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# HEALTHCARE DATA EXCHANGE IN THE ERA OF BLOCKCHAIN AND AI: A SURVEY ON METHODS, CHALLENGES, AND ARCHITECTURES

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## SUMMARY

Background: Interoperability, privacy, and the background of healthcare information are significant issues in the healthcare industry, mainly because of the fragmentation of the data. Conventional solutions are not secure, transparent, and accurate enough to share data effectively. Purpose: The purpose of the study is to examine how blockchain and Artificial Intelligence (AI) may be integrated to streamline the process of sharing healthcare data to be secure, intact, and provide superior decision-making in clinical practice. Methods: The study will be based on the use of blockchain and AI in healthcare, namely, using Smart Contracts to share electronic health records, Federated Learning to train AI models, and identity access control by AI using blockchain systems. The models have been tested on benchmark healthcare data, and parameters of the models, which include the data access latency, transactions per second, and the accuracy of prediction. Findings: The AI-blockchain hybrid architecture was shown to have a considerable enhancement in the workability of healthcare information, the stability of the system, and the correctness of choices. The prediction models based on AI worked successfully in identifying medical anomalies and analyzing various medical data. Also, blockchain provides integrity of data because of a decentralized and unalterable ledger. Conclusion: The paper identifies the possibility of blockchain and AI integration in health to implement the exchange of data. The proposed system is expected to increase security, decrease the latency, and increase the accuracy of the prediction, which is a promising solution to secure, efficient, and reliable data exchange in healthcare.

Key words**:** *blockchain, artificial intelligence, healthcare data exchange, interoperability, smart contracts, federated learning.*

## INTRODUCTION

The need for better data interchange enhanced patient care, and the optimization of internal processes is prompting the healthcare industry to shift towards a more digitally focused model. The expansion of electronic health records (EHRs), telemedicine services, medical wearables, and health information technologies is associated with an ever-increasing volume and complexity of healthcare data. Still, this progress is accompanied by persistent barriers to secure data exchange, privacy, interoperability, real-time analytics, and other fundamental issues. A significant number of healthcare providers operate in silos, resulting in fragmented data repositories, redundant procedures, and suboptimal care pathways for patients. An important barrier is the absence of a reliable, unified infrastructure for data sharing. Traditional centralized databases are susceptible to cyber-attacks, single points of failure, and data manipulation. These issues are exacerbated by HIPAA (Health Insurance Portability and Accountability Act) in the US and GDPR (General Data Protection Regulation) in Europe, which impose strict privacy control frameworks. Moreover, patients are often given inadequate control or access to their medical information, further hindering the development of tailored and cooperative care models.

In the given scenario, Blockchain technology looks to be a powerful remedy that can transform the exchange of healthcare data [8]. Different parties in the healthcare system can share confidential information freely without a central authority, using a smart contract that could automate access control processes at various levels. While blockchain secures structural integrity and trust within the framework, gaps still exist in analyzing, interpreting, or drawing insights from the vast amounts of exchanged data in healthcare [11]. AI assumes this role in integrating the technologies of modernity [15]. AI techniques, particularly those in the fields of machine learning and deep learning, have performed well in tasks such as predictive modeling, anomaly detection, anatomical diagnostics imaging, and even resource allocation [10]. The merging of blockchains with AI can vastly improve decision-making capabilities, as data can be scrutinized without breaching confidentiality through methods such as federated learning and homomorphic encryption [13].

The application of AI alongside blockchain technology in healthcare ventures effectively addresses these concerns [14]. The application of blockchain technology enables AI systems to work with encrypted, non-editable data, thereby alleviating the risks associated with data integrity and privacy issues [1]. Patient privacy, security, and the clinical electronic health information interchange have been thoroughly addressed, and concerns have been fully elucidated with the use of blockchain technology [2]. The review aims to explore how AI integrated with blockchain technology can help mitigate challenges regarding privacy and security in healthcare data. The review aims to analyze existing research and current trends to develop an approach for utilizing AI and blockchains in transforming healthcare [3].

