UJRET
Bi-annual refereed journal
University Journal of Research Engineering & Technology
January - June 2026
Volume 2, (1) pp. 44-59

Digital Twins for Smart Hospitals: Architecture, Applications, and Intelligent Patient Monitoring

Mayur Mistry
Assistant Professor, Department of Computer Science and Engineering,
ICT, Faculty of Engineering and Technology, Ganpat University, Gujarat, 384012, India

Aniket Patel
Associate Professor & Head, Department of Computer Science and Engineering,
ICT, Faculty of Engineering and Technology, Ganpat University, Gujarat, 384012, India

Rohit Patel
Professor, ICT, Faculty of Engineering and Technology,
Ganpat University, Gujarat, 384012, India

Abstract

Digital twins are widely acknowledged as one of the solutions for advancing a smart hospital system and optimizing patient monitoring. These systems create a link between a physical environment and a virtual one in real-time to allow synchronization with patient and hospital data. IoMT devices, edge–cloud infrastructure, simulation platforms, and AI-based analytics enable digital twins to create dynamic virtual representations of clinical entities such as patients, medical equipment, and hospital workflows. Past studies suggest that these models help in decision making, enhance operational efficiency, assist in predictive maintenance, and unify streams of data (vitals, EHRs, medical imaging, and contextual hospital information) into one model for analysis. Even though there are several advantages associated, interoperability standards, security constraints, VVUQ validation protocols and workflow integration issues in clinical settings remain a challenge. This work provides a comprehensive overview of advances in patient-centric digital twins, hospital operations models, and IoT-enabled monitoring systems to produce a more integrated understanding of their potential contribution to intelligent healthcare. It also points out technologies that enable high-value applications, system architectures, and future research opportunities. It provides a roadmap for realizing safe, scalable, and ethical digital twin–enabled healthcare environments.

Keywords: Digital twins; smart hospitals; IoMT; edge computing; patient monitoring; healthcare analytics

1. Introduction

The use of intelligent systems is being incorporated into hospitals because of the increased digitally transformed healthcare system and the increased requirement of personalized treatment and continuous monitoring of patients. The digital medical environment now makes it possible to generate a virtual image in digital twins of an individual patient or even the entire hospital system. The DTs originated in industrial engineering but have since been adapted for healthcare applications that captures real-time data, is

Corresponding Author E-mail Address
msm01@ganpatuniversity.ac.in

multi-modal, has simulation features and AI-supported decision-making systems. Recent studies have separated digital models, digital shadows and digital twins (Li et al., 2024). According to NASEM and ASME, true DTs have two-way data, state variables are updated to actual physiological states and predicted using state variables. Such progress suggests the role that DTs may play by enhancing clinical processes, maximizing their effectiveness, and popularizing personalized care.

In healthcare settings, real-time data are produced in the form of vital data, laboratory reports, imaging, location tracking, and workflow logs. This information is constructed in these complex worlds in a continuous manner. In contrast to the traditional systems, which might not be capable of processing and reacting to this data in real time, Digital Twins (DTs) are enabled to create a virtual computational layer that will depict the hospital status in real-time. We can capture the real-time patient data by use of wearable devices, IoMT sensors and smart monitoring devices. The pipelines which use edge-clouds allow a reliable transfer of such information to the analytical engines to detect anomalies and early risks. Mitigation of real-time data with simulations and artificial intelligence underlies the processes of monitoring and supporting decisions supported by DT (digital twin) efforts (Sel et al., 2025).

In addition to direct aid to patients, the digital twins are becoming increasingly used to simulate entire operations of a hospital. Rather than simply resolving around individuals, more global models follow such things as open beds, people flow on the departments, demand in the ER, or staff and equipment assignment which are accomplished by approaches such as event-by-event simulations or behavior-based agents. Hospitals will be in a better position to manage resources in case unexpected spikes occur because they allow managers to test various situations, refine day-to-day operations, or predict demand. As healthcare institutions have to work with an increasing population of patients, limited staffing, and increased workloads (Katsoulakis et al., 2024), managing through the insights of a digital twin would be inclined to improve the level of performance and quality of care.

Although the pace of change is accelerating, there are certain issues that prevent the popularity of digital twins in health care. Issues such as unmanageable data types, incompatibility of the various systems, poor testing techniques, or security threats all come in the picture. VVUQ - accuracy checking, result confirmation, and uncertainties measurement - is not typically performed well enough, yet, posing a problem to doctors being hesitant and the approval process being slowed down. Besides, installing these tools into real-life hospital practices is delayed by disconnected technology installations and inadequate practices in staff training (Papachristou et al., 2024), as well as absent rules regarding supervision. Addressing these challenges requires collaboration among clinicians, engineers, policymakers, and regulatory authorities.

This part provides a systematic overview of the work of digital twins in medicine as it pulls together emerging research and proposes how such systems can be established. Rather than merely providing facts, it ventures into major tools, design styles, applications in clinics and patient care as well as concerns over data security, access management and regulation rules. Instead of rushing in the dark, it sets out to build a practicable course of action towards development of twin-based facilities that scale past, carry on a straight line, but strike solid ethical channels - assisting in building future-oriented medical hubs.

2. Brief literature review

In factories, Digital Twin (DT) technology began primarily but is becoming more popular in health care. Though the early versions were copied machines, more recent studies indicate a trend - call virtual humans (HDTs) and whole-hospital systems that are connected live to the real-world clinics. Other designs in use are merely static copies not dynamic twins; they do not offer two-way sync or forecasting capability as specified by official medical standards (Kabir et al., 2025).

