

Digital Twin in Healthcare

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Abstract:

Healthcare is increasingly becoming a data-intensive field in which electronic health records, medical imaging, laboratory measurements, wearable sensors and molecular information are collected across a patient's lifetime. Digital twin technology offers a way to combine these heterogeneous data into a continuously updated computational representation of a patient, organ, device or healthcare process. Unlike a static medical record or an isolated computer simulation, a healthcare digital twin is intended to represent relevant characteristics of a physical counterpart and support monitoring, prediction, simulation and decision-making. Recent research shows that healthcare digital twins can be developed at different scales, ranging from individual organs such as the heart to patient-level models and hospital operations. Artificial intelligence, mechanistic modelling, Internet of Things devices, cloud and edge computing, medical imaging and multi-omics data can contribute to the construction and updating of a twin. Such systems may support personalized treatment planning, early detection of deterioration, surgical planning, clinical trial design, drug response prediction and optimization of hospital workflows. This paper reviews the concept, architecture, enabling technologies, applications and limitations of digital twins in healthcare. Particular attention is given to data integration, model validation, interoperability, privacy, cybersecurity and ethical responsibility. Although digital twins have substantial potential for precision healthcare, a complete whole-body twin remains a research objective rather than a routine clinical product. Their safe adoption will depend on reliable data, validated models, explainable decision support, strong governance and meaningful participation of clinicians and patients.

Keywords — Digital Twin, Healthcare, Precision Medicine, Artificial Intelligence, Medical Imaging, Internet of Things, Predictive Analytics, Clinical Decision Support, Digital Health, Virtual Human Twin.

I. INTRODUCTION

Healthcare systems have moved from paper-based records toward connected digital environments in which information can be collected, stored and analysed at increasingly large scale. Electronic health records provide longitudinal clinical information, while medical imaging, laboratory systems, genomics, wearable devices and remote monitoring platforms add further dimensions to the patient's health profile. The resulting data environment creates an opportunity to move from retrospective documentation toward predictive and simulation-based healthcare [1], [2], [12].

A digital twin is commonly understood as a dynamic digital representation of a physical entity that is connected to data from its real-world

counterpart. In healthcare, the physical entity may be a patient, an organ, a medical device, a treatment process or an entire hospital. The representation can be updated as new observations become available and can use computational models to estimate states that are difficult or impossible to measure directly. The healthcare literature therefore uses the term for systems with different levels of scope and complexity, rather than for one standardized technology [1], [2], [3], [7].

The idea is particularly relevant to precision medicine. Traditional clinical decisions often rely on population-level evidence combined with a patient's current measurements. A digital twin seeks to add a patient-specific computational layer in which the individual's history, physiology,

anatomy, environment and response to previous interventions can be represented. A clinician could then compare possible interventions in a virtual environment before selecting a strategy for the real patient. In cardiovascular medicine, for example, patient-specific computational models have been proposed to support diagnosis, prognosis and treatment planning [4], [12].

The potential benefit extends beyond individual treatment. Digital twins can represent healthcare processes such as patient flow, operating-room scheduling and resource utilization. Hospital-level twins can combine data from people, equipment and processes to provide a continuously updated operational view and support decision-making. At a broader scale, digital twins can contribute to population-health modelling by allowing researchers to examine likely effects of interventions under different scenarios [5], [13], [15].

Despite these opportunities, healthcare presents a much harder twinning problem than many engineering applications. Human physiology is multiscale, partially observable and highly variable between individuals. Clinical data are often incomplete, noisy, distributed across institutions and stored using different formats. A model can also be computationally impressive without being clinically useful. Consequently, the objective is not to create a perfect digital copy of a person, but to construct a validated model that is sufficiently accurate for a clearly defined clinical or operational purpose [3], [7], [10].

II. DIGITAL TWIN IN HEALTHCARE

This journal paper was prepared through a focused review of peer-reviewed research articles, review papers and technical literature on digital twins in healthcare. The literature was examined with emphasis on definitions, data sources, modelling approaches, clinical and operational applications, validation requirements, interoperability, security, privacy and ethical considerations. Recent reviews were used to identify recurring themes, while representative application studies were considered to understand how digital twins are being translated into practical healthcare settings [1], [2], [3], [7], [12].

