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Leveraging Blockchain-Enabled Digital Twins in Healthcare

Master's Thesis (30 ECTS)

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Abstract:

The healthcare industry faces increasing challenges like rising costs, fragmented data, and a growing demand for personalized care. Digital Twin (DT) technology offers a promising response by enabling real-time monitoring and predictive analytics through virtual replicas of physical entities. However, its adoption in healthcare remains limited due to concerns about data security, interoperability, and system scalability. This study proposes a blockchain-enabled DT framework designed specifically for healthcare applications. The framework integrates secure data sharing, traceability, and tamper resistance through blockchain technology. Developed using the Design Science Research (DSR) methodology, the framework design is informed by a Systematic Literature Review (SLR) that identifies core DT components and implementation challenges in healthcare contexts. A prototype was implemented using a smart patient room scenario to demonstrate feasibility. The system combines IoT sensors, Azure Digital Twins (ADT), and Ethereum-based blockchain logging to support real-time monitoring and secure data handling. Evaluation through stakeholder interviews revealed that the system was perceived as intuitive, technically sound, and clinically relevant, though limited in functionality due to its prototype nature. The results of this work demonstrate how DT and blockchain technology can be integrated into a cohesive framework that supports secure, responsive, and modular digital healthcare systems. Additionally, this work offers both practical insights and theoretical contributions toward advancing the role of emerging technologies in modern healthcare systems.

Keywords:

Digital Twins, Healthcare Systems, Blockchain, Internet of Things

CERCS:

P170 Computer science, numerical analysis, systems, control

Plokiahelal põhinevate digitaalsete kaksikute kasutamine tervishoius

Lühikokkuvõte:

Tervishoiusektor seisab silmitsi järjest kasvavate väljakutsetega, nagu suurenevad kulud, killustatud andmed ja kasvav vajadus isikupärastatud ravi järele. Digitaalse kaksiku (inglise keeles Digital Twin ehk DT, ja sarnaselt allpool) tehnoloogia pakub paljutõotavat lahendust, võimaldades füüsiliste üksuste virtuaalsete koopiade kaudu reaalsajas jälgimist ja ennustavat analüütikat. Siiski on selle rakendamine tervishoius endiselt piiratud andmeturbe, koostalitlusvõime ja süsteemi skaleeritavusega seotud murede tõttu. Käesolevas uurimistöös pakutakse välja plokiahelal põhinev DT-raamistik, mis on loodud spetsiaalselt tervishoiurakenduste jaoks. Raamistik integreerib turvalise andmeajamise, jälgitavuse ja võltsimiskindluse plokiahela tehnoloogia abil. Raamistik on välja töötatud disainiteaduse uurimismetoodika (Design Science Research, DSR) põhjal ning selle kujundamisel on aluseks süstemaatiline kirjanduse ülevaade (Systematic Literature Review, SLR), mis tuvastab DT põhikomponendid ja rakendamise väljakutsed tervishoiu kontekstis. Teostatavuse näitamiseks rakendati prototüüp, mis põhines nutika patsienditoa stsenaariumil. Süsteem ühendab IoT-andurid, Azure Digital Twins (ADT) ja Ethereum-i-põhise plokiahela logimise, et toetada reaalsajas jälgimist ja turvalist andmetöötlust. Sidusrühmade intervjuude põhjal selgus, et süsteemi peeti intuitiivseks, tehniliselt usaldusväärseks ja kliiniliselt asjakohaseks, kuigi selle funktsionaalsus oli piiratud prototüübi tasemel. Selle töö tulemused näitavad, kuidas DT ja plokiahela tehnoloogiat saab integreerida sidusaks raamistikuks, mis toetab turvalisi, reageerimisvõimelisi ja modulaarseid digitaalset tervishoiu süsteeme. Lisaks pakub see töö nii praktilisi teadmisi kui ka teoreetilisi panuseid uute tehnoloogiate rolli edendamiseks kaasaegses tervishoiusüsteemis.

Võtmesõnad:

Digitaalsed kaksikud, tervishoiusüsteemid, plokiahel, asjade internet

CERCS: P170 Arvutiteadus, arvanalüüs, süsteemid, kontroll

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¹<https://www.grammarly.com>

²<https://chatgpt.com>

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1 Introduction

Digital Twin (DT) technology is considered one of the innovative advancements in many areas, including the healthcare field. As virtual replicas that accurately mirror physical entities' behavior, properties, and current status, DT models provide deep insights into system performance [22]. DT has received a lot of attention in many fields in the past few years. In healthcare, DT can help with problems like high costs, a lack of system connections, and the challenge of delivering timely, personalized care. These issues can slow down critical decisions, delay urgent treatment, and compromise patient outcomes in the long run. By creating dynamic virtual models of healthcare systems, including patients, medical devices, clinical processes, and many others, DT enables providers to forecast disease progression, fine-tune treatment strategies, and enhance clinical decision-making [50]. Though DT has vast potential in healthcare, it is still new among them, thus many challenges remain, like keeping data secure, ensuring different systems can work well together, and finding the right way to scale things up [15].

Besides, the blockchain technology plays an important role in bridging these gaps. In most of the productive circumstances, healthcare data is constantly being shared, which is highly sensitive; thus, robust systems are needed to keep it secure, accurate, and private. Blockchain provides a decentralized, tamper-proof way to do this, making it easier to share data securely. Such a setup builds trust, supports collaboration, and helps keep things aligned with the rules. Plus, blockchain's strength in handling distributed transactions fits well with the scalability demands of data centers, making it easier to use across a range of healthcare settings [17].

This study looks into how blockchain-based DT frameworks are being used in healthcare, highlighting what is working and where the gaps are. The study also designed and built the DT-based system to help improve healthcare systems and show how DT-based systems can work in real-world settings.

1.1 Motivation

Today's healthcare systems are under tremendous pressure, from the growing need for personalized care to the ongoing problem of wasted resources and costs. Problems are normally addressed only after they occur, making it difficult to provide timely and effective treatment when needed most. On top of that, data is often scattered, and systems lack interoperability, making things even harder.

DT can help intelligently solve some of these problems and create updated virtual patient health models. The participants, like clinicians, could try different treatments, predicting how the condition might worsen, which helps in making better choices. This approach can potentially improve the quality of medical care and enable earlier interventions that benefit both patients and healthcare providers [50].

DTs also look promising for improving how healthcare operates, modeling how

resources are used, monitoring the performance of medical equipment, and helping hospitals spot issues and find better ways to run things more efficiently [31]. DT can help healthcare systems run better to meet the needs of patients.

However, even with various emerging DT use cases, DTs in healthcare are still new. Many issues need to be addressed, one of the major issues is keeping health data secure and private, which is still a big concern. In addition, many existing DT systems have difficulties in integrating complex and various healthcare environments, which may limit their usefulness in practice [2].

This study aims to investigate these challenges by looking at how a blockchain-enabled DT framework can be designed and built. Integrating with blockchain helps tackle some of the real-world problems that current systems face. The goal is to support ongoing work to better use DTs in healthcare and get a clearer picture of what they can do, as well as better understand their potential impact.

1.2 Problem Statement

One of the critical issues in healthcare today is the lack of advanced simulation tools and the practical solutions associated with them. When it comes to personalized medicine, for example, this gap makes it difficult to predict how a disease will evolve or to develop a treatment plan that is truly appropriate for each individual. Without reliable multivariate modeling and analysis, treatment decisions may ultimately vary from patient to patient. This makes predicting outcomes more difficult and reduces the overall effectiveness of medical treatments [46, 50].

The inability of the healthcare sector to effectively optimize resource allocation and workflows leads to wasted resources, increased costs, and reduced operational efficiency, which collectively contribute to further operational inefficiencies [31]. Besides, in most cases, many healthcare providers and professionals are unprepared for complex or emergency situations due to a lack of proper training in high-fidelity simulations, which increases the risk of poor clinical outcomes [7]. Moreover, data processing continues to be a major obstacle in healthcare. When data is fragmented, making accurate decisions becomes difficult. Without robust security measures, the likelihood of patient data being compromised or tampered with is even greater.

DT can be an effective technology for addressing the aforementioned issues. For instance, by creating virtual copies of the entities, like the patients, patient treatments, and even healthcare facilities, DT has the potential to improve the way the overall healthcare system operates [21].

1.3 Research Questions

To address the challenges discussed in the previous section, we need to formulate the research question by targeting. A generalization is presented here, the main research

question (**RQ**) of this thesis is: *How can Digital Twins enhance healthcare systems?*

This main RQ is at the heart of this study and aims to explore the transformative potential of DT in healthcare. This paper also needs to design, implement, and evaluate a framework for the healthcare domain. Naturally, the main research question is divided into five sub-research questions for a more in-depth and hierarchical exploration.

- **RQ1: What are the key components of DTs in healthcare?**

This question is the very first step in this study, which focuses on identifying and defining the essential elements of a DT in the healthcare context. We need to determine the data sources, components, modeling approaches, integration mechanisms, and other aspects that may compose a DT model. RQ1 acts as the basis for the design of our DT framework, further it is essential to come up with solutions that meet the needs of modern healthcare systems.

- **RQ2: How is blockchain being used in Healthcare DTs?**

Apart from DT itself, we need to consider the other core of this study - blockchain. So, this question explores the application of blockchain technology in the healthcare digital twin. RQ2 aims to identify which roles blockchain plays within the solution to the Healthcare Digital Twin (HDT) system, focusing on the specific roles blockchain plays in addressing challenges of data security, integrity and interoperability in healthcare.

- **RQ3: How can DTs be designed for healthcare systems?**

Based on the understanding of the key components and blockchain applications, a proposed DT architecture is required. This research question explores the principles and methodologies required to design a DT for healthcare. RQ3 lies in exploring how to ensure that the designed framework is practical, adaptable, and aligned with real-world healthcare requirements.

- **RQ4: How can the proposed DT framework be implemented?**

This question investigates the practical implementation of the designed digital twin framework in healthcare settings. It focuses on creating a demonstrable framework that integrates IoT, data analytics, and blockchain technologies to address specific healthcare scenarios.

- **RQ5: How can the proposed DT framework be evaluated?**

This question examines methods for evaluating the proposed framework. It aims to assess the implemented DT framework with various evaluation methods and criteria to be adopted.

1.4 Research Method

This study employs a Design Science Research (DSR) methodology to develop blockchain-enabled DT solutions for healthcare systems and to address the proposed RQs. This section details the adopted methodology and associated research processes.

1.4.1 Design Science Approach

DSR is a research methodology focused on creating and evaluating artifacts to address identified problems. It emphasizes iterative development, where artifacts such as models, systems, or frameworks are designed and refined through testing and evaluation [24, 51]. It combines theoretical exploration with practical application to ensure that solutions are conceptually sound and operationally effective, which is particularly effective in exploring the application of technology in specific domains, complementing the use of blockchain-enabled DT in healthcare in this study.

The DSR approach is suitable for studies that develop innovative solutions and evaluate their practicality. In this study, the main aim of DSR is to design, develop, and evaluate blockchain-enabled DT solutions that will lead to improving healthcare.

1.4.2 DSR Stages

To operationalize the DSR, this study follows a structured approach to develop a generalized DT solution for healthcare systems. The study is guided by the six-stage process proposed by Peffers et al. and Dresch et al., providing a systematic framework for addressing the proposed RQs, as shown in the text and Figure 1 below [12, 13, 24].

1. **Problem Identification:** Identify core challenges in healthcare systems using SLR to establish research gaps and validate the need for a DT framework.
2. **Objective Definition:** Define clear objectives to develop a DT framework guided by insights from the SLR.
3. **Design and Development:** Design a comprehensive DT framework with architectural components and blockchain mechanisms.
4. **Demonstration:** Apply the framework to a healthcare use case to showcase its functionality and practical applicability in a particular setting.
5. **Evaluation:** Evaluate the framework through metrics, ensuring its effectiveness in healthcare scenarios.
6. **Communication:** Present the findings and contributions of the study while summarizing the key insights and outcomes.

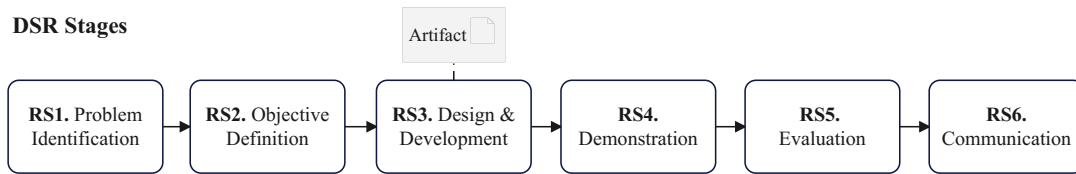


Figure 1. Design Science Research Stages

RS1: Problem Identification The first phase of the DSR is Problem Identification and Motivation. As described in Section 1.1 (Motivation) and Section 1.2 (Problem Statement), some critical issues in the healthcare system include decentralized data, limited interoperability, and existential needs such as security and scalability. These issues indicate the necessity of a robust DT framework incorporating emerging technologies like blockchain. While Section 1 outlines some existing challenges, the RS1 is further supported by an SLR, presented in Section 3. It examines existing work on DT and blockchain in healthcare, offering a theoretical foundation by analyzing key components, integration challenges, and current developments. This review helps refine the problem space and identifies research gaps, directly addressing RQ1: *What are the key components of DTs in healthcare?* and RQ2: *How is blockchain being used in Healthcare DTs?*

RS2: Objective Definition Building on the SLR findings and the analysis of healthcare system challenges, this stage defines the objectives for a flexible DT framework that integrates blockchain technologies across various healthcare contexts. Reviewing existing frameworks informs the essential features and design considerations, directly addressing RQ3: *How can DTs be designed for healthcare systems?*

RS3: Design and Development This stage focuses on designing and implementing a comprehensive DT framework, as detailed in Section 4 (Proposed Framework). This framework outlines the HDT architecture and key components. And it is designed based on insights derived from SLR in order to shape a more granular and practical solution. RS3 addresses RQ3: *How can DTs be designed for healthcare systems?* and begins to explore RQ4: *How can the proposed DT framework be implemented?*

RS4: Demonstration Section 5 (Implementation) demonstrates the practical application of the proposed HDT framework by implementing a healthcare use case to validate the functionality and applicability of the framework. This stage focuses on RQ4: *How can the proposed DT framework be implemented?* by providing empirical evidence in the real-world context.

RS5: Evaluation This stage aims to evaluate necessary metrics of the proposed DT framework in healthcare, illustrated in Section 6 (Evaluation). The evaluation criteria are based on established guidelines and include qualitative assessment. RS5 addresses RQ5: *How can the proposed DT framework be evaluated?*, focus on appropriate metrics and validation methods.

RS6: Communication The final stage of the DSR process, which focuses on communicating the results of the study, covers Sections 7 (Discussion), and 8 (Conclusion). RS6 presents the main findings, emphasizing the proposed DT framework’s contribution, practical implications, and theoretical relevance to healthcare research.

Table 1 presents an overview of the DSR process implemented in this study, summarizing the key artifacts or contributions associated with each research phase.

Table 1. DSR Research Stages and Corresponding Contributions

Research Stage	Thesis Contribution / Artifact
RS1.	Outlined initial challenges; refined and contextualized through an SLR, identifying key DT components, integration challenges, and research gaps (RQ1 and RQ2).
RS2.	Defined objectives for a flexible DT framework based on SLR findings and healthcare needs, addressing core design considerations (RQ3).
RS3.	Designed and developed the HDT framework, guided by SLR insights (RQ3 and RQ4).
RS4.	Demonstrated the framework’s implementation through a healthcare use case, validating functionality and applicability in real-world contexts (RQ4).
RS5.	Evaluated the framework with proper criteria aligned with established guidelines, focusing on effectiveness and feasibility (RQ5).
RS6.	Communicated findings, emphasizing the framework’s contributions, practical implications, and theoretical relevance.

1.5 Contributions

This study follows the DSR methodology with the goal of building a blockchain-enabled DT framework for the healthcare domain, aiming to address potentially critical issues such as security, interoperability, and practical applications. The main contributions of this study are:

- A structured DT framework, incorporating key functional components and integrating blockchain technology into security concerns.
- Proof of Concept (PoC) implementation to demonstrate the feasibility of the framework in healthcare scenarios.
- For the implemented PoC, we formulate a suitable evaluation procedure to assess the system's applicability and performance.

1.6 Thesis Structure

The subsequent sections of this thesis are organized as: Section 2 provides the overall background, including fundamental concepts related to DTs, blockchain, and their applications in healthcare systems, acting as the baseline of the study. Section 3 presents the SLR, summarizing the literature review questions, data sources, paper selection, and the findings that highlight the current state and challenges of DTs in healthcare along with the blockchain. Section 4 describes the proposed blockchain-enabled DT framework, its architecture, design and the composition of essential components. Section 5 details the implementation of the proposed framework and demonstrates the prototype for a specific use case. Section 6 mainly focuses on evaluation, including the method selection, the concrete evaluation procedure, and the feedback. Section 7 raises the implications of this study, describes both theoretically and practically, and briefly discusses this paper's limitations and suggests future work directions. Finally, Section 8 concludes the thesis, reviewing the study process and summarizing the study outcomes.

2 Background

This section lays the baseline for the study by investigating existing DTs and blockchain in healthcare systems, using the DSR methodology as a guide. The major aspects we focus on include the related concepts and typical applications of DT and blockchain, as well as how to integrate these technologies into healthcare solutions.

