as tools for personalized medicine, where digital replicas of patients can simulate treatment options and predict outcomes [17–19]. The integration of AI and machine learning (ML) into DTs has enhanced their predictive and autonomous capabilities, making them indispensable tools for optimizing operations [20,21]. Additionally, there is an increasing adoption of DTs in precision medicine and hospital management to aid in decision-making and the management of complex medical data [14–16]. These immersive digital platforms facilitate the creation of intricate virtual environments that replicate physical realities, support the integration of AI and ML for enhanced decision-making, and enable the unprecedented sharing of information and resources [22]. Healthcare also stands to benefit from these innovations through virtual simulations for training and enhanced patient interaction [23]. Digital twins can augment patient care through virtual consultations, remote monitoring, and even virtual surgeries [24]. Additionally, virtual environments facilitate collaboration among medical professionals, enabling multidisciplinary team meetings [25]. Overall, this transformation is expected to lead to more personalized, efficient, and accessible healthcare services [26].

Immersive digital technologies have evolved from a conceptual idea to a practical tool with real-world applications. The intersection of DTs and healthcare represents a new frontier in medical innovation by combining the predictive and analytical capabilities of DTs with the immersive and interactive nature of these virtual environments [9]. This systematic review aims to explore the current state of Digital Twin applications in healthcare, with specific research objectives:

**R01:** How are DTs integrated with emerging technologies in healthcare?

**R02:** What are the technologies and tools available for building a DT in healthcare?

**R03:** What are the benefits and challenges of implementing DTs in healthcare?

**R04:** What are the key research gaps and future directions in the study of DTs in healthcare?

This study provides a structured overview of the current landscape, identifies gaps in existing research, and proposes directions for future exploration. By doing so, it contributes valuable knowledge to the ongoing discourse on digital health innovation, remote monitoring, virtual care, and positioning DTs as a foundational element in healthcare systems. The findings of this review will be particularly relevant to researchers, healthcare professionals, and policymakers interested in the future of healthcare in the digital age as they seek to understand the potential of these technologies to revolutionize healthcare delivery, address current challenges, and identify future research directions.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



## 2. Materials and Methods

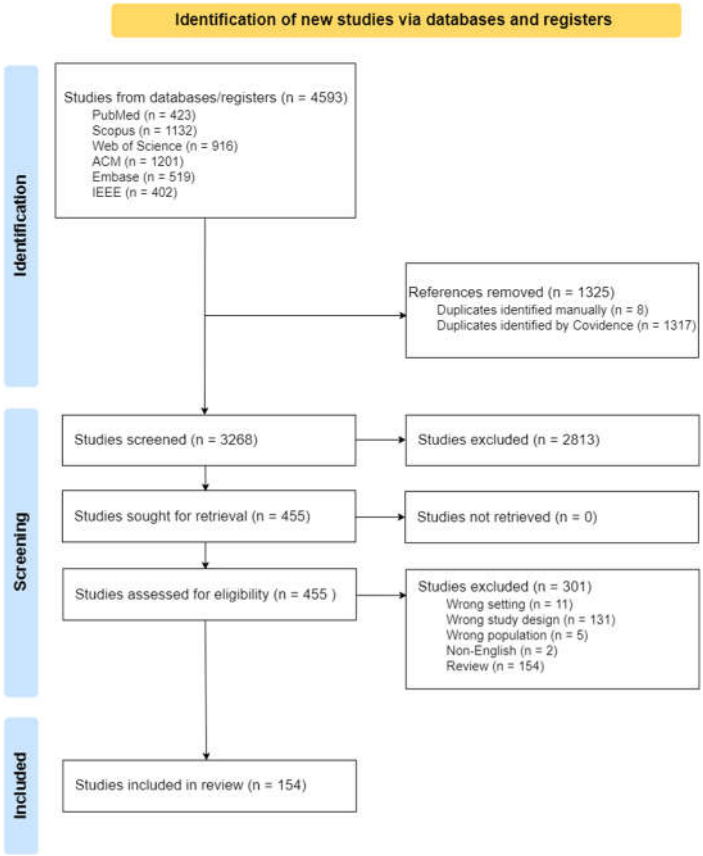
### *2.1. Search Strategy*

Records were identified through a comprehensive database search using a set of carefully selected search terms. We targeted seven widely recognized medical and educational databases: ACM, PubMed, Scopus, Web of Science, ACM Digital Library, Embase, and IEEE Xplore Digital Library. To ensure that our results accurately captured relevant publications, the search string was iteratively refined. The final search string employed was: ("digital twin" OR "DT") AND ("health" OR "healthcare" OR "medicine" OR "hospital" OR "clinic*"). The asterisk (*) serves as a wildcard character, allowing the inclusion of all words sharing the same stem (e.g., both "clinic" and "clinical" were captured in our search). The search was executed by screening the titles and abstracts of the articles in the selected databases. The search covered peer-reviewed publications from January 2014 to June 2024. This rigorous search yielded 4,593 records for initial screening.

### *2.2. Screening Process*

The identified records were imported into Covidence, a web-based collaboration software platform that streamlines the production of systematic and other literature reviews (www.covidence.org). A two-stage screening process was independently conducted by two authors (D.V. and A.U.). The first stage involved reviewing the titles and abstracts, followed by a more detailed full-text review in the second stage. A team of ten reviewers participated in the full-text reviews. Any disagreements among reviewers were resolved through discussions to reach consensus.

This systematic review's main objective was to provide an overview of the transformative potential of DTs in healthcare systems. As such, studies focusing on the intersection of DTs, and healthcare were given priority. Papers were excluded if they were published in non-English, conference abstracts, media articles, editorials, or letters. After applying these criteria through a manual screening process, the number of studies included in this systematic review was 154 (Figure 1).




© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



**Figure 1.** Search strategy and publication screening process: PRISMA flowchart.

## 3. Results

### *3.1. Current Applications and Use Cases of Digital Twins in Healthcare*

The expansion of DT technologies offers significant potential across the healthcare sector, particularly in optimizing hospital operations, enhancing management strategies, and advancing personalized and precision medicine. These technologies leverage existing 3D visualization and modeling techniques—augmented with medical imaging, real-time sensor data, and AI—to create immersive digital simulations that benefit both patients and healthcare professionals.

In our review of current DT applications and use cases in healthcare, we have classified them into six distinct categories based on their purpose and scope. In Figure 2 and Table 2, we provide an overview of these six primary categories, highlighting the diverse ways in which DT technology is being utilized in the healthcare sector.




**Figure 2.** The current applications of Digital Twins in healthcare. Abbreviations: AR, augmented reality; DT, digital twin; VR, virtual reality.

#### 3.1.1. Healthcare Facility Management

In hospital infrastructure, DTs have shown their ability to significantly enhance facility management and workflow efficiency [28]. They can predict mechanical failures and improve patient experiences by enabling administrators to simulate various workflow scenarios within a virtual hospital environment [29]. By accelerating these operational improvements, DTs optimize staff scheduling, maximize space utilization, automate supply chain processes, and enhance patient experiences (e.g., reducing discharge delays, shortening wait times in emergency departments and

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



medical imaging services, etc.). Additionally, DTs are utilized alongside VR to provide immersive onboarding experiences for healthcare staff in new facilities, allowing them to familiarize themselves with the environment and workflows before the facility becomes operational. This application minimizes potential disruptions and facilitates smoother transitions as the facility becomes fully functional [30].

Moreover, the integration of sensors into hospital infrastructure transforms these environments into highly responsive and intelligent systems. Sensors embedded in patient rooms enable real-time monitoring of vital signs, room conditions, and patient mobility, all of which can be tracked within the DT. This data can be combined with AI to support predictive analytics, enabling forecasting of changes in patient acuity or need for critical hospital equipment—such as mechanical ventilators or continuous renal replacement machines [31]. Furthermore, environmental sensors that monitor air quality add another layer of safety in keeping operating room sterility [29,32] and supporting early intervention and maintenance for deviations [29,32].

#### 3.1.2. Personalized and Precision Medicine

The advancement of personalized medicine has introduced the concept of DTs as dynamic replicas of patients, created from their historically and longitudinally collected data. Herein lies the notion of deep phenotyping and digital phenotyping, where large amounts of patient data from electronic medical records, genomic assays, medical imaging, wearable devices, and more can be aggregated to construct individualized human DTs [16]. These DTs can give physicians the ability to test and visualize the effects of various treatment options in the virtual environment before their implementation. A DT constructed from cardiac imaging has already been successfully used to plan a transcatheter aortic valve replacement (TAVR) implantation in a high-risk patient [33]. Surgeons used a live overlay of the model and to precisely deploy the TAVR device in the position optimized by the simulation.

Such DTs may be instrumental for physician assistance, patient assessment, and designing novel interventions. To ensure the relevance and effectiveness of a dynamic DT, it must be continuously updated with the most current data, ideally with minimal burden on the individual. Successful implementation of a dynamic DT begins with a FAIR (Findable, Accessible, Interoperable, and Reusable) data set, which serves as the foundation for training and testing algorithms. The outputs from these algorithms should then be translated into actionable medical or lifestyle advice. A personalized DT could comprehensively represent an individual by reflecting various aspects of their life from birth to death, encompassing elements such as work, relationships, learning, and personal growth.

#### 3.1.3. Healthcare Delivery

From the patient's perspective, a DT has the potential to transform healthcare delivery with the introduction of telecommunication systems that substitute or augment in-person meetings. In this DT application, patients can sit in a virtual waiting room with stress-relief virtual interactions and interact with photorealistic avatars of their doctor from the comfort of their own home [34,35]. These extended reality (XR) visits could include 3D anatomical visualizations to help patients communicate their symptoms (e.g., the exact location of their pain) and help providers explain diagnoses and proposed treatments. These applications can increase healthcare accessibility for rural populations and individuals with mobility impairments or transportation challenges (e.g., the elderly). Similarly, the patient's hospital experience can be simulated, equipping patients anticipating a scheduled admission with the appropriate expectations and exposure to an otherwise anxiety-inducing environment.

**Digital** twins that incorporate at-home sensors and/or wearable devices (e.g., smart watches or continuous glucometers) can provide doctors with longitudinal patient data that extend beyond the vital signs and laboratory values traditionally limited to measurements collected during clinic visits and inpatient hospitalizations [34–36]. By constructing robust datasets with the use of Internet of

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



Medical Thing (IoMT) devices, DTs can transform how people are involved in their health care—providing the opportunity to augment the amount of data available to their healthcare professionals and giving patients a larger picture of health and behavior. This data can then be used to detect and predict healthcare conditions and abnormalities [34,36,37].

#### 3.1.4. Educations and Training

The integration of large user data with advanced pattern recognition algorithms significantly enhances the accuracy of DTs in healthcare, enabling more precise outcome predictions and improved simulation and training scenarios [38]. DTs facilitate the acquisition of new knowledge about complex systems through virtual representation, such as virtual operations on organs like the heart and liver. This capability supports the training and coaching of healthcare professionals. Moreover, the simulation capabilities of DTs can be expanded to model complex systems (i.e., full intensive care unit [ICU] rooms) and enhance their functionalities. A large-scale study involving 1,522 healthcare staff demonstrated the feasibility, tolerability, and acceptability of large-scale VR onboarding using DT technology, underscoring its potential in diverse healthcare settings [39].