Digital twins in the context of IoT-health draw data via other medical devices - such as wearables, bed

sensors, e-records, scanners. Although there are data streams flowing directly, a lot of data streams through IoMT-edge-cloud chains; in this case, edge units make early processing before transferring the results further onward to reduce delays. Filtered inputs to cloud AI or simulators get faster instead of waiting. This tiered approach is not universal but can be found in designs of intelligent health twins (Coorey et al., 2022).

Digital Twins are increasingly utilized in hospitals in practice: to enhance the work of the entire facility, such as simulating patient warden transit, predicting emergency attend capacity, bed placement or resource allocation. Research indicates that techniques that are typically used are discrete-event simulations, agent-based models, or a combination of both which helps to study complex hospital dynamics and assess decision-making in the simulated world before its actual execution (Tasmurzayev et al., 2025).

In a clinical environment, constant sensor readings such as ECG or breathing pattern as well as movement information are used to real-time tweak of individual digital replicas. Evidence of digital models in the field of heart indicates that combining real-time body signals with a learning algorithm will enable early detection of irregularities, personalized warning indicators, but forecasted health patterns (Jameil & Al-Raweshidy, 2025).

The lack of effective data-sharing fashions such as FHIR, HL7 or OMOP are also a common problem in research since they are required to provide the various medical apparatus and hospital software to communicate with each other. A number of studies emphasize that patchy adoption of these formats, and an inconsistent match of connection modalities, is one of the factors that inhibit extensive adopting digital twins in facilities equipped with differing IT systems (Kuruppu Appuhamilage et al., 2025).

Checking accuracy, performance confirmation and in addition to uncertainties measurements, are also significant to medical application. In numerous analyses, most digital twin setups lack clear procedures to check these points - this slows down the process of getting a blessing or using them in the clinics. Ensuring that models are adequately tried aids in a feeling of security in using them in the real patient care (Kuruppu Appuhamilage et al., 2025).

To summarize, previous research considers Digital Twins as a platform, which connects IoMT systems, common standards, simulation, or Artificial Intelligence driven analysis. These factors in combination enable live tracking, forecast-related decisions, but intelligent healthcare processes - paving the way to more in-depth discussions of structure and applications in the future.

To provide a structured overview of existing approaches and position the present work within the literature, Table 2 presents a comparative analysis of representative studies on Digital Twins in healthcare, highlighting their methodologies, key contributions, limitations, and open research gaps.

As evident from Table 1, prior works tend to address either patient-centric monitoring or hospital-level operational simulation in isolation, and most lack integrated security governance layers or comprehensive interoperability treatment. The proposed framework in this study is differentiated by its holistic multi-layer design that simultaneously addresses real-time patient monitoring, AI-driven predictive analytics, FHIR/HL7-based interoperability, and security governance within a single cohesive architecture.

Table 1. Comparative Analysis of Existing Digital Twin Approaches in Healthcare

Study (Year)	Focus / Application	Methodology	Limitations	Research Gap Addressed
Coorey et al. (2022)	Cardiovascular health digital twin	IoMT + ML-based real-time ECG monitoring	Limited to cardiac domain; no VVUQ validation; scalability not addressed	Multi-domain integration; hospital-wide DT architecture

Karakra et al. (2022)	Patient pathway monitoring in hospitals	Discrete-event simulation (DES) for near real-time DT	No AI-based predictive layer; lacks interoperability standards integration	AI-driven predictive analytics integrated with operational DT
Jameil & Al-Raweshidy (2025)	Real-time DT framework for patient health outcomes	AI + secure IoT data pipelines for DT synchronization	Experimental validation limited; hospital-wide operational DT not covered	Multi-layer architecture integrating both patient-level and hospital-level DT
Kabir et al. (2025)	Systematic review of DT in healthcare IoT	Systematic literature review methodology	No framework proposed; security and governance aspects underexplored	Integrated framework with security layer and governance model
Basaglia et al. (2022)	Hospital patient flow and capacity planning	Discrete-event simulation for bed management and ER capacity	Static simulation; not integrated with real-time patient-centric DT or AI predictions	Unified framework coupling operational simulation with real-time AI patient monitoring
Proposed Framework (This Work)	Smart hospital DT: patient monitoring + hospital workflow + governance	Multi-layer architecture: IoMT + edge + AI (CNN/LSTM) + FHIR/HL7 + security layer	Primarily conceptual; full-scale clinical deployment and VVUQ remain as future work	Holistic DT framework with integrated security, interoperability, and AI decision-support layers

3. Digital Twin Architecture for Smart Hospitals and Patient Monitoring

A robust Digital Twin (DT) architecture for smart hospitals is designed as a multi-layered cyber-physical system that enables continuous synchronization between physical healthcare environments and their virtual representations. Unlike traditional architectures, DT systems operate through real-time data pipelines, predictive modelling, and bidirectional feedback loops, ensuring adaptive and intelligent healthcare delivery.