2.1 Digital Twins

Digital Twins (DTs) are virtual models that reflect real-world objects, systems, or processes [22]. DT was first used in industries like aerospace, and has since moved into a broader range, including healthcare. Its rapid growth is due to IoT, Artificial Intelligence (AI), and Machine Learning (ML) advances. In healthcare, DTs can represent patients, medical devices, clinical processes and many others, it can constantly update real-time data from IoT devices, sensors and medical records, helping healthcare providers make better decisions and deliver more accurate personalized care. The core of DT is a digital copy of a real-world object or system that is kept in sync through continuous data exchange, creating a two-way connection between the physical and digital worlds. Specifically in healthcare, DT can model patients themselves, specific organs, or even medical devices, enabling real-time tracking, diagnosis, and prediction of disease progression. These DTs can synchronize data and simulations for different scenarios by combining IoT, AI, and other emerging technologies. Giving physicians and healthcare teams valuable insights, helping them make better, more informed decisions [55, 57].

2.1.1 Components and Architecture

Healthcare DTs typically consist of several major components, each of which is critical to keeping the digital version synchronized with the real world one in real time: (i) *Physical Entity* is a real-world counterpart, such as a patient, medical device, or hospital infrastructure. (ii) *Virtual Model*: A digital replica of a physical object. It is built from a computational model that could mimic real-world states, behaviors, and possible outcomes. (iii) *Data Acquisition Layer*: This part is responsible for collecting data from sources such as IoT devices, wearables, medical sensors and electronic health records (EHRs). It continuously acquires data and updates the virtual model [23, 55]. (iv) *Data Integration and Processing*: Here, the collected data is processed and combined. AI and ML and other technologies can help transform this data into useful insights and predictions. (v) *Simulation and Analytics Engine*: This is where the system analyzes data and performs simulations. It allows healthcare professionals to test different scenarios, such as how a treatment might work, how a disease might progress or how a patient might react. [14]. (vi) *Feedback Loop*: This connection allows information to flow back and forth between the real world and the digital world in both directions. It helps to keep

all information up to date in real time, allowing participants to act quickly on feedback from the system [50, 55].

Typically, the architecture of healthcare DT is also presented in the form of hierarchical levels, with each level being responsible for the management and processing of data at different period in the system workflow:

Layer 1. Data Acquisition: Where real-time data is gathered from sources like IoT devices, sensors, and EHRs.

Layer 2. Data Processing: Clean, categorize, and combine data collected from different sources into useful, actionable information.

Layer 3. Virtual Representation: DT models are constantly updated with incoming data to reflect real-world occurrences, then simulate conditions and behaviors.

Layer 4. Simulation and Feedback: This layer runs simulations to predict possible changes. The results of the simulations help guide decision-making and are fed back into the healthcare system again.

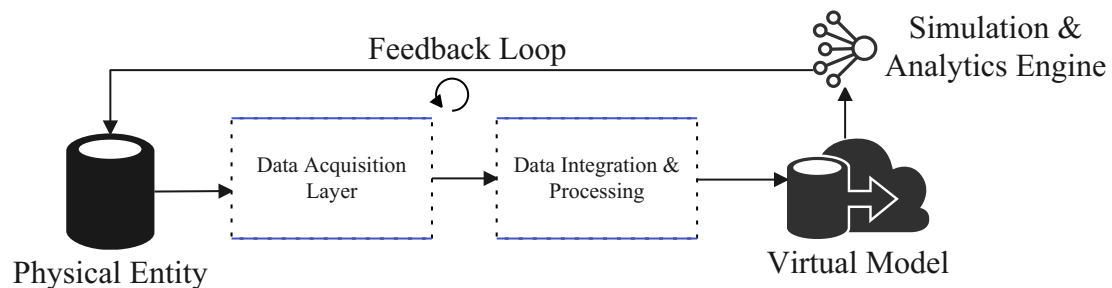


Figure 2. Cyclical Workflow of the DT System

Figure 2 illustrates the cyclical nature of a DT system. The system collects, processes and analyzes real-time data from the physical world, then sends back predictions and feedback to help improve the way things work in the real world.

2.1.2 Digital Twin Applications in Healthcare

DTs have found many applications in the healthcare sector and offer innovative approaches to healthcare system operations.

Personalized Medicine: One of the prominent uses of DT in healthcare is personalized medicine. By using real-time data, a patient’s medical history, and even genetic information, DTs can simulate patient-specific health scenarios. This helps to choose the appropriate treatment plan, reducing side effects. For example, in cardiovascular care, physicians can model a DT of a patient’s heart to predict the effects of potential surgeries and fine-tune treatment plans [55].

Predictive Diagnostics: DT work relies on data, so this data-driven approach enables predictive analytics in a certain degree. For example, the ability to detect disease

progression early and facilitate timely intervention. For chronically ill patients, DT can monitor them over time to predict complications such as heart failure or respiratory problems, enabling patients to manage themselves proactively and reducing the likelihood of emergency treatment [23].

Hospital Management: Hospital management can employ DTs to streamline workflow and resource allocation. Enabling tracking equipment usage, simulating patient flow, and predicting resource shortages by creating a digital replica of the hospital setting helps to identify operational bottlenecks in hospitals early and improve overall efficiency [23].

Medical Device Management: DTs are also applied to medical devices, to be able to track the operational status of these devices. For example, DTs take real-time data from devices such as imaging machines or surgical robots, which can help identify potential problems before a malfunction occurs. This makes it easier to plan ahead for equipment maintenance and reduces the chance of problems in critical processes [14].

Medical Training: DTs give healthcare professionals a safe, hands-on way to train in nearly realistic scenarios, like simulating complex surgeries and emergencies, allowing medical students and medical staff to practice and improve their decision-making skills without putting actual patients at risk [55].

Briefly, DTs are already having a positive effect on healthcare. These applications demonstrate DTs' capabilities in helping improve the way healthcare is delivered [52].

2.2 Healthcare Systems

The healthcare system is a broad concept encompassing treatment, clinical practice, and medical technology to provide healthcare services. It covers everything from patient care to hospital administration and then to general public health programs, and plays a vital role in maintaining the health and well-being of communities.

2.2.1 Domains and Applications of Healthcare Systems

The healthcare system addresses many critical areas of both medicine and public health, some of which are listed below.

Health Monitoring: Ongoing health monitoring has become an important part of modern healthcare, and the popularity of wearable devices like smart bands has made it easy for the masses to track their health data by enabling real-time tracking of vital signs such as heart rate, blood pressure, and oxygen saturation. Healthcare providers may now remotely observe patients using wearable devices, IoT, and remote monitoring platforms. This makes early intervention easier and significantly lowers hospital readmission [20].

Surgical Procedures: Surgical procedures have been transformed by developments in intraoperative navigation, robotic surgery, and imaging technologies. Surgeons can now perform minimally invasive procedures with greater precision, which means patients recover faster, and the outcomes are typically better [8].

Hospital Management: Using a smart hospital management system can help organize workflow and make better use of resources. Hospitals can use digital tools to plan staff shifts, manage supplies, keep track of bed availability, and ensure that operations run smoothly, even in hectic settings [31].

Chronic Disease Management: The healthcare system is crucial to the management of chronic diseases like diabetes, hypertension, and cardiovascular diseases. Physicians can track a patient's health over time and modify treatments if needed by collecting and analyzing data with the aid of digital tools. In this way, patient compliance improves, and thus their health tends to improve [16].

Emergency Response: For emergency medicine situations, the healthcare systems can rely on rapid response protocols, real-time data analysis, intelligent triage tools, and more to ensure that patients receive the correct treatment in time. And the technology like telemedicine can allow remote experts to intervene in diagnosing and guiding the treatment of these emergency cases, thereby further enhancing the overall quality of medical services [19].

2.2.2 Technological Integration in Healthcare Systems

The introduction of advanced technology has indeed changed the way healthcare work is done; now, healthcare work is more efficient, accurate, and people have easier access to medical services. The following are some potential technologies that can complement the healthcare system.

Artificial Intelligence (AI) is one of the most popular technologies nowadays, and AI tools can be utilized in healthcare systems that can mine big data sets, identify patterns, predict disease outcomes, and assist in diagnosis. For example, AI models can be used to analyze and detect early signs of cancer from imaging data [57].

Internet of Things (IoT) connects various elements of healthcare systems, from patient monitors to hospital infrastructure, ensuring smooth data flow and improving decision-making capabilities [18].

Electronic Health Records (EHRs) centralize patient information, offering a comprehensive overview of medical histories and enabling seamless coordination among healthcare teams. This reduces unnecessary testing and ensures continuity of care [6].

Telemedicine can significantly extend the coverage of medical services so that patients do not have to travel far to acquire expert treatment. This has proven particularly useful in global health emergencies such as the COVID-19 pandemic.

The healthcare system is crucial in treating individual illnesses and overall health, preventing disease, and addressing public health challenges. By integrating and utilizing these innovations, healthcare providers can respond more effectively to emerging challenges while delivering more comprehensive care.

2.3 Blockchain

Blockchain is a decentralized, distributed, and immutable ledger system that records transactions between multiple computers, using cryptographic methods and consensus mechanisms to ensure that data is secure, transparent, immutable, and easy to track. While blockchain was initially used for cryptocurrencies, it is now used in various applications such as finance, supply chain, and healthcare [2].

Blockchain excels in security, reliability, and effectiveness because it is built on a few basic principles. *(i) Decentralization*: Instead of a central authority managing everything, blockchain decentralizes control to a peer-to-peer network and reduces the chance of having a single point of failure or attack. *(ii) Immutability*: Once data is recorded on the blockchain, it cannot be changed or deleted, helping to ensure the integrity and trustworthiness of the data. *(iii) Transparency*: Transactions can be tracked by any participant with access, making it easier to hold parties accountable [25].

Data on a blockchain is stored in “blocks” that are linked sequentially to form a “chain”. Each block contains several key elements: a list of transactions with timestamps, its own unique hash value, and the hash value of the previous block. Such a structural setup makes it easy to detect any unauthorized attempts to tamper with data, helping to keep the system secure.

2.3.1 Blockchain Types and Platforms

Blockchain is a pillar of many decentralized systems that want to make transactions secure and transparent. To better understand how blockchain technology works and the application areas, it is helpful to first understand the main types of blockchains and the platforms built upon them [40, 53].

Blockchain Types Blockchain networks are generally categorized into two main groups based on access control and governance structure. **Permissionless Blockchains** are open to all, allowing unrestricted access to a public network where anyone can join, verify transactions, and maintain the network, which also means everything is transparent. Bitcoin (BTC) and Ethereum (ETH) are typical examples. Transactions are secured using consensus mechanisms like Proof of Work (PoW) and Proof of Stake (PoS). Permissionless blockchain is widely used in cryptocurrencies, Decentralized Finance (DeFi), and public Decentralized Applications (DApps) [40]. **Permissioned Blockchains**, on the other hand, allow only approved participants to join and interact with the network. This setup provides more control, better privacy protection, and smoother operations for the particular. Therefore, this type of blockchain is especially suitable for organizations that require data confidentiality and restricted access to nodes. Examples include Hyperledger Fabric (HLF) and Corda, which are commonly used in enterprise environments, including industries such as healthcare, finance, and supply chain [53].

Blockchain Platforms Several blockchain platforms have been developed, each built to meet the different needs of various industries.

Ethereum, a public network that stands out for its powerful smart contract capabilities, allowing developers to build DApps. As Ethereum migrates to Ethereum 2.0 and moves to a PoS system, Ethereum is working to improve its scalability and efficiency, thus it is extensively applied in DeFi, supply chain tracking, and even healthcare, especially for secure data sharing and automation of complex processes [1, 37, 49].

Hyperledger Fabric (HLF) is a permissioned blockchain tailored for enterprises. HLF uses a modular architecture and is channel-based to keep transactions between specific parties private. It is particularly valuable for applications in industries such as finance, healthcare, and logistics, where privacy, efficiency, and regulatory compliance are critical [37, 38].

Corda is another well-known permissioned blockchain that is intended for use by financial institutions and businesses. It ensures that transactions are only disclosed to appropriate parties, enhancing privacy and minimizing data redundancy. It is ideal for businesses like trade finance, cross-border payments, and managing legal contracts [38].

EOS is known for its high performance, scalability, and low transaction costs. It utilizes a Delegated Proof of Stake (DPoS) system, which allows for high throughput, making it ideal for large-scale projects such as gaming applications, social media platforms, and more [54].

Stellar is a public blockchain designed for cross-border financial transactions. It is designed for fast, affordable, and secure international transactions, and its native token, Lumens (XLM), facilitates easy access to financial services. Therefore, Stellar is particularly suitable for small transactions, remittances, and some financial institutions [1].

Integrating Blockchain Types and Platforms The choice of blockchain technology should be based on specific application requirements. Public blockchains such as Ether and Stellar are suitable for open, decentralized environments, and in such scenarios, the transparency and accessibility of the system are particularly important. In contrast, Permissioned chains such as HLF and Corda are better suited for enterprise applications that emphasize privacy protection, permission control, and compliance requirements. Given that Ethereum has powerful smart contract capabilities and can effectively support DApps, it is adopted as the blockchain platform in this study.

2.3.2 Applications in Healthcare

Blockchain technology has shown a vast potential for application in the healthcare sector, especially in data sharing and supply chain management, with significant advantages. On the one hand, blockchain enables secure and controlled sharing of healthcare data, helping healthcare organizations exchange information while safeguarding patient privacy and complying with regulations [17]. On the other hand, its tamper-evident recording

mechanism supports the full-process tracking of pharmaceuticals and medical devices, which helps to counter counterfeiting and improve supply chain transparency and quality control [10]. In addition, blockchain has shown practical application value in clinical trial data management, health insurance claims automation, and many others, undoubtedly benefiting the healthcare system.

2.3.3 Enhancing DTs with Blockchain

Integrating blockchain technology into DTs provides several key enhancements, significantly improves the functionality and reliability of these virtual models. A significant advantage is enhanced data security. Blockchain ensures that the real-time data feeding into DTs is secure, maintaining the information accuracy and integrity of the information [2]. Another important benefit is auditability. Blockchain provides an immutable record of changes made to the DTs, facilitating easy tracking and tracing. Considering the healthcare sector, integrating blockchain and DTs has considerable potential to drive innovation in healthcare, and the synergy of the two technologies can facilitate more reliable and transparent healthcare practices.

3 Systematic Literature Review

Though DTs have massive potential in healthcare, their implementation brings challenges, especially in data privacy and system interoperability. Solving these issues requires a comprehensive understanding of DTs' components and the approach that blockchain can enhance their functionality.

This section supports RS1 by addressing RQ1: *What are the key components of DTs in healthcare?* and RQ2: *How is blockchain being used in Healthcare DTs?* Through an SLR [27], the study identifies the core requirements of DTs and examines how blockchain can be applied to enhance their capabilities. The findings can inform the subsequent design of the proposed DT framework.

3.1 Review Questions

This review focuses on RQ1 and RQ2, while offering insights relevant to other research stages. We refined the questions and formulated four specific literature review questions (LRQs). More specifically, the SLR is guided by these four key questions that contribute to a comprehensive understanding of DT in healthcare.

- **LRQ1.** Which use cases apply DT in healthcare?
- **LRQ2.** What are the key components of DTs in healthcare?
- **LRQ3.** What limitations are discussed related to HDT?
- **LRQ4.** How has blockchain been used with DT?

LRQ1 Identifies the use cases where DTs are applied in healthcare, providing insights into practical scenarios and their relevance. This helps inform the framework's applicability and supports selecting relevant use cases for implementation and validation.

LRQ2 Focuses on identifying the core component issues of HDT, directly addresses RQ1 and lays the foundation for designing a functional and interoperable framework.

LRQ3 Investigates the limitations and challenges associated with implementing DT in healthcare. Addressing this question can help identify research gaps and refine the goals and design of the framework.

LRQ4 Examines how blockchain is integrated with DTs in healthcare. This question helps address RQ2 by finding out how the blockchain enhances the effect of HDT.

3.2 Data Sources and Search Strategy

We conducted an SLR in four major academic databases, including the ACM Digital Library, IEEE Xplore, ScienceDirect, and SpringerLink. The selection of these sources is due to the broad coverage of high-quality peer-reviewed literature related to computer science and health sciences. ACM Digital Library and IEEE Xplore focus on DT, IoT, and blockchain from a computing and engineering perspective, while ScienceDirect and SpringerLink include more articles from the health sciences.

Next, a search strategy is formulated to comprehensively identify relevant literature about DTs in healthcare and focus on integrations with blockchain. The following list of search strings is established to obtain relevant literature on this topic, overlaying these topics to provide as comprehensive coverage as possible.

```
((("Digital Twins" OR "Digital Twin" OR "DT")
AND
("Healthcare" OR "Health Care" OR "Health Systems")
AND
(("Blockchain" OR "Distributed Ledger" OR "DLT") OR (" ")))
```

This query structure ensures a prime focus on the intersection of DTs and healthcare, with the optional inclusion of blockchain-related terms. Parentheses around "blockchain" keywords are set to allow flexibility in adjusting the search scope to specific research needs. To further increase search recall and precision, common synonyms, and acronyms are included in the query statement, such as "Digital Twins" – "DT"; "Healthcare" – "Health Systems"; similarly, blockchain is often referred to as "Distributed Ledger Technology (DLT)" and the string encompasses this as well.

In addition, the search strings for each database are slightly adjusted to account for differences in search syntax. The process of searching will then proceed, and the literature will be screened based on explicit inclusion and exclusion criteria to ensure that the selected studies are highly relevant to the LRQs of this review.

The **Inclusion Criteria (IC)** prioritizes recent research on applying DTs in healthcare, focusing on studies incorporating blockchain to capture the latest advances and research trends. The selected papers focus on DTs as frameworks or systems designed to improve healthcare outcomes, particularly in core components, real-world use cases, and blockchain integration, ensuring a comprehensive understanding of current methodologies and supporting the design guideline of the proposed framework.

