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SPECIAL FOCUS PAPER

Digital Twins in Biomedical Engineering: A Systematic Review of Applications and Future Challenges

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ABSTRACT

Digital twins (DTs) are a part of computational biomedical engineering, which allows us to come up with real-time virtual copies of biological systems, medical equipment, and clinical procedures. With the help of patient-based data, sensor signals, and modern modeling methods, DTs are opening up huge avenues for personalized treatment and early diagnosis. The methodology for this study involves a systematic literature review and manual thematic synthesis in order to find out the key patterns and insights relevant to the topic. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines and consists of those articles that are peer-reviewed and published in English during the time frame of 2015–2026. Global scientific databases such as Google Scholar, Scopus, Web of Science, PubMed, and IEEE Xplore were used. The comprehensive review indicates that the largest part of the Digital Twins applications is related to the areas of cardiovascular modeling, oncology, orthopedics, surgical planning, and chronic disease management. Most of the implementations are a combination of physiological models with machine learning algorithms and patient data from sensors. From a business, economic, and healthcare management perspective, DTs support data-driven decision-making, operational efficiency, cost optimization, and strategic planning in healthcare organizations, contributing to value creation, economic efficiency, and sustainable health systems. Challenges related to computational complexity, model interpretability, data integration, ethical governance, and regulatory approval still persist. The application of DTs leads to a complete transformation in the areas of biomedical engineering, clinical decision-making, and sustainable health systems, thus providing patient-oriented, data-informed, and economically efficient healthcare solutions. Future research should prioritize explainable modeling, longitudinal validation, and interdisciplinary collaboration to enable safe and effective adoption.

KEYWORDS

digital twins (DTs), biomedical engineering, cardiovascular, orthopedic, cancer treatment

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1 INTRODUCTION

Healthcare has adopted digital twins (DTs) technology because computational modeling, artificial intelligence, and biomedical data science have rapidly combined their capabilities. The DT paradigm started in engineering as a system that creates a real-time virtual model, which has now extended its use to medicine for developing personalized patient treatment plans [1]. Clinical decision-making now uses simulation-based approaches, which treat DT as essential elements in precision medicine that provide patients with customized diagnostic methods and treatment plans based on their changing health conditions [2].

In biomedical contexts, a DT represents a continuously updated virtual counterpart of a patient that integrates molecular, physiological, imaging, and lifestyle data over time [1]. DTs differ from traditional static models because they establish live connections that link actual processes with their virtual representations, which allows users to track how medical conditions will progress and how treatment will affect their health [3]. DT establishes itself as groundbreaking technology through its ability to change healthcare systems from traditional methods of disease treatment into advanced models that utilize predictive analytics and preventive medical practices.

The literature shows that DT medical systems could be an important integrative strategy in future medicine, combining computer simulation with practical medical application. An example of how DT for the heart can combine multiple imaging methods, such as echocardiograms, computational fluid dynamics, and electrical models of the heart to create a virtual model of the heart that can predict how it will work, as well as simulate what happens when blood flows through, allows for a more accurate classification of heart failure types and risk of bad consequences from heart failure [3].

In addition to disease management, DTs are transforming the life cycle of medical devices and biomedical systems. For example, through the use of computational DT models, it is possible to evaluate how an implant will behave biomechanically when experiencing loads that would be experienced in vivo, as well as to assess fatigue failures and predict long-term durability, which will help in decreasing the number of times prototypes have to be repeated in physical prototyping and accelerate the pace of the regulatory review process [4]. This has minimized dependence on conventional experimental methods and expedited regulatory approval, safety, and efficacy results. The ability to predict patient-specific responses to devices has also improved personalized healthcare solutions.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Literature review

Although DT technology was originally developed for use in engineering systems, the use of DT is becoming prevalent in the biomedical engineering community, and it is recognized as being a major enabler of precise medicine. In the past, the majority of literature describing DT referred to them as dynamic two-way virtual copies of physical systems that created real-time replicas [5]. The most recent studies in health care have expanded the definition of DT to include patient-specific virtual models of patients that incorporate a wide range of clinical data, including genomic, imaging, biosignal, and streaming sensor data [6] [7]. In the context of precision medicine, DTs are valuable tools for predicting disease progression, mimicking therapeutic options, and stratifying risk within several areas of medicine, including cardiology, oncology, neurology, and musculoskeletal medicine [8] [9] [10]. In addition to clinical

applications, there is a growing body of literature describing the implementation of DT at the system level to optimize hospital workflows and integrate smart medical cyber-physical systems (CPS) [11] [12]. The persistent issues preventing the widespread implementation of DT technology include a lack of data interoperability, difficulties related to the validation of models, the need for ethical governance, regulatory harmonization, and promoting the economic sustainability of the systems [13] [14]. The key findings synthesized from the literature are depicted in Table 1.

