

Review Article

From Simulation to Implementation of the Impact of Digital Twins on Healthcare System

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ABSTRACT

Digital Twin (DT) technology has emerged as a new healthcare framework that enables medical professionals to create virtual models of patients, clinical settings, and entire health systems through real-time data processing. Digital twin technology began as an engineering and manufacturing tool that industrial organisations developed using Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and cloud-edge computing technologies. The review examines how healthcare digital twins have shifted from theoretical simulation tools to active, real-time systems that help doctors make treatment decisions while improving system efficiency. The research begins by identifying the fundamental elements of healthcare digital twins and their technological foundations. The research investigates four main application areas: patient-centric models for personalised care; predictive analytics and operational twins to optimise hospital resources and manage workflows; digital twins for device monitoring and predictive maintenance; and population-level twins for public health surveillance and epidemic response. The review examines key implementation obstacles, including data privacy problems, technical interoperability issues, ethical dilemmas, and the need for regulatory and standardisation systems. The review provides researchers, clinicians, and policymakers with essential resources to understand how digital twin technologies will change future healthcare systems.

1. INTRODUCTION

In recent years, digital twins have gained popularity across industries, but their application in healthcare is just beginning. A digital twin functions as a virtual duplicate of any physical object, including machines, systems, and living organisms, by establishing ongoing data communication with its physical counterpart to create simulations, make predictions, and improve operational performance over time [1,2]. The system functions as an active model because it represents a physical object through a data-centric system that evolves with new information emerging over time.

The aerospace, manufacturing, and energy sectors have created digital twins for predictive maintenance, design validation, and system optimisation, among other applications [3,4]. The successful application of these

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techniques in these domains enables researchers to pursue their application in healthcare, which presents greater challenges, higher variability, and increased risk than those domains.

Digital twins in healthcare enable organisations to connect simulation technology with their real-world operational needs [5]. Technological infrastructure development, including sensor connectivity, computing, and AI/ML systems, has reached a stage where organisations can move from using digital twins as educational tools to operational systems that provide decision support, optimisation, and personalised interventions [6,7]. The study raises critical questions about digital twin development and implementation processes in healthcare settings. The research evaluates digital twin performance across three key areas: outcomes, expenses, and system efficiency. The organisation faces multiple challenges, including technical hurdles, ethical challenges, regulatory requirements, and internal organisational barriers.

Accordingly, this paper addresses the following aims:

1. To explain the fundamental concepts and types of digital twins in a healthcare context.
2. To trace the enabling technologies and mechanisms that allow simulation models to evolve into real-time, operational digital twins.
3. To review prominent applications across clinical care, hospital operations, device management, and public health.
4. To analyse the key challenges and barriers to adoption.
5. To present case studies illustrating early implementations; and
6. To identify future directions and research priorities for scaling digital twins across healthcare systems.

The research paper shows that digital twins have evolved from initial academic simulations into operational systems that transform clinical decision-making, hospital operations, preventive care delivery, and system resilience management. Moving from simulation to real-world execution requires new technological developments, major changes in health system design and management, and personalisation to improve patient outcomes and operational efficiency.

2. The Concept of Digital Twins in Healthcare

2.1 Definition and Foundational Principles

How useful is the digital twin? Simply put, it's a paradigm that says a physical entity has a twin, some virtual entity that can be accessed, interrogated, and manipulated for making decisions about a physical system. Grieves and, later, NASA's systems engineering community offered a clearer definition: a digital twin comprises a physical product or process, a virtual representation, and, lastly, a two-way data exchange linking the two [8]. A digital twin does not only need a definition; it also requires research into a dynamic updating mechanism fed by data from its physical counterpart, enabling real-time predictive simulation to support decision-making [9]. The proposed definition's domain in health care extends to patients, organs, populations, or even entire hospitals. The system combines different types of data streams, including electronic health records, disease data, omics data, and real-time physiological signals generated by sensors and digital devices [3]. Physicians use virtual patient models that update continuously to track changes from actual body movements so that they can test different treatments digitally before clinical testing.

The system currently requires users to exchange data between two parties in real time. According to the National Academies definition, a virtual twin requires synaptic connections which enable physical entity changes to create continuous updates for the virtual twin system [9]. The virtual model serves as an experiential learning system which continuously adjusts to the present medical condition of patients and healthcare facilities. This setup requires users to connect wearable sensor devices, bedside monitor systems, laboratory information systems, and

environmental sensors to digital twin systems through IoT networks. The analytics layer, which combines mechanistic and AI models, enables incoming data streams to produce practical insights for creating personalised treatment guidelines, making operational modifications, and generating predictive alerts.

As shown in Figure 1, the real-time feedback loop ensures that implemented interventional measures modify the physical system's behaviour, and the twin incorporates these changes in near real time. This feedback makes the digital twin different from a monodirectional digital shadow or a digital model. A digital shadow records data from a physical system and cannot drive changes, whereas a digital twin enables two-way interactivity [9].

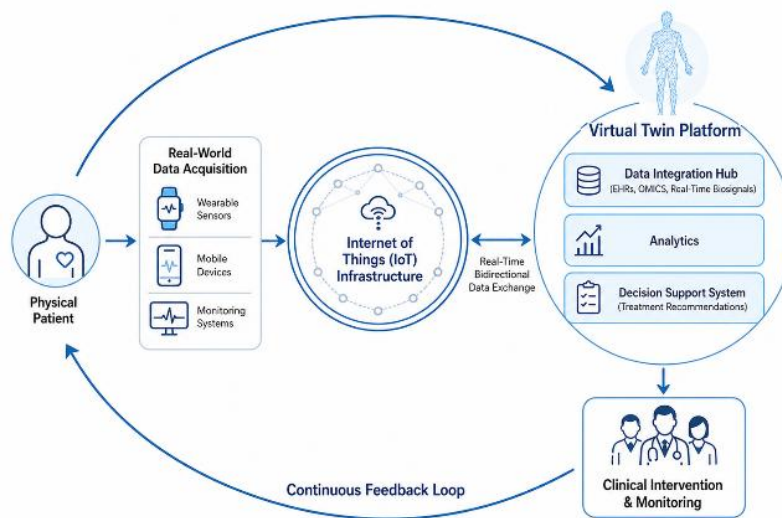


Figure 1: Conceptual architecture and data flows

The conceptual architecture of a healthcare digital twin consists of a physical system (patient, organ or hospital), a digital representation, and infrastructure for real-time data and control (Figure 1). Sensors and devices collect continuous streams of multi-scale data, such as heart rate, imaging, genomic variants, and resource utilisation, and send them to an analytics layer. This layer fuses mechanistic models with machine-learning algorithms to generate predictions, risk stratification and suggested interventions. An interface layer delivers the twin's outputs (e.g., dosing recommendations, alarm thresholds or staffing changes) to clinicians, administrators or automated actuators. Because the physical system responds to these interventions, the resulting new data feed back into the twin, closing a cyber-physical loop. This coupling supports three areas of medical practice: personalised medicine, adaptive hospital operations, and population-level planning.