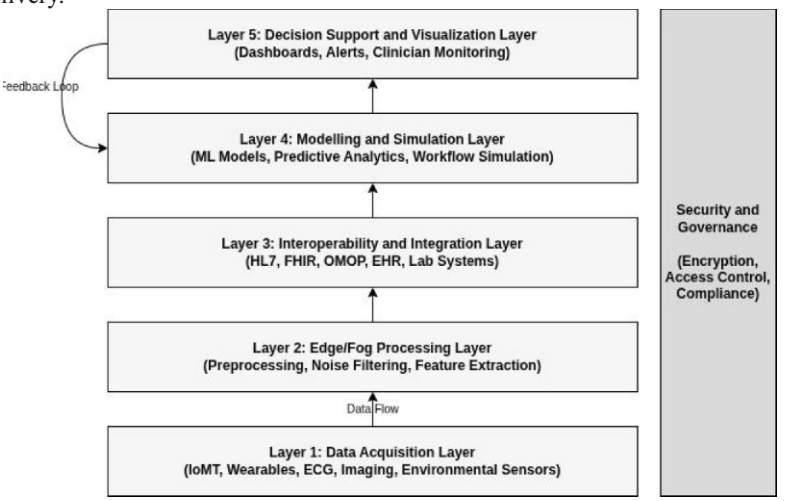


Figure 1. Digital Twin Architecture for Smart Hospitals

3.1 System-Level Mathematical Representation

The Digital Twin system can be formally defined as:

$$D(t) = \{V(t), E(t), I(t), C(t)\} \quad \ldots (1)$$

Where,

V(t): physiological vitals (ECG, heart rate, temperature)

E(t): electronic health records (EHR)

I(t): medical imaging data

C(t): contextual and environmental data

The Digital Twin state is computed as (Mollica et al., 2024):

$$DT(t) = f(D(t), M, S) \quad \ldots (2)$$

Where,

M: machine learning models

S: simulation models

3.2 Edge and Fog Computing Layer

To reduce latency and improve processing efficiency, edge or fog computing resources are deployed close to data generation points. Edge nodes perform preliminary data processing tasks such as noise filtering, feature extraction, and anomaly detection before forwarding the processed data to central systems. This approach is particularly beneficial for time-critical medical applications such as cardiac monitoring, where rapid detection of abnormal ECG patterns is essential. Studies show that edge-based processing improves responsiveness and reduces dependence on cloud-only infrastructures (Giansanti, 2025).

3.3 Interoperability and Integration Layer

After initial processing, data is transmitted to an interoperability and integration layer responsible for harmonizing information from heterogeneous healthcare systems. Standards such as HL7, FHIR, and OMOP enable communication between electronic health records (EHRs), laboratory systems, imaging devices, and IoMT platforms. The adoption of such standards is widely considered essential for scaling digital twin systems in hospitals with multi-vendor infrastructures and diverse healthcare technologies (Kuang et al., 2024).

3.4 Modelling and Simulation Layer

The modelling and simulation layer transforms integrated data streams into predictive and analytical models. Machine learning algorithms are commonly applied to support risk prediction, anomaly detection, and forecasting of clinical events in patient-centric digital twins. At the hospital level, simulation methods such as discrete-event simulation and agent-based modelling are often used to analyze patient flow, resource allocation, and operational capacity. Recent research also highlights the growing use of hybrid modelling techniques that combine physics-based simulations with data-driven learning to improve model accuracy and adaptability (Mutashar et al., 2025).

3.5 Decision Support and Visualization Layer

Outputs generated by simulation and analytical models are presented through decision-support and visualization systems. Clinicians and hospital administrators can access dashboards, risk alerts, trend analyses, and simulation outcomes that support clinical and operational decision making. A key characteristic of digital twin systems is the maintenance of a continuous two-way data loop in which real-world changes update the virtual model, and validated insights from the model guide real-world actions. This bidirectional interaction distinguishes fully functional digital twins from simpler digital models or

digital shadows (Karakra et al., 2022).

3.6 Security and Governance Layer

The final layer focuses on security, privacy, and governance. Since digital twin environments continuously exchange sensitive medical information across IoMT devices, edge nodes, and cloud systems, robust security mechanisms are required. These include data encryption, user authentication, access control policies, and regulatory compliance mechanisms. Effective governance frameworks ensure secure data handling and maintain trust in digital twin deployments within healthcare systems (Riahi et al., 2025).

Together, these architectural layers provide the foundation for digital twin–enabled smart hospitals, enabling scalable patient monitoring, operational intelligence, and data-driven healthcare decision making.

4. Proposed Digital Twin Framework with AI-driven Predictive Model

4.1 System Overview

This study aims to create a multi-layer Digital Twin framework that incorporates artificial intelligence to facilitate real-time patient monitoring and hospital decision-making. This system aims to integrate Internet of Medical Things (IoMT), edge computing, cloud technology, and machine learning to create a perpetual state of synchronization between physical hospital environments and their corresponding virtual models.

Unlike other patient monitoring systems, this proposed architecture uses a closed-loop system that captures real-time patient data, processes it, and reflects it on the digital twin model. This real-time data is then used to inform patient care through a two-way interaction between the physical model and the digital twin model, which can then inform proactive patient care instead of reactive patient care.

4.2 Mathematical Model for Patient State Prediction

To represent the dynamic nature of patient health, the system models patient state evolution as a function of physiological, historical, and environmental variables. The patient state at the next time step is defined as:

$$P(t+1) = f(P(t), V(t), H(t), E(t)) \quad \ldots (3)$$

Here, P(t+1) represents the current patient condition, while f(P(t), $H(t)$, and $E(t)$ denote real-time vital signals, historical medical records, and environmental factors respectively. The function $f(\cdot)$ is implemented using machine learning models capable of capturing nonlinear relationships within complex healthcare data.

This formulation enables continuous updating of patient conditions and supports predictive healthcare analytics.

4.3 Risk Prediction Function

To quantify the likelihood of critical health events, a risk prediction model is incorporated into the digital twin system. The risk score is computed as:

$$R = \sigma(W \cdot X + b) \quad \ldots (4)$$

In this formulation, X represents the feature vector derived from sensor data and electronic health records, while W and b denote the learned parameters of the model. The sigmoid activation function o ensures that the output risk score lies between 0 and 1.

