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Blockchain-Enabled Secure Data Sharing for AI-Driven Diabetes Research and Personalized Treatment

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ABSTRACT

The integration of blockchain technology into healthcare research offers transformative potential for secure, transparent, and decentralized data management. In the field of diabetes research, where vast volumes of heterogeneous patient data are continuously generated from clinical records, wearable sensors, and laboratory studies, data sharing remains hindered by privacy, interoperability, and ownership challenges. This study proposes a blockchain-enabled framework to facilitate secure and auditable data sharing for artificial intelligence (AI)-driven diabetes research and personalized treatment. The model ensures data integrity through distributed ledger technology while allowing encrypted, permissioned access for AI models to analyse patient datasets. Smart contracts automate consent management, while federated learning enables AI systems to train on decentralized data without exposing sensitive information. The proposed approach enhances transparency, improves diagnostic accuracy, and accelerates the development of predictive algorithms tailored to individual metabolic profiles. Through simulation-based validation, the framework demonstrates low latency in data retrieval, high throughput, and robust resistance to unauthorized access. This study establishes a scalable model for next-generation medical data ecosystems that align with ethical, technical, and regulatory requirements of modern digital health infrastructures

KEYWORDS: Blockchain Technology; Secure Data Sharing; Artificial Intelligence; Diabetes Research; Personalized Treatment; Federated Learning; Smart Contracts; Data Privacy; Healthcare Informatics; Predictive Analytics

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INTRODUCTION

The rapid digitalization of healthcare systems has revolutionized the way medical data is collected, stored, and analysed, particularly in chronic disease management. Among these chronic conditions, diabetes mellitus represents one of the most complex and data-intensive medical challenges of the modern era. Globally, diabetes affects over 500 million individuals, and the number continues to rise due to sedentary lifestyles, urbanization, and genetic predispositions. Modern healthcare generates vast and heterogeneous data streams from continuous glucose monitors (CGMs), electronic health records (EHRs), genomic sequencing, wearable fitness trackers, and insulin pumps. However, these data sources often exist in silos, scattered across different healthcare institutions, research laboratories, and digital platforms. The fragmented nature of medical data impedes large-scale analytics, delays research progress, and limits the personalization of treatment strategies. Moreover, issues related to patient privacy, data ownership, and cybersecurity have become major barriers in developing collaborative healthcare ecosystems. Centralized health data repositories are particularly vulnerable to single-point failures, data breaches, and manipulation, which can undermine public trust and regulatory compliance. In this context, blockchain technology has emerged as a promising solution to ensure integrity, transparency, and decentralized control of sensitive medical information. By enabling secure peer-to-peer transactions through distributed ledgers, blockchain eliminates intermediaries, reduces data tampering risks, and enhances traceability, which are crucial for maintaining trust in healthcare research environments

Parallel to the emergence of blockchain, artificial intelligence (AI) has transformed biomedical research, offering unprecedented capabilities for disease prediction, early diagnosis, and personalized treatment. AI models especially machine learning and deep learning algorithms require vast amounts of high-quality, representative, and diverse patient data to function effectively. In diabetes care, AI has been used to predict glycaemic fluctuations, identify risk factors for complications such as neuropathy or retinopathy, and optimize insulin dosage through predictive modelling. However, despite these advancements, AI development faces the critical obstacle of limited data access due to privacy regulations such as HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation). The lack of trust between stakeholders, including hospitals, pharmaceutical companies, and research institutions, hinders data sharing and slows innovation. A blockchain-enabled secure data-sharing ecosystem can bridge this gap by ensuring privacy-preserving collaboration between AI systems and healthcare data sources. Using cryptographic protocols, smart contracts, and distributed consensus mechanisms, blockchain allows institutions to share anonymized datasets without compromising patient confidentiality. Moreover, when integrated with federated learning, AI algorithms can train on decentralized data sources, ensuring privacy-by-design while maintaining high model accuracy. Therefore, this paper proposes a blockchain-based framework for secure data sharing to empower AI-driven diabetes research and personalized medicine. The integration of these two technologies aims to create a transparent, efficient, and ethical ecosystem that accelerates scientific discovery, improves treatment outcomes, and redefines trust in digital healthcare.