2.2 Classification of Digital Twins in Healthcare

2.2.1 Individual Patient Level Digital Twins

Individual digital twins (Indi DTs) are high-resolution models of a single patient. The medical field defines Indi DTs as precise anatomical models that show how multiple organs function together and how their physical state evolves; researchers create them from multi-omics data, continuous patient monitoring, and long-term medical records [10]. The team uses network models to create a complete patient physiological profile, which they use to project treatment effects and disease progression, enabling doctors to customise patient care. A systematic review of patient digital twins emphasised that such twins should be viewable digital replicas containing multidimensional patient-specific information and used to inform decisions [8]. Organ-level variants of Indi-DTs include virtual models of specific organs (e.g., heart or pancreas) or disease processes; workflow-level twins simulate care pathways within departments (e.g., radiology units) and are used to optimise scheduling and

resource allocation. Crucially, patient digital twins move beyond static predictors by dynamically updating their state and recommending interventions based on ongoing data [8].

2.2.2 Population Level

Population digital twins (pop-DTs) operate at the cohort level rather than the individual level. They are built by integrating clinical records, public health datasets, and genomic information to model disease patterns within groups [8]. Pop-DTs continuously incorporate new data to refine a multidimensional “disease space” representing population heterogeneity; they thus support risk stratification, subphenotype identification, and evaluation of public health interventions. Because population models are less computationally demanding than individual twins, they can explore policy scenarios, estimate disease burden, and optimise resource allocation across healthcare systems. Some authors propose using pop-DTs as learning health-and-disease models that feed insights into Indi-DTs to inform personalised predictions [10].

2.2.3 System-level and hospital-level digital twins

Beyond patients and populations, digital twins can model healthcare processes and infrastructure. These system-level or hospital-level twins replicate the operational state of clinical units, hospitals or healthcare networks to improve efficiency and safety. A scoping review of digital twins for healthcare management categorises such applications into three broad domains: (1) process or production twins, which support trauma workflows, intensive-care unit operations or supply chain logistics; (2) product design twins, which focus on digital health product development and wearable integration; and (3) system performance twins, which capture and analyse operational data to guide resource planning [11]. For example, a digital twin of a critical care ward uses a dual-layer architecture to monitor the real-time state of beds, staff, and equipment, and uses discrete event simulation to optimise patient flow and resource utilisation [12]. In other implementations, hospitals interface with command centres to manage bed assignments, ventilator distribution and staffing [11]. These applications show that digital twins extend beyond clinical decision-making to operational and strategic management.

2.2.4 Typology by maturity: from digital models to intelligent twins

Healthcare digital twins can be categorised into different maturity stages which determine their interactive capabilities. The established framework identifies four development stages, starting with static models that function as offline virtual replicas without any connection to real-time data and progressing to digital mirrors that use scheduled data refreshes to maintain the system. The system starts with digital shadows that allow real-time data transmission from physical systems to digital platforms and progresses to intelligent digital twins which enable interactive data sharing through their adaptive artificial intelligence functions [11].

The intelligent twin, which relies on incoming data streams, develops its learning abilities to forecast upcoming situations. At the same time, its built-in system shows complete digital twin capabilities through its physical system alteration recommendations. The emerging debate among digital models, digital shadows, and digital twins suggests that only the digital twin enables two-way communication and decision-making [9]. Patient-centred reviews also identify three categories: simulation digital twins for virtual experimentation, monitoring digital twins for tracking patient states, and research twins for hypothesis testing [8]. Stakeholders can evaluate whether an implementation meets the digital twin definition by using these maturity levels as assessment tools [8].

3. Technological Foundations

Digital twin applications in health systems rely on several advanced technologies that create a living virtual replica of patients and medical assets based on their core functions [13]. The foundational technologies include Internet of Things (IoT) sensor networks, which collect data from their installation sites; edge computing and cloud computing systems, which deliver their data processing power for handling large data volumes; big data

platforms, which enable health data management through their capabilities to handle extensive datasets; and artificial intelligence (AI) and machine learning (ML) systems, which use their advanced modelling functions to conduct analysis [11,14]. Healthcare systems and devices need interoperability standards and secure communication protocols that enable real-time data exchange and proper communication between components. The system consists of multiple elements that create a structured environment enabling continuous bidirectional data transfer between a patient and their digital twin for real-time monitoring, simulation, and feedback [15]. This section presents the complete technological foundation of healthcare digital twins, including sensors and AI algorithms, and shows how they connect to form a strong system framework.

The diagram shows how organisations connect their data systems through processing stages and feedback mechanisms. The system uses multiple IoT sensors and medical devices to gather real-time patient information, which moves through secure networks to both edge and cloud computing systems. The big data infrastructure, along with interoperability standards, enables integration and storage of diverse data streams, including vital signs from wearables, hospital imaging, and electronic health records. The digital twin core receives continuous updates through AI/ML-driven analytics, which operate at both cloud and edge layers to create a software model that simulates patient states and predicts future outcomes. Output and feedback loops: Clinicians receive insights from the twin, including anomaly alerts and treatment optimisations, while the system returns information to IoT devices like insulin pumps and monitoring devices, creating a physical-world loop through actuators and decision support systems. The twin system uses real-time bidirectional exchange to create a replica of patient status, which then provides active support for medical treatments.

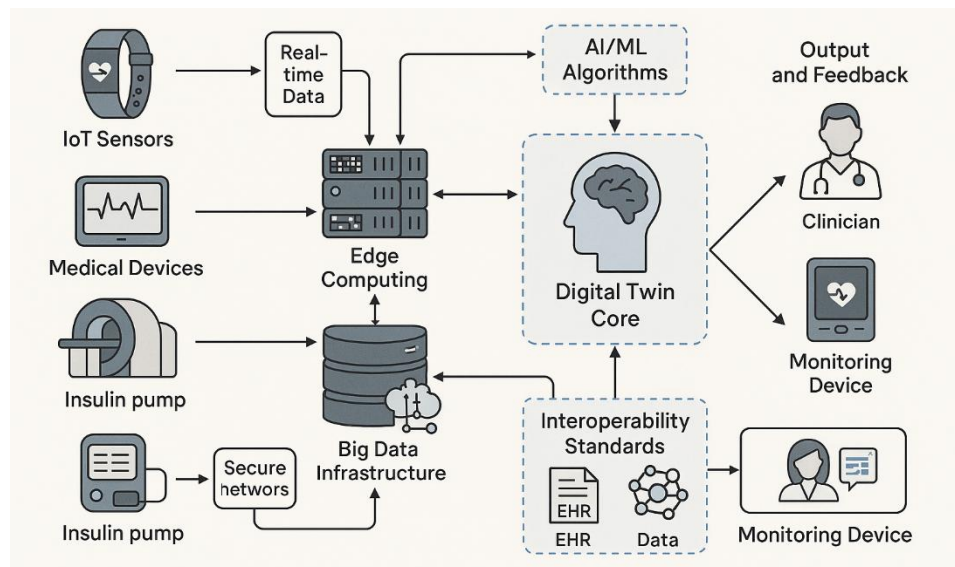


Figure 2: Conceptual ecosystem of a healthcare digital twin

3.1 Internet of Things and Sensor Networks

The IoT system functions as a network that converts patients' physical status into digital formats that healthcare systems use for treatment. IoT sensors serve as essential tools used by different user groups and applications through wearable biosensors, implantable devices, and hospital smart equipment for continuous monitoring of patient vital signs and environmental conditions. The Internet of Medical Things (IoMT) healthcare system gains vital information through IoT sensor installations that record data on vital signs, medication adherence, and imaging results. The system uses both wired and wireless communication methods to transmit data, which it uses to create digital models of the collected information [14]. The continuous availability of small wireless sensors enables more straightforward collection of extensive time-series data, which reduces the essential components of a contemporary digital twin system. For example, ECG monitors, glucose sensors and inhalers

function as wearables that transmit ongoing patient data to the digital twin in real time to show current patient health status.

