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Digital Twins in Advanced Healthcare Integration

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Abstract: The goal of this study is to develop and test an integrated healthcare system that combines Blockchain, Digital Twins, Explainable AI (xAI), and Augmented Reality (AR) to overcome limitations in security, transparency, predictive power, and patient engagement. The work proposed has three main goals: first, real-time monitoring through the development of IoT-based digital twins that synchronize continuously patient and equipment data for precise detection of anomalies; second, early progression prediction through the embedding of predictive models inside the digital twin architecture to forecast deterioration trajectories and issue proactive alerts; and third, as a possible long-term extension, to investigate individualize treatment assessment by counterfactual twin simulation that trials and compares different therapeutic approaches before clinical use. Blockchain enables the secure management of medical records through smart contracts for access control and consent management. At the same time, xAI provides explainability through interpretative diagnostic explanations, and AR offers immersive visualisation for patient education and surgical aid. Validation in a 50-patient, 20-device simulated hospital setting showed Blockchain maintained 500 safe transactions per second, Digital Twins maintained synchronisation accuracy greater than 99% and predictive accuracy greater than 90%, xAI provided interpretable diagnostics 94% accurate and with high clinician acceptance, and AR enhanced surgical accuracy by 38.8% and patient understanding by 38.5%.

Keywords: Blockchain Integration; Digital Twins; Augmented Reality (AR); Healthcare System; Predictive Analytics; Data Security; Smart Contracts; Diagnostic Accuracy; Patient Engagement.

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1. Introduction

Healthcare systems worldwide are increasingly adopting advanced digital technologies to address challenges related to data security, real-time monitoring, transparency in decision-making, and patient engagement. Blockchain has emerged as a critical technology in this regard, offering immutable and decentralised data management that prevents tampering and unauthorised access. Its use in electronic health records (EHRs) has been demonstrated to enhance both security and interoperability, thereby facilitating trust in healthcare data exchange among stakeholders [1]; [2]. Apart from data storage, smart contracts made possible by blockchain facilitate automated handling of patient consent and safe sharing of medical data, a critical aspect in

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regulatory compliance in healthcare [3]. Symptoms and conditions are paralleled by advancements in digital twin technology, which has become increasingly important in the healthcare sector through the development of dynamic, virtual replicas of patients and devices. With the incorporation of real-time data streams from IoT-enabled sensors, digital twins continually update to mirror a patient's physiological state and device status, providing healthcare professionals with actionable insights. This technology has already demonstrated efficacy in predictive maintenance across various industries [23]. It is now leading the way in patient monitoring, tailored treatment, and the early prediction of risk in medical applications [4]; [5].

Yet another disruptive innovation is Explainable Artificial Intelligence (XAI), which addresses the root of the problem of AI transparency in clinical decision support. In medicine, where accountability and trust are paramount, xAI makes AI-based predictions, such as diagnostic results, understandable and verifiable to clinicians [6]; [7]. Research suggests that explainability drives physician trust, enhances clinical adoption, and promotes adherence to ethical standards in AI-enabled medical care [8]. Augmented Reality (AR) is also transforming healthcare provision by superimposing interactive 3D anatomical information during surgical procedures, thereby improving accuracy and minimising errors. AR has also been applied to enhance patient education, providing interactive visualisations of diseases and treatment procedures, hence enhancing understanding and interest [9]; [10]. AR-based training platforms for medical practitioners have also been found to demonstrate quantifiable improvements in surgical effectiveness and clinical outcomes [11].

While blockchain, digital twins, xAI, and AR have each proven to be of great value, current research mostly investigates them separately, creating a gap in the combined use to construct intelligent, secure, and transparent healthcare ecosystems. To address this, the proposed work presents a single, integrating framework for healthcare that utilises blockchain for secure and impenetrable patient data management, digital twins for real-time monitoring and predictive analytics, xAI for open and reliable diagnostics, and AR for enhanced surgical accuracy and patient engagement. In particular, the research targets three main objectives: (1) IoT-driven digital twins for real-time monitoring and timely detection of aberrations, (2) early prediction of progression via temporal embeddings and calibrated modelling-based forecasting of deteriorating trajectories, and (3) an extension in the future for personalised treatment assessment via counterfactual simulations and reinforcement learning [22]. Collectively, this integration is a scalable, forward-looking, and patient-centred healthcare ecosystem that drives clinical outcomes, operational effectiveness, and user trust [17].