The **Exclusion Criteria (EC)** are intended to ensure that this review focuses on peer-reviewed literature relevant to the topic. Therefore, early access (before 2018), conference abstracts, and book chapters are all excluded. Papers lacking a clear healthcare context or a substantive discussion of DT components and blockchain integration are also excluded since they provided limited relevant insights into answering LRQs.

As summarized in Table 2, four IC entries and five EC entries are defined to guide the screening process following the initial query.

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria (IC)	
IC1.	Utilizing DT for healthcare.
IC2.	Exploring DT use cases in healthcare.
IC3.	The paper should discuss the architecture and components of DT in healthcare.
IC4.	Discussing blockchain for HDT.
Exclusion Criteria (EC)	
EC1.	Published before 2018.
EC2.	Literature not in English.
EC3.	Literature is not freely available or accessible through university subscriptions.
EC4.	Non-peer-reviewed sources.
EC5.	Explicitly do not contain any information to answer LRQs.

Table 3. Literature Number after Initial Query

Database	Number of Literatures
ACM DL	329
IEEE Xplore	729
ScienceDirect	1,176
SpringerLink	1,650

Table 3 above shows that the initial query returned 3,884 articles after deleting duplicates. Thereafter, we applied a hybrid screening strategy based on established IC and EC. First, an initial screening is conducted using EC1 to EC4, to narrow the candidate to 1,706 articles. Subsequently, the remaining literature titles and abstracts will be examined per the IC. Lastly, EC5 is used for quick full-text screening, and 18 articles are eventually screened for SLR.

3.3 Data Extraction and Analysis

To address the LRQs, we used a structured approach to extract relevant data from selected papers, including collecting key metadata, concise summaries, and content highly related to the LRQs. Table 4 presents the data extraction format.

Table 4. Updated Data Extraction Form

Data Item	Description	Relevant LRQ(s)
Research Work, Year	Title and publication year of the research paper.	All LRQs
Healthcare Use Case	Specific healthcare domain or scenario where DT is applied.	LRQ1
Objective and Contribution	Objectives, goals, and main contributions of the research, such as advancing DT technology or exploring blockchain integration.	LRQ1, LRQ4
Key Components of DTs	Core elements of DT frameworks in healthcare.	LRQ2
Blockchain Applications	Specific roles of blockchain in DTs.	LRQ4
Challenges and Limitations	Identified challenges in DT and blockchain integration in healthcare.	LRQ3, LRQ4

The insights derived from the SLR serve as a foundational input for the subsequent stages of the DSR process. To systematically address the LRQs, we conducted a thematic analysis of the extracted data using a manual coding strategy. Each selected paper was examined based on a consistent set of attributes, including DT components, healthcare use cases, challenges, and blockchain involvement, as outlined in the data extraction above. These attributes were then grouped into analytical categories aligned with the LRQs. Recurring patterns, such as common DT architectures, application domains, and privacy-related concerns, were identified and compared across studies to support a cross-sectional synthesis. The complete extraction results are provided in Appendix II, including a statistical distribution of healthcare-related DT use cases (Figure 20), a detailed summary of all reviewed studies (Table 10), and an overview of blockchain integration approaches (Table 11).

3.4 Presentation of Results

LRQ1: Which use cases apply DT in healthcare?

The literature identifies several key application areas for DT in enhancing healthcare processes. Notable ones include personalized medicine, in which patient-specific virtual models can simulate treatment outcomes and disease progression, especially in cardiovascular care and oncology areas. By offering virtual replicas for the operation process, DT aids in surgical planning and simulation, lowering risk.

Additionally, DT can monitor patients in real time, manage hospitals, and optimize resource allocation. It has also been used in public health. These diverse use cases show that DT is crucial to advancing the healthcare system.

LRQ2: What are the key components of DTs in healthcare?

We recap the consensus of most studies and summarize the six core components of HDT, which create dynamic links between physical entities and their virtual counterparts. These include the physical entity, its virtual model, data acquisition, data transmission, data Processing and analytics, and feedback and control mechanisms. This architecture forms the basis of the HDT service, and a detailed explanation list is in the Section 4.

LRQ3: What limitations are discussed related to HDT?

Though DT has shown many advantages in healthcare, most of the papers recognized many of its limitations. A significant issue is interoperability, as integration across different healthcare systems is difficult due to the lack of standardized protocols. Data privacy is a critical issue, and DT relies on data that collects sensitive information that could be exposed to security flaws. In addition, DT relies on real-time data, but the computational demands of processing real-time, large-scale data pose an obstacle. Many DT solutions have not been validated in the real world; some are tested in controlled environments, while others are just in theory. Besides, scalability is the limitation that hinders the deployment of DT frameworks in complex healthcare ecosystems.

LRQ4: How has blockchain been used with DT?

The convergence of HDT and blockchain is mentioned in some literature, mainly resolving issues related to data security, among others. Blockchain enhances data integrity by protecting real-time streams and providing tamper-proof storage for sensitive health information. Additionally, smart contracts automate processes such as access control within DT systems, improving efficiency. It also supports decentralized data management, enables secure data sharing. Therefore, utilizing these features brought by blockchain enhances the reliability and scalability of the HDT system.

3.5 Answer to RQ1

RQ1: What are the key components of DTs in healthcare?

In response to RQ1, the SLR identifies six fundamental components for building effective healthcare DTs. These include (i) *Physical Entity*, which refers to the real-world object being replicated, such as patients, medical devices, or healthcare processes. This physical entity serves as the foundation for creating a virtual model; (ii) *Virtual Model* is the digital representation that simulates the physical entity's real-time behaviors, conditions, and outcomes; (iii) *Data Acquisition*, involves IoT-enabled sensors and other sources that continuously collect real-time data from the physical entity; (iv) *Data Transmission* technologies that maintain synchronization between the physical and digital environments; (v) *Data Processing and Analytics*, involves AI, ML, and other methods to extract valuable insights, predict outcomes, and enable complex simulations; (vi) *Feedback and Control*, mechanisms allow the system to provide real-time interventions and adjustments. Together, these components form the foundation for creating dynamic and responsive HDTs.

3.6 Answer to RQ2

RQ2: How is blockchain being used in Healthcare DTs?

In response to RQ2, blockchain is integrated with HDT to enhance its security and system functionality. Blockchain supports a decentralized ledger structure, ensuring that each interaction of the DT system is traceable and verifiable. And deploying smart contracts enables better automation and enhances system scalability. Blockchain supports cross-system sharing of controlled data while maintaining strict access control and improving interoperability. In short, blockchain integration transforms HDT into a more robust, trustworthy, and scalable system that is better equipped to meet the demands of the modern healthcare environment.

3.7 Summary

This section addressed the first two RQs by conducting an SLR to investigate the essential components of DTs in healthcare (RQ1) and examine the role of blockchain within such systems (RQ2). By formulating four focused LRQs, the study synthesized current research trends, identified practical use cases, and outlined the technical building blocks and prevailing challenges of HDTs. The analysis revealed a consistent set of core components for HDT architectures. It highlighted how blockchain enhances data security, integrity, and interoperability, establishing a foundation for the framework proposed in the following section.

4 Proposed Framework

Building on the results of the SLR in Section 3, while many studies have explored the application of DT and blockchain technologies in healthcare, there are still gaps in terms of practical integration and system design. Existing studies mostly focus on specific aspects, but few approaches provide integrated frameworks that support scalability.

To bridge these gaps, this section follows the DSR approach, corresponding to *RS3: Design and Development*, and introduces a blockchain-enabled DT framework tailored to the specific needs of healthcare systems. This section focuses on answering the *RQ3: How can digital twins be designed for healthcare systems?*.

4.1 Design Goals

The proposed framework addresses the critical challenges identified through the SLR and RQs. Specifically, it focuses on four design goals: (i) *Enhancing data security and privacy* by applying blockchain technologies to protect sensitive health information; (ii) *Supporting real-time monitoring and feedback* through dynamic, continuously updated Digital Twin models; (iii) *Ensuring scalability and interoperability* by developing a modular structure that allows easy integration with existing healthcare systems; and (iv) *Enabling clinical decision support* by embedding predictive analytics to assist healthcare professionals in making informed decisions.

These goals guide the structure of the proposed system and ensure that the integration of DT and blockchain technologies is practical, scalable, and aligned with healthcare needs. They build upon insights from RQ1 and RQ2, and directly address RQ3 concerning the design of integrated DT systems for healthcare.

4.2 Design Artifacts

Following the DSR methodology, this section presents the core design artifacts that support the development of the HDT framework. (i) *User Stories* capture stakeholder needs in a structured way, ensuring the framework addresses the perspectives of healthcare providers, patients, and administrators. (ii) *Use Cases* specify the main system functionalities and interactions, illustrating how users engage with the HDT system under different scenarios. (iii) *Conceptual Class Diagram* outlines the high-level structure of the framework, mapping key components and their relationships.

4.2.1 User Stories

We set up several user stories to capture stakeholder requirements and guide system design, as summarized in Table 5. Each story represents a specific interaction within the HDT framework, reflecting the needs and goals of different user groups.

Table 5. User Stories for the HDT Framework

ID	User Story	Goal
US-01	As a clinician, I want to remotely monitor patient conditions via their DTs, so that I can identify early warning signs and provide timely interventions.	Enhance patient monitoring and proactive treatment.
US-02	As a hospital administrator, I want to analyze DT data of hospital operations, so that I can optimize resource allocation and improve efficiency.	Reduce operational costs and enhance hospital management.
US-03	As a surgeon, I want to simulate complex surgeries using patient-specific DTs, so that I can improve precision and minimize surgical risks.	Improve surgical outcomes through simulation and planning.
US-04	As a medical researcher, I want to access anonymized patient DTs, so that I can conduct predictive analytics and improve disease diagnosis models.	Enable data-driven research and predictive healthcare.
US-05	As a physiotherapist, I want to track patient rehabilitation progress using DT motion analysis, so that I can adjust recovery programs dynamically.	Improve rehabilitation outcomes through AI-driven feedback.

4.2.2 Use Cases

The use cases summarized in Table 6 define the core functionalities of the HDT framework. They capture key system interactions and behaviors as a foundation for system operations and align the framework with real-world healthcare scenarios. Each use case is detailed in Appendix IV (from Table 12 to Table 16).

4.2.3 Conceptual Class Diagram

We build a conceptual class diagram that provides a high-level abstraction of the HDT system, outlining the main entities and their relationships. It is represented as an object-oriented structure, which is outstanding for modularity and scalability. And as shown in Figure 3, entities are organized to promote adaptability across different applications.

Table 6. Summary of Use Cases

ID	Use Case	Summary Description
UC-01	Smart Patient Room with DT Monitoring	Real-time monitoring of patient vital signs, movement, and environmental factors, with automatic adjustments and alerts for anomalies.
UC-02	DT-Assisted Preoperative Planning	Simulation of surgical procedures using patient-specific DTs to optimize precision and anticipate risks.
UC-03	Intensive Care Unit (ICU) Risk Prediction and Early Intervention	AI-driven prediction of critical ICU events based on real-time patient data to enable early clinical interventions.
UC-04	DT-Based Drug Interaction Simulation	Simulation of drug interactions and side effects tailored to individual patient profiles, supporting safer medication planning.
UC-05	Remote Rehabilitation Monitoring with DTs	Continuous tracking of rehabilitation progress via DT motion analysis and AI-driven feedback.

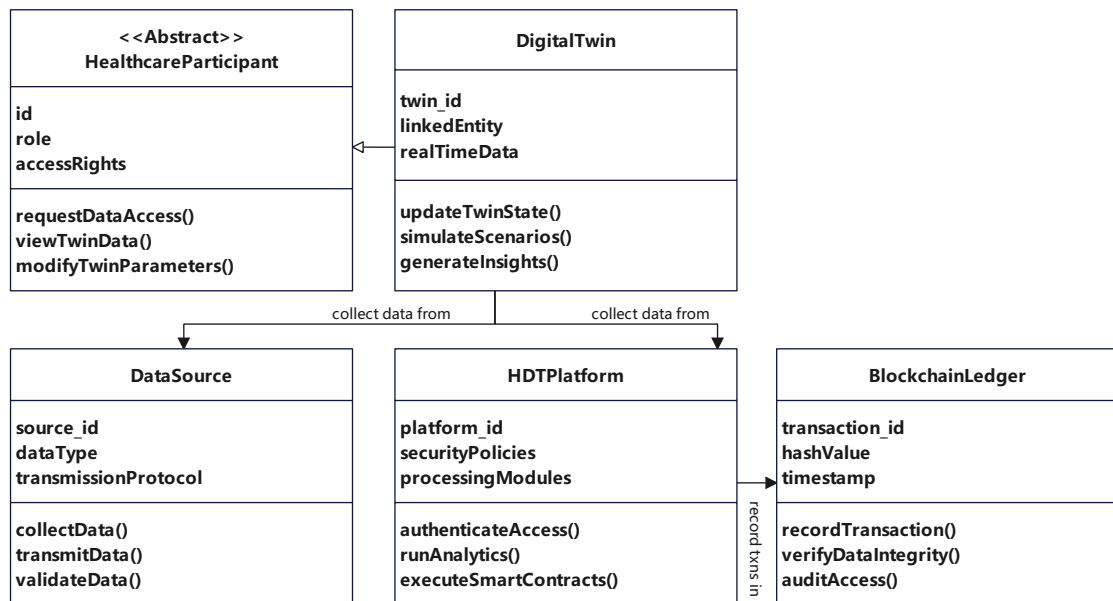


Figure 3. Conceptual HDT Class Diagram

4.3 Architecture Overview of the HDT Framework

The proposed HDT framework introduces a scalable and secure architecture. Unlike static models, it establishes a real-time, bidirectional link between physical healthcare entities—patients, devices, and workflows—and their digital counterparts.

The architecture is organized into four interconnected layers: the *Physical and Perception Layer* for data collection, the *Infrastructure and Communication Layer* for secure transmission and processing, the *Digital Twin Processing and Analytics Layer* for model creation and predictive analysis, and the *Interaction and Decision Support Layer* for delivering insights to users. This layered structure enables continuous synchronization between physical operations and digital models, and a detailed description of each layer and its workflow is provided below.

4.3.1 HDT Four-Layer Architecture

The HDT framework is organized into four interconnected layers:

1. **Physical and Perception Layer**

This layer captures real-world healthcare data from patients, medical staff, infrastructure, and the environment. Sources include IoT-enabled wearables (e.g., smart bands), hospital assets (e.g., robotic surgical systems, automated beds), and environmental sensors (e.g., air quality monitors). Data acquisition may occur through continuous or event-driven mechanisms, with edge computing applied for preliminary processing to reduce latency.

2. **Infrastructure and Communication Layer**

It is mainly responsible for secure data transmission, storage, and processing. For instance, blockchain ensures data integrity, while cloud and decentralized storage solutions provide scalability. Edge computing and high-performance computing (HPC) support real-time analytics and complex simulations. And the newest network (e.g., 5G/6G) enables seamless data exchange, with interoperability protocols ensuring system-wide compatibility.

3. **DT Processing and Analytics Layer**

This core layer constructs and updates DTs using real-time data. AI-driven analytics support predictive modeling, diagnostics, and workflow simulations. Integrated feedback mechanisms enable actionable insights and automated responses.

4. **Interaction and Decision Support Layer**

This layer provides interfaces for stakeholders. For example, clinicians can access DT visualizations and make decisions, patients receive personalized dashboards, and administrators utilize analytics for hospital management. Real-time alerts and

automated workflows support clinical interventions, while blockchain audit logs ensure data transparency.

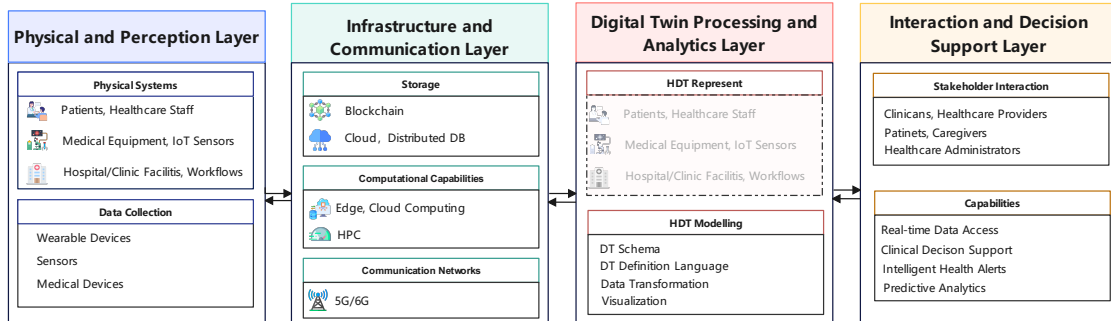


Figure 4. HDT Architecture

Each layer contributes to seamlessly integrating physical healthcare operations with digital models. As illustrated in Figure 4, the architecture enables the integration of different technologies as demanded.

4.3.2 Workflow of the Architecture

The workflow of the proposed HDT system ensures continuous control of how DT processes data across all architectural layers. It operates through four main phases, as shown in Figure 5 and the text below.