IoT devices establish communication links through gateways, using standard protocols and existing internet connections. Various digital twin implementations use MQTT and RESTful APIs to transmit sensor data to backend systems through lightweight publish/subscribe protocols. The healthcare sector depends on dependable, low-latency connections because ICUs need IoT systems to send alarms and patient metrics in real time. Advanced middleware systems and IoT platforms process data streams by temporarily storing information at local gateways and edge devices before transmitting it to cloud storage. Wireless body area networks (WBANs) together with hospital Wi-Fi networks create a continuous sensor network for patients by connecting wearables and bedside devices [16]. The integrated IoT system uses each sensor and instrument as a node which transmits data to the single twins data integration pipeline.

The IoT sensor layer creates two problems for data quality assessment because it generates more healthcare data that arrives faster than existing data analysis systems can handle. Wearable technology and ambient sensors produce constant, high-frequency data streams that grow into extremely large datasets over time. This data explosion creates both an opportunity and a challenge: the twin's accuracy improves with real sensory data, including continuous vital-sign monitoring, activity tracking, and medication-event recording, but maintaining data quality and consistency becomes difficult because of sensor drift, sensor failures, and sensor noise. The ingestion stage requires real-time data filtering and anomaly detection as critical components which protect the system from incoming corrupted data and false data. Edge computing (discussed below) often helps by preprocessing raw sensor data near the source to reduce noise and volume [16]. IoT sensor networks function as the digital twin's "sensory organs," providing continuous multimodal patient data and environmental information.

3.2 Edge and Cloud Computing Infrastructure

Most digital twin systems rely on cloud computing because it provides scalable storage and computing power as needed. The healthcare digital twin system uses cloud resources to store hospital-wide patient data from multiple sources, which the system collects from all available hospital sources. Cloud data lakes and databases contain all memory components of the digital twin, which include historical electronic health records, genomic data, medical imaging results, and streaming IoT data [16]. The cloud enables hospitals to run the most demanding analytics and simulation work that local hospital hardware cannot handle. Personalised organ simulations and deep learning diagnostic models require substantial CPU and GPU resources, which cloud infrastructure provides through elastic capacity. Cloud systems create interoperability by functioning as a central point that combines data from all connected clinics and medical devices. The implementation used the necessary cloud infrastructure for IoT and Digital Twin through AWS IoT and Azure Digital Twins to handle device data processing and storage, enabling real-time analysis [17]. The cloud system enables digital twins to expand their operational scope by incorporating advanced models and big data without overloading local computing resources.

The real-time nature of edge computing: Cloud computing requires data collection from worldwide locations to perform extensive computations, but edge computing enables processing near patients, supporting immediate needs for fast, continuous service. At the care delivery point, edge devices (including on-premises servers, smart gateways, and powerful hospital workstations) perform initial data processing and analytics to reduce cloud data transmission needs, according to [16,17]. The AI system uses on-the-edge data from both the hospital network and the wearable device to deliver real-time feedback and intervention capabilities that function normally during cloud connectivity problems. These time-sensitive applications require this capability because medical professionals must make life-and-death decisions within milliseconds during cardiac monitoring and closed-loop insulin delivery. Edge computing nodes in an ICU digital twin environment can run local algorithms to detect arrhythmias and evaluate ventilator performance, while enabling real-time alert transmission and data aggregation for cloud-based long-term trend studies, as described in [16]. Edge computing supports the cloud

system by offloading tasks to edge devices that run critical operations for healthcare digital twin systems requiring real-time performance.

The current digital twin architecture employs edge-computing and cloud-computing solutions which provide their respective benefits through a hierarchical structure. The edge layer filters and analyses streaming data from IoT sensors, relaying only pertinent insights or reduced-size information to the cloud, thus saving bandwidth and elevating privacy. The cloud enables detailed data analysis, long-term storage, and synchronisation across devices and patient systems. Together, resource optimisation and reliability optimisation achieve their goals through this synergy, enabling edge operation of latency-sensitive control loops and cloud operation of compute-intensive predictive models [16]. Distributed processing systems protect users while enabling organisations to meet regulatory requirements. The edge performs initial processing of sensitive patient data through de-identification or encryption, then sends it to the cloud for further analysis. Hospitals implement hybrid architectures to achieve HIPAA and GDPR compliance while utilising cloud services [16]. The combination of edge and cloud computing enables local processing to function as an immediate response system while central intelligence operates as a comprehensive digital twin system.

3.3 Big Data Platforms and Data Integration Pipelines

Managing the volume and variety of healthcare data: Digital twins require data to survive, collecting longitudinal records and high-resolution data streams that fit the "big data" description in terms of volume, velocity, and variety. Therefore, big data platforms enable the storage, integration, and orchestration of heterogeneous data feeds that inform the twin [14]—among these platforms, distributed file systems and databases, such as Hadoop/HDFS clusters or cloud data lakes, scale storage to petabytes. They also include parallel processing frameworks, such as Apache Spark, to analyse large datasets efficiently. In a healthcare setting, this data can include continuous readings from IoT sensors, as well as extracted EHR, medical imaging, lab results, genomics, and PROs. Integrating these heterogeneous sources is a great engineering challenge. Integration pipelines bring in a variety of data from devices and IT systems using non-analogous formats and/or standards-defined manners. For example, it might ingest streaming JSON data from wearables, HL7/FHIR messages from hospitals, and DICOM images from radiology, then transform them into a uniform representation in the twin's database.

Real-time data streaming and analytics: Most of the time, an up-to-date digital twin will pair its big data infrastructure with streaming data processors to handle real-time data streams. Common streaming data processing technologies include Apache Kafka and stream processing engines, which capture IoT sensor data as quickly as possible for on-the-fly trend detection, event flagging, and other real-time actions. This real-time processing layer keeps the digital twin's state up to date, rather than updating it at set intervals. For instance, the streaming pipeline might merge heart rate and blood pressure from various wearables and deliver summary statistics to the twin every few seconds. As a result, a clinician observing the twin sees a live picture of the patient. The pipeline requires data acquisition from IoT gateways or APIs. It includes buffering, queuing, preprocessing (filtering, normalisation, and timestamp alignment), and database storage to enable analytical queries and AI model updates. Pipeline engineering must focus on data quality because it requires sensor anomaly filtering and missing-data imputation to prevent garbage from destroying the twin model's integrity [16].