Table 1. Key findings synthesized from the systematic literature review

Ref	Author(s), Year	Focus Area	Key Contribution	Quality
[1]	Bruynseels et al., 2018	Ethics in DT	Governance & autonomy issues	Moderate
[2]	Sun et al., 2023	Updates & challenges	Architecture & AI integration summary	High
[3]	Coorey et al., 2022	Cardiovascular DT	CVD modeling framework	High
[4]	Tudu et al., 2025	Medical device DT	Device modeling integration	Moderate
[5]	Kamel Boulos & Zhang, 2021	Precision public health	Population-level DT vision	High
[6]	Chen et al., 2024	Networking architecture	Human DT communication architecture	High
[7]	Silva & Vale, 2025	Personalized medicine	Clinical translation discussion	Moderate
[8]	Wu et al., 2022	Oncology DT	Imaging-based modeling integration	High
[9]	Diniz et al., 2025	Musculoskeletal	Surgical planning applications	Moderate
[10]	Tortora et al., 2025	Clinical DT principles	Architecture classification	High
[11]	Rahim et al., 2024	Cyber-physical systems	DT-based CPS platform	High
[12]	Ghatti et al., 2023	Methods overview	Taxonomy of modeling methods	Moderate
[13]	Vallée, 2024	Future vision	Strategic roadmap	Moderate
[14]	Papachristou et al., 2024	Precision medicine	Advancements mapping	High
[15]	Sahal et al., 2022	Personal DT	Conceptual architecture	Moderate
[16]	Sun et al., 2022	Future healthcare DT	Ecosystem framework	Moderate
[17]	Zhang et al., 2024	Healthcare applications	Categorized DT applications	High
[18]	Cellina et al., 2023	Radiology DT	Imaging-based DT	Moderate
[19]	Khan et al., 2022	Industry 4.0 healthcare	DT & healthcare revolution link	Moderate
[20]	Saratkar et al., 2025	Drug development	DT in pharma pipeline	High
[21]	Xames & Topcu, 2024	Healthcare systems	Research trends & realization challenges	High
[22]	Meijer et al., 2023	Validation challenges	Modeling & data integration gaps	High
[23]	Sadée et al., 2025	AI & precision medicine	AI-integrated medical DT	High
[24]	Katsoulakis et al., 2024	Health DT landscape	Use-case mapping	High
[25]	Sharma & Kaur, 2025	Hybrid AI framework	Patient-specific hybrid DT model	High

Source: Constructed by author.

2.2 Research questions

The research questions formulated are listed below-

RQ1. What are the current applications of DT technology in biomedical engineering?

RQ2. What technological architectures and computational frameworks are used to develop DT in biomedical contexts?

RQ3. What clinical, operational, and economic benefits are associated with the implementation of DT in healthcare systems?
RQ4. What technical, ethical, regulatory, managerial, and economic challenges hinder the large-scale adoption of DT systems?

2.3 Theoretical framework

The present study employs an integrated theoretical approach, which describes the structure of DT in biomedical engineering as consisting of three paradigmatic constructs that are interrelated: CPS Theory [15], Precision Medicine Theory [16], and Socio-Technical Systems Theory [17].

To begin with, CPS theory provides the technological framework for DT. CPS describes systems as being composed of tightly coupled networks of physical components, computational models, sensors, communication networks, and control elements. In the field of medicine, this implies the constantly evolving, bi-directional relationship between the physiological condition of a person and the digital object symbolizing the same [6] [11]. The CPS perspective facilitates the comprehension of how the four system components (layer of data gathering, communication networks and communication protocols, computational engines, and feedback) can be used to allow real-time synchronization and predictive simulation of a DT system.

Secondly, Precision Medicine Theory gives a clinical rationale for the concept of DT. Precision medicine involves the diagnosis and treatment of patients through personalized therapy and diagnosis based on the genetic and environmental background of a patient and their lifestyles, as compared to other patients. DT helps with this model because it converts a partially electronic version of a health record to an active, reactive, and adaptable model of learning, which can forecast disease development and simulate therapeutic reactions [7] [8]. In this regard, DT handles decision support, shifting the healthcare system's patients to reactive intervention instead of preventive and predictive care models.