While 3D anatomical visualization has grown increasingly popular as forms of digitally enhanced training and surgical planning techniques—and has even led some medical schools to eliminate or forgo cadaver labs—DT and generative AI technologies can expand upon current systems to simulate complex "what if" clinical scenarios. As previously discussed, hospital DTs show great potential for training hospital personnel in new clinical environments [30]. These DTs can also be used as an interactive training playground that enables practice clinical scenarios for providers and trainees. Thus, the DT could become a risk-free environment where trainees can perfect difficult procedures and interventions before taking these skills to the real-world [40].

#### 3.1.5. Public Health

Just as DTs can be applied to microscopic systems, they can also be used on a larger scale to model disease behavior, policy implementation, and population health. Smart health cities have been proposed as DTs of geographical areas that incorporate public health factors to promote population wellness, track the spread of disease, and monitor hospital resources and beds [41,42]. As such, a DT can act as an epidemiological surveillance system for early outbreak detection. Moreover, by testing public health events scenarios in silico, public health planners can estimate the impact of urban planning and assess the efficacy of implemented courses of action, such as isolation or vaccination protocols and resource allocation [15]. By enabling more effective and timely responses to public health crises, DTs can mitigate the spread of disease, reduce economic burdens, and help prevent medical supply shortages.

Such approaches can also be adopted for hospitals and smaller ecosystems to make business cases for new services and to gauge the impact of policy changes, quality improvement initiatives, and run route cause analyses.

#### 3.1.6. Clinical Research

In the United States, the average Phase 3 clinical trial costs tens of thousands of dollars per patient and can reach over $52 million in total costs, depending on the therapeutic field of study [43]. DTs have attracted attention in the clinical research sphere for their potential to reduce the barriers facing randomized controlled clinical trials with the introduction of silico trials. One prominent application of this technology is the creation of "synthetic patients" to serve as control arms in comparative trials, allowing for more robust single-arm interventional clinical studies. Prior to human studies, synthetic patients can be used to predict patient response to treatment, optimize human trials, and help prevent adverse events by guiding optimal drug dosages and treatment combinations. This approach reduces iatrogenic risks and facilitates clinical trials in cases where

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



certain clinical data are missing or where administering a placebo poses ethical challenges (e.g., rare and serious diseases).

DTs can extend beyond synthetic patients by integrating aggregated data from historical clinical trials, external data sources like IoT devices, and from specific, updated patient data included in trials. Virtual clinical trials using DTs are already being developed by companies including Unlearn AI and Merck, while NVIDIA and the University of Florida are creating tools like SynGatorTron to construct control groups from patient records [44].

**Table 2.** A breakdown of Digital Twin applications and use cases in existing studies on Digital Twins in healthcare.

| Study References | DT Application | Use Case |
|---|---|---|
| [1–31] | Healthcare Facility Management | • Intelligent DT hospitals with continuous lifecycle integration<br>• Automated maintenance requests and supply chain management<br>• Monitoring hospital systems to optimize energy consumption, manage facility faults, and improve guest flow<br>• SplitFed learning for cost-efficient and privacy-focused healthcare systems |
| [2,5,6,8–10,13–18,25,31–56] | Personalized & Precision Medicine | • Personalized treatment and surgical planning<br>• Simulating patient responses to medication for optimized dosing<br>• Enhanced diagnostic and prognostic capabilities<br>• Evaluating non-medical factors, such as social and environmental influences, during consultations |
| [2,6,9,10,12–14,17,18,25–31,35,37–39,41–43,46,47,51–67] | Healthcare Delivery | • Conducting consultations in a well-designed virtual environment<br>• Teleconsultation featuring photorealistic doctor avatars<br>• Remote patient monitoring and management<br>• Simulating hospital experiences within a virtual environment<br>• Enhancing visits with AR/VR/XR for improved communication<br>• Continuous health monitoring via wearable devices<br>• Advancing emergency room services and trauma management |
| [6,13,25,27,39,40,42,46,47,51,55,56,59,60,62–65,68–70] | Education & Training | • Orientation and training with VR hospital DTs<br>• Generative AI-driven clinical and surgical scenarios for ICU management and critical care training<br>• Supplementing anatomy labs |
| [6,8,9,13,18,27,41,54,55,59,61–66,71,72] | Public Health | • Public health monitoring systems<br>• Epidemiological surveillance for early outbreak detection<br>• Health policy simulation and resource allocation optimization |
| [5,6,9,13,18,24,25,27,29,38,42,46,56,60,63,65–67,69,70,73–76] | Clinical Research | • Virtual in silico clinical trials and simulations |

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



| | |
|---|---|
| | • Synthetic control arm and drug testing within virtual populations<br>• Disease modeling<br>• Simulation of patient trajectories in critical illnesses |

*3.2. Key Technologies for Digital Twin Implementation*

The successful implementation of DT systems relies on the seamless integration of several key technologies. These systems typically harness real-time data from IoT devices and sensors, leveraging AI and ML to enable predictive analytics, diagnostics, and optimization. Moreover, DT systems utilize interactive visualization tools and secure cloud services to provide scalable and user-friendly interfaces. From the existing literature, the core components of contemporary DT systems can be categorized into three primary areas: hardware systems, software systems, and user interaction.

3.2.1. Hardware Systems

The foundation of DT systems lies in robust data collection, integration, and transmission mechanisms. The hardware employed for data collection typically includes IoT devices, sensors, wireless sensor nodes (e.g., ESP32 Wi-Fi sensors), pulse oximeters, and wearable devices. These devices are designed to gather a wide range of data, including patient electronic health records (EHRs), electroencephalograms (EEGs), motion and facial signals, as well as environmental parameters like temperature, humidity, airflow, and contaminants [32]. Various hardware services and middleware tools facilitate data integration, such as Raspberry Pi [10] platforms or Simple Object Access Protocol (SOAP) and Representational State Transfer (REST), respectively. These tools manage network applications, handle data acquisition, and store information in databases. Additionally, several studies have explored the use of blockchain technology for secure health data management and decentralized storage, highlighting its potential for enhancing data security and integrity [11,41,52,53].

3.2.2. Software Systems

The software systems underpinning DTs are typically composed of data processing, simulation, and modeling tools, such as AnyLogic, AutoCAD, SolidWorks, Modelica, and SysML. These tools are crucial for analyzing and visualizing data in real-time. For instance, the TB-SFENet (Three-Branch Spatiotemporal Feature Extraction Network) has been utilized for sensor data analysis in motion and emotion recognition [93]. AI algorithms further enhance user interaction by analyzing patient motion and facial expressions, recommending targeted questions during anamnesis, suggesting movement tests, detecting anomalies in real-time, and assisting in diagnosis by correlating visual cues with musculoskeletal activity [34]. Other studies have implemented supervised ML algorithms to classify normal versus abnormal respiration rates, achieving 96.9% accuracy in multi-class classification and 95.8% accuracy in binary classification [46].

3.2.3. User Interaction

User interaction in DT systems involves the real-time display of data through advanced visualization platforms, such as the Unreal Engine 5 (UE5) [54], which can depict user data (i.e., motion, positioning, and emotional states) with the aid of AR and VR tools [55]. For example, Building Information Modeling (BIM) has been used to digitally represent physical assets [32], with integration through tools like Autodesk Revit and Navisworks, visualization via platforms like Power BI, and through third-party tools such as VCAD. DT platforms are implemented across various interfaces, including mobile apps [56,57] and web applications [59,60], to ensure accessibility and user engagement.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



#### 3.2.4. Key Differences and Emerging Trends

The key differences among existing DT systems stem from the specific tools and platforms employed. For instance, some systems utilize Node-RED for middleware [61], while others rely on cloud-based services such as Microsoft Azure [62,63] or AI tools [64]. A critical focus across many studies is the efficient exchange and communication of data. While some research emphasizes interoperability frameworks and service-oriented architectures [55], others may not elaborate as extensively on these aspects. Additionally, the choice of hardware and sensors varies widely depending on the project's requirements, ranging from wearable devices to complex IoT sensor grids. Recent trends in literature indicate a growing emphasis on edge computing, which is crucial for reducing latency, enhancing real-time responsiveness [31], data security, and system scalability [32,48]. These factors are increasingly recognized as critical for the robust and secure design of DT systems, ensuring their effectiveness and reliability in diverse applications.

### *3.3. Data Generation for Digital Twin Implementation*

The data collection and integration process involves deploying sensors to capture real-time information from physical devices, such as wearable sensors and medical equipment. In cases where there is limited real time data, synthetic data can be generated using traditional ML models or large language models (LLMs) to supplement the dataset [65]. Historical data, such as equipment performance logs or past patient records, is also valuable for building predictive models. Additionally, annotation of raw data is essential to distinguish between different conditions and diagnoses. Given the sensitivity of healthcare data, ensuring data security through compliance with regulations, proper anonymization, and encryption is imperative to maintain patient confidentiality [66].

### *3.4. Research and Development Resources for Digital Twin in Healthcare*

The development and implementation of DTs in healthcare are supported by a range of advanced research and development resources, including state-of-the-art models, datasets, and platforms (Table 3). Current DT models employ sophisticated techniques leveraging the latest advancements in AI, ML, and simulation to create highly accurate and predictive replicas of biological systems. These models are critical for enabling personalized medicine, real-time monitoring, and predictive analytics within the healthcare domain. Complementing these models are several high-quality datasets that provide the necessary data foundation for training and validating DTs. These datasets, sourced from clinical trials, patient records, and biomedical research, are curated to ensure they are comprehensive, accurate, and representative of diverse patient populations. Additionally, a variety of DT platforms are available, offering robust tools for the creation, management, and deployment of DTs across different healthcare applications. These platforms integrate various technologies, including cloud computing, big data analytics, and IoT, to support the dynamic and scalable needs of healthcare DTs. Together, these resources, as shown in Table 3, form a critical infrastructure that drives innovation in the field and enables the development of more effective, personalized, and predictive healthcare solutions through DTs.