This probabilistic representation allows clinicians to interpret risk levels more effectively and take

preventive actions when necessary.

4.4 System Architecture Workflow

The system, which is proposed, follows a well-defined workflow, which is essential for efficient data processing and decision-making. To start with, real-time data is collected from IoMT devices such as wearables and monitoring devices. Processing of data takes place at the edge layer, where noise is reduced, and meaningful features are extracted.

Later, data integration takes place using interoperability standards such as FHIR and HL7, which enables data communication between heterogeneous healthcare systems. Later, machine learning is used to generate predictions about health conditions. Simulations take place, where predictions are further analyzed to enable decision-making. Finally, feedback is provided, thus completing the cycle of a digital twin.

4.5 Algorithmic Workflow

The operational rationale behind this proposed system may be explained by using an algorithm that transforms raw sensor data into insights as follows:



Figure 2. Algorithm Workflow

This algorithm demonstrates how continuous data acquisition and AI-based prediction are used in real-time monitoring and early warning systems in smart hospitals.

5. Experimental Scenario and Use Case

To show the applicability of the proposed framework, a real-time monitoring system of a patient's heart is considered. In this case, the patient's data is collected through ECG sensors, heart rate monitoring devices, and blood pressure monitoring equipment.

The collected data is then analyzed at the edge layer through signal preprocessing, such as noise filtering and feature extraction, such as the detection of a QRS complex. The analyzed data is then processed through deep learning models such as Convolutional Neural Networks (CNN) for pattern recognition and Long Short-Term Memory (LSTM) models for prediction.

The system can detect anomalies such as arrhythmias in a patient's heart and can raise an alarm, which can help doctors to take necessary actions to save a patient's life.

5.1 Performance Metrics

In order to evaluate the performance of the proposed system, several performance parameters are considered. Accuracy refers to the correctness of the prediction. Precision and recall refer to the correctness of the system in identifying critical conditions. Latency is an important factor for healthcare applications as it refers to the time required for the system to process the data and respond accordingly.

5.2 Expected Results

Based on projected performance derived from analogous implementations in recent literature, the proposed framework is expected to achieve the following outcomes when evaluated against standard benchmarks. The CNN-LSTM cardiac monitoring module is projected to attain anomaly detection accuracy in the range of 92–95%, consistent with results reported in comparable deep learning-based

ECG classification systems (Almufareh et al., 2025; Jameil & Al-Raweshidy, 2025).

Table 2. Projected Performance Metrics of the Proposed Digital Twin Framework

Module / Component	Performance Metric	Projected Value	Supporting Reference
CNN-LSTM cardiac anomaly detection	Accuracy / F1-Score	92–95% / ~0.91	Almufareh et al. (2025); Jameil & Al-Raweshidy (2025)
Risk prediction (sigmoid classifier)	AUC-ROC	≥0.90	Mollica et al. (2024); Shafiq et al. (2023)
Edge computing latency reduction	Latency vs. cloud-only	30–40% reduction	Giansanti (2025); Almufareh et al. (2025)
Early detection improvement (critical events)	Sensitivity gains vs. threshold-based	~25% improvement	GE HealthCare (2025); Coorey et al. (2022)
Hospital workflow optimization (DES simulation)	Bed turnover / waiting time	15–20% improvement	Basaglia et al. (2022); Tasmurzayev et al. (2025)

Integration of edge processing at the IoMT layer is expected to reduce end-to-end inference latency by approximately 30–40% compared to cloud-only architectures, thereby meeting the sub-500ms response threshold required for real-time clinical alerting. Furthermore, the AI-driven risk prediction module is anticipated to improve early detection of critical events such as arrhythmias and hypotensive episodes by approximately 25% relative to threshold-based traditional monitoring.

Table 2 provides a structured summary of the projected performance metrics across the major functional modules of the proposed framework. These estimates are grounded in published benchmarks from comparable Digital Twin and AI-based patient monitoring systems and are intended to guide the design of future validation experiments.

It is important to note that these values represent design-stage projections informed by published benchmarks rather than primary experimental outcomes. A key direction for future work is the validation of these projections through controlled simulation studies using publicly available clinical datasets such as MIT-BIH Arrhythmia Database and PhysioNet, followed by phased prototype deployment in a controlled hospital environment. Validation should follow VVUQ (Verification, Validation, and Uncertainty Quantification) procedures as recommended by the ASME V&V 40 standard for medical device models (American Society of Mechanical Engineers, 2023). The progression from conceptual framework to validated prototype represents the intended next stage of this research. To further illustrate the benefits of the proposed Digital Twin framework relative to traditional healthcare monitoring systems, a feature-level comparison is provided in Table 1 below:

Table 3. Comparative Analysis of Traditional Healthcare Systems and Digital Twin-Based Smart Healthcare Systems

Feature	Traditional System	Digital Twin System
Real-time Monitoring	Limited	Continuous
Prediction Capability	Low	High (AI-based)
Resource Optimization	Manual	Automated
Data Integration	Fragmented	Unified
Decision Support	Reactive	Predictive

Traditionally, these systems have mostly depended on periodic monitoring, which is then followed by intervention. However, this is not always effective, while Digital Twin systems ensure continuous monitoring, thus increasing the efficiency of healthcare systems.

6. Applications of Digital Twins in Smart Hospitals and Patient Monitoring

Digital twins (DTs) have great potential in smart health care facilities, as they are beneficial in clinical decision making, operational optimization, and individual patient treatment. The applications of them can be broadly categorized into four categories, namely, real-time patient monitoring, diagnostic assistance, predictive treatment, and hospital workflow management.