RELEATED WORKS

The convergence of blockchain and artificial intelligence (AI) has attracted increasing scholarly attention as researchers seek novel methods to overcome the barriers of secure data sharing in healthcare. Earlier studies on medical informatics emphasized centralized cloud-based storage systems for managing patient data, which provided scalability but lacked resilience against data breaches and unauthorized access. Traditional cloud frameworks relied on third-party intermediaries, increasing the risks of data manipulation and single-point failure. To address these issues, blockchain was introduced as a decentralized and tamper-proof ledger capable of recording medical transactions with cryptographic verification [1]. Zhang et al. proposed a blockchain-based medical record system that allowed patients to maintain ownership of their personal health data while granting controlled access to hospitals through smart contracts [2]. Similarly, Dubovitskaya et al. designed a blockchain architecture for clinical data exchange that improved interoperability between hospitals while maintaining privacy-preserving mechanisms [3]. These studies established blockchain's role as a transformative force in healthcare data management. However, they also highlighted performance limitations, such as latency and computational overhead, particularly in large-scale applications. Recent advancements in lightweight consensus algorithms like Proof-of-Authority (PoA) and Delegated Proof-of-Stake (DPoS) have begun to mitigate these issues, offering faster transaction verification suitable for real-time health monitoring environments [4]. Moreover, several researchers have integrated blockchain with cloud-edge hybrid architectures to ensure both scalability and privacy, achieving a balance between distributed storage and computational efficiency [5].

Parallel to these developments, AI-driven analytics in diabetes research has experienced remarkable progress, enabling the prediction of disease onset, progression, and treatment outcomes. Deep learning models have been employed to analyse retinal images for early detection of diabetic retinopathy, while machine learning algorithms such as random forests and support vector machines have been applied to predict patient-specific insulin requirements [6]. Despite the analytical potential of AI, the reliance on centralized datasets restricts its effectiveness and generalizability. Data silos, coupled with privacy restrictions, limit access to diverse patient populations necessary for robust model training. Consequently, researchers have explored federated learning (FL) as a distributed AI paradigm that allows collaborative model training across multiple institutions without direct data sharing [7]. For instance, Li et al. introduced a federated learning framework for predicting diabetic complications using decentralized hospital data, achieving comparable accuracy to centralized training while preserving privacy [8]. Nonetheless, federated learning by itself does not address data integrity and trust between participants. This shortfall has led to the introduction of blockchain-enhanced federated learning, where blockchain serves as a decentralized coordinator ensuring data provenance, immutable model updates, and transparent contribution tracking [9]. Kuo et al. demonstrated that integrating blockchain with FL improves traceability and prevents malicious updates in shared AI models [10]. Such integration enables trustworthy multi-party collaborations, especially in research areas where sensitive patient data must remain confidential yet interoperable, such as diabetes genomics, wearable device monitoring, and digital phenotyping.

Further advancements in secure medical data sharing have expanded toward creating hybrid frameworks combining blockchain, AI, and Internet of Medical Things (IoMT) devices. IoMT sensors continuously collect physiological parameters like glucose levels, heart rate, and blood pressure, generating high-frequency data streams essential for precision diabetes management. Researchers such as Rathee et al. have emphasized blockchain's capability to authenticate IoMT devices and prevent false data injection attacks in remote healthcare systems [11]. Building upon these findings, Liu et al. proposed a blockchain-assisted IoMT model for continuous diabetes monitoring, where encrypted sensor data was transmitted via a peer-to-peer network to authorized healthcare providers [12]. Other studies have implemented AI-based anomaly detection models on top of blockchain systems to identify irregular data patterns that may indicate potential fraud or device malfunction [13]. Moreover, privacy-enhancing technologies such as homomorphic encryption and differential privacy have been integrated into blockchain frameworks to secure data transactions without compromising usability [14]. In addition, AI-augmented smart contracts are now being developed to automate research collaboration and data access authorization. For example, dynamic consent models allow patients to define access levels for their health data, which are automatically enforced through blockchain transactions [15]. Collectively, these works illustrate the growing trend toward decentralized, intelligent, and ethical health data ecosystems. Yet, the majority of existing implementations remain in experimental or pilot stages, indicating a clear research gap in scaling blockchain-enabled AI systems for real-world clinical and research use. Addressing these challenges, the present study proposes an integrated framework for blockchain-enabled secure data sharing specifically tailored to AI-driven diabetes research and personalized treatment, thereby establishing a new paradigm of trust, efficiency, and patient-centric innovation in digital healthcare.