The big data platforms used in digital twin systems serve two main functions: system expansion and integrating various data types into unified patient data models through data fusion technology. The process requires semantic interoperability because it enables researchers to combine patient data which exists in multiple formats from various sources. The system implements health data warehouses with common data models (OMOP, for example) to create a unified schema that maps all medical data to a common framework [14]. The integration pipeline begins with patient identifier matching across datasets, enabling the team to synchronise data that includes time and context information through knowledge graph and ontology methods that link data elements (e.g., linking a medication record to its corresponding lab results and sensor observations). Through this process, all data becomes accessible for analytical work which digital twins perform on their 360-degree data repository. The current state of big data, together with emerging data science techniques, creates a competitive advantage

that enables digital twins to achieve complex integration tasks through their existing infrastructure [11]. The digital twin ecosystem relies on big data platforms and pipelines as its circulatory system, transporting raw data from multiple sources and producing processed data that the twin's analytical core uses for analysis.

3.4 Artificial Intelligence and Machine Learning Integration

The digital twin brain uses artificial intelligence and machine learning technology to convert digital twin data into intelligent predictive systems. AI/ML algorithms analyse integrated data to identify patterns that model physiological processes and predict future patient health states using available ML classifiers, deep learning, and physics-informed models. The ML models track vital signs and laboratory test results to determine when a patient might experience a negative health outcome. Pathology exists in medical images, which computer vision algorithms use to assess twin medical images. Healthcare digital twins have received fidelity upgrades from deep learning systems, including neural networks and the latest large language models [16]. A digital twin implements multiple AI models, including one that continuously assesses patient risk through vital sign and EHR data updates, another that uses biophysical modelling with machine learning to simulate organ function, and another that delivers treatment optimisation recommendations based on previous medical outcomes. The digital twin system uses AI to shift from basic data collection to a full operational support system that assists decision-making. The virtual experiment needs predictive analytics and reinforcement learning methods to simulate how patients would respond to specific drugs and therapies, helping doctors make evidence-based treatment choices. ML models use extensive health data to customise the digital twin according to individual needs. The twin uses algorithms to identify unique patient characteristics from population data and individual history, helping it make tailored predictions about genomic factors and lifestyle habits [17]. AI plays a critical role in continuous twin updates by using online learning with fresh data and model retraining to maintain prediction accuracy as the patient's condition evolves. Digital twins play a crucial role in cardiology by enabling AI-powered simulations to create a patient's heart model from available imaging, ECG, and hemodynamic data, helping predict heart disease and assess surgical impacts on virtual heart models [14]. These results show how AI/ML systems in healthcare have evolved from static functions into intelligent agents that can learn and adjust their behaviour [14].

Digital twin model creation relies on AI technology, extending its capabilities beyond analytical functions. Machine learning creates unified multimodal data representations through generative models, which can restore missing physiological signals and construct 3D anatomical models from limited data sources. The research team used AI to develop a digital heart model based on a medical image database containing over 250 million images and records [14]. The peer organ twin was created through AI processes that automatically segment and register image data. When combined with AR/VR visualisation technologies, the system creates realistic simulation environments that doctors can use for training and surgical procedure preparation. Digital twin technology, which analyses extensive health data to understand complex disease patterns and provide usable medical insights, forms the cognitive layer of AI and machine learning economies, enabling doctors to fully use digital twins for personalised medicine applications [17].

3.5 Interoperability and Standardisation in Healthcare Data

Healthcare environments require interoperability because multiple devices and information systems create different data formats. Interoperability is a fundamental requirement for digital twin systems, which must combine data from multiple sources, including electronic health records, laboratory systems, imaging systems, and personal IoT devices. Organisations need to adopt recognised data and communication standards to exchange information across different platforms. Digital twin platforms face challenges in data integration because different devices for heart monitoring, insulin delivery, and hospital bed tracking, all used in case studies, show variations in their data encoding methods [16]. The existing medical IoT device ecosystem suffers from fragmentation because there are no standard data transmission methods, and APIs act as barriers to system integration [16]. To this end, current healthcare digital twin initiatives leverage existing health informatics standards and advance new ones for the specific needs of real-time, streaming data.

Key healthcare data standards: Several established standards facilitate interoperability in digital twin implementations:

- HL7 (Health Level 7): A longstanding framework of standards for exchanging clinical data. HL7 v2 messages focus on events such as admissions or lab results, and HL7 v3 documents provide structured ways to exchange patient information. These are generally used to feed EHR data (demographics, medical history, etc.) into the twin's database in a predictable format [14].
- FHIR (Fast Healthcare Interoperability Resources): Modern standards by HL7 designed to interchange health data in web-friendly formats (JSON, XML) and using a REST API approach. These FHIR specifications define resources (Patient, Observation, Medication, etc.) that encapsulate most clinical data elements, facilitating the extraction of data from EHR systems or remote patient monitoring devices into a digital twin. For example, the sensor reading can be represented as an FHIR Observation resource with standard codes for the quantity being measured. Given FHIR's popularity, many health devices and apps now support it natively, simplifying integration into the twin's pipeline [14].
- DICOM (Digital Imaging and Communications in Medicine): Radiological images are the principal modality of imaging data: CT, MRI, and X-rays. If a digital twin integrates radiological images or real-time image acquisition data, the DICOM standard supports transferring large image files and metadata. It ensures the twin can interpret them correctly.

OMOP Common Data Model: Data from various healthcare sources can be organised according to a standard schema (Networks of Observational Health Data Sciences and Informatics). As a result, the digital twin platform can perform patient- or institution-level analytics more easily when EHR and observational data are converted into OMOP tables. The twin can efficiently handle enormous volumes of structured health data using OMOP and enable research-grade analytics on integrated data [14].

By leveraging these standards, a digital twin system can speak the same language as hospital information systems and personal health devices, greatly reducing integration friction. Standardisation enables hospitals to use digital twin solutions across platforms. Data format standards establish a foundation for interoperability, requiring hospitals to adopt common clinical terminologies for semantic data connections.

Existing standards cannot achieve complete interoperability because their implementation processes encounter ongoing difficulties. Existing standards do not apply to many legacy systems and proprietary devices, which need interface engines and middleware for data translation. Healthcare organisations are developing real-time data streaming standards. At the same time, multiple initiatives seek to establish open standards that support continuous monitoring data movement through FHIR-based subscriptions and event messaging systems. The research community and industry are actively calling for open platforms and reference architectures for healthcare digital twins, with standard APIs and data models, to enable plug-and-play devices and analytics modules [16]. Existing standards can be applied through initiatives like Integrating the Healthcare Enterprise (IHE) to demonstrate their usefulness in digital twin interoperability. Digital twin technology requires standard data exchange methods together with semantic definitions to create a complete patient data profile. As standards progress toward widespread use, the integration process between digital twins and clinical workflows will become more efficient.