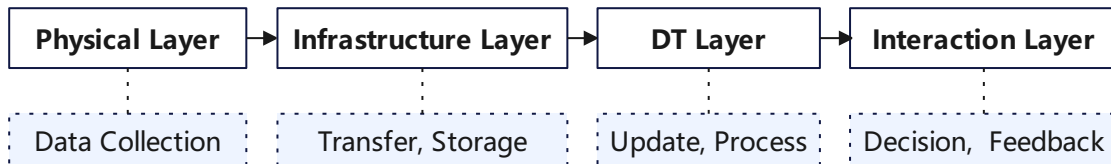


Figure 5. Workflow of the HDT Architecture

Phase 1 – Data Collection (Physical Layer → Infrastructure Layer) Sensors, medical devices, and other monitoring tools capture raw data. Before transmission, edge computing nodes help perform preliminary filtering and encryption.

Phase 2 – Data Transmission and Storage (Infrastructure Layer) The filtered data is securely transmitted to cloud platforms, blockchain networks, and distributed storage systems. HPC and AI models can process the incoming information, preparing it for further analysis.

Phase 3 – DT Updates and Processing (DT Layer) The processed data updates the corresponding data-driven models to ensure that DTs accurately reflect changes in the real world. AI-driven analysis can also be used to generate predictive insights and decision recommendations based on the latest information.

Phase 4 – Decision Support and Feedback (Interaction Layer) Healthcare participants receive real-time alerts, reports, and recommendations. Automated responses, such as modifying treatment plans, are triggered based on predictive insights.

4.4 Framework Component

The HDT framework extends the overall architectural design and is built on six key components: physical entities, virtual models, data acquisition, data transmission, data processing and analysis, and feedback and control. These components are consistent with the findings of SLR in Section 3 and the answers in **RQ1**, addressing the core challenges of healthcare digitization.

Rather than revisit the detailed definitions of each component, this section focuses on their integration within the four-tier architecture described in Section 4.3. As shown in Figure 6, the component diagram maps each element to its corresponding architectural layer, highlighting their interactions and roles in the system. The framework is based on three guiding principles: modularity, extensibility, and interoperability, ensuring flexible configuration and seamless integration with a wide range of healthcare technologies.

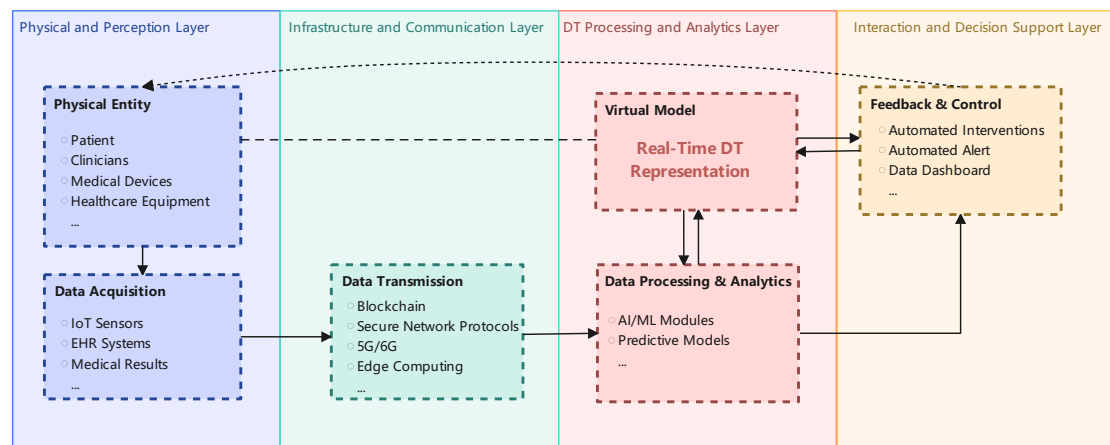


Figure 6. Components of the HDT Framework

4.5 Answer to RQ3

RQ3: How can DTs be designed for healthcare systems?

Designing DTs for healthcare requires a layered and component-driven approach that addresses the medical environment's dynamic, sensitive, and complex nature. The proposed HDT framework adopts a four-layer architecture—Physical and Perception, Infrastructure and Communication, DT Processing and Analytics, and Interaction and Decision Support—that organizes system functionalities in a structured way. Building on this architecture, six core components (Physical Entity, Virtual Model, Data Acquisition, Data Transmission, Data Processing and Analytics, and Feedback and Control) can be built according to needs and work together.

In addition to structural design, practical implementation demands attention to security, scalability, interoperability, and compliance. The HDT framework should be a comprehensive blueprint for developing healthcare-oriented DTs, enabling DTs to accurately represent physical entities, and actively supporting the process of healthcare delivery improvement.

4.6 Summary

This section addresses RQ3 by presenting a blockchain-enabled DT framework tailored to healthcare systems. The framework demonstrates how DTs can be structured to ensure security, interoperability, and real-time decision support through defined design goals, user stories, use cases, and a four-layer architecture. Integrating core components into a modular and scalable design provides a practical foundation for implementing DTs in complex healthcare environments.

5 Proposed Framework Implementation

This section presents the implementation of the proposed HDT framework, following the DSR methodology—RS4: Demonstration. The aim is to validate the conceptual design through a practical healthcare use case, and answers RQ4.

The implementation integrates IoT sensors for real-time monitoring, constructs HDT models using Microsoft Azure Digital Twins (ADT), and incorporates blockchain technology for data security. By using actual hardware components, cloud DT services, and the blockchain network, the system demonstrates the feasibility of applying the HDT framework in real-world healthcare environments.

5.1 Selected Use Case – Smart Patient Room

A smart patient room scenario is selected to demonstrate the practical application of the HDT framework. The specific implementation of this use case includes using IoT-based sensors to monitor patients' vital signs and ward conditions, building a complete visual DT model in the ADT platform, combining blockchain technology to ensure data integrity, and providing an AI-enabled dashboard to visualize real-time data and obtain recommendations. The following subsections detail the justification for selecting this use case, its system design, and the corresponding workflow within the HDT framework.

5.1.1 Use Case Justification

The smart patient room is selected as the use case because it is close and consistent with real-world healthcare scenarios and is easy to implement. Monitoring patient vital signs and room conditions through IoT sensors is a feasible scenario that can be implemented in a prototype setting. This choice can demonstrate the capabilities of the HDT framework in real-time data integration, system interaction, and decision support without introducing excessive complexity.

In addition, the smart patient room provides an easily manageable environment for testing key aspects like continuous monitoring, anomaly detection, and secure data management. In contrast with large-scale healthcare scenarios, it provides a centralized and controllable setting. Therefore, selecting this use case is meaningful for framework validation as it satisfies real-world scenarios and technically feasible environments.

5.1.2 Use Case Description

We name the prototype "Smart Patient Room Monitoring System", which represents a practical application of the HDT system. It uses IoT-enabled sensors to collect real-time data on patient vitals and room conditions. These data streams continuously update the

DT model, enabling dynamic patient and room condition monitoring and automated alerts when anomalies are detected.

This use case (UC-01-HDT-POC) is an extended implementation of UC-01 introduced in Section 4.2.2, refined to integrate anomaly detection, AI-embedded suggestions, and secure data management via blockchain. The detailed system interactions, actors, and workflow are provided in Appendix III (Table 17).

5.1.3 Use Case Diagram

Figure 7 presents the use case diagram for the smart patient room, capturing the main system functions and illustrating the core interactions among key actors: the patient, clinician, smart hospital infrastructure, and the HDT system.

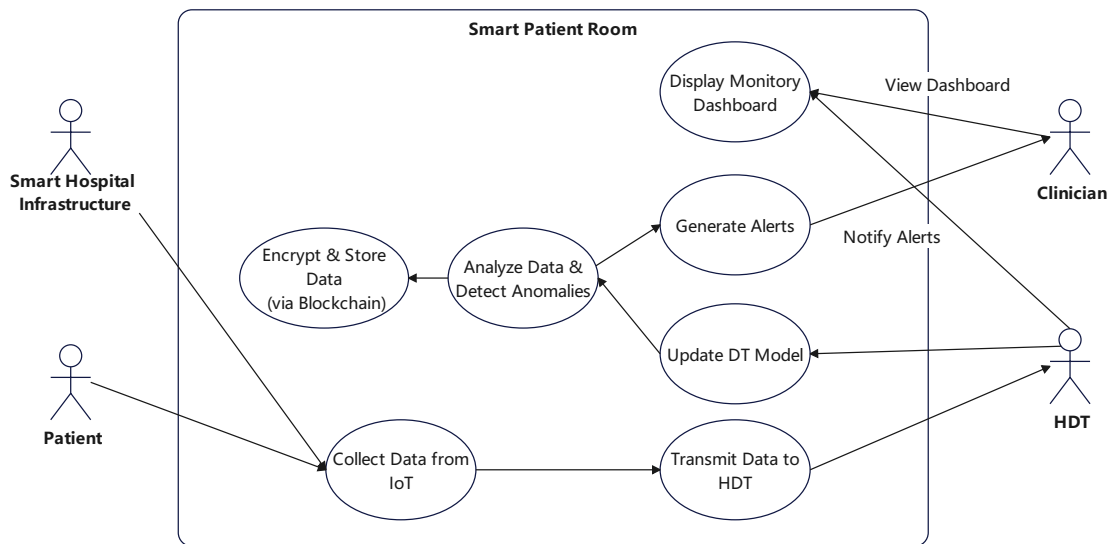


Figure 7. Use Case Diagram of Smart Patient Room

5.2 Smart Patient Room HDT Design

The Smart Patient Room HDT is designed based on the proposed architecture and components in Section 4, which integrates patient health monitoring with real-time environmental data collection. It aggregates patient physiological metrics and hospital room environmental parameters into a unified digital representation.

Each patient is modeled through a Patient DT, capturing key indicators such as body temperature, heart rate, and blood oxygen levels. Similarly, the room is represented by a Room DT, monitoring temperature and humidity factors. These models are structured hierarchically, with child DTs handling specific measurements. Figure 8 illustrates the

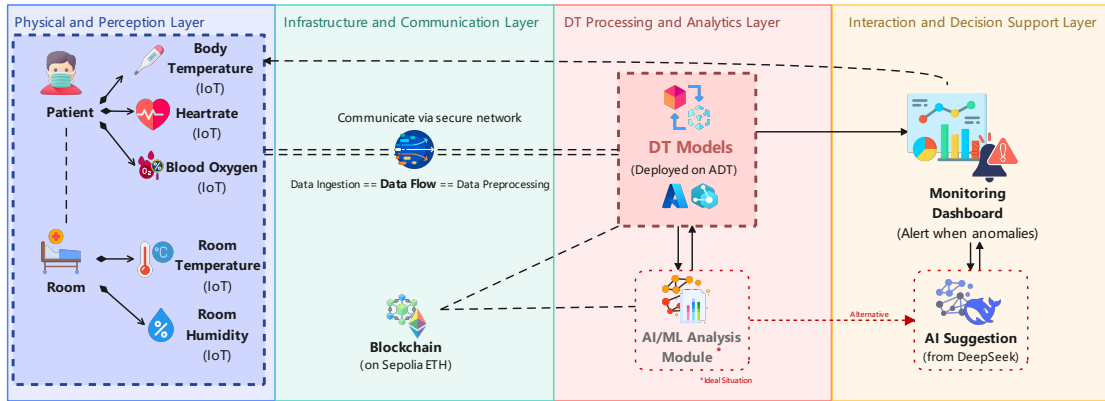


Figure 8. Smart Patient Room HDT Architecture

overall system architecture, showing how patient and room models interact to enable continuous monitoring and adaptive responses in real-time. It is also necessary to clarify that, though we have delineated a 4-tier architecture, the actual situation is that the components in each tier can adjust and deploy differently. Hence, the tier architecture is only a design reference rather than a strict constraint. For instance, as shown in the third and fourth layers in Figure 8, ideally, this prototype will be implemented by deploying a data analytics module with AI/ML in the DT Layer. However, Generative AI (GenAI) is introduced and deployed in Layer 4 as an alternative in the actual demonstration.

5.3 HDT Model Representation

Implementing the prototype requires a structured and extensible DT model. The DT can be defined using the Digital Twins Definition Language (DTD), a standardized modeling language for specifying entities, attributes, and relationships. Therefore, we use DTD to construct each entity, its attributes, and the relationships between different components within the system. We develop two core models per our requirements: the Patient DT model, the Room DT model, and their corresponding child models.

Patient DT Model It provides a dynamic digital patient representation by integrating critical health parameters. It captures static information, the patient's identity and diagnosis, and real-time physiological data through interconnected child DTs. Specifically, the temperature DT monitors changes in body temperature to support early detection of fever or hypothermia. Heart rate DT tracks heart rhythm to identify abnormalities such as tachycardia or bradycardia. Meanwhile, SpO₂ DT measures blood oxygen saturation, which is critical for recognizing respiratory conditions such as hypoxia.

Room DT Model Complementing patient DT, it models the patient room environment to support patient recovery. By continuously monitoring environmental parameters, the Room DT helps maintain conditions conducive to recovery. The child DTs include Room Temperature DT, which tracks temperature conditions to ensure patient comfort, and Room Humidity DT, which monitors humidity levels to prevent adverse health effects associated with air quality.

Here, we show an abstract representation of the DT relationships as Figure 9, demonstrating the structure of the entire HDT and its relationships. The DTDL code for the Patient DT and the Room DT can be found in Appendix V (Listing 2 and 3), where complete DTDL including child DT models is available in GitHub repository (Repo).

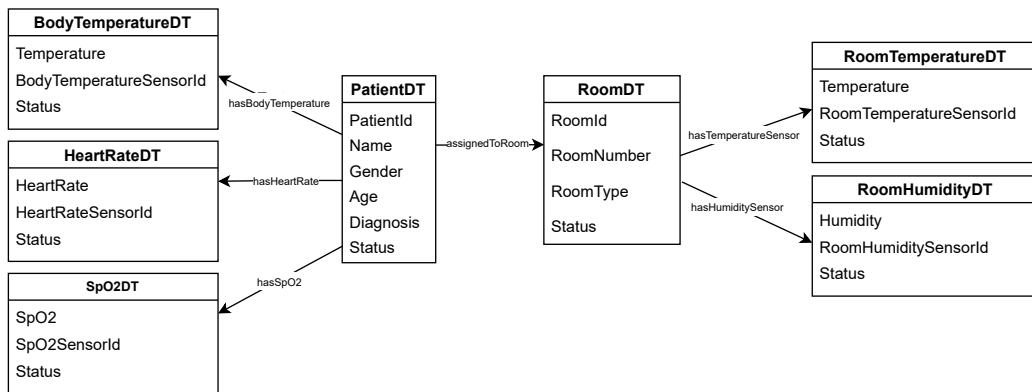


Figure 9. Overview of HDT Models

5.4 IoT Setting

To realize the data collection for the HDT prototype implementation, an IoT-based sensing system is developed, employing the Arduino Mega 2560 as the central microcontroller unit (MCU). This setup enables real-time data acquisition from multiple sensors monitoring patient vital signs and environmental conditions within the "Smart Patient Room" setting.

The Arduino Mega 2560 is chosen for its abundant General-purpose input/output (GPIO) pins and multiple serial communication interfaces, making it ideal for multi-sensor integration. The system incorporates a MAX30102 module for pulse oximetry and heart rate monitoring, a MAX30205 sensor for precise body temperature measurement, and an AM2320 digital sensor for environmental temperature and humidity. An OLED12864 display (based on the SSD1306 driver) provides immediate visualization of collected sensor data. Communication uses the Inter-Integrated Circuit (I²C) protocol to connect multiple modules efficiently, while serial ports are reserved for debugging and potential system expansions.

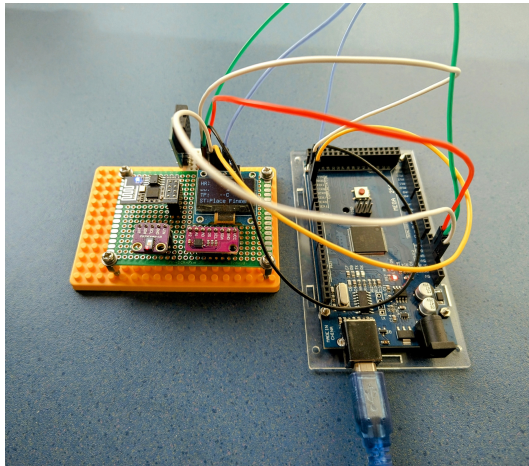


Figure 10. IoT System Setting

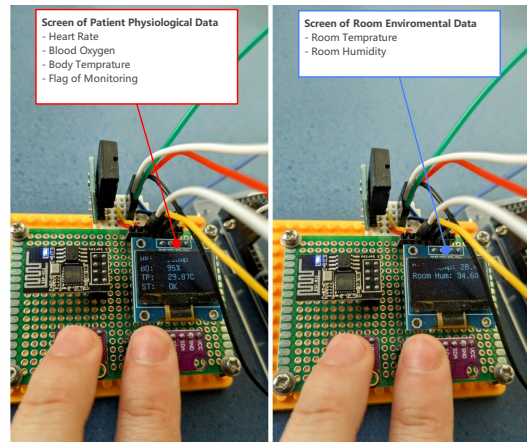


Figure 11. IoT Screen Visualization

Figure 10 and Figure 11 show the physical IoT deployment and real-time display. Moreover, the concrete hardware connections are summarized below in Table 7.

Table 7. IoT Components Connection

Pin	Function	Connected Modules
3.3V	Power Supply	Other 3.3V Modules
5V	Power Supply	MAX30102, MAX30205, AM2320, OLED12864
GND	Ground	Common Ground for All Modules
18 (TX1)	Serial Communication	External Debugging/Modules
19 (RX1)	Serial Communication	External Debugging/Modules
20 (SDA)	I ² C Data Line	MAX30102, MAX30205, AM2320, OLED12864
21 (SCL)	I ² C Clock Line	MAX30102, MAX30205, AM2320, OLED12864

The MCU preprocesses raw sensor data before transmission to the HDT system, where it updates the patient and room DT models in ADT. The OLED display allows local, immediate feedback on vital signs during operation. In short, this IoT setup is the physical foundation for the smart patient room use case, and its firmware code for data acquisition and transmission is in the project's Repo.