Socio-technical theory also provides the necessary organizational/managerial element to enable a large-scale implementation of DT in healthcare settings. Healthcare organizations function as a complex set of interdependent ecosystems that include interactions among technology development, human actors, governance systems, economic constraints, and ethical norms. The introduction of DT will not only affect clinical workflows from a technological perspective but will also continue to change how resources are allocated, regulatory requirements are followed, and performance is measured in these healthcare institutions [11, 12]. Success at implementing DT from a socio-technical perspective requires three components working together: (1) clarity regarding the technological capability of the DT, (2) willingness of clinicians to adopt and use the DT technology, and (3) alignment between the policy framework and budget/resource allocations for the proposed technology being implemented.

By connecting these three theoretical constructs, this research identifies DT as a multi-layered system composed of: (1) technological infrastructure (CPS), (2) patient-specific clinical intelligence (precision medicine), and (3) integration of organizational and financial components (socio-technical systems). This integrated framework provides the basis for systematically evaluating the application of DT, the barriers/limitations to implementation, and future directions as a new healthcare ecosystem and not merely as a new technology.

3 METHODOLOGY

The research uses a systematic literature review method to study the technological growth, current use, and future challenges of DT technology in the field of biomedical engineering. The review process followed the guidelines established by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [18], as shown in Figure 1. In the beginning, there are 365 records from the database search. The total number of records examined before removing duplicates was 110. Out of these 365 records, 255 were screened based on their titles and abstracts, and as a result of this screening, 168 articles were removed from consideration because of being irrelevant, having conceptual limitations, or not dealing with healthcare issues. Then there were 87 full articles evaluated for eligibility; however, there were 62 that were eliminated from the final qualitative synthesis because they did not have a clearly stated methodology or their underlying frameworks overlapped with other studies, resulting in a total of 25 studies that were included in the final qualitative synthesis after reviewing their methodology with the Critical Appraisal Skills Program. Studies were considered high quality when they clearly stated their research goals, used suitable and solid methods, dealt with bias, and shared findings that were checked and reliable. Studies were rated moderate quality if there were small issues with how they were done or some details missing in the report, while low quality meant there were bigger problems with the study design, lack of clear data, or problems checking the results.

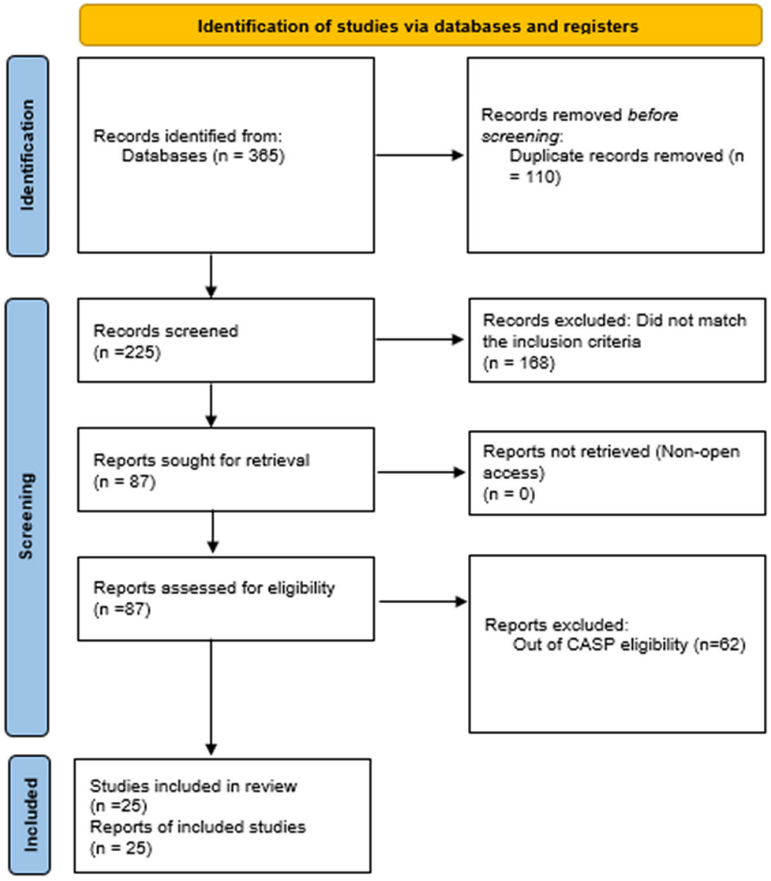

Fig. 1. PRISMA flowchart

Source: Constructed by author.