**Table 3.** Available resources for building Digital Twins.

| | Name | Description | Reference |
|---|---|---|---|
| **Digital Twin Model** | CardioInsight | Noninvasive 3D cardiac mapping system | [67] |
| | Siemens Healthineers DT model | Digital construction of the heart based on patient-specific data | [68] |
| | Virtual human V2.0 | A large population of human DTs consisting of high-resolution anatomical models | [69–71] |

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



| | | | |
|---|---|---|---|
| | Living Heart Model (LHM) | Developed by the living heart project, represents the state of the art in cardiac FE simulation | [72] |
| | DTMS | DT for MS revolutionizes diagnosis, monitoring, and therapy, enhancing patient well-being, reducing costs, and preventing disease progression | [73] |
| | Philips DT | Developed by Philips, this tool accurately models a health system, allowing virtual evaluation of changes on hospital KPIs | [97] |
| | Sanofi's DT | Simulates a compound's MOA in digital patients, assessing its impact on disease pathways and evaluating drug performance across treatment contexts | [98] |
| | Insilico Medicine DT | The platform integrates cellular metabolic models and ML to create predictive DTs, identifying metabolic limitations through time-resolved intracellular and extracellular data analysis | [99] |
| **Datasets** | MIMIC-III | Includes de-identified data from 40,000 critical care patients at Beth Israel Deaconess Medical Center (2001-2012) | [74] |
| | Cancer Genome Atlas Programe (TCGA) | Contains over 2.5 petabytes of genomic, epigenomic, transcriptomic, and proteomic data | [100] |
| | Human Connectome Project | Features extensive neuroimaging data from 1,200 healthy adults, detailing brain activity and connectivity | [101] |
| | eICU Collaborative Research Database | A multi-center database with de-identified data from 200,000 ICU admissions across the U.S. (2014-2015), including severity measures, diagnoses, and neural data | [102] |
| | Synthea | Synthea is an open-source tool that generates synthetic patients and models their medical histories | [103] |
| | UK BioBank | The UK Biobank Data Showcase summarizes data from 500,000 participants, including imaging, genetics, health linkages, biomarkers, and activity monitors | [104] |
| | NVIDIA Omniverse Enterprise | Powered by NVIDIA OVX, it enables enterprises to create precise DTs with enhanced AI capabilities | [105] |
| | Azure Digital Twins | Azure DTs is a robust PaaS product for developing twin graphs of diverse settings, including buildings, industries, farms, and cities | [106] |
| **Platforms** | AWS IoT TwinMaker | AWS IoT TwinMaker simplifies DT development for real-world systems like buildings, factories, and production lines | [107] |
| | Google Supply Chain Twin | Google's supply chain twin helps companies consolidate and analyze data, providing a comprehensive view of | [108] |

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



| | |
|---|---|
| | suppliers, inventories, and related information |

*3.5. Open Issues and Challenges*

Despite the promising potential of DTs in revolutionizing healthcare, their implementation is fraught with significant challenges that must be addressed to realize their full capabilities. The integration of multiple emerging technologies, including AI, IoT, big data, and robotics, introduces a range of technical, ethical, and socio-economic issues that are compounded by the early-stage development of these technologies [75]. Technical limitations such as data acquisition, integration, and infrastructure design are critical barriers to the effective deployment of DTs. Moreover, ethical concerns, particularly regarding patient privacy, data security, and equitable access, further complicate their widespread adoption in healthcare. Addressing these challenges through multidisciplinary collaboration and the development of standardized frameworks is essential for the successful integration of DTs into healthcare and for unlocking their transformative potential.

3.5.1. Data Acquisition and Integration

Data acquisition and integration are critical yet challenging aspects of developing DTs in healthcare, given the fragmented and diverse nature of data sources across the industry [76]. Achieving seamless interoperability between DT components—such as electronic health records, medical devices, and wearable sensors—requires establishing standardized data formats, communication protocols, and data-exchange mechanisms [77,78]. The complexity is further heightened by the necessity for real-time data synchronization and multimodal fusion, which are essential for creating accurate, adaptable DT models that reflect the dynamic nature of healthcare [81]. Additionally, integrating DTs into a System of Systems (SoS) presents substantial challenges, particularly when dealing with varying data formats, levels of abstraction, and lifecycle phases of the original systems [82]. This process is further complicated by the need to protect intellectual property, especially when DTs cross organizational boundaries [83]. Moreover, the development of advanced, user-friendly graphical user interfaces (GUIs) for DTs is crucial for ensuring cohesive vertical integration and providing a seamless user experience, making data acquisition and integration a multifaceted challenge that demands comprehensive solutions.

3.5.2. Data Privacy and Security

The deployment of DTs in healthcare, while offering substantial advancements, is accompanied by critical challenges in data privacy and security [84]. DT systems necessitate the aggregation and analysis of extensive patient data, raising the risk of breaches, unauthorized access, and misuse. The integration of DTs with IoT and cloud computing technologies further amplifies these vulnerabilities, necessitating stringent security measures to protect sensitive information. Implementing robust encryption protocols, secure storage solutions, and rigorous access controls is essential to safeguard patient data. Additionally, compliance with regulatory frameworks such as HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) is imperative [52], adding another layer of complexity to data management within DT ecosystems. The continuous synchronization between physical and virtual systems—fundamental to the fidelity of DTs—introduces risks that could lead to deviations and potential harm if compromised by malicious actions [85]. The severe implication of potential cyberattacks, including data breaches and financial losses, underscore the necessity for comprehensive cybersecurity strategies and strict data protection measures to ensure the secure and effective use of DTs in healthcare.

3.5.3. Digital Twin Modeling

The development of DT models is met with substantial challenges, particularly in modeling the complex interplay of human behaviors, physiological structures, and the myriads of factors

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



influencing health outcomes. These challenges are compounded by socio-ethical concerns, including privacy issues and the high costs associated with DT healthcare system development, which may contribute to widening socioeconomic disparities and limit access to this advanced technology [75]. Furthermore, the accurate validation and verification of DTs are hampered by the inherent variability in human physiology, disease trajectories, and individual patient characteristics, necessitating rigorous testing and continuous refinement of models against real-world patient data [86]. Future advancements in this field are expected to focus on creating multi-scale models that integrate data from various observational levels to enhance the predictive power and clinical applicability of DTs in managing complex health conditions.

#### 3.5.4. Computing Infrastructure and Scalability

The integration of DTs in healthcare necessitates a robust computing infrastructure that can handle the significant computational demands, storage needs, and data-processing capabilities required for real-time monitoring and analysis. Scalability is a critical issue [87], as healthcare organizations must manage the vast amounts of data generated by DTs while ensuring efficient resource allocation to maintain high performance. Future developments in high-performance computing, combined with advancements in big data, IoT, and 5G technology, are expected to enhance the accuracy and real-time capabilities of DTs and enable detailed, responsive models. However, the creation of DT environments requires substantial investment in reconfiguring both software and hardware platforms, posing a significant financial challenge that may restrict adoption to larger organizations with sufficient resources [88]. To overcome these barriers, ongoing research and development of open repositories are essential, as they democratize access to DT technology and enable smaller entities to contribute and innovate [89]. By fostering collaboration through common platforms and modular architectures, the healthcare industry can ensure that DTs become more accessible.

#### 3.5.5. Regulation and Ethical Considerations

The deployment of DTs in healthcare introduces a complex array of ethical and regulatory challenges that must be meticulously managed to ensure their responsible use [90]. Key ethical considerations include securing informed consent from patients, addressing data ownership and control, and maintaining patient autonomy throughout the DT development process. Additionally, it is crucial to prevent the exacerbation of existing health disparities by ensuring that DTs do not become a tool for inequality [75]. To foster trust and ethical practices, the development of DTs must adhere to stringent ethical guidelines that promote responsible data sharing, data anonymization, and transparency. On the regulatory front, the rapidly evolving landscape demands the establishment of clear policies and protocols that balance the need for innovation and the protection of patients' rights [92]. This includes validating and approving DT models through rigorous methodologies to ensure their reliability and clinical utility. Furthermore, the legal implications of DTs, particularly in areas such as medical malpractice and informed consent, require careful consideration to avoid unintended consequences [94]. Addressing these ethical and regulatory challenges is essential to the successful and equitable integration of DTs into healthcare, ensuring that all patients can benefit from this transformative technology.

#### 3.5.6. User Acceptance and Adoption

The widespread adoption and effective implementation of DTs in healthcare are contingent upon overcoming significant barriers related to user acceptance and adoption [95]. Healthcare professionals may resist integrating DTs into their practice due to concerns about the accuracy, reliability, and potential disruptions to existing workflows [75]. These challenges can be substantial roadblocks to the successful deployment of DTs. To address these concerns, it is essential to establish robust education and training programs that thoroughly acquaint healthcare providers with the

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



benefits, capabilities, and limitations of DT technology. Additionally, actively engaging patients in the decision-making process and addressing their specific concerns can enhance their acceptance and support for DT applications [39]. A comprehensive, multidisciplinary approach that integrates technological innovation with policy, ethical considerations, and stakeholder collaboration is critical to ensuring that DTs are adopted effectively, ultimately leading to improved patient care and enhanced healthcare outcomes.

## 4. Discussion and Future Directions

The future of the DT in healthcare is poised to be transformative, yet it faces a range of challenges across several critical areas. This discussion synthesizes the key findings of the review in relation to the four guiding research questions: R01 – How are DTs integrated with emerging technologies in healthcare?; R02 – What are the technologies and tools available for building DTs in healthcare?; R03 – What are the benefits and challenges of implementing DTs in healthcare?; and R04 – What are the key research gaps and future directions in the study of DTs in healthcare?

The discussion is organized into five thematic areas that reflect the dominant research trajectories identified across literature: Digital Humans and Avatars, 3D Asset Generation and Object Recognition, Generative AI and Outcome Prediction, Education and Immersive Training, and Data Standardization, Integration, and Privacy.

### *4.1. Digital Humans and Avatars (RQ1)*

The pursuit of realism in digital humans and avatars in virtual ecosystems is crucial for enabling naturalistic interactions, which have significant applications in psychology [96], medical education [109–111], and immersive simulations [112]. Achieving this level of realism hinges on two primary components: photorealism and naturalistic movement [96]. Recent advancements in generative adversarial networks (GANs) [113] and 3D photogrammetry, such as neural radiance fields [114], are driving the creation of highly photorealistic avatars [115,116], although these techniques often require expensive equipment. To make avatar creation more accessible, ongoing research focuses on reducing the computational load to allow the use of more portable devices like mobile phones [117] and XR headsets [118]. Complementing these approaches, recent work has shown that low-cost smartphone-based scanning pipelines can now generate photorealistic avatars comparable to multi-camera rigs, reducing production costs by over 90% and enabling non-experts to create high-quality digital humans [119]. Simultaneously, avatar movement enhancement is being addressed through advanced ML methods that utilize motion capture databases [120], sparse inertial measurement unit (IMU) [121], color-depth data [54,122], and user-generated video content, thereby reducing reliance on costly motion capture systems [123]. These innovations are further strengthened by recent "codec-avatar" systems that animate a user's face directly from VR headset cameras using cross-view self-supervised learning, enabling robust real-time facial expressions even when the face is only partially visible [124]. These developments suggest that interactions with digital humans will increasingly mirror real-life social presence and behavior, offering a compelling alternative to physical interactions in various fields.

### *4.2. 3D Asset Generation and Object Recognition (RQ2)*

The incorporation of DT technologies into medical simulations demands sophisticated 3D asset generation and object recognition capabilities, which are essential for accurately replicating medical environments. Traditionally, the creation of VR scenes is a time-consuming, labor-intensive process involving the manual design of 3D models, texture mapping, and precise placement of assets [125,126]. However, the advent of generative AI techniques is revolutionizing this process by enabling the automatic generation of 3D assets from simple user inputs and the creation of textures based on model morphology and textual descriptions [127]. These advancements not only accelerate the asset creation process but also offer greater flexibility [128] and facilitate creative experimentation

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



[129,130]. Moreover, the integration of DT and immersive technology components with real-world applications, particularly in medical education and surgical assistance, necessitates robust object recognition and tracking [131,132]. Current 3D object recognition systems face significant challenges in dynamic environments and in detecting high-resolution objects within complex settings [133,134]. Emerging technologies, such as diffusion models [135], are expected to enhance the robustness of object recognition, allowing for more accurate and automated identification of surgical instruments and other critical components during medical procedures [136,137]. Notably, diffusion models can also generate synthetic surgical scenes for pretraining models when real data is limited [138]. As these technologies continue to evolve, they will streamline the development of advanced digital healthcare applications and their integration with real-world environments, ultimately reducing the need for extensive manual input and enhancing the overall efficiency and accuracy of medical simulations.