5.5 Data Ingestion

After the deployment of the IoT sensor infrastructure, the next step involves establishing a reliable pipeline for transferring real-time sensor data into the HDT system, that is, the ADT platform. This process is known as data ingestion, which is essential for synchronizing physical entities and their corresponding digital models.

Python scripts are developed in this implementation to collect sensor readings from the Arduino-based IoT setup and stream the data into ADT. The ingestion scripts handle data parsing, transformation, and secure transmission to update the real-time DT models.

5.5.1 IoT Data Ingestion

The IoT data ingestion component captures, processes, and integrates real-time sensor data streams into the ADT platform. In our implementation, Arduino-based sensors collect critical patient biometrics (heart rate, SpO₂, body temperature) and environmental parameters (room temperature, humidity). The ingestion pipeline uses Python scripts that establish serial communication with IoT sensors at a predefined baud rate. Incoming sensor data is parsed using regular expressions to extract numeric values from each data packet. These values are then structured into JSON objects containing timestamps, sensor IDs, and corresponding measurements.

Executing scripts to update each sensor's digital twin via the ADT software development kit (SDK) and the ADT Application Programming Interface (API), ensuring real-time synchronization between physical sensors and their virtual counterparts. The communication enables immediate reflection of state changes in the digital environment. The pipeline incorporates error handling and logging mechanisms to maintain data integrity and detect anomalies. We implemented preliminary blockchain integration for data encryption as an additional security measure. The sensor data and sensor ID object notation files are periodically encrypted, with encryption keys tracked via Secure Hash Algorithm 256-bit (SHA-256) hashes anchored to the Ethereum Sepolia. Further details about blockchain-based tamper-proof provenance are discussed in Section 5.6.

The complete implementation of this IoT data ingestion pipeline is outlined in Procedure 1, with source code available in the Repo.

Procedure 1: IoT Data Ingestion

Data: Incoming sensor data stream

Result: Updated ADT, encrypted data file, and storage of the encryption key hash on Ethereum blockchain

1 Initialization:

2 Load environment variables and import required libraries;

3 Initialize ADT CLI;

4 Initialize Web3 client and smart contract for Ethereum Sepolia network;

5 Configure serial port and baud;

6 Initialize global aggregated data list;

7 **while** *program is running* **do**

8 **if** *data available on the serial port* **then**

9 | Read a line from the serial port;

10 | **if** *line matches expected format* **then**

11 | | Parse data into {HeartRate, SpO₂, BodyTemperature, Flag,
12 | | RoomTemperature, RoomHumidity};

12 | | **Evaluate Sensor Status:**

13 | | Determine sensor statuses using evaluation functions;

14 | | **Update ADT:**

15 | | Update sensor values and statuses using DT update functions;

16 | | Update overall patient and room status;

17 | | **Aggregate Data:**

18 | | Construct a record with timestamp, sensor data, and sensor IDs;

19 | | Append record to the global aggregation list;

20 | **else**

21 | | Prompt data parsing failed;

22 | **if** *30 seconds have elapsed since last aggregation* **then**

23 | | **Process Aggregated Data in a New Thread:**

24 | | 1. Copy and clear the global aggregation list;

25 | | 2. Save the aggregated data to a JSON file;

26 | | 3. Encrypt the JSON file using AES-GCM and save as an encrypted file;

27 | | 4. Retrieve sensor unique IDs from ADT and form a sensor ID string;

28 | | 5. Compute SHA256 hash of the encryption key;

29 | | 6. Store the key hash on the Ethereum blockchain via the smart contract;

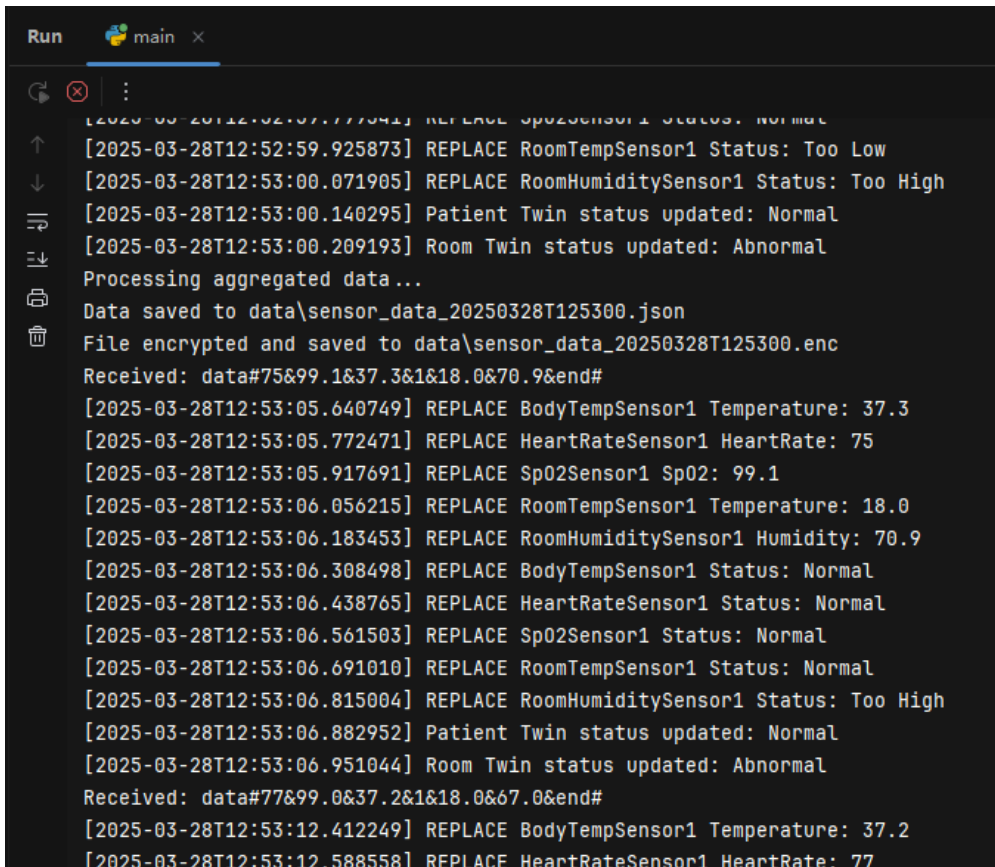
30 | | Reset the aggregation timer;

31 | Wait for a defined read interval (5 seconds);

5.5.2 DT Visualization in ADT Explore

The designed DT models are first deployed to ADT. The deployment process involves registering the DTDL models into the ADT instance using the Azure CLI and SDK. It defined each twin's schema, properties, and relationships, establishing the foundation for dynamic data synchronization.

Once the models are registered, the IoT sensor data streams are mapped to corresponding twin properties in the ADT. Real-time updates to vitals and room parameters are reflected immediately within the digital environment. Also, anomaly detection or status changes at the sensor level would automatically trigger updates for the associated patient or room twin. Visualizations are done through Azure Digital Twins Explorer (ADT Explorer), a built-in graphical interface. This tool enables viewing live telemetry data associated with each DT, navigating relationships between entities, such as the link between a patient twin and its assigned room twin. We can also manually query and update twin properties to validate ingestion logic.



```
Run main x
[2025-03-28T12:52:57.777841] REPLACE SpO2Sensor1 Status: Normal
[2025-03-28T12:52:59.925873] REPLACE RoomTempSensor1 Status: Too Low
[2025-03-28T12:53:00.071905] REPLACE RoomHumiditySensor1 Status: Too High
[2025-03-28T12:53:00.140295] Patient Twin status updated: Normal
[2025-03-28T12:53:00.209193] Room Twin status updated: Abnormal
Processing aggregated data...
Data saved to data\sensor_data_20250328T125300.json
File encrypted and saved to data\sensor_data_20250328T125300.enc
Received: data#75&99.1&37.3&1&18.0&70.9&end#
[2025-03-28T12:53:05.640749] REPLACE BodyTempSensor1 Temperature: 37.3
[2025-03-28T12:53:05.772471] REPLACE HeartRateSensor1 HeartRate: 75
[2025-03-28T12:53:05.917691] REPLACE SpO2Sensor1 SpO2: 99.1
[2025-03-28T12:53:06.056215] REPLACE RoomTempSensor1 Temperature: 18.0
[2025-03-28T12:53:06.183453] REPLACE RoomHumiditySensor1 Humidity: 70.9
[2025-03-28T12:53:06.308498] REPLACE BodyTempSensor1 Status: Normal
[2025-03-28T12:53:06.438765] REPLACE HeartRateSensor1 Status: Normal
[2025-03-28T12:53:06.561503] REPLACE SpO2Sensor1 Status: Normal
[2025-03-28T12:53:06.691010] REPLACE RoomTempSensor1 Status: Normal
[2025-03-28T12:53:06.815004] REPLACE RoomHumiditySensor1 Status: Too High
[2025-03-28T12:53:06.882952] Patient Twin status updated: Normal
[2025-03-28T12:53:06.951044] Room Twin status updated: Abnormal
Received: data#77&99.0&37.2&1&18.0&67.0&end#
[2025-03-28T12:53:12.412249] REPLACE BodyTempSensor1 Temperature: 37.2
[2025-03-28T12:53:12.588558] REPLACE HeartRateSensor1 HeartRate: 77
```

Figure 12. Console Log of Real-Time Data Updates

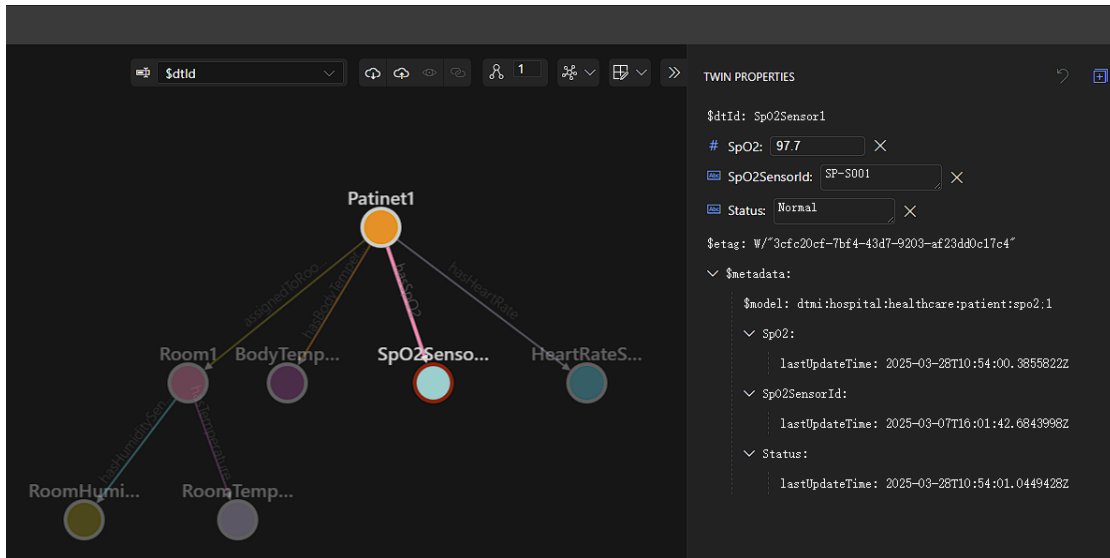


Figure 13. Twins Graph Visualization in ADT Explorer

Figure 12 displays a console log capturing real-time updates of patient vitals and room conditions as received from the IoT layer. Figure 13 shows the twins graph rendered in ADT Explorer, highlighting the relationships among patients, rooms, and individual sensor components.

5.6 Blockchain Integration

This section describes the blockchain-based security module, which strengthens data integrity, confidentiality, and transparency for the HDT. By leveraging the Ethereum Sepolia testnet, the encryption key is stored immutably on-chain. Solidity smart contracts, Hardhat deployment tools, and Python-based interaction scripts achieve it.

5.6.1 Smart Contract Deployment

The security mechanism centers on the smart contract, in *DataKeyStorage* case, designed to record the SHA-256 hash of encryption keys generated during IoT data aggregation. This contract is written in Solidity, extending OpenZeppelin's Ownable standard and restricting key storage operations to the contract owner, further enhancing security.

The `storeEncryptionKey` function records a sensor ID and corresponding key hash while emitting a `KeyStored` event for auditability. The key-value mappings offer transparent, tamper-proof verification for all encrypted datasets. The concrete smart contract is shown as Listing 1.

```

1 // SPDX-License-Identifier: MIT
2 pragma solidity ^0.8.0;
3 import "@openzeppelin/contracts/access/Ownable.sol";
4
5 contract DataKeyStorage is Ownable {
6     mapping(string => bytes32) private keyStorage;
7     uint256 public keyCount;
8
9     event KeyStored(string indexed sensorId, bytes32 keyHash, uint256
    ↪ timestamp);
10
11     constructor() Ownable(msg.sender) {}
12
13     function storeEncryptionKey(string memory sensorId, bytes32
    ↪ keyHash) external onlyOwner {
14         keyStorage[sensorId] = keyHash;
15         keyCount++;
16         emit KeyStored(sensorId, keyHash, block.timestamp);
17     }
18
19     function getEncryptionKey(string memory sensorId) external view
    ↪ returns (bytes32) {
20         return keyStorage[sensorId];
21     }
22 }

```

Listing 1. Solidity Code for DataKeyStorage Smart Contract

Deployment is handled via the Hardhat framework, using an Infura Remote Procedure Call (RPC) endpoint to connect to Sepolia. Private keys and API tokens are secured via environment variables. Successful contract deployment is confirmed and verified on an ETH block explorer platform- Etherscan, as shown in Figure 14.

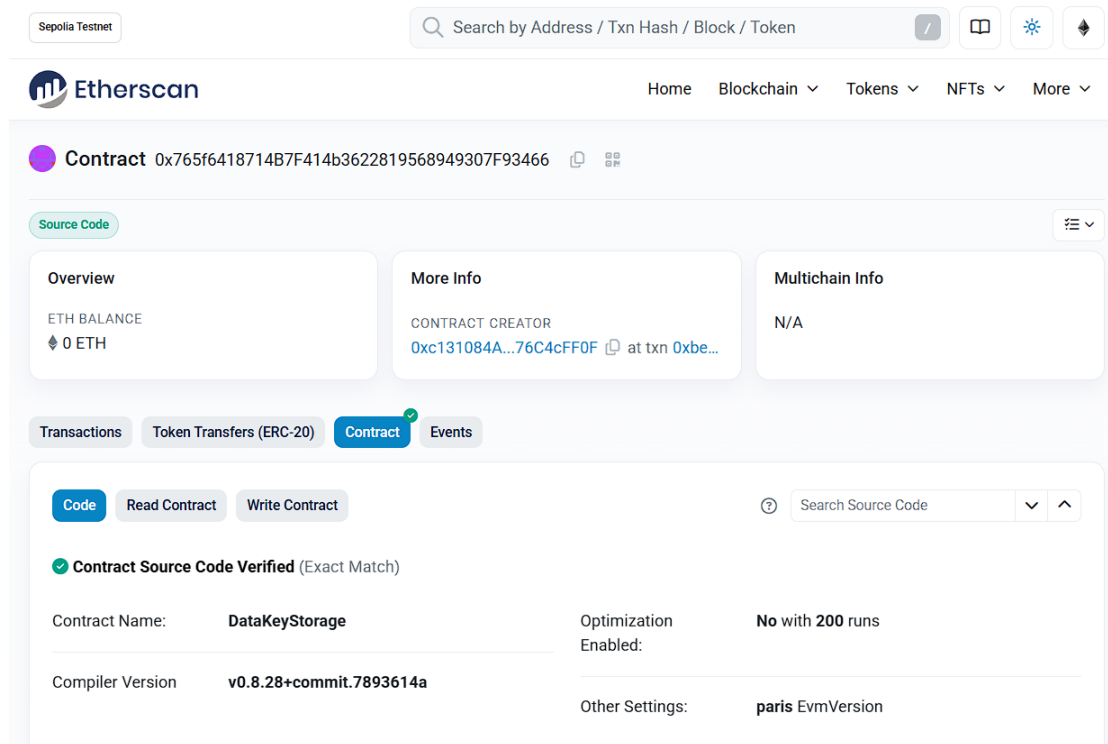


Figure 14. Contract Deployment Verified on Sepolia Etherscan

5.6.2 Encryption and Blockchain Storage

Our system employs a hybrid security approach, combining local encryption with blockchain verification. After data aggregation, each sensor batch undergoes AES with Galois/Counter Mode (AES-GCM) encryption with a dynamically generated key. The system stores the encrypted data locally while recording cryptographic verification elements on-chain. The process of the encryption and anchoring on the block follows a specific cryptographic protocol, as the Procedure 2 illustrates, code is stored on the Repo.

Procedure 2: Sensor Data Encryption and Blockchain Integration

Data: Aggregated sensor records from IoT devices

Result: Locally encrypted data with blockchain-anchored verification

- 1 Generate cryptographically secure 256-bit AES key;
 - 2 Apply AES-GCM encryption to the serialized sensor JSON;
 - 3 Persist encrypted file (.enc) alongside its encryption key file (.key) locally;
 - 4 Derive SHA-256 hash from the encryption key;
 - 5 Establish connection to Ethereum Sepolia testnet;
 - 6 Transmit key hash via `storeEncryptionKey(sensorId, keyHash)`;
 - 7 Verify transaction completion and log confirmation hash;
-

This setting creates a security boundary where sensitive encryption keys remain isolated on trusted devices while cryptographic fingerprints are immutably recorded on-chain. It enables independent validation of data integrity without exposing the underlying cryptographic material. Figure 15 demonstrates the successful implementation of this verification mechanism, including console output and Etherscan verification.