The researchers performed a complete database search to locate all applicable peer-reviewed studies. Researchers used Scopus, Web of Science, PubMed, IEEE Xplore, and Google Scholar as their main research databases. The specific Boolean search string used was ("DT" OR "virtual twin" OR "computational twin" OR "in silico twin" OR "patient-specific DT").

AND

("biomedical engineering" OR "healthcare" OR "medicine" OR "medical device" OR "clinical application" OR "hospital")

AND

("application" OR "simulation" OR "implementation" OR "model")

AND

("challenge" OR "limitation" OR "future direction" OR "economic" OR "management" OR "governance" OR "cost" OR "return on investment")

3.1 Inclusion criteria

- Peer-reviewed journal articles and conference papers
- Studies focusing on DT applications in healthcare or biomedical engineering
- Articles discussing technical, clinical, managerial, or economic implications
- English language publications
- Published between 2015 and 2026

3.2 Exclusion criteria

- Industrial/manufacturing DT without healthcare context
- Editorials, commentaries, short communications
- Non-English publications
- Studies lacking methodological clarity

Qualitative thematic analysis was employed. The chosen studies were comparatively evaluated to discern emerging themes and trends. This allowed for a well-rounded assessment of DT not only as technological developments but also as socio-technical phenomena with wider economic and governance undertones.

4 FINDINGS

The analysis of the literature revealed that the applications of the DT in biomedical engineering can be categorized into five major 5 domains.

4.1 Personalized and precision medicine

The best application field of DT is patient-specific modeling of precise healthcare. Several research studies have theorized Digital Human Twins (DHTs) or Personal DT (PDT) to be a dynamic computational facilitation of physiological, genetic, behavioral, and environmental data to predict individualized health models [6], [14], [19].

One of the studies points to the bidirectional communication between physical patients and their DT and enables real-time communication with clinical data and AI-based predictions of the disease progression [14]. Similarly, another study has further expanded this concept by developing actionable personal DT that combines blockchain and AI to facilitate optimal treatment decisions, especially in scenarios such as COVID-19 care and cancer survivorship [19]. The integration of IoT, Big Data, and AI technologies makes high-resolution patient modeling feasible for precise diagnosis and personalized therapy, which was also suggested [20]. DT can help identify potential health problems before they get worse and assist in the planning of interventions for each patient as they get older [13]. A study suggested multiscale simulations will include genetic data, imaging, and data from wearables to assist in making clinically significant, patient-centered decisions [7]. Accordingly, these two works underscore that the majority of DT applications in biomedicine will focus on predictive personalization by transitioning from a reactive model (scope of current healthcare) to proactive, data-driven precision medicine. It is noted with the help of the literature that predictive modeling may reduce the number of unnecessary interventions (e.g., ordering tests/procedures), decrease adverse drug events, and optimize the delivery of therapies that, in turn, will support long-term sustainability of healthcare system costs.

4.2 Disease-specific DT

The second primary field of application uses DT systems, which concentrate on studying diseases through their research in oncology, neurology, and cardiology. An image-guided DT in oncology, where tissue-scale mathematical models integrated with medical imaging enable simulation of tumor growth and therapeutic response, is discussed [8]. The method enables clinicians to simulate treatment methods through in silico testing before actual treatment starts, which results in better treatment outcomes through reduced treatment failures. The digital health twins transform neurological research into new tools for studying complex neurodegenerative disorders [10]. Multiscale simulations will develop patient-specific therapeutic design in emerging fields, which include cardiology and pharmacogenomics [7]. Multimodal deep learning, together with embodied AI agents, can solve biological diversity problems that obstruct disease modeling progress [21]. Also, the systems achieve economic and clinical efficiency by reducing pointless treatments and enhancing resource efficiency.