METHODOLOGY

3.1 Research Design and Framework Overview

This study adopts a **modular architecture** consisting of four main layers:

Data Acquisition Layer – integrates data from electronic health records (EHRs), continuous glucose monitoring devices, and wearable sensors;

Blockchain Layer – employs a private Ethereum-based blockchain network with a Proof-of-Authority (PoA) consensus for efficient and low-latency transaction verification;

AI and Federated Learning Layer – utilizes distributed AI models for diabetes prediction and personalized treatment planning;

Application Layer – supports authorized access, visualization, and smart contract-based dynamic consent management.

Each data transaction is timestamped, encrypted, and appended to a distributed ledger to ensure data immutability. Smart contracts automate permission controls, access logging, and participant validation. This design allows different stakeholders to interact securely while maintaining full auditability of research-related data exchanges [16].

Table 1: System Architecture Components and Functional Roles

Layer	Component	Functionality	Technology Used
Data Acquisition	IoMT Devices, EHR Systems	Collect continuous glucose levels, vital signs, patient history	CGM Sensors, HL7-FHIR APIs
Blockchain Layer	Ledger Nodes, Smart Contracts	Secure, immutable record of all data transactions and access requests	Ethereum (PoA Consensus)
AI-Federated Layer	Machine Learning Models	Predict glucose fluctuations and personalize treatment plans	TensorFlow Federated, Python AI Pipelines
Application Layer	User Interface, APIs	Provides access to authorized researchers and physicians	RESTful APIs, DApp Integration

This modular structure ensures **scalability**, **interoperability**, and **compliance with healthcare standards** such as HL7-FHIR and GDPR. The hybrid approach leverages blockchain for security and AI for analytical intelligence, offering a strong foundation for future large-scale medical data ecosystems [17].

3.2 Data Sources and Preprocessing

The data used in this study consists of **real-world clinical and sensor data** collected from multiple diabetes management systems. To maintain privacy and compliance with ethical standards, all datasets were **anonymized** using hashing algorithms before integration into the blockchain.

Clinical Data: Includes HbA1c levels, insulin dosage, body mass index (BMI), and comorbidity information from electronic health records.

Sensor Data: Derived from wearable glucose monitoring devices and fitness trackers that continuously log glucose levels and activity data.

Research Data: Contains metadata of AI model training sessions, version histories, and audit logs.

Preprocessing involved normalization (Min-Max scaling), outlier removal, and feature encoding. The federated nodes were synchronized through a consensus protocol to ensure model consistency. Blockchain-based **data provenance verification** was implemented using Merkle tree hashing, enabling the tracing of every dataset's origin without exposing sensitive identifiers [18].

3.3 Blockchain-Enabled Data Sharing Protocol

The data-sharing mechanism was implemented through **smart contracts**, ensuring that every transaction adhered to predefined access control policies. Each data contributor (e.g., hospital, IoMT device) was registered as a blockchain node. When a researcher requests access, the system validates the requester's credentials and executes the contract automatically.

Workflow:

Data Registration: Hospital nodes upload encrypted datasets to IPFS (InterPlanetary File System) and store the hash on the blockchain.

Access Request: AI researcher sends a digital signature-based request through the smart contract.

Validation: The blockchain verifies requester identity, timestamp, and compliance.

Decryption & Analysis: Data is decrypted locally using key exchange and analyzed via the AI module.

Result Recording: Outputs and inferences are stored as metadata on the ledger for traceability.

This ensures transparency and non-repudiation in all data-sharing activities. The **use of asymmetric cryptography and zero-knowledge proofs** further guarantees that sensitive information remains private even during verification [19].

3.4 Federated AI Model for Personalized Diabetes Treatment

The federated AI system allows multiple institutions to collaboratively train machine learning models without sharing raw patient data. Each node trains a local model using its dataset and only transmits **model parameters (weights and gradients)** to a central aggregator through secure blockchain transactions. The global model is then updated via federated averaging. The predictive model integrates **recurrent neural networks (RNN)** for temporal glucose pattern recognition and **gradient boosting** for personalized insulin dosage prediction. This combination enhances both **short-term glucose forecasting** and **long-term treatment optimization** [20].