3.6 System Architecture and Communication Protocols

The four-layered architecture serves as the fundamental structure for a system to operate successfully, while digital twin technology requires various technological elements for implementation. Per se, layered architecture is often conceptualised to abstract away concerns-from data generation to its utilisation [17]. The lowest layer is the physical layer (Layer 1), which comprises the patient and the medical devices, meaning the sensors, actuators, and clinical equipment that interact with the patient. The data source layer, which describes Layer 2, functions as the acquisition layer and needs IoT gateways and device managers to collect and organise all sensor data. The interface and communication layer in Layer 3 manages secure data transmission between physical and digital

domains. This layer implements the communication protocols and middleware that bind devices to the backend systems. It establishes system connections through message brokers and IoT hubs that support protocols such as MQTT, CoAP, and HTTP/REST, ensuring streaming data reaches its destination without fail. Some healthcare contexts have incorporated industrial IoT frameworks, such as the OPC Unified Architecture (OPC-UA), to standardise machine-to-machine communication, improve interoperability, and enhance the security of information exchange [17]. The communication layer is also responsible for the most common scenario: bi-directional data flow, which not only sends sensor data up but also transmits control signals or updates from the digital twin down to actuators or alerting devices. A twin may therefore actively influence its own physical counterpart, such as adjusting a ventilator setting or prompting a patient notification based on twin analysis.

Above the communication layer are processing and modelling layers. The data processing layer (Layer 4) receives raw data, preprocesses it, and performs analytics to derive meaning from the information. This is where real-time analytics, edge computing operations, and initial data fusion connect the lower physical layers with the higher decision layers. Next, at the cloud or data repository layer (Layer 5), centralised resources maintain data storage, historical databases, and large-scale computations. In many designs, this layer represents the cloud infrastructure (or data centre) where the aggregated data are stored in repositories and subjected to complex analyses (for instance, longitudinal trend analysis or training machine learning models). Finally, the top layer is the cognition or digital twin model layer (Layer 6), where the digital twin simulation and AI-driven decision-support functions reside [17]. Effectively, this is the "virtual patient," or the collection of computational models reflecting the patient's status. The system uses advanced algorithms to process incoming data and create predictive models that produce risk assessments, therapy suggestions, and alert notifications. This layer connects to user applications and includes a clinician dashboard and a virtual reality demonstration of the twin system, completing the process from raw data to usable insights.

The digital twin architecture enables real-time, closed-loop communication between the physical system and its virtual twin. Network designers must choose communication protocols and network settings because these choices determine which methods create the least delay and best connection performance. Most IoT devices use publish-subscribe messaging systems to send data to specific topics that the twin platform monitors for real-time updates. IoT platforms often use protocols like MQTT because they are lightweight and support many-to-many device communication. The hospital network uses message standards (like HL7 ORU messages for real-time observations) to transmit clinical events into the twin system. The system architecture often uses an IoT gateway or edge server at the hospital network boundary to aggregate device data and maintain a secure link to the cloud. The gateway translates protocols from Bluetooth devices to MQTT and HTTP for cloud transmission and performs initial data processing. Secure communication should be established at all stages because industry standards require encrypting data in transit via TLS/SSL, devices should authenticate with certificates or tokens, and medical IoT networks should be segmented for security [16].

The diagram in Figure 1 above shows how IoMT sensors connect to edge nodes through secure protocols which enable real-time data transmission. The return path is equally important because when the digital twin produces control commands or alerts, these signals travel back through the communication layer to the designated device or application. A twin system can detect worsening patient health outcomes, allowing it to automatically notify an infusion pump to adjust medication dosages or send an alert to a clinician's smartphone. The system architecture enables physical actuators to receive event-driven outputs while subscribing to control signals from the digital twin. OPC UA and similar frameworks establish a bidirectional connection through which data flows between cyberspace and the physical world in standardised formats, which enable data to transmit back and forth between these two domains [14].

The current digital twin implementation requires middleware services to provide three functions: messaging, device management, and state synchronisation. The system provides an API layer which external applications use to access digital twin information from electronic health records and user dashboards. The API layer provides access to twin services through web services and GraphQL queries which meet data standards. The architectural design needs to support scalability because multiple devices will connect to the system when medical staff treat

multiple patients at once. Cloud-native design addresses this challenge through microservices that handle specific functions, containerised deployment that enables system mobility, and auto-scaling clusters that manage unpredictable processing demands. The architectural design includes a digital twin register that maintains all active twins, their current status, and links to their associated data sources. The system architecture combines hardware and software elements into an integrated system which needs careful management of communication protocols and data system design to enable the digital twin to operate in real time as the patient.

3.7 Security and Privacy Considerations

Data security at all levels-Healthcare digital twins need security protection because their system handles sensitive health records, and security violations could lead to dangerous situations through medical actions based on twin data. A breach or malfunction could be disastrous not only for privacy but also for the creation of potentially grievous medical misjudgments. Therefore, robust safety measures are embedded across each layer of the digital twin architecture [16]. At the device and sensor level, secure device authentication should be implemented to prevent unauthorised devices from feeding or extracting data, and anti-tampering techniques should be used, encrypting data at the origin, if possible, for IoT devices. Network communications are secured using encryption protocols (TLS for IP-based communication, or proprietary encryption for specialised links). Edge computing nodes and gateways deploy firewalls and intrusion detection systems to monitor anomalies in IoMT network traffic. One study, for instance, offers a hybrid anomaly-based intrusion detection system designed for IoMT networks, providing a testbed to analyse cyber threats and bolster IoT security defences [16]. This system may detect atypical *modus operandi*, which could indicate malware infection or attempted device hijacking, by placing affected devices in temporary isolation so they cannot bring the twin or the larger network down with them.

Now manage-really valuable policies concerning importance and keras on-the-cloud and data repository aspects onset access controls. Patient data is commonly stored encrypted at rest in databases, with stricter user authentication measures and audit trails for access to twins. Healthcare providers commonly use these encryption techniques before transmitting highly sensitive information to the cloud [14]. Role-based access control limits who can query or modify the digital twin to only those authorised for this use. This can be followed by tokenisation or pseudonymisation so the newly created digital twin can acquire and process information without revealing patient identity. Some digital twins include additional security measures through blockchain implementation, aiming to develop a tamper-proof log of all transactions related to data and access events [16]. Logging every data update and every twin interaction helps provide accounting, transparency, and traceability, which will prove valuable for forensic analysis while assuring data integrity. Other works have proposed combining blockchain with advanced cryptography schemes such as conditional bitcoin or temporal wallets, along with elliptic curve cryptography, to secure IoT-based healthcare twins; they show high threat-detection accuracy while protecting data [16].