The methodology is organized around the lifecycle of a healthcare digital twin: acquisition of physical-world data, construction and calibration of a virtual representation, continuous synchronization, analysis or simulation, and use of the resulting information for decision support. This structure makes it possible to compare patient-level twins with organ-level and hospital-level twins while recognizing that their technical requirements differ [3], [6], [7].

A. Evolution from Digital Models to Healthcare Digital Twins

Computer-based modelling has long been used in medicine for anatomical visualization, physiological simulation, medical-device design and treatment planning. These models, however, are not automatically digital twins. A conventional model may be created once and used for a particular analysis, whereas a twin is associated with a physical counterpart and is intended to remain linked to observations from that counterpart. The distinction becomes important when the objective is continuous monitoring or prediction rather than one-time simulation [1], [3], [7].

Healthcare digital twins emerged from the convergence of modelling and simulation with sensors, electronic records, artificial intelligence, cloud computing and large-scale data analytics. Early applications were often highly specialized. Examples include models of cardiac electrophysiology, glucose regulation and individual anatomical structures. Current research is moving toward broader patient-level representations that combine multiple data modalities and support several stages of the care pathway [2], [4], [10], [12].

The concept is also expanding from isolated patient twins to networks of related twins. A patient may have linked representations of organs, implanted devices, treatments and care processes, while a hospital may maintain twins of rooms, equipment and workflows. This hierarchical view is consistent with recent frameworks that describe healthcare digital twins across multiple complexity scales [6], [7], [10].

B. Healthcare Data Sources and Twin Construction

The quality of a digital twin depends strongly on the quality and relevance of its input data. Electronic health records provide diagnoses, medications, procedures, laboratory results and clinical observations. Medical imaging contributes anatomical and structural information from modalities such as CT, MRI, ultrasound and other scans. Wearables and connected medical devices can supply near-continuous measurements such as heart rate, activity, temperature, oxygen saturation and glucose-related signals. Genomic, proteomic and other multi-omics measurements can provide deeper biological information when available [1], [2], [12].

Constructing a twin requires these sources to be transformed into a common representation. Data cleaning, temporal alignment, missing-value handling, normalization and feature extraction may be necessary before modelling. Imaging data may require segmentation and reconstruction, while clinical text may require natural-language processing. A model can then combine data-driven methods with mechanistic or physics-based equations. The choice depends on the intended use, available data and the level of physiological detail required [3], [7], [12].

An important principle is purpose-specific twinning. A cardiac twin intended to predict arrhythmia does not need to model every biological process in the body. Similarly, a hospital operations twin may focus on patient movement, staff, beds, equipment and scheduling rather than detailed physiology. Defining the target decision first helps control data requirements and prevents unnecessary complexity [3], [4], [5], [15].

C. Architecture of a Healthcare Digital Twin

A practical healthcare digital twin can be described as a layered architecture. The physical layer contains the patient, organ, device or healthcare facility being represented. The data-acquisition layer collects observations from electronic records, sensors, imaging systems, laboratory instruments and other sources. An integration layer performs identity matching, synchronization, transformation and quality checks

so that information from different systems can be combined [3], [7], [14].

The virtual layer contains the computational representation. Depending on the application, it may include anatomical models, physiological equations, statistical models, machine-learning models, knowledge graphs or combinations of these. A simulation and inference layer uses the representation to estimate current state, predict future behaviour or compare intervention scenarios. The decision-support layer presents relevant results to clinicians, patients or hospital managers, ideally with uncertainty information and explanations rather than unexplained predictions [2], [3], [12].

The connection between physical and virtual layers is bidirectional in advanced systems. Real-world observations update the twin, while model outputs can influence decisions or, in tightly controlled cyber-physical systems, trigger actions through connected devices. Because clinical consequences can be significant, human oversight is especially important when model outputs are used for diagnosis or treatment [6], [7], [11].

D. AI and Computational Modeling

Artificial intelligence provides important capabilities for healthcare digital twins, but it is only one component of the overall system. Machine-learning models can identify patterns in longitudinal data, estimate risk, classify images, forecast patient trajectories and infer missing information. Deep learning is useful when high-dimensional data such as medical images or waveforms are available. Natural-language processing can convert unstructured clinical notes into structured information that can be incorporated into a twin [12].