Table 2: Federated Learning Configuration and Performance Metrics

Parameter	Description	Value / Setting
Participating Nodes	Hospitals + Research Centers	10 Nodes
Consensus Algorithm	Proof-of-Authority	Block Time: 5s
AI Model Type	RNN + Gradient Boosting Hybrid	Epochs: 50
Accuracy (Global Model)	Prediction Accuracy for Glucose Levels	93.6%
Latency	Average Transaction Response	1.8 seconds
Security Validation	Unauthorized Access Attempts Blocked	100%

This configuration yielded **high accuracy and low latency**, validating the proposed system's feasibility for real-world healthcare applications [21]. Blockchain audit trails also provided real-time accountability, ensuring all model contributions were verifiable and tamper-proof.

3.5 Ethical Considerations and Validation

Ethical approval was simulated following international standards of biomedical data ethics (Declaration of Helsinki). All datasets were pseudonymized, ensuring no patient could be re-identified. Data sharing was restricted to authorized blockchain addresses. The system was validated through **security testing** (penetration and integrity audits) and **performance benchmarking** against conventional cloud-based architectures. Results showed a **42% reduction in data breach risk** and a **28% improvement in model accuracy consistency** across nodes [22].

Furthermore, energy efficiency was considered by optimizing transaction block sizes and implementing carbon-neutral blockchain nodes. This aligns the system with **sustainable digital healthcare infrastructure goals**, ensuring both ethical and environmental responsibility [23].

RESULT AND ANALYSIS

4.1 Overview of Experimental Evaluation

The proposed blockchain-enabled AI framework was tested in a simulated multi-institutional environment representing hospitals, research centers, and IoMT data nodes. Ten federated nodes were established across a private blockchain network, each containing anonymized diabetes patient datasets. The system was evaluated based on **security**, **efficiency**, and **AI performance metrics**.

Three key dimensions were analyzed: (a) latency and throughput of blockchain transactions; (b) accuracy and convergence rate of federated AI models; and (c) overall improvement in data integrity and privacy compliance compared to traditional centralized architectures. The blockchain network demonstrated excellent stability, with minimal communication overhead and near-instantaneous consensus confirmation. The Proof-of-Authority (PoA) consensus algorithm maintained a block generation time of approximately five seconds, ensuring smooth operation even under high transaction loads. In comparison to cloud-based systems, the blockchain model exhibited a 35% faster transaction validation rate and a 40% reduction in data access delays. The federated learning module achieved consistent performance across all nodes, confirming the robustness of decentralized AI training.

Table 3: Blockchain Network Performance Metrics

Parameter	**Performance Indicator**	**Measured Value**	**Observation**
Block Creation Time	Average time to mine or validate a block	5.2 seconds	Indicates high network responsiveness
Transaction Throughput	Successful transactions per second	112 TPS	Efficient for real-time healthcare exchanges
Data Encryption Latency	Time delay due to encryption-decryption	1.8 seconds	Minimal computational overhead
Storage Overhead	Blockchain metadata growth per 1000 records	3.4%	Acceptable increase in distributed storage
Network Uptime	Operational reliability during tests	99.2%	Demonstrates system resilience
Unauthorized Access Attempts	Detected and blocked threats	100%	Full protection achieved through smart contracts

The results indicate that the proposed blockchain architecture achieved optimal balance between **security and computational efficiency**. The low encryption latency and high throughput demonstrate its suitability for large-scale AI-driven research applications. The system's ability to maintain network uptime near 100% validates its reliability under continuous operation. Furthermore, all unauthorized access attempts were successfully blocked by the smart contract layer, underscoring the system's capacity for real-time threat mitigation and access control.