### *4.3. Use of Generative AI and Improved Outcome Prediction (RQ1, RQ3)*

The integration of generative AI (GenAI) with DT technologies is significantly advancing personalized medicine by enabling detailed modeling of individual patient characteristics and prediction of health outcomes [139,140]. GenAI algorithms are particularly adept at identifying abstract patterns and complex temporal data, making them invaluable for customizing diagnoses and treatments [141]. This is particularly valuable in diseases, such as cancer, where extensive databases of tumor and patient genetics and treatment response profiles can be leveraged for early detection and intervention [142–145]. Moreover, DTs have been effectively applied to the modeling of individual organs [146], providing in-depth insights into human physiology and enhancing the predictive accuracy of medical models. Recent practical implementations show that AI-based models (including GAN-driven wound healing predictors and YOLOv8-based Lung-DT system) can be used to build disease-specific digital twins capable of forecasting healing progression and classifying conditions in real time [147].

GenAI also facilitates the generation of synthetic patient data and addresses challenges posed by imbalanced datasets and limited representation of certain populations by filling gaps in longitudinal patient records, thereby promoting more equitable and accurate predictions [148]. It can be used to preserve anonymity and minimize privacy concerns in sensitive data, especially in domains such as mental health [149]. Care must be taken, however, to ensure seed data and characteristics used to generate such data are representative of all populations involved. Misrepresentation of patient groups can lead to blind spots in risk prediction and exacerbation of disparity [150]. End user literacy is also critical in safe and effective implementation. As the number of AI tools embedded in systems of ever-increasing scale are being developed, clinicians must be aware of the pit falls of AI and predictive models [151]. Local validation, routine checking for prediction errors, and adoption of new methods for AI auditing and quality improvement are essential [152].

### *4.4. Better Education and Immersive Training (RQ3)*

The use of VR in medical education has provided a valuable platform for structured training [153], but these scenarios cannot fully capture the dynamic and unpredictable challenges of real-world practice [154,155]. Interactive intelligent avatars, powered by LLMs, offer the potential to revolutionize medical training by introducing more realistic and varied scenarios. These avatars can be tailored to simulate a wide range of medical roles (e.g., patients and healthcare providers) [156,157] and exhibit diverse behaviors and personalities [158]. Integrated with DT technology, LLM-driven avatars provide a safe and effective means for healthcare professionals to practice rare and complex medical situations, improving preparedness and competency [159]. Moreover, the use of avatars as standardized patients [160,161] can alleviate the logistical challenges and costs associated with human actors. Enhancing these simulations with advanced haptic feedback, such as tactile [162], kinesthetic [163,164], and thermal responses [165], brings the training experience closer to real-life interactions. Meta-analysis of randomized controlled trials comparing high fidelity simulations low

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



fidelity counterparts show improvement in knowledge (standardized mean difference (SMD) = 0.38; 95% confidence interval (CI): 0.18–0.59, P = 0.0003) and skill (SMD = 0.63; 95% CI: 0.21–1.04, P = 0.003) as compared to low fidelity counterparts [166].

### *4.5. Data Standardization, Integration, and Privacy (RQ1, RQ3)*

The fragmented state of current digital ecosystems, marked by the use of disparate plugins and standards across companies, poses significant challenges to its adoption in the healthcare sector, where seamless integration of systems like EMR (Electronic Medical Record System), PACS (Picture Archiving and Communication System), LIS (Laboratory Information System) is crucial. Efforts to unify these systems through platforms such as Ensemble with Hadoop are underway, but the lack of standardized formats and consistent security levels, especially real-time data streaming, remains a major barrier. This issue is particularly pronounced in developing countries [167], where infrastructure is still being developed to handle large-scale data integration. The future success of intelligent healthcare systems hinges on the deployment of next-generation technologies like 5G and 6G [168,169], which offer the necessary speed, low latency, and connectivity to support complex, real-time data exchanges and extended virtual environments.

Moreover, the challenges of data privacy and security are becoming increasingly critical. The sheer volume of personal and medical data within these virtual spaces is susceptible to manipulation [170], particularly with the rise of advanced generative AI algorithms [171]. Traditional privacy mechanisms are insufficient to address these complexities, necessitating the creation of advanced privacy frameworks that could include techniques such as dynamic avatar disguising and quantum communication [172,173] for secure data transmission. Quantum communication (leveraging the principles of quantum mechanics) offers enhanced security by utilizing quantum keys, which are resistant to cloning and ensure data integrity through the Heisenberg uncertainty principle [174,175]. These advancements are essential to safeguarding user data and ensuring the secure and effective operation of intelligent digital healthcare systems.

### *4.6. Limitations of the Study (RQ4)*

Despite offering a comprehensive synthesis of current literature on DTs in healthcare, this study presents several limitations inherent to systematic reviews in emerging and multidisciplinary fields. Although the review encompassed seven major academic databases and followed a rigorous selection process, relevant studies published in non-indexed venues, gray literature, or proprietary industry reports may have been excluded. This exclusion potentially omits cutting-edge commercial developments, particularly from private technology firms and healthcare startups that often lead to DT deployment but publish limited peer-reviewed material. Given the rapid evolution of DT technologies, AI integration, and XR applications, some included studies may already be partially outdated by newer frameworks or computational advances. Another persistent challenge is the lack of standardized terminology and evaluation metrics across studies. Many papers use varying definitions of “digital twin,” “virtual model,” or “simulation system,” which complicates direct comparison. Furthermore, the absence of consistent metrics for evaluating DT performance, accuracy, and clinical impact limits the ability to conduct meta-analyses or quantitative comparisons.

A substantial proportion of the reviewed works were conceptual frameworks or prototype demonstrations rather than validated clinical deployments. This restricts the generalizability of findings to real-world healthcare settings, where DT integration must comply with clinical, regulatory, and ethical constraints. Additionally, due to privacy and regulatory restrictions such as HIPAA and GDPR, most studies relied on synthetic or small-scale datasets, limiting representativeness and reproducibility. The scarcity of publicly available healthcare DT datasets further hinders independent verification and benchmarking of existing models. Another limitation lies in the interdisciplinary nature of the field. The intersection of DTs with AI, IoT, XR, and blockchain spans multiple disciplines, leading to fragmented methodologies and inconsistent integration approaches. While this diversity reflects innovation, it also introduces difficulty in

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



synthesizing unified insights or proposing standardized development pipelines. Moreover, the majority of reviewed publications originated from technologically advanced nations such as the United States, China, and several European countries. This concentration limits understanding of DT adoption in resource-constrained settings, where infrastructure, funding, and regulatory environments differ substantially.

## 5. Conclusions

This systematic review underscores the significant potential of digital twins in shaping intelligent healthcare, where the integration of DTs, AI, and XR could revolutionize clinical practice through personalized treatment, predictive interventions, and real-time monitoring. However, realizing this vision requires overcoming substantial challenges, including the need for standardization, ethical governance, and addressing privacy, data security, and accessibility disparities. Intelligent digital systems offer a transformative opportunity to create a more connected, efficient, and patient-centric healthcare system, but achieving this will depend on interdisciplinary collaboration and a commitment to ethical and sustainable innovation. As this digital frontier advances, addressing these challenges will be crucial to fully unlocking the benefits of DT-enabled intelligent healthcare and ensuring it contributes to equitable and effective healthcare for all.

**Supplementary Materials:** None.

**Author Contributions:** Conceptualization, Z.H. and A.B.; methodology, Z.H. and A.B.; formal analysis, Z.H., D.V., A.U., Y.M., A.D.; writing—original draft preparation, all authors; writing—review and editing, all authors; supervision, Z.H. and A.B.; All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** No new data were created or analyzed in this study. Data sharing is not applicable to this article.

**Acknowledgments:** The authors sincerely appreciate the invaluable contributions of Ayush Patel, Jing Lyu, Amreena Pathan, Sri Kondapalli, and Aiden Jose for their efforts in importing references and data extraction using Covidence.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AI | Artificial intelligence |
| AR | Augmented reality |
| BIM | Building information modeling |
| CI | Confidence interval |
| DTs | Digital twins |
| EEG | Electroencephalograms |
| EHR | Electronic health records |
| EMR | Electronic medical record system |
| FAIR | Findable, Accessible, Interoperable, and Reusable |
| GANs | Generative adversarial networks |
| GDPR | General data protection regulation |
| GenAI | Generative AI |
| GUIs | Graphical user interfaces |
| HIPAA | Health Insurance Portability and Accountability Act |
| ICU | Intensive care unit |

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



| | |
|---|---|
| IMU | Inertial measurement unit |
| IoMT | Internet of Medical Thing |
| IoT | Internet of Things |
| LHM | Living heart model |
| LIS | Laboratory information system |
| LLMs | Large language models |
| ML | Machine learning |
| PACS | Picture Archiving and Communication System |
| REST | Representational state transfer |
| SMD | Standardized mean difference |
| SOAP | Simple object access protocol |
| SoS | System of Systems |
| TAVR | Transcatheter aortic valve replacement |
| TB-SFENet | Three-branch spatiotemporal feature extraction network |
| TCGA | Cancer genome atlas program |
| UE5 | Unreal engine 5 |
| VR | Virtual reality |
| XR | Extended reality |

## References


1. Glaessgen, E.; Stargel, D. The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles.; April 23 2012.
2. Booch, G.; Rumbaugh, J.; Jacobson, I. The Unified Modeling Language User Guide; The Addison-Wesley object technology series; Addison-Wesley: Reading Mass, 1999; ISBN 978-0-201-57168-4.
3. Wang, G.G. Definition and Review of Virtual Prototyping. Journal of Computing and Information Science in Engineering 2003, 2, 232–236, doi:10.1115/1.1526508.
4. Grieves, M. Digital Twin: Manufacturing Excellence through Virtual Factory Replication. 2015.
5. Grieves, M. Product Lifecycle Management: The New Paradigm for Enterprises. International Journal of Product Development - Int J Prod Dev 2005, 2, doi:10.1504/IJPD.2005.006669.
6. Tuegel, E.J.; Ingraffea, A.R.; Eason, T.G.; Spottswood, S.M. Reengineering Aircraft Structural Life Prediction Using a Digital Twin. International Journal of Aerospace Engineering 2011, 2011, 154798, doi:10.1155/2011/154798.
7. Qi, Q.; Tao, F. Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access 2018, 6, 3585–3593, doi:10.1109/ACCESS.2018.2793265.
8. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. IEEE Transactions on Industrial Informatics 2019, 15, 2405–2415, doi:10.1109/TII.2018.2873186.
9. Turab, M.; Jamil, S. A Comprehensive Survey of Digital Twins in Healthcare in the Era of Metaverse. BioMedInformatics 2023, 3, 563–584, doi:10.3390/biomedinformatics3030039.
10. Awan, K.A.; Din, I.U.; Almogren, A.; Rodrigues, J.J.P.C. MediTwin: A Web 3.0-Integrated Digital Twin for Secure Patient-Centric Healthcare in the Metaverse. IEEE Trans. Consumer Electron. 2024, 1–1, doi:10.1109/TCE.2024.3409845.
11. Moztarzadeh, O.; Jamshidi, M. (Behdad); Sargolzaei, S.; Keikhaee, F.; Jamshidi, A.; Shadroo, S.; Hauer, L. Metaverse and Medical Diagnosis: A Blockchain-Based Digital Twinning Approach Based on MobileNetV2 Algorithm for Cervical Vertebral Maturation. Diagnostics 2023, 13, 1485, doi:10.3390/diagnostics13081485.
12. Sai, S.; Prasad, M.; Garg, A.; Chamola, V. Synergizing Digital Twins and Metaverse for Consumer Health: A Case Study Approach. IEEE Trans. Consumer Electron. 2024, 70, 2137–2144, doi:10.1109/TCE.2024.3367929.
13. Nofer, M.; Gomber, P.; Hinz, O.; Schiereck, D. Blockchain. Bus Inf Syst Eng 2017, 59, 183–187, doi:10.1007/s12599-017-0467-3.
14. Hassani, H.; Huang, X.; MacFeely, S. Impactful Digital Twin in the Healthcare Revolution. Big Data and Cognitive Computing 2022, 6, 83, doi:10.3390/bdcc6030083.
15. Kamel Boulos, M.N.; Zhang, P. Digital Twins: From Personalised Medicine to Precision Public Health. JPM 2021, 11, 745, doi:10.3390/jpm11080745.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