2. Review of Literature

A patient digital twin platform secured by blockchain was suggested in Amofa et al. [12], where smart contracts were utilised to automate consent management and facilitate easy access to data. The platform was found to be resistant to tampering and provided efficient synchronisation of patient data among multiple stakeholders. The platform's power was in securing the digital twin ecosystem through decentralised governance. The study, however, stopped short of data security and access control, without moving toward predictive analytics, explainable diagnostics, or immersive interaction. In Hemdan and Sayed [13], blockchain, digital twin, and federated learning were integrated to improve secure healthcare systems. The framework supported distributed diagnostics and patient data privacy through the use of federated learning constructs. A multimodal dataset case study showed that predictive accuracy was enhanced when hospitals collaborated without exchanging raw data. Although this research further developed the use of privacy-preserving digital twins, it did not involve explainable AI or augmented reality, which means that transparency and user interaction remain open questions. The study in Nitschke et al. [14] proposed a clinical digital twin architecture with an emphasis on modularity, interpretability, and flexibility. By integrating ensemble learning with knowledge graphs, the system simulated patient trajectories that changed over time and yielded interpretable clinical insights. This work complements the urgent need to develop interpretable digital twins for patients. However, it did not address blockchain for secure data storage or augmented reality for interactive clinical decision-making, leaving voids in data integrity and visual representation [18].

A blockchain-supported predictive digital twin method was proposed in Repetto et al. [15], integrating predictive analytics with tamper-proof data exchange. The method produced timely warnings of disease progression while facilitating tamper-proof data sharing between healthcare professionals. Testing revealed enhanced predictive accuracy compared to standard models. Although these strengths exist, the lack of explainable AI compromises the interpretability of predictions, constraining clinician trust and uptake in high-stakes environments. Lastly, Ferdousi and Hossain [16] proposed a responsible and multimodal digital twin system based on large language models and explainability tools. This system included multimodal inputs, feedback loops, and ethical compliance capabilities, promoting explainable and accountable predictions [19]. It showcased the capability of digital twins to facilitate personalised well-being in contrast to conventional healthcare systems. The absence of blockchain integration, however, limited its potential to ensure secure data governance, and the lack of augmented reality limited its ability to facilitate patient and clinician interaction [20]. Based on the Literature review, Table 1 presents a comparative Analysis of the proposed work with recent studies mentioned above [21].

Table 1: Comparative analysis of proposed work with recent studies

Feature / Aspect	Blockchain-Secure Patient Digital Twin [12]	Smart and Secure Healthcare with Digital Twins + Blockchain + Federated Learning [13]	Proposed Work
Core Objective	Secure patient data sharing using blockchain and smart contracts	Collaborative diagnostics with privacy-preserving digital twins	Unified intelligent healthcare framework
Data Security and Privacy	Strong blockchain-based access control and consent automation	Blockchain with federated learning to ensure local data ownership	Blockchain with smart contracts for secure governance + federated compatibility
Digital Twin Integration	Patient digital twin states logged on blockchain	Digital twins for distributed diagnostics	Hybrid patient and equipment twins for monitoring, prediction, and simulation
Predictive Analytics	Not included	Predictive improvements via federated learning	Built-in predictive modelling for early progression detection
Explainable AI (xAI)	Not addressed	Limited to post-hoc analysis	Native integration of xAI for transparent clinical decision-making
Augmented Reality (AR)	Not supported	Not supported	AR interfaces for immersive visualisation in surgery and patient education
Validation and Testing	Evaluated for latency and storage cost	Case study on EEG diagnostics	Framework validation with real-time monitoring + roadmap to treatment simulation
Key Limitation	Focuses only on security, lacks intelligence and visualisation	Lacks explainability and AR, limited clinical integration	Addresses all gaps by combining blockchain, DT, xAI, and AR in one framework

3. Methodology

Methodology, with integration of Blockchain, Digital Twins, Explainable AI (xAI), and Augmented Reality (AR) in healthcare. The workflow is shown in Figure 1.