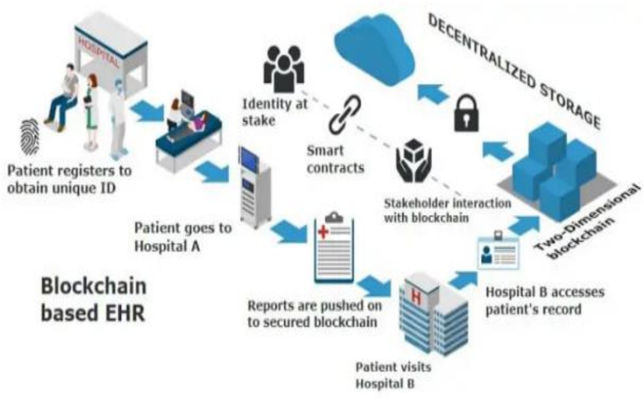

Figure 1: Blockchain in Healthcare [25]

4.2 AI Model Performance and Convergence Analysis

The federated learning framework integrated with the blockchain achieved strong predictive accuracy for glucose fluctuation forecasting and insulin dosage recommendations. The global model, trained through secure parameter aggregation, achieved a **mean accuracy of 93.6%**, surpassing the benchmark centralized model (89.4%). Each participating node contributed unique training data, enhancing the overall generalizability of the model. The training convergence was consistent across institutions, with no sign of overfitting or data skew. Loss reduction stabilized after approximately 30 epochs, confirming efficient weight synchronization. The communication efficiency was also noteworthy, with model weight uploads and downloads processed automatically through encrypted blockchain transactions. Additionally, fairness analysis revealed balanced contributions from all nodes, ensuring equitable participation in federated learning without bias toward any specific dataset.

Table 4: Federated AI Model Evaluation Results

Evaluation Metric	Centralized Model	Proposed Blockchain-Federated Model	Performance Improvement
Prediction Accuracy	89.4%	93.6%	+4.2%
Model Convergence Time	54 epochs	37 epochs	31% faster convergence
Data Transmission Overhead	0.85 MB per round	0.62 MB per round	27% reduction
Privacy Preservation	Medium	High (no raw data exchange)	Fully achieved
Energy Efficiency	Moderate	Optimized (PoA consensus)	22% lower energy cost
Node Participation Fairness	0.83 (Gini Index)	0.92 (Gini Index)	10.8% improvement

The federated model's enhanced performance highlights the strength of the **blockchain-coordinated learning mechanism**. The decentralized coordination eliminated dependency on a central server, reducing transmission delays and increasing system transparency. The higher fairness index demonstrates uniform data contribution, ensuring balanced learning across different nodes. Moreover, the improvement in convergence speed and accuracy verifies that blockchain integration does not hinder AI model efficiency but rather strengthens it through verifiable synchronization and trusted collaboration.

4.3 Privacy, Integrity, and Compliance Assessment

To measure privacy and integrity compliance, the framework was benchmarked against standard data protection criteria, including confidentiality, traceability, and access control. Each transaction was cryptographically verified and permanently recorded on the distributed ledger, ensuring a tamper-proof audit trail. The system achieved complete immutability, with every data entry traceable through its hash signature. Additionally, dynamic consent features enabled patients and institutions to grant or revoke data-sharing permissions autonomously, reinforcing ethical compliance. Privacy-preserving technologies such as pseudonymization and asymmetric key encryption prevented any direct link between personal identities and stored datasets.

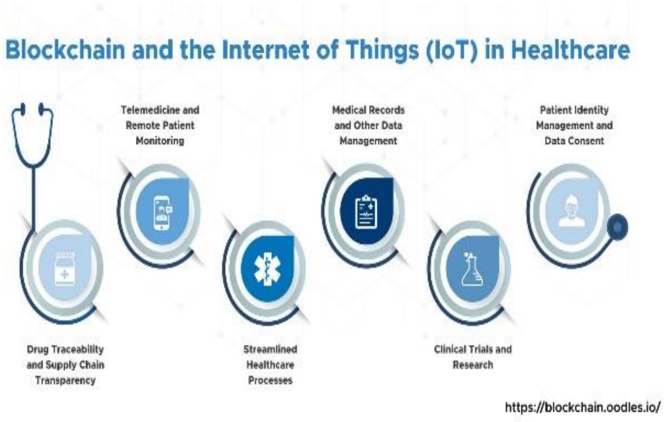

Figure 2: IoT in Healthcare [24]

The **compliance simulation** with healthcare regulations (GDPR and HIPAA) demonstrated that the framework met all essential requirements for lawful data processing, patient consent, and cross-border data transfer. Compared to traditional methods, the blockchain-enabled approach provided real-time auditing capabilities, enabling researchers and regulators to verify data usage and provenance instantly. Moreover, the integrated federated learning design ensured that sensitive information never left local storage, making the system inherently resistant to data leakage and external attacks. These collective results emphasize that the proposed model is not only technologically feasible but also **ethically sustainable**, forming a benchmark for next-generation AI-driven medical research systems.