Privacy and regulatory compliance: Because digital twins aggregate comprehensive patient data (possibly the entirety of one's medical and personal health information), safeguarding patient privacy and meeting compliance requirements is non-negotiable. Regulations in the United States (HIPAA) and Europe (GDPR) establish strict requirements for handling personal health information, which extend to digital twin technologies. Compliance entails obtaining informed consent for data use, anonymising data when using twin data for research, and giving patients control over which data streams are integrated into the digital twin. The architecture proposed by researchers allows digital twins to incorporate privacy-preserving features, such as the ability to "unlearn" personal data upon patient request, thereby conforming to the right to be forgotten under GDPR [16]. Advanced federated learning schemes developed by the research team enable hospitals to train models remotely while keeping data secure by sharing only model parameters, protecting users' privacy during AI development for digital twins technology. Differential privacy techniques may also be used when analysing twin data across population levels, adding statistical noise to the results so individuals cannot be re-identified [16]. Another research avenue is secure multi-party computation, which enables collaborative analysis of twin data across

multiple sources while keeping underlying data confidential and maintaining patient anonymity in a multi-hospital study.

Medical twin security thus encompasses protecting data from unauthorised access and thereby ensuring the safety and reliability of twin actions. This will validate any safety procedure for automated control actions the twin can implement (like changing doses) and ensure they cannot be maliciously or erroneously triggered. Strongly recommend types of cybersecurity testing, such as "red teaming," or looking for vulnerabilities in communication between the twin and devices, for instance, ensuring that a false data injection attack cannot mislead the twin into recommending dangerous behaviour or actions. Some researchers have begun addressing this by applying deep learning techniques to scan base code for vulnerabilities in consumer twin healthcare applications, building bidirectional contexts in the software to enable early patching at the onset, especially as we look into a 6G-enabled medical IoT that is further interconnected [16]. Whether cyber-resilience is directly correlated with the ability to operate under attack has attracted much more attention in such critical safety systems. Audits and compliance checks ensure ongoing surveillance-regular digital twin platforms that may need to be certified just like any other medical device or clinical software. In that sense, the entire stack on which the healthcare digital twin stands relies on multi-layer security, including encryption, access control, intrusion detection, and log-keeping using blockchain technology, and, of course, privacy-preserving analytics to keep the twin and its corresponding patient data private [16].

4. Applications for Digital Twins in Healthcare

4.1 Patient-Centric Models

Digital twins can serve as dynamic virtual patient models that integrate multi-modal personal health data (e.g. genetics, medical imaging, wearables) to simulate an individual's physiology and disease trajectories. By fusing IoT-connected sensors and electronic health records with AI and machine-learning algorithms, these models continuously update in real time and can predict future health states. For example, Saratkar et al. [17] note that modern healthcare DTs "integrate advanced tools like artificial intelligence (AI), the Internet of Things (IoT), and machine learning (ML) to create dynamic, data-driven replicas of patients". These virtual patients enable precise, personalised care: clinicians can simulate disease progression, test alternative therapies *in silico*, and optimise treatment plans based on individual risk factors. Strocchi et al. [18] describe a cardiac digital twin for diabetic patients that is updated over time with the available clinical data. In acute settings, specialised organ models – for instance, the Living Heart Project's DT – have been used to refine cardiac device design and predict device-tissue interactions more quickly than traditional bench tests [11]. Machine-learning analysis of the twin's data streams can forecast critical events: Kabir et al. report that DTs "use real-time data to make accurate predictions about people's health outcomes" [16], enabling earlier interventions.

By enabling *in silico* trials, patient-centric DTs can also reduce the cost and duration of clinical studies. Strocchi et al. show that virtual twin cohorts can optimise patient recruitment by providing quantitative data for power calculations, making trials more efficient [18]. In practice, wearable-enabled DT prototypes (e.g. smartphone "DTCoach" or CloudDTH frameworks) have demonstrated real-time monitoring and self-management support for chronic conditions [11]. Overall, patient-centric DTs promise improved outcomes and safety – but at the cost of new challenges. Their deployment raises data privacy and security concerns (managing highly sensitive personal and genomic data), demands high-fidelity models and vast compute power, and faces regulatory hurdles for clinical use. As Sadée et al. emphasise, merging AI/ML with mechanistic (physiology-based) models may help overcome some limitations of each approach [19]; nonetheless, interoperability, validation, and bias remain to be fully addressed in real-world settings.

4.2 Operational Models

The system is primarily used to manage healthcare operational activities and supply chain processes. Digital twins serve as virtual representations that enable hospitals to simulate operations by creating virtual models of

hospitals, wards, supply chains, and entire care networks to optimise workflow, capacity, and resource distribution. Operational digital twins use real-time data streams from multiple sources (including RFID tags, bed sensors, and patient monitors) to predict future bottlenecks and perform "what-if" analysis. Kuruppu et al. created a digital twin framework that uses discrete-event simulation to optimise intensive care unit workflows in near real time through emulation of ideal processes[12]. The digital twin system tracks patient and staff movement data, uses simulation technology to detect delays and understaffing, and provides solutions. Digital twins optimise clinical functions by studying workflow patterns and resource distribution methods, leading to smoother operational procedures and better patient outcomes, according to Vallée et al. [3].

These examples show practical applications that deliver precise results. Siemens Healthineers and partners used hospital management software and DT analytics to create simulations that predicted staffing needs and equipment distribution for better operational efficiency. GE Healthcare's command centre used DT technology to develop a dashboard that monitored ventilator and bed availability statewide during the COVID-19 outbreak. The twins received real-time system stress information through direct feeds, enabling Oregon's command centre to forecast critical care bed and ventilator shortages and allowing hospitals to share resources, reducing resource allocation problems [11]. Organisations used DT-driven operational models to reduce waiting periods, prevent overcrowding, and improve care delivery coordination.

The system uses cloud analytics to collect hospital-wide data, relies on IoT networks to monitor equipment and patient movements in real time, and employs simulation engines such as discrete-event and agent-based modelling to create predictive scenarios. The organisation will improve operational efficiency and resilience, but it will face challenges arising from implementation limits. The model may oversimplify human factors, and integrating data across older systems may be impossible; staff need to develop trust in virtual recommendations before they will follow them. The validation process for system-level twins proves difficult because the system needs continuous data flow, which creates problems for maintaining stability while tracking errors. As Vallee et al. note, to truly integrate DT predictions into clinical workflows, a stock model of practice must shift toward continuous monitoring and proactive intervention [3]. Hospitals that test DTs must tackle technical challenges such as sensor reliability and data privacy, and they must also address cultural obstacles that require change management to achieve full DT value.

4.3 Medical Equipment and Device Management

Digital twins play a vital role in helping hospitals maintain medical equipment and devices. Creating virtual replicas that correspond to actual machines allows hospitals to implement predictive maintenance procedures while achieving operational efficiency goals. For example, Li et al. implemented an IoT-driven digital twin platform for large imaging and therapeutic devices: operational logs are fed into the twin to "fully reconstruct the dynamic usage patterns" and provide 24/7 remote monitoring [20]. The twin flags unusual behaviour and estimates component wear, enabling maintenance before catastrophic failure. In the study, real-time alerts on equipment status (shutdown, standby, downtime) and risk warnings guided technicians to act in time, while a predictive model of component lifespan enabled "proactive, foresighted equipment maintenance management, effectively controlling maintenance costs" [20]. In effect, each piece of hospital hardware gains a virtual sensor network and analytic layer.