16. Venkatesh, K.P.; Raza, M.M.; Kvedar, J.C. Health Digital Twins as Tools for Precision Medicine: Considerations for Computation, Implementation, and Regulation. npj Digit. Med. 2022, 5, 150, s41746-022-00694–00697, doi:10.1038/s41746-022-00694-7.
17. Bruynseels, K.; Santoni De Sio, F.; Van Den Hoven, J. Digital Twins in Health Care: Ethical Implications of an Emerging Engineering Paradigm. Front. Genet. 2018, 9, 31, doi:10.3389/fgene.2018.00031.
18. Armeni, P.; Polat, I.; De Rossi, L.M.; Diaferia, L.; Meregalli, S.; Gatti, A. Digital Twins in Healthcare: Is It the Beginning of a New Era of Evidence-Based Medicine? A Critical Review. Journal of Personalized Medicine 2022, 12, 1255, doi:10.3390/jpm12081255.
19. Cellina, M.; Cè, M.; Alì, M.; Irmici, G.; Ibba, S.; Caloro, E.; Fazzini, D.; Oliva, G.; Papa, S. Digital Twins: The New Frontier for Personalized Medicine? Applied Sciences 2023, 13, 7940, doi:10.3390/app13137940.
20. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access 2020, 8, 108952–108971, doi:10.1109/ACCESS.2020.2998358.
21. Rosen, R.; von Wichert, G.; Lo, G.; Bettenhausen, K.D. About The Importance of Autonomy and Digital Twins for the Future of Manufacturing. IFAC-PapersOnLine 2015, 48, 567–572, doi:10.1016/j.ifacol.2015.06.141.
22. Dwivedi, Y.K.; Hughes, L.; Baabdullah, A.M.; Ribeiro-Navarrete, S.; Giannakis, M.; Al-Debei, M.M.; Dennehy, D.; Metri, B.; Buhalis, D.; Cheung, C.M.K.; et al. Metaverse beyond the Hype: Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy. International Journal of Information Management 2022, 66, doi:10.1016/j.ijinfomgt.2022.102542.
23. Kyaw, B.M.; Saxena, N.; Posadzki, P.; Vseteckova, J.; Nikolaou, C.K.; George, P.P.; Divakar, U.; Masiello, I.; Kononowicz, A.A.; Zary, N.; et al. Virtual Reality for Health Professions Education: Systematic Review and Meta-Analysis by the Digital Health Education Collaboration. Journal of Medical Internet Research 2019, 21, e12959, doi:10.2196/12959.
24. Haleem, A.; Javaid, M.; Pratap Singh, R.; Suman, R. Exploring the Revolution in Healthcare Systems through the Applications of Digital Twin Technology. Biomedical Technology 2023, 4, 28–38, doi:10.1016/j.bmt.2023.02.001.
25. Petrigna, L.; Musumeci, G. The Metaverse: A New Challenge for the Healthcare System: A Scoping Review. J Funct Morphol Kinesiol 2022, 7, 63, doi:10.3390/jfmk7030063.
26. Mystakidis, S. Metaverse. Encyclopedia 2022, 2, 486–497, doi:10.3390/encyclopedia2010031.
27. Ball, M. The Metaverse: And How It Will Revolutionize Everything; National Geographic Books, 2022; ISBN 978-1-324-09203-2.
28. Peng, Y.; Zhang, M.; Yu, F.; Xu, J.; Gao, S. Digital Twin Hospital Buildings: An Exemplary Case Study through Continuous Lifecycle Integration. Advances in Civil Engineering 2020, 2020, 8846667, doi:10.1155/2020/8846667.
29. Karakra, A.; Fontanili, F.; Lamine, E.; Lamothe, J. HospiT'Win: A Predictive Simulation-Based Digital Twin for Patients Pathways in Hospital. In Proceedings of the 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI); IEEE: Chicago, IL, USA, May 2019; pp. 1–4.
30. Zackoff, M.W.; Rios, M.; Davis, D.; Boyd, S.; Roque, I.; Anderson, I.; NeCamp, M.; Gardner, A.; Geis, G.; Moore, R.A. Immersive Virtual Reality Onboarding Using a Digital Twin for a New Clinical Space Expansion: A Novel Approach to Large-Scale Training for Health Care Providers. The Journal of Pediatrics 2023, 252, 7-10.e3, doi:10.1016/j.jpeds.2022.07.031.
31. Oppus, C.M.; Santiago, P.R.A.; Torres, J.B.M.; Mercado, N.A.M.; Cabacungan, P.M.; Cao, R.P.; Cabacungan, N.G.; Tangonan, G.L. A Digital Twin Approach of A-Vent Wireless Sensor for Real-Time and Predictive Monitoring of Patient Ventilator Asynchrony. In Proceedings of the 2023 15th International Conference on Electronics, Computers and Artificial Intelligence (ECAI); IEEE: Bucharest, Romania, June 29 2023; pp. 1–5.
32. Harode, A.; Thabet, W.; Dongre, P. A Tool-Based System Architecture for a Digital Twin: A Case Study in a Healthcare Facility. ITcon 2023, 28, 107–137, doi:10.36680/j.itcon.2023.006.
33. Obaid, D.R.; Smith, D.; Gilbert, M.; Ashraf, S.; Chase, A. Computer Simulated "Virtual TAVR" to Guide TAVR in the Presence of a Previous Starr-Edwards Mitral Prosthesis. Journal of Cardiovascular Computed Tomography 2019, 13, 38–40, doi:10.1016/j.jcct.2018.09.009.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




34. Trobinger, M.; Costinescu, A.; Xing, H.; Elsner, J.; Hu, T.; Naceri, A.; Figueredo, L.; Jensen, E.; Burschka, D.; Haddadin, S. A Dual Doctor-Patient Twin Paradigm for Transparent Remote Examination, Diagnosis, and Rehabilitation. In Proceedings of the 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); IEEE: Prague, Czech Republic, September 27 2021; pp. 2933–2940.
35. Kim, T.; Kwon, H.-S.; Cho, K.; Woo, W. Holistic Patient Assessment System Using Digital Twin for XR Medical Teleconsultation. In Proceedings of the Proceedings of the Augmented Humans International Conference 2024; ACM: Melbourne VIC Australia, April 4 2024; pp. 72–78.
36. Gupta, D.; Kayode, O.; Bhatt, S.; Gupta, M.; Tosun, A.S. Hierarchical Federated Learning Based Anomaly Detection Using Digital Twins for Smart Healthcare. In Proceedings of the 2021 IEEE 7th International Conference on Collaboration and Internet Computing (CIC); IEEE: Atlanta, GA, USA, December 2021; pp. 16–25.
37. Kobayashi, T.; Fukae, K.; Imai, T.; Arai, K. Dementia Sign Detection System Using Digital Twin. In Proceedings of the 2021 Ninth International Symposium on Computing and Networking (CANDAR); IEEE: Matsue, Japan, November 2021; pp. 127–133.
38. Dumas, M.; Fay, A.-F.; Charpentier, E.; Matricon, J. Digital Twins in Healthcare: State of the Art and Potential Use Cases in a Hospital Setting. Medecine Sciences: M/S 2023, 39, 953–957.
39. Zackoff, M.W.; Davis, D.; Rios, M.; Sahay, R.D.; Zhang, B.; Anderson, I.; NeCamp, M.; Rogue, I.; Boyd, S.; Gardner, A.; et al. Tolerability and Acceptability of Autonomous Immersive Virtual Reality Incorporating Digital Twin Technology for Mass Training in Healthcare. Sim Healthcare 2023, doi:10.1097/SIH.0000000000000755.
40. Rovati, L.; Gary, P.J.; Cubro, E.; Dong, Y.; Kilickaya, O.; Schulte, P.J.; Zhong, X.; Wörster, M.; Kelm, D.J.; Gajic, O.; et al. Development and Usability Testing of a Patient Digital Twin for Critical Care Education: A Mixed Methods Study. Front. Med. 2024, 10, 1336897, doi:10.3389/fmed.2023.1336897.
41. El Azzaoui, A.; Kim, T.W.; Loia, V.; Park, J.H. Blockchain-Based Secure Digital Twin Framework for Smart Healthy City. In Advanced Multimedia and Ubiquitous Engineering; Park, J.J., Loia, V., Pan, Y., Sung, Y., Eds.; Lecture Notes in Electrical Engineering; Springer Singapore: Singapore, 2021; Vol. 716, pp. 107–113 ISBN 978-981-15-9308-6.
42. Piedrahita, A.R.; Castellanos-Garzón, J.; Betancur, J.E.; Canizales, M.T.; Henao-Agudelo, J.S.; Martinez, L.A.R.; Lopez-Mejia, S. Exploring the Use of Digital Twin in Smart Healthcare: A Case Study of Dengue Epidemic Control and Prevention. In Trends in Sustainable Smart Cities and Territories; Castillo Ossa, L.F., Isaza, G., Cardona, Ó., Castrillón, O.D., Corchado Rodriguez, J.M., De La Prieta Pintado, F., Eds.; Lecture Notes in Networks and Systems; Springer Nature Switzerland: Cham, 2023; Vol. 732, pp. 183–193 ISBN 978-3-031-36956-8.
43. Sertkaya, A.; Wong, H.-H.; Jessup, A.; Beleche, T. Key Cost Drivers of Pharmaceutical Clinical Trials in the United States. Clinical Trials 2016, 13, 117–126, doi:10.1177/1740774515625964.
44. Peng, C.; Yang, X.; Lyu, M.; Smith, K.E.; Costa, A.B.; Flores, M.G.; Bian, J.; Wu, Y. GatorTron and GatorTronGPT: Large Language Models for Clinical Narratives.
45. Croatti, A.; Gabellini, M.; Montagna, S.; Ricci, A. On the Integration of Agents and Digital Twins in Healthcare. J Med Syst 2020, 44, 161, doi:10.1007/s10916-020-01623-5.
46. Khan, S.; Alzaabi, A.; Iqbal, Z.; Ratnarajah, T.; Arslan, T. A Novel Digital Twin (DT) Model Based on WiFi CSI, Signal Processing and Machine Learning for Patient Respiration Monitoring and Decision-Support. IEEE Access 2023, 11, 103554–103568, doi:10.1109/ACCESS.2023.3316508.
47. Madubuike, O.C.; Anumba, C.J.; Agapaki, E. Scenarios for Digital Twin Deployment in Healthcare Facilities Management. JFM 2023, doi:10.1108/JFM-10-2022-0107.
48. Burattini, S.; Montagna, S.; Croatti, A.; Gentili, N.; Ricci, A.; Leonardi, L.; Pandolfini, S.; Tosi, S. An Ecosystem of Digital Twins for Operating Room Management. In Proceedings of the 2023 IEEE 36th International Symposium on Computer-Based Medical Systems (CBMS); IEEE: L'Aquila, Italy, June 2023; pp. 770–775.
49. Harode, A.; Thabet, W.; DuLaney, M.B. Digital Twin in Healthcare Facilities: Linking Real-Time Air Quality Data to BIM. In ECPPM 2022 - eWork and eBusiness in Architecture, Engineering and Construction 2022; CRC Press: London, 2023; pp. 188–195 ISBN 978-1-003-35422-2.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