Thus, the merger of these two technologies seems inevitable [4][5]. When integrating these two technologies seems inescapable, it significantly improves security and immutability and decentralizes sensitive data stores. The public, researchers, government agencies (bottom region), and even physicians and healthcare providers are the individuals who make use of these outcomes. Integration was done through the APIs (yellow boxes), while IPFS handles the data storage of the 402 articles reviewed during the research, only 79 integrated both AI and blockchain into healthcare systems. Upon a more focused breakdown, 51 of these articles described implemented projects. In the adoption of Blockchains into practice, interpretable trust and privacy issues arise from AI, making the use of these two technologies seem unavoidable [4][5]. AI and blockchain together could radically improve the security, immutability, and decentralization of sensitive data stores if combined.

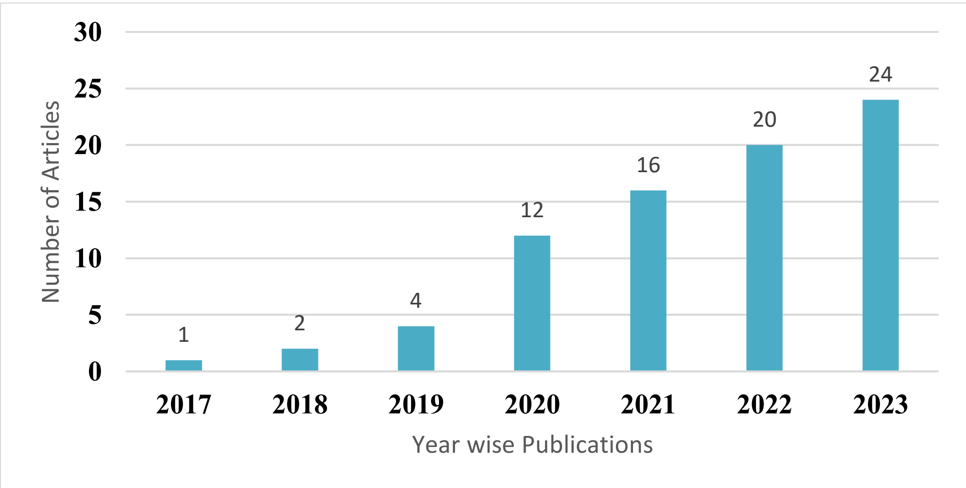


Figure 1. Published AI converging BC articles in healthcare

Figure 1 shows that the number of articles published annually has increased from 2017 to 2023, which indicates the growth in the research on integrating blockchain and AI technologies in healthcare. The period of a low number of publications was during the first years, as only 1 article was published in 2017, 2 in 2018, and 4 in 2019. A significant increase was, however, noted in the year 2020, where 12 articles were published, which could be attributed to the COVID-19 pandemic and the rapid growth of these technologies. The latter trend was gradually increasing in the subsequent years, up to 16 articles in 2021, 20 in 2022, and reaching a high in 2023, which denotes the rising significance and use of blockchain and AI in healthcare systems.