Similarly, digital twins are increasingly used to design and test medical devices. Advanced organ-level models allow engineers to simulate how a new stent, valve, or ventilator setting will perform before patient trials. For instance, the FDA-backed Living Heart project created a validated heart twin to evaluate cardiac implants in silico, and FEops' heart-twin platform enables personalised planning of TAVI and other procedures [11]. These applications use advanced biomechanical simulation with real patient data and AI analysis. Digital twins improve product manufacturing and supply chain operations by enabling Siemens and Atos to create exact virtual models of pharmaceutical production systems, improving drug development processes.

Key elements include IoT sensors that provide operational and performance data to the digital twin system, cloud computing that enables expanded data processing, and machine learning algorithms that detect anomalies

to support ongoing calibration and deliver degradation-pattern diagnostics for the twin system. The system reduces operational interruptions and maintenance costs while extending equipment lifespan. Widespread adoption faces three main obstacles: challenges in data integration and the need for high-quality sensor data, along with regulatory requirements for digital twin systems that influence clinical decision-making. Kueper et al. stated that predictive models require strict validation because errors in device-twin predictions can lead to incorrect maintenance decisions that could endanger patient health [16]. Hospitals need to resolve interoperability problems and build trust before they can achieve scalable twin-based maintenance and realise the return on investment seen in early applications.

4.4 Public Health and Epidemiology

Public health planning and epidemiology now use population-wide digital twins as new tools. These twins create digital representations of entire communities and urban areas and complete health systems, enabling models to forecast disease transmission, allocate resources, and assess treatment performance. The twin creates a digital version of health emergency operations, enabling preventive measures and real-time detection, along with early warning systems and intelligent emergency response management, which enhances crisis response capabilities and system resilience [21]. A city-scale twin uses hospital capacity data and mobility pattern data, together with demographic risk factor data, to forecast outbreak locations, enabling health authorities to start testing and vaccination efforts before outbreaks occur.

Rehan et al. present a Societal Digital Twin (SDT) as a solution to control infection spread through an outbreak management process, with five distinct operational phases, from outbreak initiation to recovery. The SDT ingests real-time epidemiological and social data at every stage to assess control strategies through agent-based and network simulation methods. The twin can maintain constant surveillance over epidemic development while providing strategic solutions for public health emergency management through its monitoring function during pandemics [21]. DT-driven models have been applied to forecast hospital surges during COVID-19 and optimise the distribution of ventilators and vaccines across regions. Kabir et al. show that a digital twin (DT) can represent the wide-ranging dynamics of hospital operations and population health patterns, enabling simulation of public health responses and prediction of health outcomes [16].

Establishing these models depends on three technological advancements: big data analytics to process extensive epidemiological datasets, cloud computing to run large-scale simulations, and AI forecasting. The models can use a hybrid approach that combines mechanistic systems using SEIR differential equations with machine-learning predictions to model complex systems. The twin will calibrate using real-time signals generated by IoT and mobile networks from sources such as mobility or wastewater sensors. Effective public health DTs improve situational awareness and enable better-targeted interventions that can lead to life-saving outcomes. Data privacy concerns arising from population-scale data use, and the need for system governance, create a contentious issue because of their severity. Model uncertainties create major challenges, while the twin shows amplified effects of small-scale biases that occur between urban and rural areas and between rich and poor people. The DT requires clear interpretation and trust to connect with policy-making bodies, which results in underutilization of twin recommendations when these conditions are missing.

5. Challenges in Implementation

Implementing digital twins for healthcare requires integrating extensive confidential patient information and new analytical methods into existing clinical procedures, creating multiple implementation challenges that affect data governance, system integration, ethical considerations, and regulatory requirements. The healthcare digital twin system collects personal health data, which makes data privacy and cybersecurity its most important protection needs. The healthcare system must protect patient models from unauthorised access because such incidents damage public trust and cause significant harm.

5.1 Technical Integration and Interoperability

The second major challenge the healthcare sector faces is integrating digital twins with legacy healthcare systems and heterogeneous data sources. Clinical data – from EHRs, imaging systems, lab databases, genomics, and wearable sensors – are frequently siloed into proprietary formats within isolated networks and examined on a case-specific basis. Without common interfaces, creating unified models can be tedious: hospitals may need to build custom middleware or APIs to connect admissions (ADT) systems, EHRs, device streams, etc. Adding to the complexity of real-time updates, most legacy systems were not designed to handle continuous IoT data, making synchronisation nearly impossible. Thus, technical incompatibility can impede a twin's ability to reflect a patient's actual status over time accurately. The NIH/ANSI Digital Twins Report expressly cautions that standards, "to ensure interoperability, compatibility, safety, and cybersecurity," must be introduced; universally accepted protocols will become a barrier to widespread uptake.

Efforts are underway to close these gaps. Many health IT stakeholders are now working toward common industry standards to enable integration. For example, HL7-FHIR and DICOM are increasingly used to exchange EHR and imaging data, while common data models such as OMOP help normalise research and clinical data. "Plug-and-play" architectures are being introduced, using microservices and APIs to let new twin platforms hook more easily into existing EHRs. Edge and cloud computing also play a role: some systems offload near-real-time IoT data processing to edge devices or cloud-based solutions, relieving the burden on hospital networks. Integration, in itself, demands considerable IT modernisation. According to GAO, "digital twins require many interrelated systems and networks for large-scale data collection and transmission." As a result, interoperability and cyber-defence issues arise. Often, these challenges require costly retrofits or a new set of sharing agreements with the hospital.

5.2 Ethical Concerns

Digital twins present certain ethical dilemmas, with algorithmic bias most widely cited. Because twins are developed using patient data and predictive modelling, any prejudicial aspects of that data can greatly affect outcomes. NPJ Digital Medicine, for instance, cautions that if models are trained on biased samples, one set of recommendations from the twins could systematically misdiagnose or mistreat other opposing groups. This jeopardises not only individuals' health care but also interventions for groups predisposed to health disparities. Other ethical issues include the transparency of how algorithms work, especially to patients and clinics. Automation bias-the overdependence of clinicians on automated decisions- has encroached on the autonomy of clinicians as well as bringing into question the accountability for errors occasioned by the algorithms. Some stakeholders have warned that this unchecked trust in digital twin outputs could lead to poor decisions that resemble the overconfidence shown in the use of flawed data from the late 90s. Data ownership and consent requirements constitute two interconnected problems. The GAO report shows that patients will lose trust when their data rights remain unclear or when others share their data without required permissions. Any ethical practice must, at minimum, maintain patient control over how surrogates use their data according to ethical standards. The digital divide exists because creating and using twins requires expensive infrastructure that benefits only affluent health systems. According to their statement, the high development costs of NPJ Digital Medicine will create a digital divide that disadvantages under-resourced patients.