50. Elayan, H.; Aloqaily, M.; Guizani, M. Digital Twin for Intelligent Context-Aware IoT Healthcare Systems. IEEE Internet Things J. 2021, 8, 16749–16757, doi:10.1109/JIOT.2021.3051158.
51. Song, Y.-T. The Convergence of Digital Twin Technology and Personal Healthcare. In Proceedings of the 2023 26th ACIS International Winter Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD-Winter); IEEE: Taiyuan, Taiwan, July 5 2023; pp. 1–1.
52. Shuaib, M.; Alam, S.; Alam, M.S.; Nasir, M.S. WITHDRAWN: Compliance with HIPAA and GDPR in Blockchain-Based Electronic Health Record. 2021.
53. Benattia, B.Z.; Houda Maicha, N.E.; Kerrache, C.A.; Rathee, G.; Calafate, C.T. Implementing a Blockchain Based System for Healthcare Applications Using Digital Twin. In Proceedings of the 2023 11th International Conference on Intelligent Systems and Embedded Design (ISED); IEEE: Dehradun, India, December 15 2023; pp. 1–6.
54. Ullal, A.; Watkins, A.; Sarkar, N. A Multi-Objective Optimization Framework for Redirecting Pointing Gestures in Remote-Local Mixed/Augmented Reality.; 2022; pp. 1–11.
55. Iliuţă, M.-E.; Pop, E.; Moisescu, M.A.; Caramihai, S.I.; Tiganoaia, B. A Digital Twin Based Approach in Healthcare. In Proceedings of the 2023 24th International Conference on Control Systems and Computer Science (CSCS); IEEE: Bucharest, Romania, May 2023; pp. 356–362.
56. Banfi, F.; Brumana, R.; Salvalai, G.; Previtali, M. Digital Twin and Cloud BIM-XR Platform Development: From Scan-to-BIM-to-DT Process to a 4D Multi-User Live App to Improve Building Comfort, Efficiency and Costs. Energies 2022, 15, 4497, doi:10.3390/en15124497.
57. Ferreira, A.; Chilro, R.; Cruz-Correia, R. AnyMApp Framework: Anonymous Digital Twin Human-App Interactions. In Proceedings of the HCI International 2022 - Late Breaking Papers. Design, User Experience and Interaction: 24th International Conference on Human-Computer Interaction, HCII 2022, Virtual Event, June 26 – July 1, 2022, Proceedings; Springer-Verlag: Berlin, Heidelberg, June 26 2022; pp. 214–225.
58. Chandra, S.; Prakash, P.K.S.; Samanta, S.; Chilukuri, S. ClinicalGAN: Powering Patient Monitoring in Clinical Trials with Patient Digital Twins. Sci Rep 2024, 14, 12236, doi:10.1038/s41598-024-62567-1.
59. Deters, R.; Vassileva, J. User Models as Digital Twins: Using Webassembly Techniques to Ensure Privacy, Transparency and Control in Personalization. In Proceedings of the Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization; Association for Computing Machinery: New York, NY, USA, June 19 2023; pp. 313–314.
60. Sepasgozar, S.M.E. Digital Twin and Web-Based Virtual Gaming Technologies for Online Education: A Case of Construction Management and Engineering. Applied Sciences 2020, 10, 4678, doi:10.3390/app10134678.
61. Steinmetz, C.; Schroeder, G.N.; Sulak, A.; Tuna, K.; Binotto, A.; Rettberg, A.; Pereira, C.E. A Methodology for Creating Semantic Digital Twin Models Supported by Knowledge Graphs. In Proceedings of the 2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA); September 2022; pp. 1–7.
62. Nath, S.V.; Schalkwyk, P. van; Isaacs, D. Building Industrial Digital Twins: Design, Develop, and Deploy Digital Twin Solutions for Real-World Industries Using Azure Digital Twins; Packt Publishing Ltd., 2021; ISBN 978-1-83921-451-6.
63. Meijers, A. Hands-On Azure Digital Twins: A Practical Guide to Building Distributed IoT Solutions; Packt Publishing Ltd., 2022; ISBN 978-1-80107-397-4.
64. Lehner, D.; Sint, S.; Vierhauser, M.; Narzt, W.; Wimmer, M. AML4DT: A Model-Driven Framework for Developing and Maintaining Digital Twins with AutomationML. In Proceedings of the 2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA ); September 2021; pp. 1–8.
65. Wang, P.; Luo, M. A Digital Twin-Based Big Data Virtual and Real Fusion Learning Reference Framework Supported by Industrial Internet towards Smart Manufacturing. Journal of Manufacturing Systems 2021, 58, 16–32, doi:10.1016/j.jmsy.2020.11.012.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




66. Saeed, M.M.A.; Saeed, R.A.; Ahmed, Z.E. Data Security and Privacy in the Age of AI and Digital Twins. In Digital Twin Technology and AI Implementations in Future-Focused Businesses; IGI Global, 2024; pp. 99–124 ISBN 979-8-3693-1818-8.
67. Corral-Acero, J.; Margara, F.; Marciniak, M.; Rodero, C.; Loncaric, F.; Feng, Y.; Gilbert, A.; Fernandes, J.F.; Bukhari, H.A.; Wajdan, A.; et al. The 'Digital Twin' to Enable the Vision of Precision Cardiology. European Heart Journal 2020, 41, 4556–4564, doi:10.1093/eurheartj/ehaa159.
68. Lou, B.; Doken, S.; Zhuang, T.; Wingerter, D.; Gidwani, M.; Mistry, N.; Ladic, L.; Kamen, A.; Abazeed, M.E. An Image-Based Deep Learning Framework for Individualising Radiotherapy Dose: A Retrospective Analysis of Outcome Prediction. The Lancet Digital Health 2019, 1, e136–e147, doi:10.1016/S2589-7500(19)30058-5.
69. Chen, X.; Feng, Y.; Zhong, W.; Kleinstreuer, C. Numerical Investigation of the Interaction, Transport and Deposition of Multicomponent Droplets in a Simple Mouth-Throat Model. Journal of Aerosol Science 2017, 105, 108–127, doi:10.1016/j.jaerosci.2016.12.001.
70. Feng, Y.; Zhao, J.; Kleinstreuer, C.; Wang, Q.; Wang, J.; Wu, D.H.; Lin, J. An in Silico Inter-Subject Variability Study of Extra-Thoracic Morphology Effects on Inhaled Particle Transport and Deposition. Journal of Aerosol Science 2018, 123, 185–207, doi:10.1016/j.jaerosci.2018.05.010.
71. Feng, Y.; Zhao, J.; Chen, X.; Lin, J. An In Silico Subject-Variability Study of Upper Airway Morphological Influence on the Airflow Regime in a Tracheobronchial Tree. Bioengineering (Basel) 2017, 4, 90, doi:10.3390/bioengineering4040090.
72. Segars, W.P.; Veress, A.I.; Sturgeon, G.M.; Samei, E. Incorporation of the Living Heart Model Into the 4-D XCAT Phantom for Cardiac Imaging Research. IEEE Trans. Radiat. Plasma Med. Sci. 2019, 3, 54–60, doi:10.1109/TRPMS.2018.2823060.
73. Voigt, I.; Inojosa, H.; Dillenseger, A.; Haase, R.; Akgün, K.; Ziemssen, T. Digital Twins for Multiple Sclerosis. Front. Immunol. 2021, 12, 669811, doi:10.3389/fimmu.2021.669811.
74. Johnson, A.E.W.; Pollard, T.J.; Shen, L.; Lehman, L.H.; Feng, M.; Ghassemi, M.; Moody, B.; Szolovits, P.; Anthony Celi, L.; Mark, R.G. MIMIC-III, a Freely Accessible Critical Care Database. Sci Data 2016, 3, 160035, doi:10.1038/sdata.2016.35.
75. Popa, E.O.; van Hilten, M.; Oosterkamp, E.; Bogaardt, M.-J. The Use of Digital Twins in Healthcare: Socio-Ethical Benefits and Socio-Ethical Risks. Life Sci Soc Policy 2021, 17, 6, doi:10.1186/s40504-021-00113-x.
76. Aloqaily, M.; Bouachir, O.; Karray, F.; Al Ridhawi, I.; El Saddik, A. Integrating Digital Twin and Advanced Intelligent Technologies to Realize the Metaverse. IEEE Consumer Electronics Magazine 2022, 12, 47–55.
77. Antonelli, L.; Guarracino, M.R.; Maddalena, L.; Sangiovanni, M. Integrating Imaging and Omics Data: A Review. Biomedical Signal Processing and Control 2019, 52, 264–280, doi:10.1016/j.bspc.2019.04.032.
78. Watson, E.R.; Taherian Fard, A.; Mar, J.C. Computational Methods for Single-Cell Imaging and Omics Data Integration. Front. Mol. Biosci. 2022, 8, doi:10.3389/fmolb.2021.768106.
79. Wang, G.; Badal, A.; Jia, X.; Maltz, J.S.; Mueller, K.; Myers, K.J.; Niu, C.; Vannier, M.; Yan, P.; Yu, Z.; et al. Development of Metaverse for Intelligent Healthcare. Nat Mach Intell 2022, 4, 922–929, doi:10.1038/s42256-022-00549-6.
80. Babarenda Gamage, T.P.; Elsayed, A.; Lin, C.; Wu, A.; Feng, Y.; Yu, J.; Gao, L.; Wijenayaka, S.; Nash, M.P.; Doyle, A.J.; et al. Vision for the 12 LABOURS Digital Twin Platform *. In Proceedings of the 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC); IEEE: Sydney, Australia, July 24 2023; pp. 1–4.
81. Ooi, B.C.; Chen, G.; Shou, M.Z.; Tan, K.-L.; Tung, A.; Xiao, X.; Yip, J.W.L.; Zhang, B.; Zhang, M. The Metaverse Data Deluge: What Can We Do about It?; IEEE, 2023; pp. 3675–3687.
82. Trauer, J.; Mutschler, M.; Mörtl, M.; Zimmermann, M. Challenges in Implementing Digital Twins–A Survey.; American Society of Mechanical Engineers, 2022; Vol. 86212, p. V002T02A055.
83. Michael, J.; Pfeiffer, J.; Rumpe, B.; Wortmann, A. Integration Challenges for Digital Twin Systems-of-Systems.; 2022; pp. 9–12.
84. Alcaraz, C.; Lopez, J. Digital Twin: A Comprehensive Survey of Security Threats. IEEE Communications Surveys & Tutorials 2022, 24, 1475–1503.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