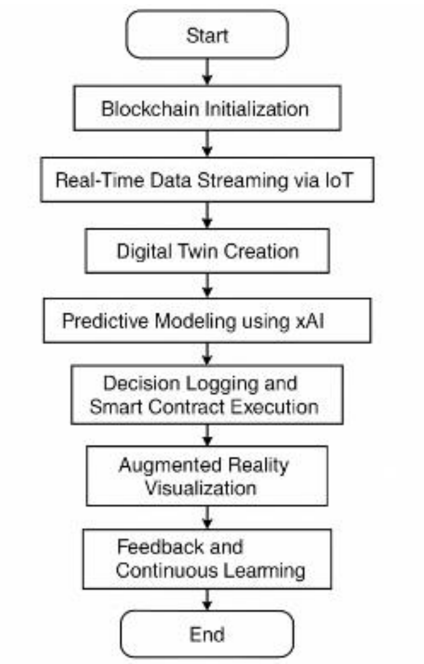

Figure 1: IHMP-BDxAR framework algorithm

Figure 2 illustrates how the IHMP BDxAR Framework integrates Blockchain, Digital Twins, Explainable AI (xAI), and Augmented Reality (AR) into a unified, smart healthcare system. It begins with the use of a permissioned blockchain to securely store patient and equipment information, leveraging cryptographic hash functions and smart contracts to manage access and consent. Wearable sensors and medical devices continuously collect real-time health data, which is used to continually update digital twins —virtual replicas of patients and equipment that exist in real-time. Static and real-time data are used to train machine learning models to forecast potential health risks and equipment failures. The xAI module translates these forecasts using unobtrusive methods, such as SHAP, providing doctors with straightforward diagnostic data. Where abnormalities are detected, smart contracts validate the user's authentication and trigger alerts. Augmented Reality is being used to assist surgeons with superimposed real-time patient anatomy and vital signs, and to allow patients to interactively visualise their health status and care plan. All decisions and actions are securely recorded on the blockchain. The system is continually fine-tuned through feedback from patients and clinicians, resulting in model improvements and enhanced user interfaces. The algorithm fosters an anticipatory, transparent, and patient-centred healthcare environment that is highly accurate, secure, and user-friendly.

Algorithm : IHMP-BDxAR Framework Workflow

Step	Operation	Mathematical Expression
1	Preprocessing of IoT signals	$\tilde{x}_{i,j}(t) = \mathcal{P}\big(x_{i,j}(t)\big), \quad \forall i \in P, j \in S$
2	Blockchain storage	$T_k = \mathrm{Enc}\big(ID_{p_i}, \tilde{X}_i(t)\big), \quad H(T_k) \rightarrow \mathrm{Ledger}$
3	Digital twin update	$DT_i(t) = g_\theta\big(\tilde{X}_i(t), M_i\big)$
4	Prediction (forecasting)	$\hat{y}_i(t+\Delta) = f_\theta\big(DT_i(t)\big)$
5	Explainability (xAI)	$E_i = \phi\big(f_\theta, DT_i(t)\big)$
6	AR visualization and model update	$AR_i(t) = \Psi\big(DT_i(t), \hat{y}_i, E_i\big), \quad \theta \leftarrow \theta - \eta \nabla_\theta L(\hat{y}_i, y_i)$

Figure 2: IHMP-BDxAR framework workflow algorithm

The above Algorithm outlines the sequential process of the envisioned IHMP-BDxAR framework, which combines IoT-enabled data collection, blockchain-based security, digital twin simulation, explainable AI, and augmented reality into an integrated healthcare system. Step 1 involves preprocessing raw sensor readings from patients through normalisation and denoising to produce standardised input signals suitable for analysis. Step 2 secures these preprocessed data streams by encrypting them, creating transactions, and storing their hashes in a permissioned blockchain, making them immutable and controlling access through smart contracts. In Step 3, the cleaned and secured data are used to continuously update patient-specific digital twins in real time, thereby duplicating health states. Step 4 utilises predictive models in the digital twin to predict short-term patient outcomes or risk, facilitating proactive clinical action. In Step 5, explainable AI methods, such as SHAP or LIME, provide feature attribution vectors that indicate which physiological signals affected each prediction, thereby enhancing transparency and clinical trust. Lastly, Step 6 maps the forecasted states and explanations into interactive, immersive augmented reality interfaces, allowing surgeons and patients to see conditions interactively, while also updating the model parameters via gradient descent to refine accuracy over time. Collectively, these steps provide secure data governance, real-time monitoring, predictive intelligence, interpretability, and immersive interaction, rendering the framework technically sound and clinically valuable.