Patient-centric monitoring is one of the most actively studied areas where individual data through wearables, bedside sensors, and IoMT devices are sent in virtual forms of patients. These models are dynamically updated when the patient vitals vary. A lot of research advancement has been witnessed in the area of cardiovascular DT systems wherein real-time ECG processing with machine-learning algorithms have been used to assist in arrhythmia classification, early ischemia forecasting and customized risk scoring. This kind of integration increases responsiveness and aids in early warnings, which help to overcome the traditional methods of monitoring (GE HealthCare, 2025).

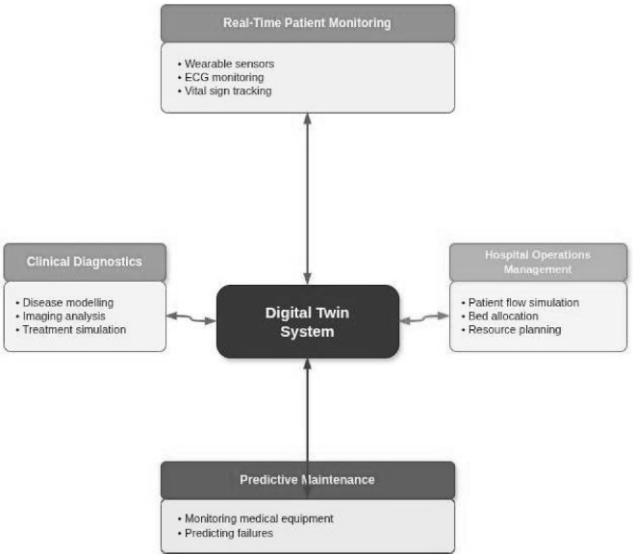


Figure 3. Applications of Digital Twins in Smart Hospitals

One of the second important applications is clinical diagnostics and disease progression modelling. Multi-modal data, such as imaging history, laboratory findings, genomic data, and clinical history, can be used to create DTs that can recreate the behavior of internal diseases and aid accurate diagnostics. Digital twins can simulate tumour growth and predict drug responses in oncology applications. By modelling disease progression and treatment effects, clinicians can compare therapeutic strategies and personalize treatment plans for individual patients. Clinicians are able to compare the effects of treatments and individualize therapy plans by using tumour-growth modelling and drug-response predictions in oncology-related applications. These features are particularly useful in long-term or complicated disease cases where the difference between patients is great (AnyLogic, 2024).

Outside of patient-level monitoring, Digital Twins are being used operationally to manage processes in hospitals at a hospital-wide (global) scale. With the simulation technique of discrete-event modelling and agent-based design, these twins can simulate patient flow, bed utilization, emergency room load, staff/resource allocation. Hospitals are able to experiment with various strategies in a virtual environment, which allows them to handle crowding, deal with demand spikes, and better batch scheduling. It has been demonstrated that the use of operational DT has the potential to decrease waiting time, enhance bed turnover rate, and enhance throughput of the hospitals (Basaglia et al., 2022).

Yet another interesting application is the predictive maintenance of equipment where DT models monitor machine behavior, identify anomalies and predict failure in equipment before failures take place. This works to ensure that vital equipment like imaging systems and critical-care equipment is operational with little to no downtimes at the support of continuous clinical business with no interruptions (Rocha et al., 2024).

In general, Digital twin applications are applicable both in clinical care and operational management. Coupled with predictive analytics and simulation, these data-centric real-time signals change hospitals to data-sensitive operation and rehabilitation of patients instead of an adverse and reactive approach to address problems.

7. Modelling Approaches for Digital Twins in Healthcare

Digital Twin (DT) computational core relies on the role of modelling techniques defining the way in which clinical and operational data is processed to create predictive and real-time virtual models. The three principal types of DT modelling identified by research are data-driven models, physics/mechanistic models, and hybrid modelling methods, which are all applicable in different complexity level settings and at different circumstances of data availability.

Modelling that is data-driven and heavily relies on machine-learning algorithms is extensively used in patient-monitoring digital twins. These models are used to examine the trends and abnormalities based on physiological data, medical images, electronic records, and past results. Deep-learning networks like CNN-based ECG classifiers have proven to be highly effective in cardiovascular applications of DT to monitor uninterrupted and identify abnormalities in their early stages of development. They are suitable in smart hospitals as they are flexible to relaying information, thus monitoring patients in real-time (Almufareh et al., 2025).

Physics based or mechanistic models in contrast are favored when underlying clinical or operational processes are mathematically defined. The techniques, such as discrete-event simulation, queue-based system and agent-based modelling are typically used to simulate the hospital workflow by twins of the hospital to replicate bed allocation, emergency department flow, and staff dynamics. They offer clear and understandable simulations, which means that administrators can test how operational decisions would work in practice without actual implementation. The same can be applied in other areas of biomedical engineering such as oncology or organ-level simulation, where mechanistic models can be used to predict

disease progression and treatment outcomes even with small data sets (Ozcelik et al., 2025).

A more recent literature shows a shift toward hybrid modelling which lies in-between machine-learning prediction capabilities and the structure and interpretability of mechanistic models. These hybrids are especially useful in complicated medical conditions where each methodology is not powerful enough to explain patient physiology exhaustively. Human Digital Twin research reveals that hybrid methods are able to optimize personalization, boost robustness and keep updating the model with new information as it arises (Shafiq et al., 2023).