Mechanistic models provide a complementary approach. They describe relationships based on physiology, anatomy or known physical principles and can sometimes provide better interpretability and extrapolation than purely statistical models. Hybrid approaches combine mechanistic models with machine learning so that patient data can calibrate parameters while physiological structure constrains predictions. Research in precision cardiology illustrates the value of combining

computational models with patient-specific observations [3], [4], [12].

Model validation is essential because predictive accuracy on historical data does not guarantee safe performance for future patients. Evaluation should include independent datasets, calibration, uncertainty estimation, subgroup analysis and clinically meaningful outcomes. Continuous updating also introduces the possibility of model drift when patient populations, sensors or clinical practices change. Therefore, a healthcare twin should be treated as a monitored clinical software system rather than a one-time machine-learning model [3], [7], [12].

E. Patient Monitoring and Precision Medicine

One of the most direct uses of a digital twin is continuous patient monitoring. Wearable and home-based sensors can provide frequent observations between hospital visits, allowing the twin to estimate changes in physiological state and identify deviations from an individual's normal pattern. Instead of relying only on population thresholds, personalized baselines can be incorporated into risk assessment. This approach may be useful for chronic disease management, rehabilitation and post-discharge monitoring [2], [12].

Precision medicine is another major application. A patient-specific model can integrate demographic, clinical, imaging and molecular information and then simulate alternative treatment pathways. The objective is not to replace clinical judgement but to provide additional evidence about how a particular patient may respond. Research has explored this idea in cardiovascular disease, diabetes, oncology and other domains, although the maturity of the evidence differs between applications [4], [12].

A successful monitoring twin should distinguish measured observations from inferred states and predictions. It should also communicate uncertainty and avoid presenting a probabilistic forecast as a confirmed diagnosis. These requirements are particularly important when automated alerts can affect patient anxiety, clinician workload or treatment decisions [3], [7], [11].

F. Diagnosis, Treatment and Surgical Planning

Digital twins can support diagnosis by combining heterogeneous observations into a coherent computational representation. In imaging-intensive specialties, a three-dimensional anatomical model can be linked with physiological or statistical models to examine disease mechanisms. In cardiology, patient-specific digital heart models have been investigated for understanding electrical activity and supporting treatment planning. Similar concepts are being explored for other organs and disease areas [4], [12]. Treatment planning is especially attractive because simulation can allow alternative interventions to be compared before acting on the patient. A clinician could examine predicted effects of different drug strategies, device configurations or surgical plans. In principle, this can reduce trial-and-error decisions and help identify high-risk scenarios. However, the usefulness of a simulation depends on whether the model has been adequately validated for the specific decision being made [3], [4], [12].

Digital twins can also support surgical preparation and rehabilitation. Patient-specific anatomy can be reconstructed from imaging, while models of movement or tissue behaviour can assist planning. During rehabilitation, sensor data can update a functional representation of the patient and help evaluate progress. These applications demonstrate that the value of a twin is not limited to diagnosis; it can potentially span the full clinical pathway [2], [10], [12].

G. Clinical Trials and Drug Development

Clinical research is another area in which digital twins may reduce uncertainty. A patient-specific computational model can be used to estimate how an individual might respond to an intervention, allowing researchers to explore treatment effects before or alongside physical trials. Digital twins may also support patient stratification by identifying subgroups with similar predicted responses [2], [8], [12].

In drug development, digital models can contribute to pharmacological and physiological simulations, prediction of drug response and identification of potentially useful treatment

strategies. Virtual populations can be constructed from patient-level models to examine a range of responses rather than assuming that every participant behaves like the average patient. Such approaches may complement, rather than replace, laboratory and clinical evidence [1], [2], [12].

A major research challenge is causal validity. A model may reproduce correlations in historical data without correctly predicting the effect of an intervention that was not previously observed. For this reason, digital-twin outputs used in clinical trials require rigorous validation, transparent assumptions and appropriate statistical methods. Recent work is examining how causal inference can be combined with digital-twin approaches for future trial design [8].