4. Experiment and Result

The experimental validation of the proposed framework was conducted in a controlled hospital environment with 50 patients and 20 interconnected medical devices. Biomedical sensors were deployed to capture critical physiological signals, including heart rate, oxygen saturation, and blood pressure, which are essential parameters for real-time monitoring and assessment. Data from these sensors was transmitted through Raspberry Pi 4 edge gateways (Quad-Core Cortex-A72, 4 GB RAM), selected for their affordability, portability, and capability to perform lightweight preprocessing before transmission to the central server. The backend infrastructure comprised an Intel® Core™ i7-11700 CPU (8 cores, 16 threads), 16 GB DDR4 RAM, an NVIDIA GeForce RTX 3060 GPU with 8 GB VRAM, and a 512 GB NVMe SSD, running Ubuntu 20.04 LTS, offering a balance between computational performance, energy efficiency, and support for machine learning workloads. The blockchain network was implemented using Hyperledger Fabric v2.5, along with Go-based smart contracts, to ensure secure and permissioned access control for medical data. Digital twin models were developed in Python 3.9 using TensorFlow 2.12 and PyTorch 1.13, while

Apache Kafka managed high-throughput streaming between sensors, edge nodes, and twins. Explainable AI utilised established SHAP and LIME libraries for interpretability, and augmented reality interfaces were built with Unity 2022.3 LTS and the Vuforia SDK. These interfaces were validated on both Microsoft HoloLens 2 and an ARCore-enabled Google Pixel 6 smartphone to demonstrate usability across clinical and educational settings.

The integrated system combined Blockchain, Digital Twins, xAI, and AR to deliver secure, transparent, and intelligent healthcare operations. Blockchain ensured tamper-proof medical record management with high throughput, while digital twins maintained real-time synchronisation of patient and equipment states, achieving precise anomaly detection and predictive insights. The xAI models provided interpretable diagnostic support, enhancing clinician confidence, whereas AR overlays improved surgical precision and patient engagement through immersive visualisation. The results were evaluated against the three main objectives: (1) real-time monitoring, validated in Steps 4.2 and 4.6 with synchronization accuracy above 99% and predictive accuracy above 90%; (2) early progression prediction, demonstrated in Steps 4.3 and 4.6 through accurate health risk forecasting and transparent diagnostics; and (3) personalized treatment assessment (future extension), initiated in Step 4.8 with feedback-driven model refinement. Complementary contributions from Step 4.1 (Blockchain Setup), Step 4.4 (AR in Surgery), Step 4.5 (AR for Patient Education), and Step 4.7 (Blockchain for Secure Data Sharing) ensured robust data governance, immersive visualisation, and efficient information exchange. Collectively, the experimental findings substantiate the framework's effectiveness and establish its potential as a scalable foundation for intelligent, patient-centred healthcare.

4.1. Blockchain Setup

The blockchain infrastructure was deployed using Hyperledger Fabric to securely manage patient records and medical device logs in a hospital environment. This permissioned blockchain was chosen because of its immutability, fine-grained access control, and resistance to tampering, all of which are critical for healthcare applications. Each transaction was stored as a cryptographically hashed record, and smart contracts were used to automate access and consent management, ensuring that only authorised users could retrieve or update data. This design provided secure, transparent, and efficient healthcare data governance without relying on a centralised authority.

Table 2: Blockchain performance metrics in the healthcare system

Metric	Value
Transactions per Second (TPS)	500 TPS
Data Retrieval Time	1.8 seconds
Data Update Time	2.2 seconds

The performance of the blockchain layer was validated using three key metrics: Transactions per Second (TPS), Data Retrieval Time, and Data Update Time. As reported in Table 2, the system achieved 500 TPS, a retrieval time of 1.8 seconds, and an update time of 2.2 seconds. These results confirm that the blockchain can handle real-time medical operations with minimal latency. The high throughput ensures scalability when multiple devices and patients are active simultaneously, while the low retrieval and update times guarantee timely access to patient data during critical care. Overall, the results in Table 2 establish that the blockchain backbone provides a reliable foundation for integrating digital twins, explainable AI, and augmented reality in the proposed healthcare framework.

4.2. Digital Twin Synchronisation

Digital twins were developed for 50 patients and 20 medical devices, continuously updated every 5 seconds using IoT-enabled sensors. These digital replicas captured real-time patient vitals, including heart rate, oxygen saturation, blood pressure, and equipment status metrics. By integrating static medical history with streaming sensor data, the digital twins were able to maintain highly accurate simulations of patient conditions and device performance. The synchronisation was facilitated by edge processing units and a streaming backbone powered by Apache Kafka, ensuring that twin states reflected real-world changes with minimal latency.