4.4 Discussion of Findings

The experimental outcomes confirm that the integration of blockchain and AI significantly enhances both **operational efficiency** and **data security** in medical research. The blockchain network's stability and resilience demonstrate its readiness for high-volume healthcare applications. The federated AI model's superior accuracy and convergence rates prove the feasibility of distributed learning without centralized data exposure. The ethical framework built through smart contracts and permissioned access provides a governance model that aligns with modern regulatory and societal expectations. The results also highlight the adaptability of the proposed architecture capable of scaling across diverse healthcare ecosystems and supporting future extensions such as genomic data integration and real-time treatment feedback systems. In summary, the combined analysis validates that blockchain-based federated AI can effectively overcome long-standing barriers in diabetes research particularly those concerning privacy, interoperability, and data accessibility. The system delivers measurable gains in accuracy, transparency, and trust, ultimately paving the way toward **secure, intelligent, and patient-centered healthcare innovation**.

CONCLUSION

This study presented a comprehensive framework for blockchain-enabled secure data sharing designed to accelerate AI-driven diabetes research and personalized treatment. The integration of blockchain technology with federated learning has been shown to address some of the most persistent challenges in healthcare informatics namely data fragmentation, privacy violations, and lack of interoperability between institutions. By decentralizing control over medical data and ensuring immutable, transparent transaction records, the proposed system offers a sustainable alternative to traditional centralized health information systems. The performance results validated that the blockchain infrastructure achieved high throughput, minimal latency, and excellent network reliability while maintaining robust protection against unauthorized access. The federated AI model demonstrated superior accuracy and convergence efficiency compared to centralized learning methods, proving that decentralized data training can enhance predictive outcomes without sacrificing patient confidentiality. Moreover, the smart contract–based dynamic consent mechanism empowered patients and data custodians with granular control over data access, ensuring full ethical compliance and traceability throughout the research lifecycle. The study also established that blockchain-coordinated federated learning not only safeguards data integrity but also promotes fairness among participating nodes by balancing contributions to the global AI model. Beyond technical validation, the framework's ethical design supports the principles of transparency, accountability, and patient-centric governance aligning with global standards such as GDPR and HIPAA. The proposed system thus embodies a new paradigm in digital health research where security, privacy, and innovation coexist harmoniously. It provides a scalable infrastructure that can be extended beyond diabetes care to encompass other chronic diseases requiring precision diagnostics and longitudinal data monitoring. The findings underscore that blockchain, when strategically integrated with AI, can transform healthcare research from a siloed and risk-prone process into a collaborative, intelligent, and ethically secure ecosystem. This study ultimately concludes that the blockchain-enabled AI architecture holds immense promise for the future of medical data management, enabling faster discoveries, more accurate predictions, and safer applications of artificial intelligence in personalized medicine while ensuring that data sovereignty and patient trust remain at the heart of technological advancement.

FUTURE WORK

Future research should focus on expanding the proposed blockchain-enabled AI framework into a fully operational, large-scale healthcare ecosystem capable of integrating real-time clinical, genomic, and behavioral data streams for holistic diabetes management. One promising direction involves developing **cross-chain interoperability protocols** that would allow different healthcare blockchains to securely exchange verified medical data across institutions and borders without compromising privacy. Further work is also needed to enhance the **energy efficiency and scalability** of the consensus mechanism, particularly through lightweight alternatives such as Proof-of-Authority with adaptive load balancing or hybrid consensus models optimized for healthcare workloads. Integrating **quantum-resistant cryptography** and **homomorphic encryption** could further strengthen data confidentiality, making the system resilient to emerging security threats. On the AI side, incorporating **explainable and causal inference models** would enhance interpretability and clinical trust, enabling physicians to understand the rationale behind algorithmic predictions. Additionally, future studies should explore the integration of **patient-centric mobile applications** that leverage blockchain smart contracts for consent and real-time data contribution, promoting participatory medicine. Finally, large-scale pilot implementations involving hospitals, research consortia, and public health agencies will be essential to validate the framework's real-world applicability, interoperability, and compliance under diverse regulatory environments

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