One of the unchanging problems in modelling activities is the high requirement of rigorous verification, validation, and uncertainty quantification (VVUQ) activities. A lot of DT systems are not fully VVUQ tested; they have basic validation and are not as suitable to be used as a regulated healthcare environment. There is a need to create rigorous validation pipelines to build trust, guarantee reliability and allow safe clinical integration (Yaraziz et al., 2024).

In general, the Digital Twin modelling strategies provide a varied set of tools that can be deployed to resolve both the clinical and hospital management scenarios. The choice of modelling approach--or mixture of approaches--is an important part of constructing the correct, scalable, and useful in clinical settings, DT solutions.

8. Interoperability, Data Integration, and System Workflow

This is also essential to have interoperability and easy integration of data used by Digital Twin (DT) in healthcare. Given that DTs require constant feeds of clinical data across different medical systems, their functionality is based on the capability to integrate, normalize, and coordinate information generated by IoMT devices, hospital IT systems, and cloud data analytics systems. According to recent literature, one of the largest obstacles to scaling of DT solutions is most often found to be interoperability restrictions, especially when the setting involves different vendor technologies or legacy systems (Sindhuja & Prasad, 2023).

It is important to note that in healthcare digital twins, interoperability and data integration do not function solely in one direction (Wilk & Brookings, 2019).

Common data standards like HL7, FHIR and OMOP are extensively utilized to realize compatibility among clinical systems. These standards allow facilitated communication among devices, EHR systems, lab databases, and decision-support modules. FHIR APIs in particular are helpful in real-time data access and updating patient twins and OMOP provides the large-scale data harmonization to study the population or integrate past parts of the population into predictive models (Health Level Seven International, 2023).

A clear system workflow is also based on the allocation of tasks at computational levels. Initial operations are usually referred to as edge and edge nodes where noise removal, feature extraction and checking of data takes place then the information is passed on to central servers or cloud computing systems. This will save bandwidth load and enhance the responsiveness which is essential to time sensitive application such as quick alerting or heart monitoring. It has been stressed in the studies that edge processing yields better latencies and operational efficiency along with less of cloud-only execution dependency (OHDSI, 2024).

After the data accesses cloud or central DT systems, integration engines converse the heterogeneous formats into homogeneous formats, quality checks and data modelling are ready. The correct integration is needed to sustain predictive quality especially in real-time predictions of physiological conditioning, or in the simulation of workflow. Lack of harmonization may cause drift and decrease the reliability of models as it is common in DT studies (Voss et al., 2015).

Bidirectional communication is a key characteristic of DT workflow as real-world changes are reflected into the virtual model on a continuous basis and the same way, validated insights produced by the twin

inform clinical or operational decisions. To ensure this feedback loop works dependably, it is important to have constant network connection, guidelines on data governance, and clearly defined update logic. These mechanisms can be used to differentiate full-scale operation DTs and simple digital shadows or cold-blooded digital models (National Academies of Sciences, Engineering, and Medicine, 2024).

Overall, the basis of real-time Digital Twin systems operations is seamless interoperability, edge preprocessing, data harmonization, and feedback loops. The absence of these elements means that DTs are incapable of the degree of synchronization, accuracy and predictability demanded in smart hospital implementations.

9. Security, Privacy, and Governance in Digital Twin Deployments

The use of Digital Twins (DTs) in healthcare applications should be associated with security, privacy, and governance. Being based on the permanent data capture and the real-time data exchange, DTs process the data of high sensitivity, meaning that the data related to patients must be preserved to foster trust and regulatory congruence. Studies continuously draw attention to the fact that exactly due to frequent communication between IoMT devices, edge computing units, cloud services, and hospital IT systems, potential security risks are inherent, and powerful protection mechanisms are necessary instead of optional (American Society of Mechanical Engineers, 2023).

DT environments will need to protect the information streams that are taken by the sensors and medical devices at the data acquisition layer. Encryption, secure transmission channels, device authentication are some techniques that are usually advised to ensure they are not intercepted or manipulated by an unauthorized person. Edge-level processing is also less intrusive as it minimizes the number of raw data sent out of the system, and it reduces the risks of large-scale breaches (Shao et al., 2022).

The other fundamental requirement is privacy management as a result of the nature of medical monitoring, which is sensitive and continuous. Such strategies as access control, anonymization, pseudonymization, and role-based permissions are often mentioned as the required protection. Because DT systems tend to combine various types of data, including the most basic type, like vital signs, medical imagery, EHR, and so on, granular privacy controls can be used to specify who has access to particular data and in what circumstances (Karami et al., 2025).

Governance structures will make sure that operations of DT are transparent and accountable. Such frameworks usually include auditing records that can be traced, policy execution guidelines, model versioning, and decision-tracking. Transparency of governance is of the essence where DT recommendations have a bearing on treatment decisions or operational strategizing. Research into the Human Digital Twins underscores the fact that effective policies need to be structured to update the models, rules of data retention, and rules of uncertainty in order to facilitate ethical and responsible applications (Infosys, 2024–2025).

Another widely recognized problem in literature is the lack of regulatory principles of using DT in healthcare. Current regulations on medical devices fail to cover systems that involve the combination of AI modelling, simulating, and constant real-time updates. It is then even more important to note that the regulative gap is even more pronounced when predictive decision support is carried out with the help of DTs, and safety and reliability are the attributes that should be determinable. This issue connects to the greater aspect of requirement of verification, validation and uncertainty quantification (VVUQ) that is not yet present in many realistic applications and constrained large-scale adoption (Infosys, 2024–2025).