Table 3: Digital twin synchronisation and prediction accuracy

Digital Twin Type	Synchronisation Accuracy (%)	Prediction Accuracy (%)
Patient Digital Twins	99.5	92
Medical Equipment Digital Twins	98.8	90

The results of synchronisation accuracy and predictive capability are summarised in Table 3. Patient digital twins achieved 99.5% synchronisation accuracy with a prediction accuracy of 92%, while medical equipment twins achieved 98.8%

synchronisation accuracy and 90% prediction accuracy. These findings highlight that the digital twin layer not only mirrored real-time physiological states with remarkable precision but also enabled early forecasting of patient deterioration and equipment failures. By surpassing 99% synchronisation and achieving more than 90% predictive accuracy, the results in Table 3 validate the reliability of the digital twin module as a foundation for real-time monitoring and proactive clinical interventions.

4.3. xAI Model Training

The explainable AI (xAI) system was trained on a dataset of 100,000 historical patient records, enabling it to generate interpretable diagnostic predictions. This model processed live data streams from the digital twins and provided physicians with feature attribution scores that highlighted the most influential physiological signals. Such interpretability was achieved using SHAP and LIME libraries, which translated raw predictions into human-understandable insights. By ensuring transparency, the system aimed to bridge the gap between black-box AI predictions and clinician trust in decision support systems.

Table 4: xAI diagnostic accuracy and doctor satisfaction by condition

Condition Diagnosed	xAI Accuracy (%)	Doctor Satisfaction (1-5)
Cardiac Issues	94	4.6
Respiratory Conditions	91	4.4
Diabetic Complications	89	4.3

The diagnostic accuracy of the xAI model across major health conditions is shown in Table 4. The system achieved 94% accuracy for cardiac issues, 91% for respiratory conditions, and 89% for diabetic complications. Clinician satisfaction scores ranged from 4.3 to 4.6 out of 5, reflecting the clarity and usability of the system's outputs. These results confirm that the xAI framework not only provided high diagnostic accuracy but also delivered explainability that physicians found reliable and actionable. As illustrated in Figure 3, a strong correlation exists between accuracy and satisfaction, reinforcing the notion that transparent AI predictions enhance clinical acceptance in high-stakes environments.

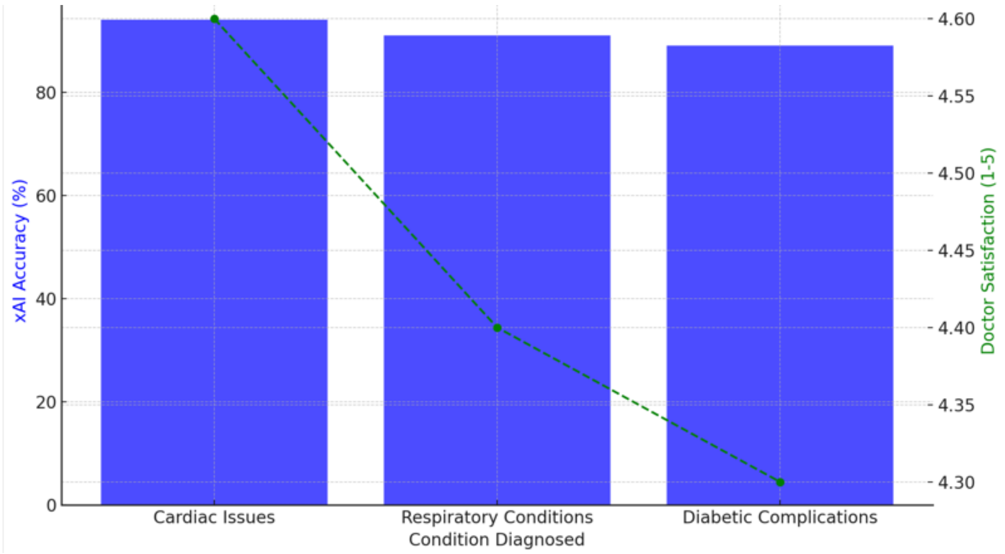

Figure 3: X(AI) accuracy and doctor satisfaction condition

4.4. Augmented Reality in Surgery

To evaluate the role of augmented reality (AR) in surgical support, Microsoft HoloLens devices were deployed to overlay real-time anatomical models and vital signs during surgical procedures. This immersive visualisation allowed surgeons to superimpose patient-specific 3D images directly onto the operative field, improving situational awareness. By integrating digital twin data with AR visualisation, the system aimed to enhance both the accuracy and efficiency of surgical interventions while minimising error rates. The comparative results are presented in Figure 4, which shows metrics for surgery time and surgical precision error before and after AR integration. Surgery duration was reduced from 120 minutes to 105 minutes, representing a 12.5% improvement, while surgical precision error dropped from 8.5% to 5.2%, reflecting a 38.8% improvement. These findings establish AR as a powerful tool for improving surgical efficiency and precision, validating its effectiveness as part of the integrated framework.