4.3 Smart hospitals and healthcare systems

DT technologies are being utilized on an institutional/system level in addition to on the patient level. DT-MCPS (DT–based Medical CPS) is a type of DT technology developed to simulate and optimize hospital operations [11]. The DT-MCPS comprises the integration of the following components: electronic medical records, real-time monitoring of a patient's physiological status, and artificial intelligence (AI)-derived analytics to help optimize hospitalization workflows and provide personalized diagnostic support. In addition, another study describes the application of DT technologies in workflows and overall hospital management, making these applications increasingly common [12]. Further discussion adds on to the DT concept by offering combined/dual-level modeling, which utilizes a digital human twin

and a digital institutional twin, to enhance organizational management and strategy processes [22]. This dual-level modeling approach permits healthcare organizations to simulate resource allocation, patient flow, and infrastructure needs. DT systems, from an aggregated level, can be useful for making population health intervention decisions at the level of public health. The DT of hospitals represents an important intermediary between biomedical engineering and healthcare management. When implementing DT in smart hospitals, hospitals can achieve greater operational efficiency, maximize staffing, improve maintenance predictive capabilities for their medical equipment, and provide better service to patients. Economically, hospitals utilizing such systems can reduce their readmission rates, have more efficient bed allocations, and have enhanced long-range infrastructure planning, thereby improving sustainability goals related to biomedical innovation and other fields of study.

4.4 Enabling technological architectures

The utilization of DT in the biomedical field depends largely on the availability of the computational architecture and the communication infrastructure required to implement it. A detailed network architecture with a layered framework for data acquisition, data communication, data computation, and data analytics is also mentioned [6]. The convergence of CPS, IoT, Big Data, Edge Computing, AI, and Machine Learning as the foundational technologies for developing DT is noted [23]. Multimodal deep learning and metaverse-enabled embodied AI agents will enhance the ability of physical and digital entities to interact in real-time [17]. The anticipated impact of blockchain and cloud computing will help improve interoperability and data governance [24]. Collectively, these sources suggest that DTs are large CPS that function as part of an integrated ecosystem and require a comprehensive data pipeline, real-time synchronization, and a scalable computational infrastructure. This level of complexity in architecture can also create opportunities and difficulties from a technical perspective, especially with respect to the validation of models, interoperability, and the reliability of systems.

4.5 Translational and healthcare systems

There are several different factors to consider when determining whether DT is relevant in clinical practice and research. Studies indicate that DT is more than just a way to model clinical data; they also have implications in translational research, in ethics, and for medical education. As an example, numerous ethical issues related to human DT, consent, data ownership, and discrimination risks, when focusing on the relationship between human DT and their ethical implications, were identified [13]. As noted, the three main barriers to widespread use of DT are data security, accessibility, and interoperability [12] [14]. In the same way, it is also emphasized that all stakeholders involved in DT creation and use must adopt a standard communication model and technical framework [23]. In addition to their typical clinical and organizational uses, several educational uses of DT during training through virtual anatomic modeling and simulation of procedures were identified [22]. While these issues need to be addressed from a management perspective, some important aspects necessary to sustain a DT deployment are: ethical governance and regulatory alignment. Additionally, without an established framework for the validation

of DT, data governance policies and reimbursement models associated with DT will limit the economic sustainability of DT.

Taken together, these application areas make it clear that DT is no longer purely experimental computational tools but are instead moving towards being comprehensive healthcare systems with important clinical, administrative, and economic implications. Yet, their adoption as a common practice requires the overcoming of technical, ethical, regulatory, and translation challenges.

5 DISCUSSION AND CHALLENGES IN IMPLEMENTING DT IN BIOMEDICAL ENGINEERING

Despite the transformative features of DT in healthcare, the reviewed study consistently highlights significant technical, ethical, regulatory, and economic barriers that hinder its large-scale clinical adoption.

5.1 Data integration, quality, and interoperability

Challenges related to integrating different types of diverse data are commonly referenced as one of the primary challenges for implementing DT. DT integrates many different modalities of data, including genomic, imaging, biosignal, wearable sensor, and electronic health record data [6], [7]. There are many barriers to achieving seamless interoperability due to a number of factors, including discrepancies in data standards, incomplete data sets, and fragmented health information systems [12] [23]. The problems associated with the architectural complexity (acquisition, communications, computation, and analytics layers) to deploy a DT have been reported [6], and other research points out the deficiency of standardized communications protocols across the CPS [23]. Lack of a common and unified data framework poses a technical instability in aligning the physical and digital patients as they are in real-time. Besides the hindrance to access to information, biological heterogeneity complicates the establishment of models that are true [21]. Research has indicated that longitudinal high-resolution data that are needed to reconstruct personalized models are not always available or are not evenly distributed within the populace, and thus the construction of these models is likely to be biased [13] [14].