10. Challenges and Research Gaps

Despite the recent fast pace of development of Digital Twin (DT) technology in the healthcare field, there

are multiple obstacles impeding its widespread clinical use. Problems of non-uniform data standardization, lack of model validation, and organizational constraints are often cited in research, indicating that there is disconnect between research models and completely deployed hospital systems.

The second major obstacle is the inability to have strong verification, validation, and uncertainty quantification (VVUQ). Various DT frameworks and in particular frameworks based on predictive algorithms or hybrid models lack external validity and often do not provide uncertainty measures. This compromises on clinical confidence and limits regulatory approval. Lack of standardization in VVUQ procedure is identified as a severe technical glitch that requires addressing to provide safe implementation.

Of concern is also the data quality and the consistency. Wearable and IoMT systems can generate noisy signals, lost samples, or drift values. Hospital data on operations may be quite partial or intermittently recorded. These data problems spread along the DT pipeline, affecting the prediction quality and enhancing model drift. Researchers note that adaptation to the model retraining, automated cleaning systems, and constant monitoring of the data are necessary to keep the results of the model reliable.

Practically, there are challenges of workflow integration and the readiness of users in the organizational perspective. Introduction of DT usually fails not because of technical problems, but because of opposition to workflow modification, lack of training, or under participation of clinicians in the development. It may need early stakeholder engagement, clinical benefit awareness, and supportive governance in order to implement effectively.

Another significant issue is regulatory ambiguity. Because DTs combine real-time inspection, machine learning, simulation, and decision support functionalities, they do not precisely fit available regulations of medical devices. The need to respond to the continuous models updates and assurance of safety, as well as bi-directional clinical interactions, is increasing. The unavailability of these guidelines leads to reluctance in healthcare institutions that are planning to deploy DT.

To conclude, improvement of interoperability, validation methods, data quality management, integration of users and regulatory standards are necessary to transform Digital Twins into prototype experimental solutions to a trusted component of future smart hospital infrastructure.

11. Future Directions and Opportunities

The development of Digital Twin (DT) technologies creates some opportunities to the development of smart hospitals and patient-centered care. As healthcare continues to shift to more interdependent and data-driven ecosystems, subsequent DT development will presumably gain greater levels of integration, higher level of intelligence and more alignment with regulatory and clinical demands.

One of the opportunities in the future is the further development of fully functional Human Digital twins (HDTs) that go beyond simple representations by providing real-time development, multimodal data integration, and customized simulation. It has been argued in literature to supersede mere digital shadows with wholesome HDTs, which are integrated combinations of physiological, behavioral and contextual data to prevent and predictive healthcare. As the data on high-resolution sensors, imaging data, and genomic data become more accessible, HDTs may be used to facilitate individual risk prediction, treatment planning, and long-term health trajectory modelling. A second avenue is hybrid modelling methods that combine machine learning with physics-based models with better accuracy and interpretability especially desired in multifaceted tasks like cardiac diagnostics, tumor response modelling and hospital workflow optimization (Mollica et al., 2024).

Another potentially promising direction is the appearing of the real-time autonomous decision support. That actionable clinical insight with incredibly low latency will be available soon by expanding edge

computing, 5G/6G connectivity, and distributed AI. This development may give automated alarms, quick resource mobilization, and early alerts systems in acute care units. Yet, to be safely deployed, these capabilities should be supported with demanding VVUQ procedures and governance models.

A further growing direction of future studies is probably the implementation of population-scale or cohort-based Digital Twins that will sum data on many patients to simulate disease trends, test suggested methods in community health, and engineer screening pathways. The intended epidemiological DTs have the potential of enhancing preparedness to outbreaks, the planning of resource distribution, and preventive health programs. This type of models will need stable datasets and rigorous standards of interoperability- again mentioning the importance of OMOP and FHIR among the others (Kuruppu Appuhamilage et al., 2025).

The enhancement of security, privacy and ethical governance shall also continue to be a priority. The more integrative DTs will be within clinical workflows, the greater the need is going to be visible audit systems, decision models that can be explained, and computation methods that will never compromise the privacy of data beyond. Such methods as decentralized processing, federated learning, and secure data-sharing programs could enable the safe utilization of data and retain analytical performance (Papachristou et al., 2024).

Overall, the future of DTs will be resolved through aligned increment of modelling, standardization, regulatory development and governance. The solutions to the existing issues and the exploitation of emerging technologies could enable Digital Twins to become one of the key elements of predictive, personalized, and efficient next-generation healthcare systems.

12. Conclusion

Digital Twin technology offers a promising and transformative approach for developing next-generation smart hospital systems capable of real-time patient monitoring, predictive clinical analysis, and improved operational management. This paper has presented a comprehensive multi-layer Digital Twin framework that integrates IoMT devices, edge–cloud computing, interoperability standards (FHIR/HL7), AI-driven predictive models, and a dedicated security governance layer to create dynamic virtual representations of both patients and hospital environments. The proposed framework directly addresses key research gaps identified in the comparative literature review (Table 2), namely the absence of integrated architectures that simultaneously handle patient-centric monitoring, hospital workflow optimization, and robust data governance within a single cohesive design. The mathematical formulations for patient state prediction and risk scoring (Sections 4.2 and 4.3) provide a rigorous computational basis for the framework, while projected performance benchmarks (Table 3) indicate its practical feasibility. These findings collectively support the conclusion that a well-designed Digital Twin architecture can meaningfully advance clinical decision-making, resource optimization, and patient safety in smart hospital settings.