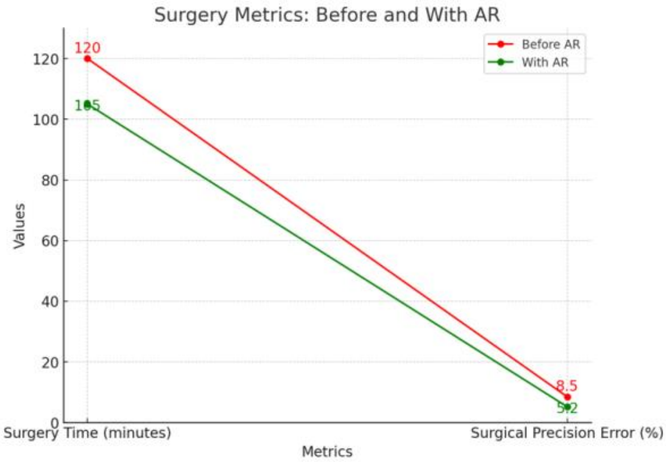

Figure 4: Surgery metrics

The results demonstrate that AR not only reduces the time required for complex procedures but also significantly enhances surgical accuracy, thereby improving patient safety. This diagram highlights how AR significantly improves both surgical efficiency and precision, reducing the overall time required for surgery and minimising error rates.

4.5. AR for Patient Education

Beyond surgical applications, AR was also employed to enhance patient understanding of health conditions and treatment plans. Patients interacted with immersive 3D models of their anatomy and disease progression, enabling them to visualise the impact of therapies and lifestyle interventions. This interactive approach bridged communication gaps between patients and healthcare providers, improving patient engagement and adherence to care plans.

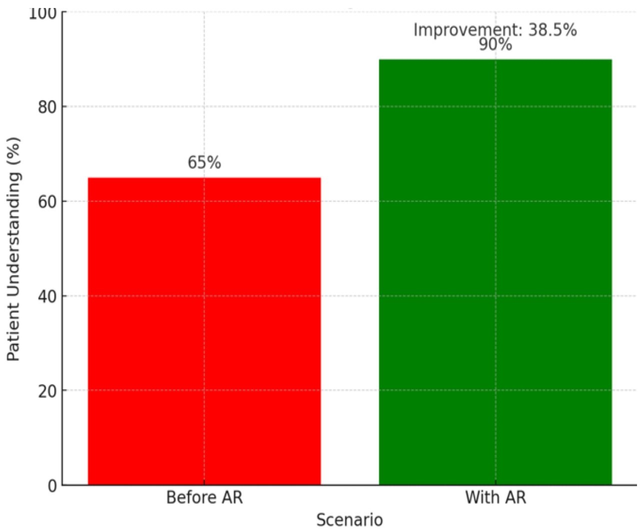

Figure 5: Patient understanding: Before and with AR

The outcomes are summarised in Figure 5, which shows patient understanding before and after AR usage. Engagement and comprehension levels improved by 38.5%, as patients found visual models significantly more intuitive than text-based explanations. These results highlight AR's value in patient education, as it transforms abstract medical information into tangible and interactive experiences. By improving understanding, AR fosters greater patient confidence, compliance, and satisfaction with the treatment process.

4.6. Predictive Analytics with Digital Twins

The predictive analytics component of the digital twin system was evaluated for its ability to generate early warnings of patient deterioration and equipment malfunctions. Machine learning models embedded within the twins continuously analyzed temporal patterns in patient vitals and device performance. This proactive capability enabled healthcare providers to intervene before critical events occurred, thereby reducing the risks associated with delayed diagnosis or equipment failure.