H. Hospital Operations and Population Health

Digital twins are not limited to individual patients. At the hospital level, a twin can represent patients, staff, beds, rooms, equipment and workflows and can be updated from operational data. Such a representation can support real-time monitoring and simulation of patient flow, resource allocation and scheduling. A proof-of-concept study of smart hospital operations demonstrated how data from people, objects and processes can be integrated to support operational decisions [5], [13], [15].

Hospital twins may help managers test scenarios before implementing them. For example, changes in appointment scheduling, bed allocation or operating-room sequences can be simulated to estimate effects on waiting time and resource utilization. This creates a virtual environment for operational experimentation while reducing the risk of disrupting real services [5], [13], [15].

At the population level, digital twins can be used for scenario analysis involving disease progression, public-health interventions or healthcare demand. The scale increases the need for careful governance because models may represent groups of people and can influence resource allocation. Population models therefore require transparency about assumptions, data coverage and potential sources of bias. [7], [11]

I. Security, Privacy, Ethics and Challenges

Healthcare digital twins process highly sensitive information. A patient-level twin may combine identity-linked clinical records, imaging, physiological signals, genetic information and behavioural data. Unauthorized access could therefore reveal a far more comprehensive profile than any single healthcare database. Privacy protection should include data minimization, strong authentication, encryption, access control, secure interfaces and careful management of data retention and sharing [9], [11], [14].

Ethical questions extend beyond cybersecurity. Patients should have meaningful information about how their data are used, how model outputs influence decisions and who is responsible when a prediction is wrong. Questions of data ownership, consent, secondary use, algorithmic bias and unequal access also become important. Ethical analyses of healthcare digital twins emphasize that combining AI, IoT and big data can reproduce or amplify the social and ethical issues associated with each component [9], [11].

Interoperability is another major limitation. Healthcare information is distributed across systems that may use different identifiers, formats and clinical vocabularies. Without reliable interoperability, the twin can become incomplete or difficult to update. Standards and common data models can help, but technical compatibility alone is not enough; semantic consistency and trustworthy identity management are also required [3], [7], [14].

Finally, the human body itself limits what can currently be achieved. Many physiological processes are only partially observed, biological parameters may be uncertain, and models can become computationally expensive as their scope increases. Recent research therefore distinguishes practical domain-specific twins from the longer-term ambition of a multiscale Virtual Human Twin. Clinical validation, regulatory pathways, cost, infrastructure, energy consumption and clinician trust will determine how quickly the technology moves from research prototypes into routine care [3], [7], [10].

III. CONCLUSION

Digital twin technology provides a framework for connecting real-world healthcare data with computational models that can monitor, predict and simulate patient or system behaviour. Its importance comes not from producing a visually realistic virtual patient, but from creating a useful and continuously informed representation that can answer a defined clinical or operational question. Current research spans organ-level models, patient-level precision medicine, clinical trials, medical devices and hospital operations [1], [2], [4], [5], [10], [15].

The most promising applications include continuous monitoring, individualized treatment planning, surgical simulation, drug-response analysis and optimization of healthcare workflows. Artificial intelligence, medical imaging, IoT devices, mechanistic modelling and cloud or edge computing provide the technical foundation for these applications. At the same time, the literature shows that the field remains heterogeneous and that the maturity of individual applications varies considerably [2], [3], [12], [13].

Future progress will depend on reliable data integration, interoperable health information, validated hybrid models, uncertainty-aware predictions and strong privacy and security controls. Ethical governance must keep pace with technical development so that patients retain meaningful control over their information and clinicians remain able to understand and challenge automated recommendations. The long-term vision of a comprehensive Virtual Human Twin is ambitious, and current systems should therefore be evaluated according to clearly defined use cases rather than unrealistic expectations of complete human simulation [7], [9], [10], [11], [14].

Overall, digital twins are best viewed as an emerging decision-support paradigm for healthcare. They can complement clinical expertise by enabling structured analysis of complex, patient-specific information and by allowing possible interventions to be explored in a computational environment. If validation, governance and interoperability are addressed carefully, digital twins may become an important

component of predictive, preventive and personalized healthcare [2], [3], [7], [12].

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