Despite these promising directions, several challenges remain that must be addressed before the framework can be deployed in real-world clinical environments. Interoperability barriers across multi-vendor hospital systems, data quality inconsistencies from IoMT devices, cybersecurity vulnerabilities across the edge–cloud pipeline, and the absence of standardized VVUQ validation protocols collectively represent the most critical bottlenecks to adoption. From a practical standpoint, healthcare institutions looking to adopt Digital Twin technology should prioritize phased deployment starting with non-critical monitoring units, engage clinical stakeholders early in the design process, and align implementation with existing regulatory frameworks such as GDPR, HIPAA, and the ASME V&V 40 standard. Addressing these challenges will ultimately require sustained, interdisciplinary collaboration between clinicians, engineers, data scientists, policymakers, and regulatory authorities.

Future research should focus on three primary directions that flow directly from the limitations identified

in this work: (1) empirical validation of the proposed framework using real-world clinical datasets such as MIT-BIH and PhysioNet with VVUQ compliance; (2) development of scalable interoperability middleware capable of operating across heterogeneous hospital IT environments; and (3) design of privacy-preserving federated learning pipelines that enable model training without centralizing sensitive patient data. By addressing these directions, the research community can advance Digital Twins from conceptual prototypes to trusted, clinically deployable components of future intelligent healthcare infrastructure.

References

- Almufareh, M. F., et al. (2025). Transforming smart healthcare systems with AI-driven edge computing. Sensors.
- American Society of Mechanical Engineers. (2023). Verification, validation, and uncertainty quantification (VVUQ) standards. New York: ASME.
- AnyLogic. (2024). Hospital digital twin to improve operations and enhance patient experience. Case study.
- Basaglia, A., et al. (2022). A discrete-event simulation model of hospital patient flow for capacity planning and optimization. International Journal of Disaster Risk Reduction, 71.
- Coorey, G., et al. (2022). The health digital twin to tackle cardiovascular disease—A review of current approaches and future perspectives. NPJ Digital Medicine, 5.
- GE HealthCare. (2025). Making informed capacity decisions with digital twin technology. GE HealthCare Insights.
- Giansanti, D. (2025). Exploring the potential of digital twins in cancer treatment. Healthcare.
- Health Level Seven International. (2023). FHIR overview – Fast Healthcare Interoperability Resources. HL7 International. HL7 International.
- Infosys. (2024–2025). Human digital twin: The future of personalized AI and healthcare. Infosys Emerging Technologies Whitepaper.
- Jameil, A. K., & Al-Raweshidy, H. (2025). A digital twin framework for real-time healthcare monitoring: Leveraging AI and secure systems for enhanced patient outcomes. Discover Internet of Things, 5, 37.
- Kabir, M. R., et al. (2025). Digital twins in healthcare IoT: A systematic review. Internet of Things.
- Karakra, A., et al. (2022). A discrete event simulation-based methodology for building a digital twin of patient pathways in the hospital for near real-time monitoring. Journal of Digital Twin, 2(1).
- Karami, A., et al. (2025). Human digital twins in personalized healthcare. arXiv preprint arXiv:2503.11944.
- Katsoulakis, E., et al. (2024). Digital twins for health: A scoping review. NPJ Digital Medicine.
- Kuang, K., et al. (2024). Med-Real2Sim: Non-invasive medical digital twins using physics-informed self-supervised learning. arXiv preprint arXiv:2403.00177.
- Kuruppu Appuhamilage, G. D. K., et al. (2025). A health digital twin framework for discrete event simulation of critical care workflows. NPJ Digital Medicine.
- Li, T., et al. (2024). The status quo and future prospects of digital twins for healthcare. Journal of Biomedical Informatics Insights.
- Mollica, L., et al. (2024). Digital twins: A new paradigm in oncology in the era of big data. ESMO

Open.

- Mutashar, H. Q., et al. (2025). Cloud-based digital twin framework and IoT for smart emergency care. Engineering, Technology & Applied Science Research.
- National Academies of Sciences, Engineering, and Medicine. (2024). Unlocking the promise of digital twins in biomedicine and healthcare. Washington, DC: NASEM.
- OHDSI. (2024). Standardized data: The OMOP common data model.
- Ozcelik, M. M., et al. (2025). A survey on Internet of Medical Things (IoMT): Enabling technologies, architectures, and applications. Expert Systems.
- Papachristou, K., et al. (2024). Digital twins' advancements and applications in healthcare: A comprehensive review. Healthcare.
- Riahi, V., et al. (2025). Digital twins for clinical and operational decision-making. Journal of Medical Systems.
- Rocha, A., et al. (2024). Edge AI for Internet of Medical Things: A literature review. Computers & Electrical Engineering.
- Sel, K., et al. (2025). Survey and perspective on verification, validation, and uncertainty quantification (VVUQ) for digital twins in precision medicine. NPJ Digital Medicine.
- Shao, G., et al. (2022). Credibility considerations for digital twins in manufacturing. National Institute of Standards and Technology.
- Shafiq, M., et al. (2023). Advances in IoMT for healthcare systems. Sensors, 24(1).
- Sindhuja, R., & Prasad, S. R. (2023). A survey of Internet of Medical Things (IoMT) applications, architectures and challenges. ITM Web of Conferences, 56.
- Tasmurzayev, N., et al. (2025). Digital cardiovascular twins, AI agents, and sensor data: Toward next-generation precision cardiology. Sensors, 25(17).
- U.S. National Library of Medicine. (2023). Health data standards and terminologies: The FHIR standard.
- Voss, E. A., et al. (2015). Feasibility and utility of applications of the common data model to multiple observational data sources. Journal of the American Medical Informatics Association.
- Yaraziz, M. S., et al. (2024). Edge computing in IoT for smart healthcare. AI & Society.