The community investigates numerous mitigation options, including governance frameworks and fairness-by-design, as solutions. Explainable AI is increasingly prominent in twins; clinicians should know why the model suggests a treatment. The team conducts model auditing and debiasing through training cohorts that include people from various ancestry backgrounds, and they will begin their ethical twin development work next. The authors from NPJ request that data rights and algorithm fairness be established through robust governance systems. Responsible implementation will require institutions to establish institutional review processes alongside patient advisory boards as a basic ethical oversight framework.

5.3 Standardisation and Regulatory Barriers

The absence of cohesive standards and regulatory uncertainty are key limitations to deploying digital twins. Globally accepted frameworks do not yet govern Digital twin systems. Data rights become more complicated because different countries have different legal requirements, including GDPR in the EU, HIPAA in the US, and China's PIPL, and multinational corporations may use various data types across international borders. In practice, this means more stringent consent and anonymisation processes when sharing twins internationally. In addition, if a twin is used for diagnostics and therapy planning, it could be considered a medical device. Regulators are still wrestling with definitions and validation of digital twins; for example, the FDA is interested in using digital twins in clinical trials, but definitions are only now beginning to emerge.

6. Future Directions

DT technologies are set to change the face of the healthcare ecosystem as they integrate with other emerging digital solutions. Future health DTs will reportedly deploy immersive interfaces and distributed architectures. For instance, AR/VR tools enable clinicians and patients to interact with digital twin models in natural, three-dimensional environments. Secure data technologies such as blockchain and distributed ledgers would provide the backbone for DT data-sharing, ensuring decentralised and tamper-proof exchange of patient information. Federated learning will allow clinical DT models to be co-trained on distributed hospital data without ever letting raw data leave local sites. Similarly, edge computing—the local processing of data on devices or “edges” of the network—will enable low-latency updates to DTs worn by patients or used in home environments for real-time monitoring, again without compromising privacy. In short, next-generation health DTs would operate as multi-technology platforms spanning IoT sensing, 5G connectivity, cloud/edge infrastructure, and AR/VR interfaces powered with AI analytics to create highly responsive and secure patient avatars.

DT scalability and roll-out across health systems is one of the most pertinent challenges. Such networks can be built for the nation or the world only when a sturdy infrastructure is in place, common data standards are defined, and new governance frameworks are established. DT models exist at the societal level to aggregate population health data and inform public health action. The “societal digital twin” could collect information on millions of people and influence mass immunisation planning, pandemic preparedness, and lifetime well-being modelling. These systems will depend on high-performance computing, 5G/6G networks, and distributed databases for maintaining real-time fidelity. Potential early adopters include government or military health systems, which can establish large-scale DT applications for population surveillance and health care (e.g., monitoring veterans or deployed populations). Large-scale implementation of digital technologies requires extensive intersectoral cooperation. Such cooperation can include developing standards, confidentiality laws, and ethical frameworks that support interoperability and public trust.

Digital twins could reshape responses to global health challenges. During future pandemics, geographically distributed DTs could simulate infection spread in real time and guide interventions, from optimising vaccine distribution to planning localised lockdowns. Reviews highlight how comprehensive DT ecosystems may “empower communities, enhance societal well-being, and assist in effectively combating pandemics” by enabling data-driven decision-making across local to global levels. Similarly, DTs can incorporate environmental and mobility data to predict outbreaks of climate-sensitive diseases (e.g. vector-borne infections) driven by weather or urban changes. For ageing populations, personalised DTs enriched with longitudinal biomarker and lifestyle data could forecast individual health trajectories and recommend preventive measures; in effect, an elderly patient’s DT might continuously update an “ageing clock” to signal emerging frailty and suggest interventions. As noted in current research, human DTs already integrate wearable biosensors, electronic health records and genomics to provide continuous simulation of an individual’s health state. In underserved or rural areas, lightweight DT platforms on mobile or edge devices could extend specialist expertise via telehealth simulations and locally adapted care plans. Across these domains, DTs support a personalised and equitable health system by aligning resources and care models with the needs of diverse populations and environments.

Numerous research lines currently work toward developing Twin capabilities. The primary research trend focuses on using first-principles physiological models together with machine learning (ML) and artificial intelligence technologies. The research team combined mechanistic heart and vascular models with deep learning, graph networks, and Bayesian filters to monitor patient risk through cardiovascular digital twin research. The hybrid models use ML to adjust simulations in real time while integrating new patient data. Generative AI has emerged as an advancing field that enables researchers to design synthetic patient data and virtual cohorts through methods such as GANs and diffusion models, creating *in silico* trials and accelerating drug-design prototypes. The research team has been exploring generative digital twins that create virtual interventions to optimise therapy through iterative learning. Future DT platforms will use real-time adaptive simulation through feedback loops that enable automatic model updates based on incoming sensor data to create treatment-scenario simulations. A diabetic patient will use his digital twin to predict how his body will respond to different dietary changes, and his system will automatically generate new insulin treatment guidelines based on those predictions. Current work even envisions DTs that trial pacing or drug therapies in simulated space before applying them to the patient. Introducing large language models and self-operating systems into digital twins will enhance decision support by providing instant explanations of forecasted outcomes and conducting real-time literature searches.

Fully developed digital twin ecosystems will enable health systems to deliver predictive, proactive, patient-centred healthcare. The future healthcare system will develop into a worldwide health intelligence system that operates through digital patient simulators that connect worldwide to stream health data for analysis by advanced data-processing systems. Experts predict that digital twins will transform healthcare delivery systems by serving as a base technology for tailored medical treatments, predictive health solutions, and ongoing patient monitoring. Over the next ten years, national digital twin networks will use de-identified patient information to study health patterns, improve resource distribution, and provide instant clinical evaluation for doctors. The health system will evolve into a learning organisation that uses data to predict outcomes of health interventions. At the same time, patient care pathways receive dynamic updates from healthcare data.

7. Conclusion

Implementing digital twins will transform healthcare delivery by enabling continuous data exchange between real medical environments and simulated clinical processes to support patient treatment decisions. The finished ones: application of individualised treatment planning, virtual surgery, hospital operations, equipment management, and epidemiological modelling- their usefulness is diverse across all its ends, as reviewed herein. Technological advances in IoT, AI/ML, and distributed computing will enable digital twins to deliver precision medicine through efficient real-time solutions that address both acute and systemic health conditions by creating and integrating virtual models that represent actual operational systems. Realising these advantages fully will face obstacles that must be overcome before implementation can begin. First, for constructed systems that aggregate sensitive personal health information, data privacy, security, and ownership must be addressed. Legacy healthcare infrastructures would also pose interoperability barriers, as would the continued absence of unified regulatory frameworks to validate and govern digital twin applications. Among other issues, algorithmic bias, transparency, and fair access would be central to ensuring that digital twins complement, rather than erode, trust and fairness in human healthcare service delivery.

Conflicts of Interest

"The authors declare no conflicts of interest".

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