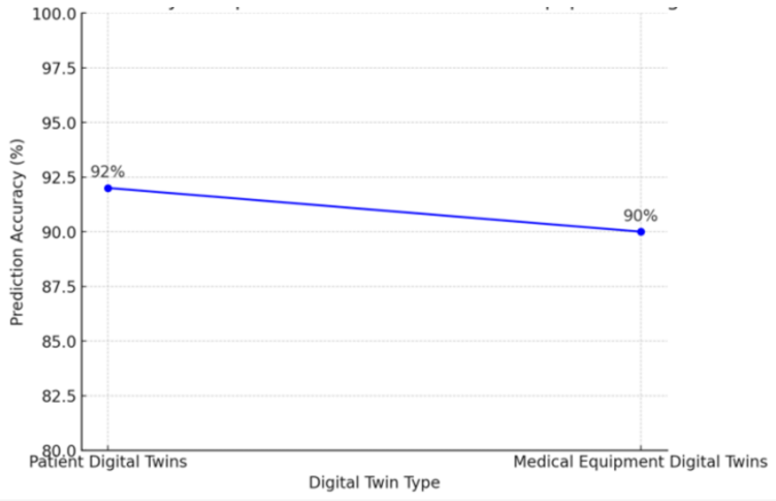

Figure 6: Prediction accuracy of patient vs medical equipment digital twins with values

The predictive performance is illustrated in Figure 6, which compares the prediction accuracies for patients and equipment. Both models achieved greater than 90% accuracy, validating their reliability for real-time decision-making in healthcare. By generating accurate early alerts, the predictive analytics module ensured timely interventions, reduced clinical risks, and improved patient outcomes. These findings confirm that predictive intelligence is a critical extension of the digital twin system, supporting proactive healthcare management.

4.7. Blockchain for Secure Data Sharing

Blockchain technology was further validated for its ability to securely share medical data across distributed healthcare providers. Smart contracts automated the process of access control and data sharing, ensuring that retrieval and updates were consistent, transparent, and compliant with patient consent policies. This interoperability enabled seamless communication across hospital departments and with external stakeholders, while preserving patient privacy.

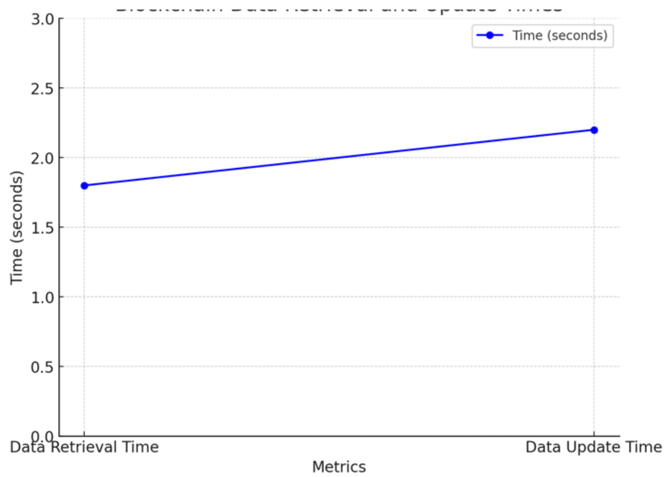

Figure 7: Blockchain data retrieval and update time performance

The results are presented in Figure 7, which compares blockchain retrieval and update times. Data retrieval averaged 1.8 seconds, while update times were slightly higher at 2.2 seconds, both of which fell under the 3-second benchmark for real-time applications. These metrics confirm that blockchain ensures fast, tamper-proof, and secure data exchange without introducing bottlenecks into clinical workflows. By combining immutability with efficiency, blockchain strengthens trust in healthcare data operations and supports integration with other modules of the framework.

4.8. Continuous Feedback and System Optimisation

The integrated system underwent iterative refinement through continuous feedback from patients, clinicians, and surgeons. This feedback loop was used to improve xAI interpretability, optimise AR interfaces, and fine-tune blockchain transaction handling. By incorporating user-driven adjustments, the framework evolved into a more adaptive and user-friendly system that better matched clinical needs.

Table 5: Feedback-based improvements in xAI diagnostic accuracy and AR usability

Metric	Before Feedback	After Feedback	Improvement (%)
xAI Diagnostic Accuracy (%)	90	94	4
AR Usability (Satisfaction, 1-5)	4.2	4.6	10

The results of this feedback process are summarised in Table 5. The diagnostic accuracy of xAI improved from 90% to 94%, reflecting a 4% increase, while AR usability satisfaction scores increased from 4.2 to 4.6, representing a 10% improvement. These findings highlight the importance of human-centred design in healthcare technology. By actively integrating clinician and patient feedback, the system achieved higher accuracy, greater usability, and improved trustworthiness, demonstrating its capacity for adaptive optimisation in real-world healthcare environments.