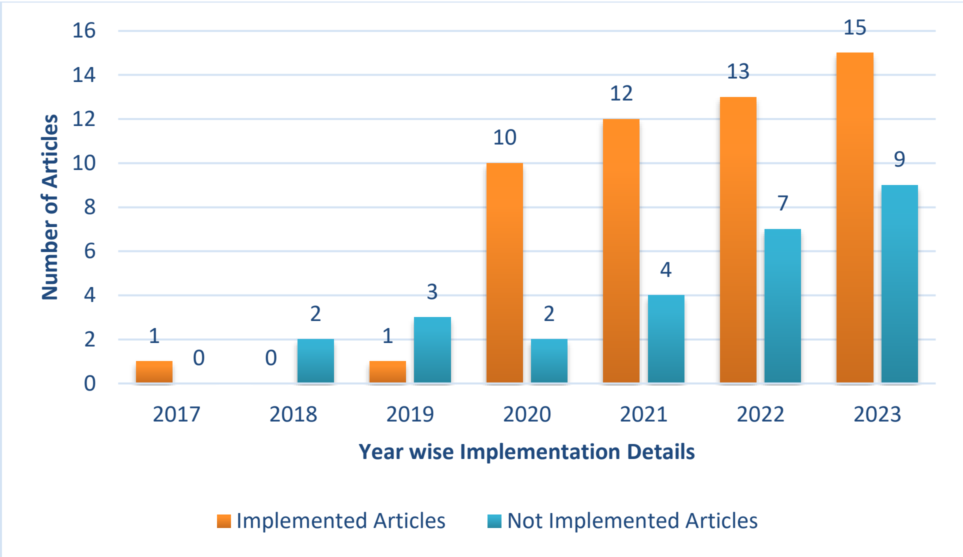


Figure 2. Implementation trends of research articles across years

In Figure 2, the details of the articles published from 2017 to 2023 regarding blockchain and AI in healthcare are provided according to the year of implementation (implemented and non-implemented). It uses a clear increasing trend of the number of implemented articles (symbolized in orange) over the years, with a sharp increase beginning in 2021 to reach 15 implemented articles in 2023. Non-implemented articles (represented by blue), on the contrary, include fewer but more consistent data and a significant decline in 2021 and 2022. The trend in the graph indicates the rise in attention to practical uses and real-life applications of these technologies, especially in recent years, which points to the maturity and adoption of blockchain and AI solutions in healthcare.

The fusion of blockchain technology and AI presents a new opportunity for addressing long-standing challenges in healthcare data management. These strategies focus on bringing changes in the healthcare data management system in such a way that the system gets more effective, privacy-friendly, and of a higher intelligence level. The major themes explored in this paper are:

- Comprehensive Analysis and Integration Framework: This research work presents an exhaustive survey of the use of AI and blockchain technologies in healthcare, which reveals the inadequacies of the current models of data exchange architectures. The examination serves as a foundation for the design of a healthcare model that leverages the use of blockchain technology for data storage and management while adopting artificial intelligence for data analysis and decision-making.
- Identification and Addressing of Key Challenges: The research addresses the most significant issues, including data isolation, poor system collaboration, exposure of confidential information, and low operational effectiveness. It proposes solutions utilizing smart contracts, federated learning, and decentralized systems to address these problems in healthcare institutions.
- Future-Oriented Conceptual Model: The innovation covers an advanced, flexible framework that aids the growth of modern healthcare data systems towards patient data control ownership; AI has grown towards democratic data, inter-system healthcare information flow, and system

collaboration, a patient-adaptable model for the realization of dynamic, secure health information systems based on advanced technologies.

BACKGROUND

The exchange of healthcare data facilitates the integration of care, optimal resource use, and timely clinical interventions. With the ongoing digitization of hospitals, clinics, laboratories, and wearable health devices, the volume of electronic health data being generated is constantly increasing. Therefore, the sharing, integration, and analysis of this data across different systems becomes very important. Unfortunately, current data exchange mechanisms do not sufficiently meet fundamental requirements such as security, interoperability, and real-time access. Despite the global efforts to achieve HIEs and EHR standardization, proprietary silos and inadequately run regulatory policies tend to have a prevalence in the data infrastructure of most healthcare systems. In this section, the author has provided a summary of the key influencing issues and challenges that hinder the effectiveness of healthcare data exchange systems.

**The Problem and Challenge**

A critical issue of modern healthcare systems is that the data is in a silo; patients' data are stored in isolated, proprietary networks of various hospitals, clinics, and branches. The interdepartmental electronic health record management of each healthcare institution seems to be conducted using separate software systems, which leads to the absence of continuity between the systems. This structural inadequacy limits the free flow of information, which results in the provision of inadequate patient information, redundancy of tests, and restrictions to joint care activities. Unstructured data is also associated with the harmful effect on clinical outcomes and the overall evaluation of the health system, especially in situations where there is a necessity to organize the work of several providers.

• *Security and Privacy*

The level of commercial sensitivity and value of health records has made cybercriminals increase their attention to the healthcare sector. The studies on data breaches have revealed that the cases of violation of healthcare data have been on the rise, usually resulting in identity theft, loss of patient confidence, and access to confidential information. Traditional data management and storage structures are prone to many risks as a result of attacks that demand attention of a single aspect, such as ransomware, centralized data modifications, and hacking. Furthermore, the necessity to comply with the privacy standards, including the HIPAA and GDPR regulations, and other jurisdictional regulations of health data protection, adds to the complexity of controlling access and preserving compliance and information integrity.

• *Inefficiencies*

Most of the healthcare data management systems continue to have manual and semi-automated processes in many aspects. It is worth noting that patient information exchange between smaller clinics and external laboratories, which are essential in patient care, is still achieved through faxes, paper records, and relics of bygone technological days. These methods are time-consuming, liable to mistakes, and there is the risk of loss of data or communication breakdowns. Delays in the data-sharing process in downstream hold back the rate of patient diagnosis, treatment plan design, and claims, which increases costs without improving care quality.