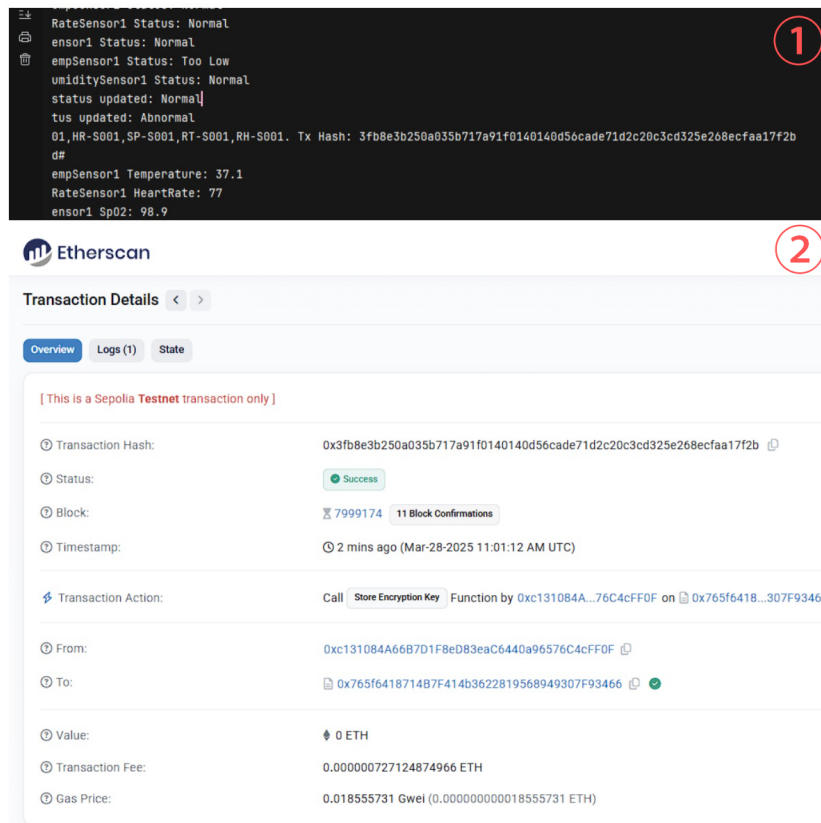


Figure 15. ① Console Output and ② Transaction Verification on Etherscan

5.6.3 Encryption Verification Protocol

To maintain cryptographic integrity throughout the data lifecycle, we implemented a comprehensive verification protocol that spans local and blockchain domains. This protocol establishes a multi-tiered validation framework, as in Procedure 3 (code is available in the Repo).

Procedure 3: Cross-Domain Cryptographic Verification Protocol

Data: Encrypted datasets, source JSONs, transaction indices

Result: Cryptographic integrity report with audit trail

```
1  foreach sensor dataset do
2      Retrieve {originalJSON, encryptedFile, encryptionKey};
3      Perform AES-GCM decryption on encryptedFile;
4      Validate decryption integrity against originalJSON;
5      Extract corresponding blockchain transaction identifier;
6      Query Sepolia network for transaction payload;
7      Decode transaction input parameters to isolate keyHash;
8      Compute local SHA-256 fingerprint of encryptionKey;
9      Assert equality: blockchainKeyHash == localKeyHash;
10     Record validation status with timestamps and identifiers;
11 Generate comprehensive audit report with verification metrics;
```

Figure 16 demonstrates the protocol's output during a verification sequence. In summary, this hybrid verification approach provides three critical security guarantees (i) *Local Cryptographic Integrity* confirms that encryption operations preserve data fidelity through full-cycle verification. (ii) *Blockchain Correspondence* establishes a cryptographic linkage between local encryption keys and their immutable on-chain representations. (iii) *Complete Audit Trail* creates a verifiable record connecting sensor identifiers, temporal metadata, and blockchain transaction receipts. In other words, this hybrid approach bridges traditional cryptographic techniques with blockchain's tamper-evident properties, ensuring data authenticity without requiring trust in centralized authorities. The audit trail created through this process enables independent verification by third parties while preserving the confidentiality of the underlying sensor data, increasing the overall security of the HDT system.

```

== Structured Files Hierarchy ==

project_root/
├─ blockchain_tx_map.json
│   └─ # Transaction mapping
├─ data/
│   └─ # Segregated data directory
│       ├── sensor_data_20250425T013117.enc
│       │   └─ # AES-GCM encrypted sensor data
│       ├── sensor_data_20250425T013117.json
│       │   └─ # Original serialized JSON
│       └── sensor_data_20250425T013117.key
│           └─ # Encryption key material

```

1

TRANSACTION ACTION

Call `Store Encryption Key` Function by `0xc131084A...`

`0x765f6418...307F93466`

[This is a Sepolia Testnet transaction only]

Transaction Hash:
`0x2939a3f68a6e65b683bc5d3bf58b2a516d0bc82438248f`

Status: Success

Block:
8188770 25960 Block Confirmations

Timestamp:
3 days ago (Apr-24-2025 10:31:24 PM UTC)

From:
`0xc131084A66B7D1F8eD83eaC6440a96576C4cFF0F`

To:
`0x765f6418714B7F414b3622819568949307F93466`

```

File 1 - Verifying: sensor_data_20250425T013117
Decryption matched JSON
Blockchain keyHash matched transaction input
Matched transaction hash: 2939a3f68a6e65b683bc5d3bf58b2a516d0bc82438248bffc1e6f566c080a79

=== Verification Summary ===
Total files verified: 1
Passed: 1
Failed: 0

```

3

Figure 16. Multi-domain Verification Process
 (① Encrypted Data, ② Etherscan Verification; ③ Console Output)

5.7 Feedback and Analysis Module

Real-time data collection and digital modeling are essential components of the HDT framework, and enabling actionable insights is also critical. The Feedback and Analysis Module is designed to transform continuous DT data streams into intuitive feedback and practical decision support, which is in Layer 4 of this HDT. This module integrates two core elements: a dynamic dashboard that visualizes real-time patient and room conditions and an AI-based analysis tool that provides data-driven recommendations.

5.7.1 Dashboard

The HDT Dashboard delivers an interactive and intuitive interface, significantly enhancing the interpretability of real-time patient data and environmental conditions within the smart patient room scenario. Implemented with web technologies and Python’s Eel framework for seamless Python-JavaScript integration, the dashboard continuously retrieves and displays the latest DT states from ADT.

Clinicians with authentication can access this structured graphical user interface (GUI) dashboard, displaying patient details, room status, and sensor measurements. Besides, the dashboard can evaluate overall system statuses, automatically activating visual alerts when abnormal or critical conditions arise. By distinguishing normal and abnormal statuses through clearly marked user interface (UI) elements, the dashboard ensures clinicians can rapidly recognize and respond to emerging healthcare events.

To clearly illustrate the functionality and usability of the HDT Dashboard, screenshots capturing critical aspects of the interface, including patient information cards, environmental monitoring panels, sensor data indicators, and alert systems, are provided, as shown in Figure 17. The visualizations validate our HDT framework’s practical implementation and underscore its value in clinical scenarios, promoting informed, timely, and effective patient care interventions.

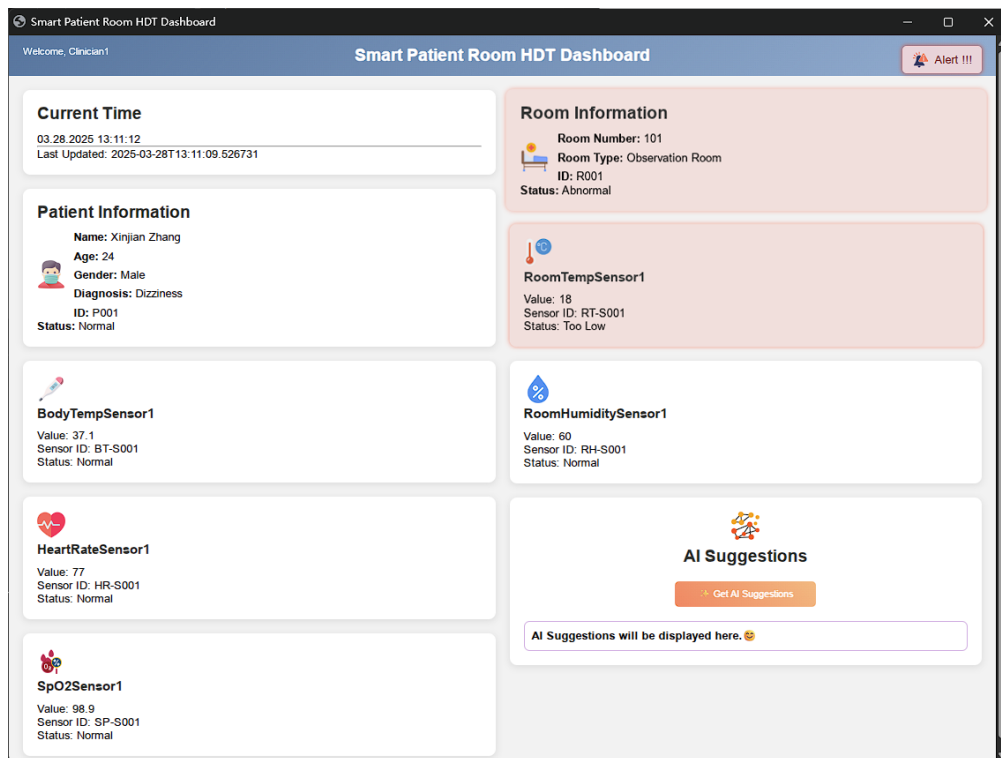


Figure 17. Smart Patient Room HDT Dashboard UI

5.7.2 AI-based Clinical Analysis

While visualization improves real-time clinical awareness, integrating intelligent analytics further amplifies the potential of DTs. To this end, an AI-based clinical suggestion engine was embedded into the HDT Feedback and Analyze Module. This engine, built upon the GenAI DeepSeek-v3 model (compatible with OpenAI's API standards), analyzes real-time DT data to generate concise, actionable clinical recommendations.

Upon user request, the module aggregates the latest patient vitals and room environmental parameters retrieved from ADT. These data points are composed into a structured clinical prompt containing demographics, diagnosis, sensor readings, and room conditions. This prompt is fed into the AI model, which returns a succinct recommendation following predefined syntax constraints to ensure clarity and relevance.

The backend uses a Python server-side script that handles ADT data acquisition and communicates with the DeepSeek API. Once the AI suggestion is generated, it is automatically integrated into the HDT Dashboard, as shown in Figure 18, providing clinicians with immediate, data-driven decision support. And the Procedure 4 indicates the core process of the dashboard and how AI works (code is available in Repo).

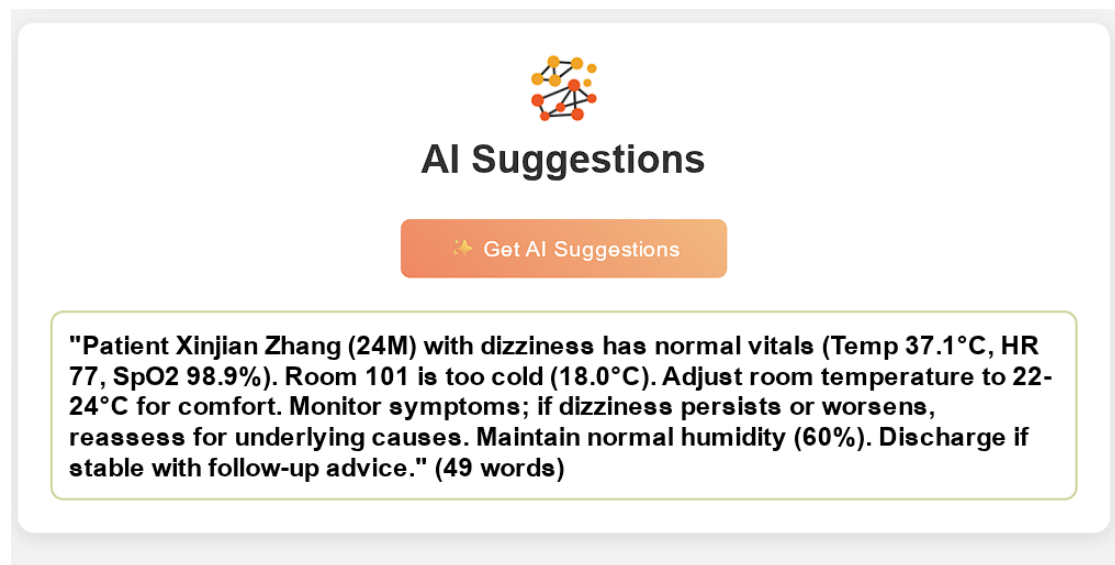


Figure 18. Real-Time AI Clinical Suggestions Integrated into HDT Dashboard

Procedure 4: DT Monitoring Dashboard and AI Clinical Suggestion

Data: User credentials, ADT configuration, Sensor mappings

Result: User authentication, aggregated ADT data, AI clinical suggestion

```
1 Load environment variables, fetch authentication info;
2 if ADT_INSTANCE_URL is missing then throw exception;
3 Initialize ADT client, DeepSeek API, and Eel web framework;
4 Map Twin IDs (Patient, Room, All Sensors);
5 Receive login request (username, password);
6 if credentials match then
7   | Set current_user; start session and data polling;
8 else
9   | Log failure; deny access;
10 Retrieve Patient and Room data via ADT client;
11 if retrieval successful then
12   | Parse info (Name, Age, Diagnosis, Status, etc.);
13 else
14   | Log error; set defaults;
15 foreach Sensor (BodyTemp, HeartRate, SpO2, RoomTemp, RoomHumidity) do
16   | Retrieve sensor data;
17   | if successful then
18     | Parse value and status;
19   | else
20     | Log error; set value=0, status="Unknown";
21 Set globalAlert to True if any status is non-"Normal";
22 Package all data with current timestamp;
23 Upon user request, construct a concise prompt from gathered data;
24 if prompt valid then
25   | Call DeepSeek-V3 API;
26   | if API call successful then
27     | Parse AI suggestion;
28   | else
29     | Log error; return error message;
30 Bind data to UI; refresh every 5 seconds; handle exceptions and log errors;
31 Upon shutdown, terminate sessions and free resources;
```

5.8 Answer to RQ4

RQ4: How can the proposed DT framework be implemented?

The proposed HDT framework is implemented via a complete system prototype centered on a realistic healthcare use case—the Smart Patient Room. Following the DSR methodology’s demonstration phase, the framework was validated in terms of sensing, modeling, analytics, and security dimensions.

At the Physical Layer, an Arduino Mega 2560 MCU is used to build an IoT network integrating biomedical and environmental sensors, enabling real-time acquisition of patient vitals and room conditions. These data streams are synchronized with ADT using standardized DTDL models to ensure structured, interoperable digital representations. A custom dashboard, developed with Python and web technologies, provided dynamic visualization and monitoring capabilities, while an AI-powered module, built on the DeepSeek model, generated real-time clinical suggestions based on the latest twin states. Besides, we introduced blockchain technology (Ethereum Sepolia testnet) to store cryptographic key hashes locally and on-chain, ensuring traceability and data integrity.

In short, this integrated implementation demonstrates the technical feasibility and practical value of the proposed HDT framework. It highlights the system’s ability to support real-time monitoring and intelligent feedback and its adaptability to meet healthcare-specific security, scalability, and operational requirements.

5.9 Summary

This section answers RQ4 by implementing the proposed HDT framework through a practical use case involving a smart patient room. The system integrated multiple components, including an Arduino-based IoT sensing layer for collecting patient vitals and environmental data, a structured DT model using ADT for real-time representation, a blockchain module to ensure data integrity through encrypted key storage and verification, and a feedback layer that combined a dynamic dashboard with AI-generated clinical suggestions. We demonstrate the feasibility of the HDT framework through this prototype, covering data acquisition, secure storage, system interaction, and decision support, and affirm its potential for real-world healthcare applications.

6 Evaluation

Evaluation is critical in validating the practicality and relevance of the developed artifact under the DSR guideline. As the proposed blockchain-enabled HDT framework remains at the prototype stage, the evaluation focuses on qualitative aspects, emphasizing usability, functionality, and real-world applicability in healthcare settings. Instead of rigorous quantitative performance testing, the goal is to assess how well the system meets practical needs, supports clinical workflows, and aligns with the research objectives.

6.1 Evaluation Criteria (for Interviews)

The following evaluation criteria are established as the foundation for guiding stakeholder interviews and structuring feedback in alignment with the RQs and the practical needs of healthcare users, covering technical performance and user experience. The selected criteria are summarized in Table 8.

Criterion	Description
Functionality	The ability of the system to perform its core tasks, including real-time biometric and environmental data capture, and secure blockchain integration.
Services	The effectiveness of functionalities such as real-time monitoring and predictive analytics in meeting healthcare users' needs.
Operations	The reliability and stability of system operations, including the robustness of data ingestion, twin updating, and alerting processes.
Usability	The intuitiveness and ease of use of the dashboard interface and the clarity of AI-generated suggestions for clinical decision-making.
Applicability	The framework's practical relevance, scalability, and potential for integration within real-world healthcare infrastructures.