5.2 Model validation and clinical reliability

The other significant challenge is validation and credibility of models in a clinical setting, and although DT is capable of simulating disease progression as well as reaction to different therapies [8] [10], the challenge of translating the simulations to valid decision support tools is tricky. Particularly, there is a gap in translation between the digital innovation of a DT and its daily use in healthcare [7], which represents the necessity of dynamic validation of the model and a joint process of creating the DT technology with clinicians. This perspective is reflected in a different study [21], which suggests various important predictive features that digitally-enabled healthcare providers must demonstrate in the context of the realization of accurate predictive fidelity, which is admittedly a major challenge when operating in complex biological systems.

5.3 Ethical, privacy, and governance concerns

Ethics stand out as one of the most complex issues in the implementation of DT. In the case of human DT, which depends on the continuous collection of data and predictive analytics, the question of informed consent, data ownership, and discrimination arises [13] [14]. According to [13], health-related segmentation may cause issues of discriminatory profiling, while [14] points out that biases may be included in AI-related predictions. The complexities of ethics in the use of DT on a population scale for public health purposes are discussed [5]. Cybersecurity is also a major issue in the implementation of DT. Studies point out the importance of data security and protection, particularly in the context of the integration of hospital-level digital infrastructure [12], [22]. The governance of DT, therefore, needs clear and transparent regulatory frameworks, accountability mechanisms, and policies for equal access to avoid technological gaps.

5.4 Economic and management barriers

Although DT offers cost-effectiveness in the long run, the initial setup of DT is highly capital-intensive in terms of computational resources, human resources, and data management systems [24] [11]. Healthcare organizations may encounter budget problems when implementing AI-based DT systems into the existing hospital setup. DT-based CPS can improve hospital management, but implementing these systems is a challenge [24]. Additionally, there is a lack of clarity on the cost-effectiveness of DT-based decision-making. If economic evaluation methods are not developed to establish cost-effectiveness, hospital managers may be reluctant to implement these systems.

5.5 Translational and adoption gaps

While several reviews point to the exciting clinical uses of DT [20] [10], the majority of DT systems are still in the prototype or experimental phase. The lack of harmonized validation criteria also holds back the translation into evidence-based practice.

Research gaps and implications are represented in Figure 2.

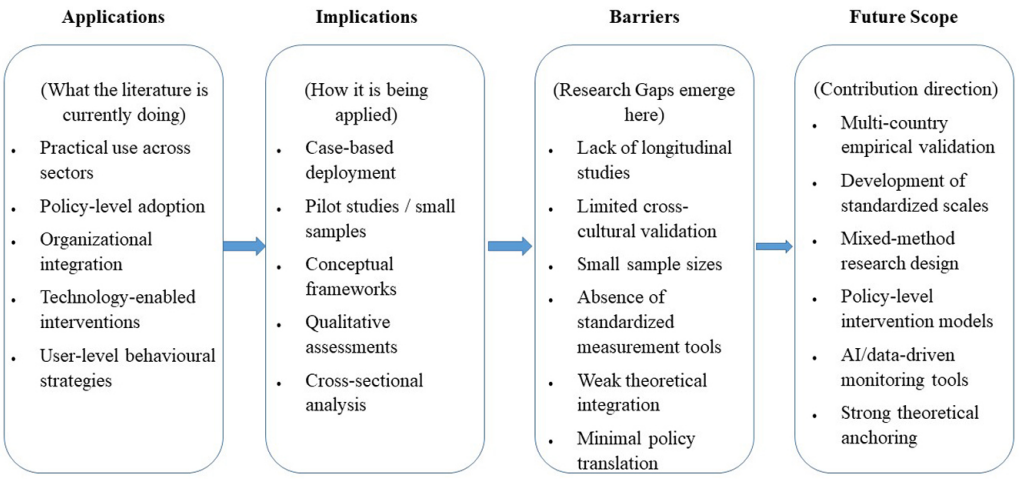

Fig. 2. Research gaps and future scope

Source: Constructed by author.