85. Suhail, S.; Iqbal, M.; Jurdak, R. The Perils of Leveraging Evil Digital Twins as Security-Enhancing Enablers Seeking More Secure and Effective Digital Representations.
86. Parvinian, B.; Pathmanathan, P.; Daluwatte, C.; Yaghouby, F.; Gray, R.A.; Weininger, S.; Morrison, T.M.; Scully, C.G. Credibility Evidence for Computational Patient Models Used in the Development of Physiological Closed-Loop Controlled Devices for Critical Care Medicine. Frontiers in physiology 2019, 10, 220.
87. Wang, E.; Tayebi, P.; Song, Y.-T. Cloud-Based Digital Twins Storage in Emergency Healthcare. In Proceedings of the 2023 IEEE/ACIS 21st International Conference on Software Engineering Research, Management and Applications (SERA); IEEE: Orlando, FL, USA, May 23 2023; pp. 331–335.
88. Alazab, M.; Khan, L.U.; Koppu, S.; Ramu, S.P.; Iyapparaja, M.; Boobalan, P.; Baker, T.; Maddikunta, P.K.R.; Gadekallu, T.R.; Aljuhani, A. Digital Twins for Healthcare 4.0—Recent Advances, Architecture, and Open Challenges. IEEE Consumer Electronics Magazine 2022, 12, 29–37.
89. Biller-Andorno, N.; Christen, M.; Witt, C. Position Paper: Artificial Intelligence in Medicine–Objectives and Recommendations for the Responsible Use of Digital Twins. 2023.
90. Iqbal, J.D.; Krauthammer, M.; Biller-Andorno, N. The Use and Ethics of Digital Twins in Medicine. J. Law. Med. Ethics 2022, 50, 583–596, doi:10.1017/jme.2022.97.
91. Han, Y.; Li, Y.; Li, Y.; Yang, B.; Cao, L. Digital Twinning for Smart Hospital Operations: Framework and Proof of Concept. Technology in Society 2023, 74, 102317, doi:10.1016/j.techsoc.2023.102317.
92. Lal, A.; Dang, J.; Nabzdyk, C.; Gajic, O.; Herasevich, V. Regulatory Oversight and Ethical Concerns Surrounding Software as Medical Device (SaMD) and Digital Twin Technology in Healthcare. Annals of Translational Medicine 2022, 10.
93. Yu, F.; Yu, C.; Tian, Z.; Liu, X.; Cao, J.; Liu, L.; Du, C.; Jiang, M. Intelligent Wearable System With Motion and Emotion Recognition Based on Digital Twin Technology. IEEE Internet Things J. 2024, 11, 26314–26328, doi:10.1109/JIOT.2024.3394244.
94. Jimenez, J.I.; Jahankhani, H.; Kendzierskyj, S. Health Care in the Cyberspace: Medical Cyber-Physical System and Digital Twin Challenges. Digital twin technologies and smart cities 2020, 79–92.
95. Barresi, G.; Gaggioli, A.; Sternini, F.; Ravizza, A.; Pacchierotti, C.; De Michieli, L. Digital Twins and Healthcare: Quick Overview and Human-Centric Perspectives. mHealth and Human-Centered Design Towards Enhanced Health, Care, and Well-being 2023, 57–78.
96. Oh, C.S.; Bailenson, J.N.; Welch, G.F. A Systematic Review of Social Presence: Definition, Antecedents, and Implications. Frontiers in Robotics and AI 2018, 5, 409295.
97. Philips Available online: https://www.usa.philips.com/healthcare.
98. Digital "Twinning": Clinical Trials Powered by AI Available online: https://www.sanofi.com/en/magazine/our-science/digital-twinning-clinical-trials-ai.
99. Shedding Light on Digital Twin, Digital Patient, Virtual Patient and Synthetic Control Arm Available online: https://insilicotrials.com/digital-twin/.
100. The Cancer Genome Atlas Program (TCGA) Available online: https://www.cancer.gov/ccg/research/genome-sequencing/tcga.
101. What Is the Connectome Coordination Facility? Available online: https://www.humanconnectome.org/.
102. eICU Collaborative Research Database Available online: https://physionet.org/content/eicu-crd/2.0/.
103. Synthea Available online: https://synthetichealth.github.io/synthea/.
104. Biobank Available online: https://www.ukbiobank.ac.uk/.
105. Assembling Digital Twins with Omniverse and OpenUSD Available online: https://docs.nvidia.com/learning/physical-ai/assembling-digital-twins/latest/index.html.
106. Microsoft Learn Available online: https://learn.microsoft.com/en-us/azure/digital-twins/overview.
107. AWS IoT TwinMaker Available online: https://aws.amazon.com/iot-twinmaker/.
108. Google Cloud for Supply Chain and Logistics.
109. Suh, I.; McKinney, T.; Siu, K.-C. Current Perspective of Metaverse Application in Medical Education, Research and Patient Care.; MDPI, 2023; Vol. 2, pp. 115–128.
110. Yang, D.; Sun, M.; Zhou, J.; Lu, Y.; Song, Z.; Chen, Z.; Yang, D.; Wu, X.; Ge, H.; Zhang, Y. Expert Consensus on the "Digital Human" of Metaverse in Medicine. Clinical eHealth 2023, 6, 159–163.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




111. Loveys, K.; Sagar, M.; Antoni, M.; Broadbent, E. The Impact of Virtual Humans on Psychosomatic Medicine. Psychosomatic medicine 2023, 85, 619–626.
112. Aloqaily, M.; Bouachir, O.; Karray, F. Digital Twin for Healthcare Immersive Services: Fundamentals, Architectures, and Open Issues. In Digital twin for healthcare; Elsevier, 2023; pp. 39–71.
113. Koh, A.J.H.; Tan, S.Y.; Nasrudin, M.F. A Systematic Literature Review of Generative Adversarial Networks (GANs) in 3D Avatar Reconstruction from 2D Images. Multimedia Tools and Applications 2024, 1–41.
114. Qin, M.; Liu, Y.; Xu, Y.; Zhao, X.; Liu, Y.; Wang, H. High-Fidelity 3D Head Avatars Reconstruction through Spatially-Varying Expression Conditioned Neural Radiance Field.; 2024; Vol. 38, pp. 4569–4577.
115. Xiang, D.; Bagautdinov, T.; Stuyck, T.; Prada, F.; Romero, J.; Xu, W.; Saito, S.; Guo, J.; Smith, B.; Shiratori, T. Dressing Avatars: Deep Photorealistic Appearance for Physically Simulated Clothing. ACM Transactions on Graphics (TOG) 2022, 41, 1–15.
116. Xiang, D.; Prada, F.; Bagautdinov, T.; Xu, W.; Dong, Y.; Wen, H.; Hodgins, J.; Wu, C. Modeling Clothing as a Separate Layer for an Animatable Human Avatar. ACM Transactions on Graphics (TOG) 2021, 40, 1–15.
117. Cao, C.; Simon, T.; Kim, J.K.; Schwartz, G.; Zollhoefer, M.; Saito, S.-S.; Lombardi, S.; Wei, S.-E.; Belko, D.; Yu, S.-I. Authentic Volumetric Avatars from a Phone Scan. 2022.
118. Bai, S.; Wang, T.-L.; Li, C.; Venkatesh, A.; Simon, T.; Cao, C.; Schwartz, G.; Wrench, R.; Saragih, J.; Sheikh, Y. Universal Facial Encoding of Codec Avatars from VR Headsets. arXiv preprint arXiv:2407.13038 2024.
119. Menzel, T.; Wolf, E.; Wenninger, S.; Spinczyk, N.; Holderrieth, L.; Wienrich, C.; Schwanecke, U.; Latoschik, M.E.; Botsch, M. Avatars for the Masses: Smartphone-Based Reconstruction of Humans for Virtual Reality. Front. Virtual Real. 2025, 6, doi:10.3389/frvir.2025.1583474.
120. Won, J.; Gopinath, D.; Hodgins, J. Physics-Based Character Controllers Using Conditional Vaes. ACM Transactions on Graphics (TOG) 2022, 41, 1–12.
121. Jiang, Y.; Ye, Y.; Gopinath, D.; Won, J.; Winkler, A.W.; Liu, C.K. Transformer Inertial Poser: Real-Time Human Motion Reconstruction from Sparse Imus with Simultaneous Terrain Generation.; 2022; pp. 1–9.
122. Ullal, A.; Watkins, C.; Sarkar, N. A Dynamically Weighted Multi-Objective Optimization Approach to Positional Interactions in Remote-Local Augmented/Mixed Reality.; IEEE, 2021; pp. 29–37.
123. Luvizon, D.C.; Habermann, M.; Golyanik, V.; Kortylewski, A.; Theobalt, C. Scene-Aware 3D Multi-Human Motion Capture from a Single Camera.; Wiley Online Library, 2023; Vol. 42, pp. 371–383.
124. Bai, S.; Wang, T.-L.; Li, C.; Venkatesh, A.; Simon, T.; Cao, C.; Schwartz, G.; Wrench, R.; Saragih, J.; Sheikh, Y.; et al. Universal Facial Encoding of Codec Avatars from VR Headsets. ACM Trans. Graph. 2024, 43, 1–22, doi:10.1145/3658234.
125. Ioannidis, L.; Antoniou, P.; Bamidis, P. Data Modelling for Visual Entities to Streamline Virtual Patient Re-Purposing in Virtual Reality.; Springer, 2021; pp. 1085–1095.
126. Daineko, Y.; Ipalakova, M.; Tsoy, D.; Alipova, B.; Kozhakhmetov, A.; Mustafina, A. Towards Metahospital: Augmented and Virtual Reality in Medicine. Procedia Computer Science 2024, 231, 373–378.
127. Bensadoun, R.; Kleiman, Y.; Azuri, I.; Harosh, O.; Vedaldi, A.; Neverova, N.; Gafni, O. Meta 3D TextureGen: Fast and Consistent Texture Generation for 3D Objects. arXiv preprint arXiv:2407.02430 2024.
128. Chen, T.; Cao, R.; Li, Z.; Zang, Y.; Sun, L. Deep3DSketch-Im: Rapid High-Fidelity AI 3D Model Generation by Single Freehand Sketches. Frontiers of Information Technology & Electronic Engineering 2024, 25, 149–159.
129. Fu, K.; Wu, R.; Tang, Y.; Chen, Y.; Liu, B.; LC, R. " Being Eroded, Piece by Piece": Enhancing Engagement and Storytelling in Cultural Heritage Dissemination by Exhibiting GenAI Co-Creation Artifacts.; 2024; pp. 2833–2850.
130. Li, M.-F.; Ku, Y.-F.; Yen, H.-X.; Liu, C.; Liu, Y.-L.; Chen, A.; Kuo, C.-H.; Sun, M. GenRC: Generative 3D Room Completion from Sparse Image Collections. 2024.
131. Shao, L.; Tang, W.; Zhang, Z.; Chen, X. Medical Metaverse: Technologies, Applications, Challenges and Future. Journal of Mechanics in Medicine and Biology 2023, 23, 2350028.
132. Chengoden, R.; Victor, N.; Huynh-The, T.; Yenduri, G.; Jhaveri, R.H.; Alazab, M.; Bhattacharya, S.; Hegde, P.; Maddikunta, P.K.R.; Gadekallu, T.R. Metaverse for Healthcare: A Survey on Potential Applications, Challenges and Future Directions. IEEE Access 2023, 11, 12765–12795.