Table 8. HDT Framework Evaluation Criteria

6.2 Semi-Structured Qualitative Interviews

We want to ensure a comprehensive evaluation, and the diverse participant pool can help capture a broad range of feedback, especially in the quantitative-only measurement. Thus, we select four participants with distinct backgrounds, each of whom is an essential stakeholder in the HDT's demand groups.

The participants included: (i) a *Medical Student*, offering clinical insight and decision-making perspectives; (ii) a *Computer Science Student*, evaluating technical functionality, usability, and feasibility; (iii) a *Nurse*, providing practical views on operational integra-

tion and daily clinical workflows; and (iv) a *Patient Representative*, reflecting end-user concerns related to data privacy, trust, and interaction comfort.

We conduct an evaluation methodology in a semi-structured qualitative interview approach. Hence, we can collect data systematically and explore participant insights flexibly. Each session, lasting approximately 10–20 minutes, is conducted individually in person or online. Before the interviews, participants are provided with a brief technical overview and a live demonstration of the HDT system workflow to ensure a shared understanding of the framework’s functionalities.

The interview protocol is structured around the evaluation criteria outlined in Section 6.1. Participants are guided through predefined questions designed to probe critical aspects mentioned before. The guiding questions are summarized in Table 9.

Criterion	Guiding Questions
Functionality	<ul style="list-style-type: none"> - Does the system accurately capture and reflect patient biometrics and environmental conditions? - Does blockchain integration enhance your trust in the system’s data security?
Services	<ul style="list-style-type: none"> - Are the real-time monitoring and predictive analytics features sufficient to support clinical or user needs? - Are there any functionalities you believe should be added or improved?
Operations	<ul style="list-style-type: none"> - Did you encounter any technical issues during system interaction? - Can you envision integrating this system smoothly into clinical workflows or daily healthcare routines?
Usability	<ul style="list-style-type: none"> - Is the user interface intuitive and easy to navigate? - Could you accomplish basic tasks without needing external guidance?
Applicability	<ul style="list-style-type: none"> - Do you see this framework as viable for real-world deployment in healthcare settings? - What practical challenges might arise during implementation?

Table 9. Interview-Based Guiding Questions

6.3 Interviews Results and Discussion

We summarize and analyze the feedback provided by the participants. This interview analysis showed that the participants gave a relatively positive evaluation of the HDT framework, especially its potential to improve the healthcare system. The medical student emphasized that the system helps to observe critical health indicators more easily. Still, accuracy cannot be guaranteed, and the decision support functions are very basic and do not meet clinical standards. The nurse similarly appreciated the interface’s simplicity, noting that it could be easily incorporated into daily routines. Still, she thought the prototype with limited functions was not enough to deploy in the real medical workflow,

and she suggested that richer alert mechanisms and integrated response actions would be necessary for real-world use. The computer science student acknowledged that the system prototype implements the basic requirements, the logic makes sense, and the workflow works. He approved the vision and technical feasibility of the HDT but expressed concerns about operational stability with larger data volumes and dependence on stable network conditions. Meanwhile, the patient representative initially had skepticism about data privacy, later acknowledging that the blockchain-based safeguards were reassuring after an explanation, although recommending more transparent explanations about how patient data is processed and stored.

The insights provided by participants emphasize the importance of enriching functionality and addressing user trust and operational clarity in future development; however, the overall assessment affirms the prototype's positive usability, technical feasibility, and clinical relevance. Detailed interview summaries and participant comments are provided in the Appendix V.

6.4 Answers to RQ5

RQ5: How can the proposed digital twin framework be evaluated?

Several options are put forward to evaluate the proposed HDT comprehensively; however, due to the implementation status of this prototype, it is evaluated via qualitative methods, specifically semi-structured interviews with stakeholders representing clinical, technical, and patient perspectives. The interviews are conducted after a simple demonstration of the HDT prototype. We record and analyze participants' feedback based on the metric-based questions to capture strengths and areas for enhancement.

This qualitative strategy proved effective at the prototype stage, offering user-centered insights that complement the quantitative performance measures. However, many systematic evaluations could complement this approach, such as usability testing using standardized metrics like the System Usability Scale (SUS) or simulation-based assessments under clinical scenarios, to validate the system more rigorously.

6.5 Summary

This section addresses RQ5 through semi-structured interviews with different stakeholders to evaluate the proposed HDT framework. We gathered insights on the system's usability, functionality, and practical applicability using predefined assessment criteria. Participants generally affirmed the framework's relevance and ease of use. They also pointed out limitations such as its early-stage maturity, limited functionality, and the need for more transparent data. We demonstrate the feasibility of the HDT framework through this prototype, including key functions such as data acquisition, secure storage, system interaction, and decision support, but acknowledge that continued improvements are necessary for practical implementation in healthcare.

7 Discussion

This section analyzes and interprets the results of the study and explores its theoretical and practical implications for the integration of DT and blockchain in healthcare, critically assesses the limitations encountered in the study and outlines potential directions for future research to enhance the applicability and robustness of the proposed framework.

7.1 Theoretical Implications

This research extends theoretical discussions on integrating DT and blockchain technologies within healthcare contexts. Existing literature often addresses these technologies separately or conceptually; this thesis, however, provides a tangible, operational model illustrating how DTs serve as real-time decision-support systems driven by live data. Regarding DT theory, this study extends the understanding of DTs beyond traditional simulation, emphasizing their role as intelligent tools.

In this study, blockchain is integrated into an HDT framework, which can provide theoretical insights into some feasible approaches to handling data, such as decentralized health information management. Specifically, smart contracts for data validation and traceability can address the key issues of trust, privacy, and data integrity prevalent in digital healthcare systems. The "data privacy" awareness aligns with recent scholarly calls advocating secure-by-design data governance approaches [28]. Besides, through iterative design and stakeholder-oriented evaluations, the practical application of the DSR methodology has shown that it is suitable as a structured practical approach for researching, including emerging healthcare technologies.

7.2 Practical Implications

From a practical perspective, the developed framework delivers immediate applicability in healthcare settings. The system provides a modular solution that is readily deployable and scalable by combining IoT sensors, cloud-based DT models, blockchain-enabled security measures, and a visualization dashboard.

The "Smart Patient Room" showcases the practical effects of this approach. It enables continuous monitoring of patients and clinical alerts when needed, helping healthcare professionals make the correct decisions at critical moments, and applies to various healthcare scenarios. Sensitive data is secured during synchronization and storage, which not only safeguards privacy but also meets the compliance requirements of the healthcare industry. Furthermore, the modular design further indicates potential for broader adoption beyond healthcare. With minor adaptations, similar DT-based systems could be effectively implemented in other scenarios, for example, the predictive maintenance in industrial settings, reflecting scalability in line with Industry 4.0 principles [35].

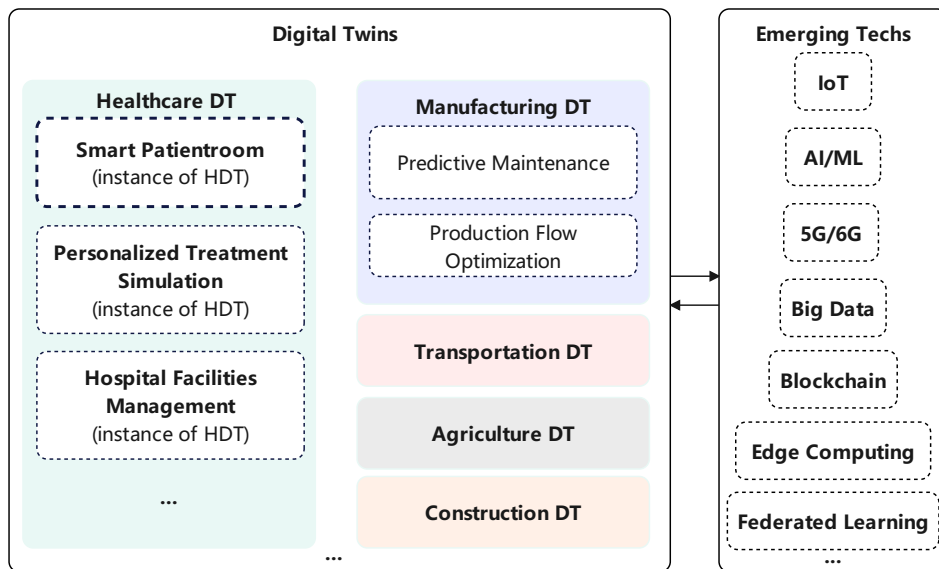


Figure 19. Widespread Application of DTs

Figure 19 highlights this broader context, depicting digital twins as part of an interconnected ecosystem alongside supporting technologies such as IoT, AI, blockchain, and edge computing. This research offers a validated prototype and a replicable blueprint for integrating DTs enhanced by blockchain and real-time analytics, and the HDT models developed in this study thus provide a practical reference for other sectors exploring secure and integrated digital solutions.

This study proposed and implemented a blockchain-enabled DT framework for healthcare. While the prototype validates technical feasibility within a smart patient room scenario, limitations remain regarding depth, scale, and system maturity. This section critically reflects on these limitations and outlines future directions that address identified gaps and enhance the framework's applicability.

7.3 Limitations

In the process of designing, implementing, and evaluating this HDT prototype, we encountered a number of constraints and challenges. The system was developed in a simplified, laboratory-like setting using low-cost microcontrollers and consumer-grade sensors. While adequate for proof-of-concept validation, these components fall short of clinical standards in terms of accuracy, robustness, and data integrity. In addition, the AI-based module depends on external APIs rather than in-house models trained on domain-specific datasets, limiting its clinical relevance and reliability.

Second, while blockchain integration successfully demonstrates encryption key traceability, its application is narrowly scoped to periodic key-hash logging on the Ethereum

Sepolia testnet. Broader implemented functionalities such as access control, consent management, and transaction verification are still in a fundamental stage. Additionally, issues like transaction latency and scalability are not addressed—critical challenges for time-sensitive systems like DTs in healthcare [28, 47].

Third, the evaluation is constrained in both scope and depth. Although the interviews with four participants offered diverse perspectives, the number of participants and the coverage of questions were insufficient to generalize findings. Moreover, the prototype lacks integration with production-level infrastructures, such as Health Level 7 (HL7) Fast Healthcare Interoperability Resources (FHIR)-compliant EHR systems [3], and does not consider edge cases like emergency response or regulatory audits. Finally, issues like data governance, long-term system resilience, and full-lifecycle interoperability are only partially explored.

7.4 Future Work

Future development should focus on transitioning from a research prototype to a deployable system. Technically, this includes upgrading hardware to clinical-grade sensors, supporting medical interoperability standards like HL7 FHIR, and integrating with hospital IT systems. Blockchain functionality should include permissioned ledgers such as Hyperledger Fabric or Corda, enabling granular access control, efficient transaction processing, and compliance with General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) [26, 58].

On the analytics side, replacing generic API-based suggestions with in-house AI/ML modules trained on longitudinal healthcare datasets would significantly improve diagnostic and predictive capabilities. This could involve incorporating time-series models, anomaly detection, and federated learning approaches for privacy-preserving computation [32, 56]. System architecture should also support edge computing and hybrid cloud deployments to optimize latency and scalability in real-world environments.

Evaluation should evolve toward a mixed-methods approach. Alongside interviews, future work should collect quantitative metrics such as SUS, alert response time, and model accuracy. Testing should involve broader user groups—clinicians, administrators, and IT specialists—over extended periods to evaluate reliability under varied operational conditions [34]. Due to the modular nature of this framework, in the future, this framework could also be extended to other domains, such as manufacturing and agriculture, to further promote the digital transformation of these industries [35].

8 Conclusion

This thesis proposed and demonstrated a blockchain-enabled Digital Twin (DT) framework tailored for healthcare applications. Guided by the Design Science Research (DSR) methodology, the study addressed integrating real-time patient monitoring, data security, and decision support into a coherent, modular system. A functional prototype was implemented using a Smart Patient Room case, combining IoT sensing, Azure Digital Twins (ADT), and Ethereum-based blockchain logging. The system was evaluated qualitatively through interviews with representative users, showing that the core concept is technically viable and positively received despite functional and scalability limitations.

It was shown that DTs can extend beyond static digital representations to function as dynamic, actionable models for healthcare monitoring. Additionally, blockchain was demonstrated as a lightweight and transparent solution for securing and verifying sensitive health-related data. Although the prototype system was implemented in a simplified environment, it did successfully validate the feasibility of the overall architecture while revealing limitations and also development opportunities in terms of technical performance, system compatibility, and user trust.

The thesis contributed a practical example of how emerging technologies like DTs and blockchain can be integrated to support secure and responsive digital health services. The proposed framework is a foundation for future research and system development to realize more scalable, interoperable, and intelligent healthcare infrastructures.

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Appendix

I. Resources

Code Repository <https://github.com/Xinjian-Zhang/healthcare-dt>

Demo Video <https://www.youtube.com/watch?v=UAMNaFfy3y4>

The demo video illustrates the complete workflow of the Smart Patient Room HDT implementation, including IoT device setup, ADT model construction, blockchain-based data operations, real-time dashboard visualization, and AI-assisted feedback.

II. SLR Extraction

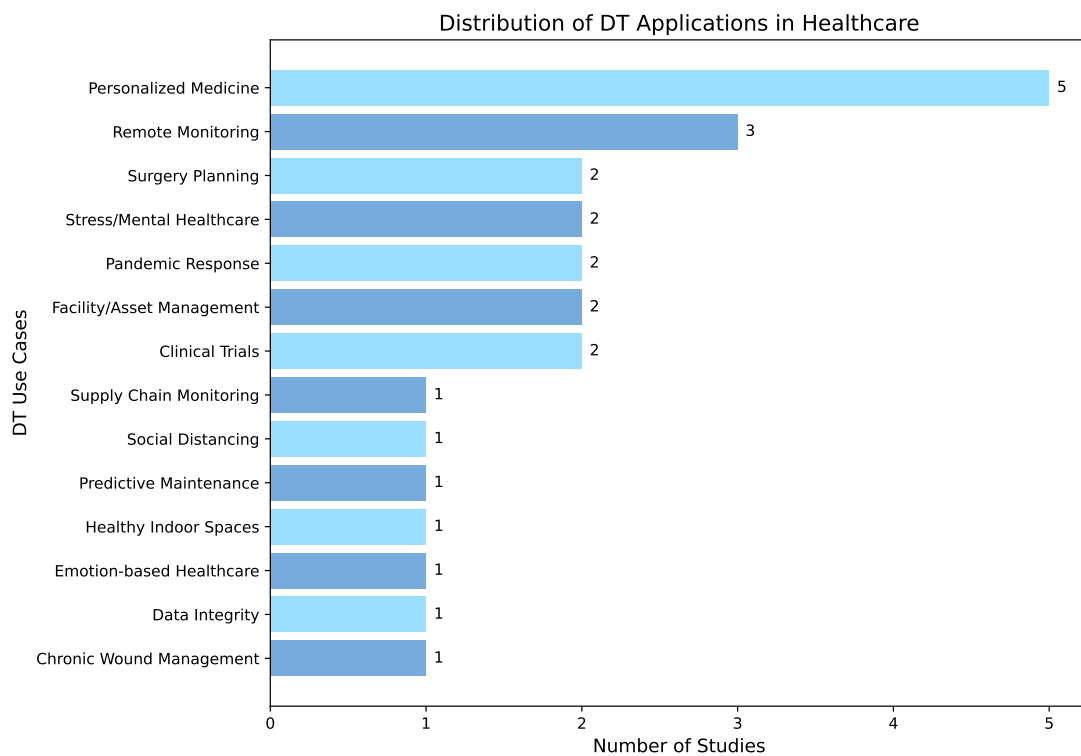


Figure 20. Statistics on DT Use Cases in Healthcare

Table 10. Extraction Summary of DTs in Healthcare

Paper	DT Components	Use Cases	Gaps	Using Blockchain
[39]	<ul style="list-style-type: none"> Physical: Chronic wound sensors Virtual: Digital wound replicas Data: Patient demographics Analytical: AI for wound healing 	<ul style="list-style-type: none"> Chronic wound management Early non-healing detection 	<ul style="list-style-type: none"> Privacy concerns Interoperability issues 	▲ Mentioned
[44]	<ul style="list-style-type: none"> Physical: Patient sensors Virtual: Personalized models Data: IoT and cloud storage Analytical: Predictive AI models 	<ul style="list-style-type: none"> Personalized medicine Operational efficiency 	<ul style="list-style-type: none"> Privacy issues High cost Scalability limits 	▲ Mentioned
[41]	<ul style="list-style-type: none"> Physical: IoT for patient data Virtual: Organ simulations Data: AI-integrated cloud 	<ul style="list-style-type: none"> Personalized medicine Disease modeling Clinical trials 	<ul style="list-style-type: none"> Privacy challenges Infrastructure gaps 	▲ Mentioned
[42]	<ul style="list-style-type: none"> Physical: IoT sensors Virtual: Smart asset replicas Data: DLT-secured storage Analytical: AI-driven predictions 	<ul style="list-style-type: none"> CPS security Supply chain monitoring 	<ul style="list-style-type: none"> Blockchain scalability High energy costs 	● Utilized
[30]	<ul style="list-style-type: none"> Physical: Biosignal sensors Virtual: Stress twins Data: JSON-LD for storage Analytical: Stress prediction AI 	<ul style="list-style-type: none"> Stress management Mental healthcare 	<ul style="list-style-type: none"> Model standardization Privacy for biometrics 	○ No
[45]	<ul style="list-style-type: none"> Physical: IoT industrial sensors Virtual: Maintenance twins Data: Blockchain for storage 	<ul style="list-style-type: none"> Predictive maintenance Asset management 	<ul style="list-style-type: none"> Scalability gaps Interoperability limits 	● Utilized