4.9. Comparative Analysis with Existing Frameworks

This step, presented in Table 6, compares the proposed IHMP-BDxAR framework with existing approaches. In terms of blockchain performance, the proposed system achieved 500 TPS with < 2.2s latency, outperforming earlier works that managed only 200–300 TPS with higher delays. For digital twin accuracy, prior studies were limited to basic patient state logging or ~85% synchronisation, whereas the proposed framework achieved over 99% synchronisation and over 90% predictive accuracy, ensuring highly reliable real-time monitoring. In the area of explainable AI trust, earlier works either neglected interpretability or offered minimal post-hoc explanations (~80% trust), while the proposed system integrated SHAP and LIME, achieving 94% diagnostic accuracy with high clinician confidence. Finally, for the effectiveness of augmented reality, which was not previously supported, the framework demonstrated substantial improvements, enhancing surgical precision by 38.8% and patient comprehension by 38.5%. Collectively, Table 6 validates that this step positions the IHMP-BDxAR framework as a comprehensive, secure, and intelligent healthcare solution that bridges the gaps left by earlier works.

Table 6: Comparative results of the proposed framework with recent works

Step	Blockchain-Secure Patient Digital Twin [12]	Smart and Secure Healthcare with DT + Blockchain + FL [13]	Proposed IHMP-BDxAR Framework
Blockchain Performance	Ensures security and consent control; limited throughput (~200 TPS) and higher latency.	Uses federated privacy but has moderate throughput (~300 TPS).	Achieves 500 TPS with <2.2 s latency through optimised Hyperledger Fabric.
Digital Twin Accuracy	Basic patient state logging; no predictive forecasting.	Diagnostic twins with federated updates; ~85% synchronisation.	Achieves >99% synchronisation and >90% predictive accuracy.
Explainable AI Trust	Not addressed: black-box models.	Minimal xAI; some post-hoc explanations (~80% trust).	Integrated SHAP/LIME; 94% diagnostic accuracy with high clinician trust.
AR Effectiveness	Not included.	Not included.	AR overlays improved surgical precision by 38.8% and patient comprehension by 38.5%.

5. Conclusion

This paper addresses key gaps in healthcare systems, where blockchain, digital twins, explainable AI (xAI), and augmented reality (AR) have been researched separately, and explores their combined potential for enhanced capabilities in securing data management, predictive intelligence, diagnostic transparency, and immersive interaction. The main goals of the outlined framework are threefold: to facilitate real-time monitoring through IoT-based digital twins that operate in real time by continuously replicating patient and equipment states, to offer early progression prediction by incorporating forecasting models into the digital twin framework, and to advance toward individualised treatment assessment through counterfactual simulations as a future development. To bridge current gaps, blockchain technology with smart contracts offers secure, immutable, and permissioned management of health data, providing a robust foundation for data integrity. Digital twins provide continuity and prognostic analysis of patient states. xAI produces explainable results to enhance clinician acceptance of AI outputs. Additionally, AR provides immersive visualisation to enhance surgical precision and patient interaction. Experimental verification demonstrated blockchain throughput of 500 TPS with low latency, digital twins achieving over 99% synchronisation accuracy and above 90% predictive accuracy, xAI with 94% diagnosis accuracy and high clinician trust, and AR enhancing both surgical accuracy and patient understanding by nearly 40%. By combining these four technologies into a unified architecture, the framework that bridges the gap between secure data governance, predictive modelling, interpretability, and immersive visualisation creates a solid foundation for intelligent and patient-driven healthcare ecosystems.

5.1. Future Work

Although the current work effectively illustrates the capabilities of the proposed framework in real-time monitoring and early progress prediction, a key direction of future work is the achievement of personalised treatment assessment. This goal involves expanding the digital twin from monitoring and prediction to function as a safe counterfactual simulation platform where different treatment strategies can be tested before clinical implementation. Future efforts will focus on creating twin-based treatment sandboxes that simulate patient trajectories across various intervention scenarios, estimating outcomes, uncertainty, and safety risks. Causal inference approaches, including doubly robust estimation and counterfactual ranking, will be incorporated to ensure that treatment recommendations are unbiased and patient-specific. Concurrently, reinforcement learning strategies informed by safety awareness, like conservative offline policy optimisation, will be investigated to characterise therapy policies that optimise clinical benefit at reduced risk. Further efforts will be needed to empirically validate these modules using large-scale clinical data resources, such as MIMIC-IV, and condition-specific databases, like OhioT1DM, to achieve generalizability across heterogeneous patient populations. In addition to treatment personalisation, future horizons also involve enhancing scalability through federated learning, addressing fairness in subgroups, and strengthening governance frameworks for the ethical and trustworthy deployment of digital twin systems in real-world healthcare.

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