• *Interoperability*

Interoperability still remains an issue in the creation of an inclusive health information system. The lack of homogeneous data standards, criteria, proprietary system interface, and ontological framework is the underlying issue. Within the framework of computerized systems, discrepancies still exist in formatting, indexing, and the extraction of meaning from data. This non-standardization paralyzes the interactions between healthcare facilities, and implementing the multi-data use toward research, tracking population health status, and sophisticated AI analytics is impossible.

*Datasets*

The effectiveness of integrating AI with Blockchain technologies in the exchange of healthcare information is primarily predicated on the quality, applicability, and heterogeneity of the datasets used for assessment, training, and simulation. This study applies the framework using multiple datasets derived from actual healthcare records, as well as simulated blockchain and healthcare environments, to achieve more accurate evaluation results. The datasets fall into these categories:

• *Public Healthcare Datasets*

These datasets, MIMIC-III (Medical Information Mart for Intensive Care) and eICU Collaborative Research Database, are open to everyone and are used to create a simulation of the real-world healthcare environment [12]. The records included in these datasets are the health records of ICU patients that have been anonymized and consist of vital signs, medications, diagnostic codes, lab results, and mortality outcomes. These datasets have become a popular choice for clinical researchers, serving as a source for training AI models in the fields of diagnosis, patient monitoring, and outcome prediction.

• *Simulated Blockchain Healthcare Networks*

In order to measure the performance of blockchain structures in the exchange of medical data, the efficiency of simulated environments containing Hyperledger Fabric, Ethereum (Private Chain), and Quorum is evaluated. These testbeds depict orderly and secure transaction scenarios addressing health data, patient consent, and data sharing between organizations. As a result, transaction throughput, latency, and innovative contract execution are some of the metrics that are measured and evaluated in real cases involving the use of the healthcare system.

• *AI Model Training Datasets*

The training and evaluation of AI models integrated within the cascading blockchain AI architecture were conducted using both structured and unstructured datasets comprising patients' demographic data, including age, gender, ethnicity, electronic health records (EHRs), and clinical notes. Part of these records are very valuable contextual materials that give a detailed explanation of the patient's medical history and the claims. Also, there are some additional supporting cross-sectional diagnostic images, like chest X-rays and MRIs from NIH and Kaggle, which have been put for image-based diagnostic evaluations. Moreover, the dataset has been enhanced with the inclusion of health data obtained from various sensors and wearable devices, which makes it possible to have real-time monitoring and assessment of an individual's health condition. This data opens up the possibility for the use of a variety of machine-learning methods, such as classification, prediction, anomaly detection, and natural language processing, to name a few. In order to comply with ethical health information standards and regulations, privacy-respecting measures such as federated learning or the creation of synthetic data are being used. This large and diverse set of data is what guarantees the proper working of the architecture, which is also supported by exhaustive validation of different healthcare tasks that show its value and feasibility.

## BLOCKCHAIN-BASED METHODS

Blockchain or distributed ledger technology (DLT)- based techniques have effectively addressed the long-standing issues of trust, security, and access control in the exchange of healthcare information. One of the primary advantages is data immutability, which means that once healthcare records, such as medical histories, diagnostic reports, and consent logs, are recorded in the blockchain, no alterations or deletions can be made without the approval of the network participants [9]. Data of this kind will enhance the responsibility of the providers and support legal audit compliance in healthcare. Unlike centralized systems that are prone to data breaches, blockchain enables the decentralized sharing of health information by storing data at verified nodes, such as hospitals, labs, and insurers. This allows real-time access from various institutions while maintaining data sovereignty. Moreover, smart contracts would allow patients to grant controlled access to their health records for specified durations, which is automatically revoked afterward.