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1




133. Luijten, G.; Gsaxner, C.; Li, J.; Pepe, A.; Ambigapathy, N.; Kim, M.; Chen, X.; Kleesiek, J.; Hölzle, F.; Puladi, B. 3D Surgical Instrument Collection for Computer Vision and Extended Reality. Scientific Data 2023, 10, 796.
134. Ran, B.; Huang, B.; Liang, S.; Hou, Y. Surgical Instrument Detection Algorithm Based on Improved YOLOv7x. Sensors 2023, 23, 5037.
135. Ho, C.-J.; Tai, C.-H.; Lin, Y.-Y.; Yang, M.-H.; Tsai, Y.-H. Diffusion-Ss3d: Diffusion Model for Semi-Supervised 3d Object Detection. Advances in Neural Information Processing Systems 2023, 36, 49100–49112.
136. Liu, D.; Wei, Y.; Jiang, T.; Wang, Y.; Miao, R.; Shan, F.; Li, Z. Unsupervised Surgical Instrument Segmentation via Anchor Generation and Semantic Diffusion.; Springer, 2020; pp. 657–667.
137. Allmendinger, S.; Hemmer, P.; Queisner, M.; Sauer, I.; Müller, L.; Jakubik, J.; Vössing, M.; Kühl, N. Navigating the Synthetic Realm: Harnessing Diffusion-Based Models for Laparoscopic Text-to-Image Generation. In AI for Health Equity and Fairness: Leveraging AI to Address Social Determinants of Health; Springer, 2024; pp. 31–46.
138. Khan, U.; Nawaz, U.; Qayyum, A.; Ashraf, S.; Xie, Y.; Khan, M.H.; Bilal, M.; Qadir, J. Surgical Scene Understanding in the Era of Foundation AI Models: A Comprehensive Review 2025.
139. Yim, D.; Khuntia, J.; Parameswaran, V.; Meyers, A. Preliminary Evidence of the Use of Generative AI in Health Care Clinical Services: Systematic Narrative Review. JMIR Medical Informatics 2024, 12, e52073.
140. Sai, S.; Gaur, A.; Sai, R.; Chamola, V.; Guizani, M.; Rodrigues, J.J. Generative Ai for Transformative Healthcare: A Comprehensive Study of Emerging Models, Applications, Case Studies and Limitations. IEEE Access 2024.
141. Sun, T.; He, X.; Li, Z. Digital Twin in Healthcare: Recent Updates and Challenges. Digital Health 2023, 9, 20552076221149651.
142. Chaudhuri, A.; Pash, G.; Hormuth, D.A.; Lorenzo, G.; Kapteyn, M.; Wu, C.; Lima, E.A.B.F.; Yankeelov, T.E.; Willcox, K. Predictive Digital Twin for Optimizing Patient-Specific Radiotherapy Regimens under Uncertainty in High-Grade Gliomas. Frontiers in Artificial Intelligence 2023, 6, doi:10.3389/frai.2023.1222612.
143. Chang, H.-C.; Gitau, A.M.; Kothapalli, S.; Welch, D.R.; Sardiu, M.E.; McCoy, M.D. Understanding the Need for Digital Twins' Data in Patient Advocacy and Forecasting Oncology. Frontiers in Artificial Intelligence 2023, 6, doi:10.3389/frai.2023.1260361.
144. Sager, S. Digital Twins in Oncology. J Cancer Res Clin Oncol 2023, 149, 5475–5477, doi:10.1007/s00432-023-04633-1.
145. Stahlberg, E.A.; Abdel-Rahman, M.; Aguilar, B.; Asadpoure, A.; Beckman, R.A.; Borkon, L.L.; Bryan, J.N.; Cebulla, C.M.; Chang, Y.H.; Chatterjee, A.; et al. Exploring Approaches for Predictive Cancer Patient Digital Twins: Opportunities for Collaboration and Innovation. Front. Digit. Health 2022, 4, doi:10.3389/fdgth.2022.1007784.
146. Hansen, J.; Jain, A.R.; Nenov, P.; Robinson, P.N.; Iyengar, R. From Transcriptomics to Digital Twins of Organ Function. Frontiers in Cell and Developmental Biology 2024, 12, 1240384.
147. Elgammal, Z.; Albrijawi, M.T.; Alhajj, R. Digital Twins in Healthcare: A Review of AI-Powered Practical Applications across Health Domains. J Big Data 2025, 12, 234, doi:10.1186/s40537-025-01280-w.
148. Giuffrè, M.; Shung, D.L. Harnessing the Power of Synthetic Data in Healthcare: Innovation, Application, and Privacy. NPJ digital medicine 2023, 6, 186.
149. Ive, J. Leveraging the Potential of Synthetic Text for AI in Mental Healthcare. Front Digit Health 2022, 4, 1010202, doi:10.3389/fdgth.2022.1010202.
150. Giuffrè, M.; Shung, D.L. Harnessing the Power of Synthetic Data in Healthcare: Innovation, Application, and Privacy. NPJ Digit Med 2023, 6, 186, doi:10.1038/s41746-023-00927-3.
151. García-Gómez, J.M.; Blanes-Selva, V.; Cenzano, J.C. de B.; Cebolla-Cornejo, J.; Doñate-Martínez, A. Functional Requirements to Mitigate the Risk of Harm to Patients from Artificial Intelligence in Healthcare 2023.
152. Nawawi, M.H.M.; Ishak, M.S.; Raes, R.F.A.; Razak, I.A.; Hasan, S.; Rahim, A.I.A. The Intersection of Quality Improvement, Artificial Intelligence and Patient Safety in Healthcare—Current Applications, Challenges


© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



and Risks, and Future Directions: A Scoping Review. Journal of Medical Artificial Intelligence 2025, 8, doi:10.21037/jmai-24-328.

153. Curran, V.R.; Xu, X.; Aydin, M.Y.; Meruvia-Pastor, O. Use of Extended Reality in Medical Education: An Integrative Review. Medical Science Educator 2023, 33, 275–286.
154. Sallam, M.; Salim, N.A.; Barakat, M.; Ala'a, B. ChatGPT Applications in Medical, Dental, Pharmacy, and Public Health Education: A Descriptive Study Highlighting the Advantages and Limitations. Narra J 2023, 3.
155. Mir, M.M.; Mir, G.M.; Raina, N.T.; Mir, S.M.; Mir, S.M.; Miskeen, E.; Alharthi, M.H.; Alamri, M.M.S. Application of Artificial Intelligence in Medical Education: Current Scenario and Future Perspectives. Journal of advances in medical education & professionalism 2023, 11, 133.
156. Kapadia, N.; Gokhale, S.; Nepomuceno, A.; Cheng, W.; Bothwell, S.; Mathews, M.; Shallat, J.S.; Schultz, C.; Gupta, A. Evaluation of Large Language Model Generated Dialogues for an AI Based VR Nurse Training Simulator.; Springer, 2024; pp. 200–212.
157. Kim, H.Y.; Ali, G.; Hwang, J. Enhancing Doctor-patient Communication in Surgical Explanations: Designing Effective Facial Expressions and Gestures for Animated Physician Characters. Computer Animation and Virtual Worlds 2024, 35, e2236.
158. Tseng, Y.-M.; Huang, Y.-C.; Hsiao, T.-Y.; Hsu, Y.-C.; Foo, J.-Y.; Huang, C.-W.; Chen, Y.-N. Two Tales of Persona in Llms: A Survey of Role-Playing and Personalization. arXiv preprint arXiv:2406.01171 2024.
159. Zalake, M. Doctors' Perceptions of Using Their Digital Twins in Patient Care. Scientific Reports 2023, 13, 21693.
160. Li, Y.; Zeng, C.; Zhong, J.; Zhang, R.; Zhang, M.; Zou, L. Leveraging Large Language Model as Simulated Patients for Clinical Education. arXiv preprint arXiv:2404.13066 2024.
161. Yan, N.; Alterovitz, G. A General-Purpose AI Avatar in Healthcare. arXiv preprint arXiv:2401.12981 2024.
162. Ryason, A.; Xia, Z.; Jackson, C.; Wong, V.T.; Li, H.; De, S.; Jones, S.B. Validation of a Virtual Simulator with Haptic Feedback for Endotracheal Intubation Training. Simulation in Healthcare 2024, 19, 122–130.
163. Watkins, A.; Ghosh, R.; Ullal, A.; Sarkar, N. Instilling the Perception of Weight in Augmented Reality Using Minimal Haptic Feedback. 2024.
164. Feick, M.; Biyikli, C.; Gani, K.; Wittig, A.; Tang, A.; Krüger, A. VoxelHap: A Toolkit for Constructing Proxies Providing Tactile and Kinesthetic Haptic Feedback in Virtual Reality.; 2023; pp. 1–13.
165. Jin, P.; Liu, J.; Yang, F.; Marchesoni, F.; Jiang, J.-H.; Huang, J. In Situ Simulation of Thermal Reality. Research 2023, 6, 0222.
166. Zeng, Q.; Wang, K.; Liu, W.-X.; Zeng, J.-Z.; Li, X.-L.; Zhang, Q.-F.; Ren, S.-Q.; Xu, W.-M. Efficacy of High-Fidelity Simulation in Advanced Life Support Training: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. BMC Med Educ 2023, 23, 664, doi:10.1186/s12909-023-04654-x.
167. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: Values, Challenges and Enablers from a Modeling Perspective. IEEE access 2020, 8, 21980–22012.
168. Aslam, A.M.; Chaudhary, R.; Bhardwaj, A.; Budhiraja, I.; Kumar, N.; Zeadally, S. Metaverse for 6G and beyond: The next Revolution and Deployment Challenges. IEEE Internet of Things Magazine 2023, 6, 32–39.
169. Adil, M.; Song, H.; Khan, M.K.; Farouk, A.; Jin, Z. 5G/6G-Enabled Metaverse Technologies: Taxonomy, Applications, and Open Security Challenges with Future Research Directions. Journal of Network and Computer Applications 2024, 103828.
170. Letafati, M.; Otoum, S. On the Privacy and Security for E-Health Services in the Metaverse: An Overview. Ad Hoc Networks 2023, 103262.
171. Gupta, M.; Akiri, C.; Aryal, K.; Parker, E.; Praharaj, L. From Chatgpt to Threatgpt: Impact of Generative Ai in Cybersecurity and Privacy. IEEE Access 2023.
172. Zeydan, E.; Blanco, L.; Mangues-Befalluy, J.; Arslan, S.S.; Turk, Y. Next-Generation Orchestration: Quantum Computing for Network Services.; IEEE, 2024; pp. 1–8.
173. Lopez, M.B.; Tang, S.; Kearns, M.; Morgenstern, J.; Roth, A.; Wu, Z.S. Scalable Membership Inference Attacks via Quantile Regression. 2023.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org | NOT PEER-REVIEWED | Posted: 6 November 2026 https://doi.org/10.20944/preprints202611.0749.v1



174. Fisher, K.A.; Broadbent, A.; Shalm, L.; Yan, Z.; Lavoie, J.; Prevedel, R.; Jennewein, T.; Resch, K.J. Quantum Computing on Encrypted Data. Nature communications 2014, 5, 3074.
175. Chawla, D.; Mehra, P.S. A Survey on Quantum Computing for Internet of Things Security. Procedia Computer Science 2023, 218, 2191–2200.

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.