[57]	<ul style="list-style-type: none"> • Physical: Wearables, imaging • Virtual: Patient-specific twins • Data: Federated learning • Analytical: Predictive AI 	<ul style="list-style-type: none"> • Personalized medicine • Remote monitoring 	<ul style="list-style-type: none"> • Privacy issues • Standardization challenges 	▲ Mentioned
[36]	<ul style="list-style-type: none"> • Physical: IoT-enabled sensors • Virtual: Facility models • Data: Centralized storage • Analytical: Process optimization 	<ul style="list-style-type: none"> • Facility management • Resource allocation 	<ul style="list-style-type: none"> • Data validation • High computational cost 	▲ Mentioned
[43]	<ul style="list-style-type: none"> • Physical: Webcams for emotions • Virtual: Emotional twins • Data: Custom datasets • Analytical: Gradient boosting 	<ul style="list-style-type: none"> • Emotion-based health-care • Stress detection 	<ul style="list-style-type: none"> • Dataset bias • Image quality dependency 	○ No
[5]	<ul style="list-style-type: none"> • Physical: Indoor sensors • Virtual: BIM-based twins • Data: IoT analytics • Analytical: Air quality AI 	<ul style="list-style-type: none"> • Healthy indoor spaces • Infection management 	<ul style="list-style-type: none"> • Health indicator gaps • Sensor deployment issues 	▲ Mentioned
[23]	<ul style="list-style-type: none"> • Physical: Health monitors • Virtual: Multi-scale twins • Data: Multi-modal integration • Analytical: Predictive modeling 	<ul style="list-style-type: none"> • Personalized medicine • Surgery planning 	<ul style="list-style-type: none"> • Interoperability issues • Ethical concerns 	▲ Mentioned
[11]	<ul style="list-style-type: none"> • Physical: Monitoring sensors • Virtual: Social distancing twins • Data: MongoDB database 	<ul style="list-style-type: none"> • Social distancing • Crowd management 	<ul style="list-style-type: none"> • Scalability issues • Privacy concerns 	▲ Mentioned
[33]	<ul style="list-style-type: none"> • Physical: IoT hospital sensors • Virtual: Inter-hospital twins • Data: Blockchain resource flow • Analytical: Patient simulations 	<ul style="list-style-type: none"> • Pandemic response • Resource optimization 	<ul style="list-style-type: none"> • Scalability gaps • High implementation cost 	● Utilized

[48]	<ul style="list-style-type: none"> • Physical: IoMT for surgery data • Virtual: Surgical twins • Data: 5G real-time processing 	<ul style="list-style-type: none"> • Surgical planning • Remote simulations 	<ul style="list-style-type: none"> • Latency issues • Limited standards 	○ No
[9]	<ul style="list-style-type: none"> • Physical: Wearable sensors • Virtual: Real-time health twins • Data: Federated learning • Analytical: Predictive AI 	<ul style="list-style-type: none"> • Remote healthcare • Clinical trials 	<ul style="list-style-type: none"> • Ethical concerns • Infrastructure costs 	● Utilized
[2]	<ul style="list-style-type: none"> • Physical: IoT patient data • Virtual: Healthcare twins • Data: Blockchain-based storage • Analytical: Predictive AI 	<ul style="list-style-type: none"> • Patient data sharing • Diagnosis optimization 	<ul style="list-style-type: none"> • Privacy challenges • Standardization gaps 	● Utilized
[29]	<ul style="list-style-type: none"> • Physical: Patient sensors • Virtual: Cloud-hosted twins • Data: Blockchain storage • Analytical: Audit tracking 	<ul style="list-style-type: none"> • Data integrity • Secure sharing 	<ul style="list-style-type: none"> • Centralization risks • Scalability limits 	● Utilized
[4]	<ul style="list-style-type: none"> • Physical: Environmental sensors • Virtual: Azure-based twins • Data: Time-series analysis • Analytical: Activity detection AI 	<ul style="list-style-type: none"> • Remote monitoring • Air quality tracking 	<ul style="list-style-type: none"> • Cloud dependency • Edge-to-cloud accuracy loss 	▲ Mentioned

Table 11. Summary of HDTs Involving Blockchain Technology

Paper ▲ <i>Mentioned</i> ● <i>Utilized</i>	Focus On
[39] ▲	• Confidentiality: Data security • Scalability: Real-time updates
[44] ▲	• Confidentiality: Privacy enhancement
[41] ▲	• Decentralization: Privacy-preserving patient data
[42] ●	• Consensus: Traceability • Smart contracts: Automation • Confidentiality: Privacy
[45] ●	• Trust: IoT data verification • Smart contracts: Automation
[57] ▲	• Confidentiality: Decentralized data storage • Smart contracts for governance
[36] ▲	• Decentralization: Data sharing security
[5] ▲	• Confidentiality: Multi-stakeholder data sharing
[23] ▲	• Confidentiality: Ethical data sharing
[11] ▲	• Confidentiality: Public health data security
[33] ●	• Consensus: Inter-hospital coordination • Confidentiality: Secure data sharing
[9] ●	• Smart contracts: Permission control • Confidentiality: Blockchain storage
[2] ●	• Smart contracts: Permission control • Confidentiality: Blockchain storage
[29] ●	• Decentralization: Secure audits • Confidentiality: Privacy audits

III. Use Cases Description

Table 12. Use Case 1: Smart Patient Room with DT Monitoring

Section	Content
ID	UC-01
Name	Smart Patient Room with DT Monitoring
Description	The HDT system continuously monitors a patient’s vital signs, movement, and room conditions, automatically adjusting environmental factors and triggering alerts when abnormalities are detected.
Actors	Patient, Clinician, Smart Hospital Infrastructure, HDT System
Pre-conditions	- IoT sensors installed and operational. - HDT system linked to patient health records. - Clinicians able to access real-time monitoring dashboards.
Post-conditions	- Environmental conditions optimized for patient comfort. - Alerts generated for detected anomalies. - Clinicians notified for critical events.
Result	Improved patient safety, optimized resource utilization, and real-time environmental adaptation.
Main Scenario	1. IoT sensors collect real-time patient and environmental data. 2. HDT system analyzes inputs and adjusts room settings. 3. Anomalies trigger alerts to clinicians. 4. Clinicians assess Digital Twin status and respond accordingly.

Table 13. Use Case 2: DT-Assisted Preoperative Planning

Section	Content
ID	UC-02
Name	DT-Assisted Preoperative Planning
Description	Surgeons interact with high-fidelity patient DTs, generated from Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and real-time physiological data, to simulate procedures, optimize surgical strategies, and anticipate potential complications.
Actors	Surgeon, Medical Imaging System, HDT System
Pre-conditions	<ul style="list-style-type: none"> - Patient DT generated from imaging data. - HDT system calibrated for surgical simulation. - Authorized access to patient models granted to surgeons.
Post-conditions	<ul style="list-style-type: none"> - Optimized surgical plan finalized. - Potential risks and complications simulated and addressed. - Data-driven insights available for surgical preparation.
Result	Reduced surgical risks, improved procedural precision, and enhanced preoperative decision-making.
Main Scenario	<ol style="list-style-type: none"> 1. Surgeon loads patient-specific DT. 2. Surgical procedures are simulated under different conditions. 3. HDT system predicts complications and responses. 4. Surgeon finalizes strategy based on simulations.

Table 14. Use Case 3: ICU Risk Prediction and Early Intervention

Section	Content
ID	UC-03
Name	ICU Risk Prediction and Early Intervention
Description	The HDT system continuously monitors ICU patients and applies AI-driven predictive analytics to detect early signs of critical conditions such as sepsis, cardiac failure, or respiratory distress.
Actors	ICU Patient, Clinician, HDT System, AI Risk Analysis Module
Pre-conditions	<ul style="list-style-type: none"> - Biometric devices connected to the HDT system. - AI models trained on clinical risk patterns. - Clinicians access to ICU DT dashboard.
Post-conditions	<ul style="list-style-type: none"> - High-risk patients identified and flagged. - Real-time alerts sent to clinical staff. - Workflow adjustments initiated for critical cases.
Result	Faster ICU interventions, reduced critical incidents, and improved patient outcomes.
Main Scenario	<ol style="list-style-type: none"> 1. HDT system collects real-time ICU data. 2. AI analytics predict potential deteriorations. 3. Alerts trigger clinical intervention. 4. Patient DTs update risk assessments dynamically.

Table 15. Use Case 4: DT-Based Drug Interaction Simulation

Section	Content
ID	UC-04
Name	DT-Based Drug Interaction Simulation
Description	The HDT system simulates metabolic responses and predicts potential adverse effects of drug combinations based on patient-specific health data and medication history.
Actors	Pharmacist, Medical Researcher, Clinician, HDT System
Pre-conditions	<ul style="list-style-type: none"> - Patient DT includes up-to-date health and medication data. - AI simulation models activated. - Clinician request for interaction analysis submitted.
Post-conditions	<ul style="list-style-type: none"> - Risks of drug combinations identified. - Alternative medication strategies recommended. - Safer, personalized treatment plans generated.
Result	Decreased adverse drug reactions, improved patient safety, and optimized pharmacological interventions.
Main Scenario	<ol style="list-style-type: none"> 1. Clinician selects intended medication plan. 2. HDT system simulates potential interactions. 3. Analysis highlights risks and suggests alternatives. 4. Final medication plan refined based on simulations.

Table 16. Use Case 5: Remote Rehabilitation Monitoring with DTs

Section	Content
ID	UC-05
Name	Remote Rehabilitation Monitoring with DTs
Description	The HDT system monitors rehabilitation exercises through motion analysis, providing real-time AI-driven feedback and allowing physiotherapists to dynamically adjust therapy plans.
Actors	Patient, Physiotherapist, HDT System
Pre-conditions	<ul style="list-style-type: none"> - Patient enrolled in HDT rehabilitation program. - Motion sensors connected and calibrated. - Therapy exercises prescribed and uploaded.
Post-conditions	<ul style="list-style-type: none"> - Patient movement data logged and analyzed. - Feedback delivered to patients and therapists. - Therapy plans adapted based on progress.
Result	Enhanced rehabilitation outcomes, personalized therapy adjustments, and improved patient engagement.
Main Scenario	<ol style="list-style-type: none"> 1. Patient performs prescribed exercises. 2. Motion data captured by HDT system. 3. AI analysis provides real-time feedback. 4. Therapy plan adjusted based on performance data.

Table 17. Use Case: Smart Patient Room Monitoring System-a HDT Prototype

Section	Content / Explanation
ID	UC-01-HDT-POC
Name	Smart Patient Room Monitoring with HDT Application
Description	The system deploys IoT-based sensors to monitor patient physiological parameters (e.g., heart rate, SpO ₂ , body temperature) and environmental factors (e.g., room temperature, humidity). Collected data updates the DT model in real time. Using algorithms to analyze the data to detect anomalies, while blockchain ensures secure, tamper-proof data storage. And a monitoring dashboard with AI suggestions is also included.
Actors	<p>Patient: The individual being monitored.</p> <p>Clinician: The healthcare provider responding to alerts and monitoring patient status.</p> <p>Smart Hospital Infrastructure: IoT sensors and devices installed in the patient room.</p> <p>HDT System: Aggregates data, updates the DT model, performs AI analysis, and manages alert generation.</p>
Pre-conditions	<ul style="list-style-type: none"> - IoT monitoring devices are installed and operational. - The HDT system is fully connected and receiving real-time data. - Clinicians have access to the monitoring dashboard. - Blockchain modules are configured for secure data recording.
Post-conditions	<ul style="list-style-type: none"> - The DT model reflects the latest patient and environmental data. - Alerts are generated when anomalies are detected. - All data transactions are securely stored on the blockchain. - Clinicians are promptly notified of timely interventions.
Result	Enhanced patient safety and clinical decision-making through real-time monitoring, predictive analytics, and secure data management.
Main Scenario	<ol style="list-style-type: none"> 1. Sensors collect physiological and environmental data. 2. Data is transmitted to the HDT system. 3. The digital twin model is updated in real-time. 4. Analyze the model for anomalies. 5. Alerts are generated for abnormal conditions. 6. Alerts and monitoring results are displayed on the clinician dashboard. 7. Data is encrypted and recorded in the blockchain. 8. Clinicians review data, receive alerts, and initiate appropriate interventions. 9. Clinicians can ask the AI model to provide suggestions.

IV. DTDL

DTDL of Patient DT

```
1 {
2   "@context": "dtmi:dtdl:context;2",
3   "@id": "dtmi:hospital:healthcare:patient;1",
4   "@type": "Interface",
5   "displayName": "Patient Interface Model",
6   "contents": [
7     {
8       "@type": "Property",
9       "name": "PatientId",
10      "schema": "string",
11      "description": "Unique ID of the patient",
12      "writable": false
13    },
14    {
15      "@type": "Property",
16      "name": "Name",
17      "schema": "string",
18      "description": "Name of the patient",
19      "writable": true
20    },
21    {
22      "@type": "Property",
23      "name": "Gender",
24      "schema": "string",
25      "description": "Gender of the patient",
26      "writable": true
27    },
28    {
29      "@type": "Property",
30      "name": "Age",
31      "schema": "integer",
32      "description": "Age of the patient",
33      "writable": true
34    },
35    {
36      "@type": "Property",
37      "name": "Diagnosis",
```

```

38     "schema": "string",
39     "description": "Diagnosis or medical condition of the
    ↪ patient",
40     "writable": true
41 },
42 {
43     "@type": "Property",
44     "name": "Status",
45     "schema": "string",
46     "description": "Current health status of the patient (e.g.,
    ↪ Healthy, Critical, Monitoring)",
47     "writable": true
48 },
49 {
50     "@type": "Relationship",
51     "name": "assignedToRoom",
52     "target": "dtmi:hospital:healthcare:room;1",
53     "description": "Relationship linking patient to a room"
54 },
55 {
56     "@type": "Relationship",
57     "name": "hasBodyTemperature",
58     "target":
    ↪ "dtmi:hospital:healthcare:patient:body_temperature;1",
59     "description": "Relationship linking patient to their body
    ↪ temperature data"
60 },
61 {
62     "@type": "Relationship",
63     "name": "hasHeartRate",
64     "target": "dtmi:hospital:healthcare:patient:heart_rate;1",
65     "description": "Relationship linking patient to their
    ↪ heart rate data"
66 },
67 {
68     "@type": "Relationship",
69     "name": "hasSpO2",
70     "target": "dtmi:hospital:healthcare:patient:spo2;1",
71     "description": "Relationship linking patient to their SpO
    ↪ level data"

```

```

72     }
73   ]
74 }

```

Listing 2. DTDL of Patient DT

DTDL of Room DT

```

1 {
2   "@context": "dtmi:dtdl:context;2",
3   "@id": "dtmi:hospital:healthcare:room;1",
4   "@type": "Interface",
5   "displayName": "Room Interface Model",
6   "contents": [
7     {
8       "@type": "Property",
9       "name": "RoomId",
10      "schema": "string",
11      "description": "Unique ID of the room",
12      "writable": false
13    },
14    {
15      "@type": "Property",
16      "name": "RoomNumber",
17      "schema": "string",
18      "description": "Room number within the hospital",
19      "writable": false
20    },
21    {
22      "@type": "Property",
23      "name": "RoomType",
24      "schema": "string",
25      "description": "Type of the room (e.g., ICU, general ward)",
26      "writable": false
27    },
28    {
29      "@type": "Property",
30      "name": "Status",
31      "schema": "string",
32      "description": "Current status of the room (e.g., Normal,
↪ Alarm, Maintenance)",

```

```

33     "writable": true
34   },
35   {
36     "@type": "Relationship",
37     "name": "hasTemperatureSensor",
38     "target": "dtmi:hospital:healthcare:room:temperature;1",
39     "description": "Relationship linking room to its
    ↪ temperature sensor"
40   },
41   {
42     "@type": "Relationship",
43     "name": "hasHumiditySensor",
44     "target": "dtmi:hospital:healthcare:room:humidity;1",
45     "description": "Relationship linking room to its humidity
    ↪ sensor"
46   }
47 ]
48 }

```

Listing 3. DTDL of Room DT

V. Interview Extracts

This appendix presents summarized insights from the four semi-structured interviews conducted during the evaluation phase of the HDT framework.

Participant 1: Medical Student

- Date: 3 Apr, 2025
- Format: Video call (15 minutes)
- Observations: "The system makes it easier to monitor critical health indicators in real-time, which could be useful in clinical settings. However, the decision support features are still too basic and lack the complexity required for real clinical decision-making. Accuracy needs further validation if it is to be trusted in practice."

Participant 2: Computer Science Student

- Date: 4 Apr, 2025
- Format: Face-to-face interview (20 minutes)
- Observations: "The interface is intuitive, and the basic workflow makes sense technically. It shows potential from a system design perspective, but the prototype feels limited in scalability. Network dependency and data handling under larger-scale deployment are aspects that would need to be addressed."

Participant 3: Registered Nurse

- Date: 9 Apr, 2025
- Format: Face-to-face interview (15 minutes)
- Observations: "The system is simple enough that nurses could pick it up quickly without much training. However, it currently only supports basic monitoring. More advanced alert systems and automatic action suggestions would be necessary to really fit into daily hospital workflows."

Participant 4: Patient Representative

- Date: 16 Apr, 2025
- Format: Face-to-face interview (10 minutes)
- Observations: "Initially, I was worried about privacy, but after hearing about the blockchain mechanism, I felt reassured. Still, it would help if the system provided clearer, simpler explanations about what happens to patient data after it is collected and stored."

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