A wide range of literature appears to show that many different areas of potential research implementation are missing. Some examples are: Longitudinal validation has no published studies, very limited cultural generalization of research, small sample sizes, lack of standardized outcomes, poor theoretical integration, and minimal application to policies. All these factors hinder large-scale clinical implementation of DT technologies within healthcare. Multi-country empirical validation, development of standardized performance measurement frameworks, developing and using mixed methods, greater connectivity between AI-based monitoring and theoretical frameworks, aligning regulatory policies at the policy level, and better anchoring to existing theories are all things that can address these deficiencies. The building blocks provided by each of these directions will help to establish maturity, scalability, and translational potential for all DT applications within precision healthcare in the future.

5.6 Discussion

Based on this systematic literature review, it is clear that the concept of DT is quickly moving beyond just academic theory to being integrated into the multiple-dimensional ecosystem of healthcare today. The reviewed literature indicates the importance of DT to the domains of precision medicine, CPS, and healthcare administration, as well as all three areas converging. The predominant use of DT remains within the area of personalized medicine, with the creation of patient-specific modeling providing predictive diagnostics in addition to optimizing therapy [8], [14], [19]. However, another emerging area of use for DT is within the hospital environment as an institutional approach, which will provide significant advancements in workflow management and system-level optimization [11], [12]. Recent studies point out that digital twins aren't just virtual copies. They're dynamic computer models that constantly bring in biological, clinical, and behavioral information to help make decisions [25]. In pediatrics, digital twins and synthetic patient data have been suggested as ways to improve in silico trials, which might help tackle ethical and practical issues when working with vulnerable groups [26]. Wearable-integrated digital twins let an individual keep track of their body in real time and adjust health plans to fit them personally, as pointed out in a study [27]. At the same time, cyber-physical system setups offer flexible ways to link the physical and digital worlds smoothly [28]. Cardiovascular forensics and disease modeling with digital twins demonstrate that they can be very handy in diagnosis and prediction [29]. The application of digital twins in clinical practice raises legitimate regulatory and ethical issues, in particular, software as a medical device (SaMD), transparency, and accountability [30]. The reliability and validation of systems have emerged as central concerns in engineering, and activities such as architecture-based trust analysis have been proposed to assist developers in ensuring that systems are safe and reliable [31]. Considering it through the lens of technology, integrating medical device innovations and the concept of a digital twin is a legitimate opportunity to transform the sector [29]. Nevertheless, it is mentioned that there are still certain issues in the form of gaps in the method, concerns about interoperability, and no reliable tests in real-life conditions [32], [33]. One of the greatest challenges on its way to clinical implementation is the maintenance of solid methods in the modeling and management of data [34]. In 2023, another step was made, and currently, hybrid AI-simulation frameworks are beginning to emerge, which could enhance personalization and

create more accurate predictions [35]. Collectively, these advancements enable digital twins to be an important component of precision medicine and AI medical systems [36]. Pilot projects are currently in process in the year 2025, which will concentrate on how to manage chronic diseases and experiment with how effective such methods are in real-life scenarios [37]. Digital twin ecosystems are increasingly associated with economic scalability, industrial control, and decision-making systems that rely on artificial intelligence. Industrial IoT–AR-integrated digital twin prototypes demonstrate measurable potential in reducing maintenance costs and improving operational efficiency in manufacturing environments [38]. The scalable IoT-based digital twin platforms enable better accessibility while optimizing resources in both remote and embedded systems [39]. The projected growth of AI in healthcare markets demonstrates the need for organizations to implement responsible digital twin technologies through essential managerial, economic, and governance requirements that need to be followed [40].

6 CONCLUSION

Digital twins is an innovative solution in the sphere of biomedical engineering that offers patient-specific and real-time simulation to enable accurate diagnostics, design personalized treatment plans, and optimize healthcare organizations. The possible applications are limitless, and they include personalized medicine, modeling of diseases, smart hospitals, and training of physicians in medical schools. Such possible applications demonstrate the expansion nature of DT systems as we move forward to advance them. However, many of the same factors that have dragged other more advanced technologies behind have taken a toll on their striving to be deployed at scale: issues of data interoperability, model testing, ethical management, cybersecurity, cost-effectiveness, and how to integrate them into the traditional health systems (translational integration) effectively. To address such hurdles, a common model validation procedure, suitable regulatory frameworks, multi-disciplinary teamwork, and financially feasible business frameworks will be required. With a commitment to responsible production and the inclusion of the diverse user community, DT will likely become the foundation for the next generation of precision-based health delivery systems.

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