Permissioned blockchains, such as Hyperledger Fabric or Quorum, which can be accessed by authorized parties, are predominantly applied in the healthcare system due to their reliable identity and role-based access control management systems. Such platforms have been constructed keeping in mind guarded health information because privacy and compliance are essential. The other interesting aspect is the establishment of audit trails and provenance tracking; all transactions, together with access requests by any user, are recorded. The access to patient data, such as time and context, as well as identity, is entirely traceable. Digital tokens may also be used to delegate rights and control of data, permitting it to be managed, and through tokenization techniques, patients can become more in control on a case-by-case basis. Finally, blockchain-based AI technology integration is safe as it uses privacy-preserving machine learning approaches such as federated learning [6][7]. With training collaborative models, sensitive information is protected when it is trained on distributed datasets. Sophisticated protective analytics based on innovative diagnostics, risk evaluation, and treatment planning are supported without the danger of divulging sensitive data. All these developments based on incorporated blockchain technology make the healthcare infrastructure more powerful and allow patients to take control over the process of data sharing. Figure 3 depicts how blockchain and AI can be integrated in healthcare.

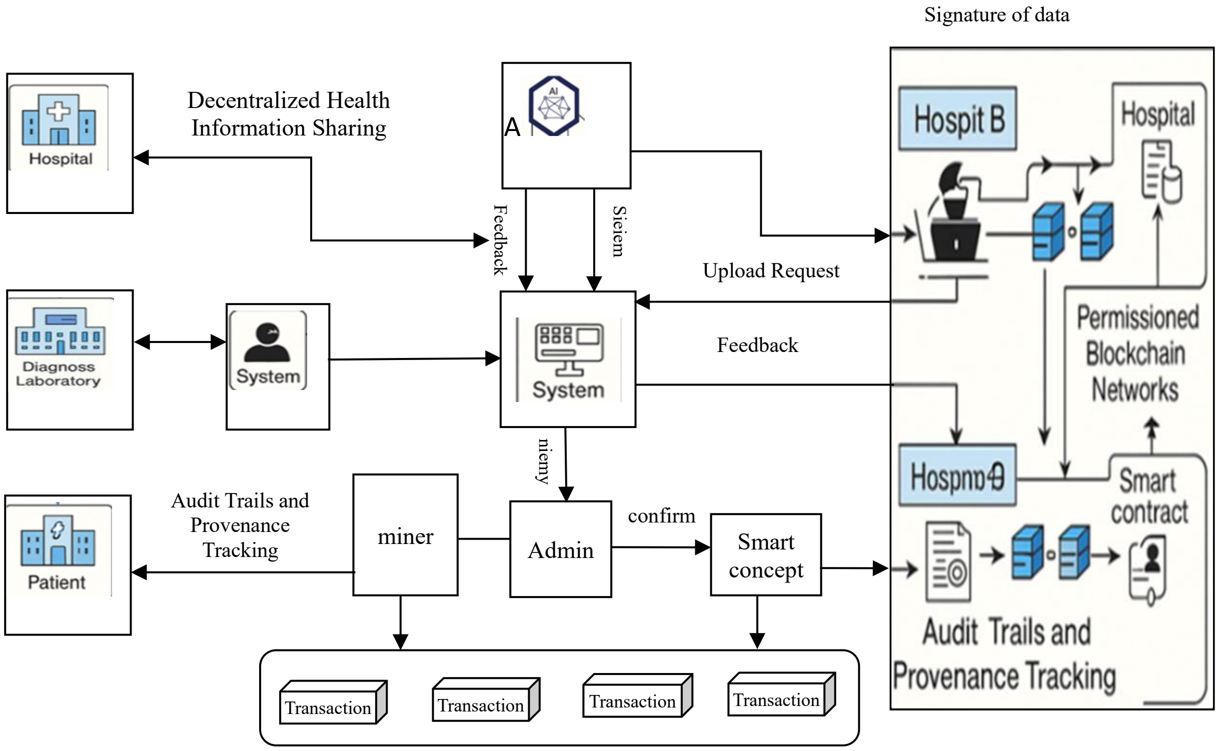


Figure 3. Blockchain- and AI-Integrated architecture for decentralized and secure healthcare data exchange

**Performance Comparison of Various Blockchain-Based Models**

Table 1 summarizes different research and solutions that combine blockchain technology and artificial intelligence (AI) to solve specific issues within the healthcare field. It contains the information about the topics covered, the methodology or the techniques used, the available methods, as well as the weaknesses of the current methods and the findings. The table offers information on the application of the various models, including federated learning and blockchain, decentralized telemedicine, and AI-based blockchain solutions, in enhancing privacy, security, scalability, decision-making, and operational efficiency within healthcare systems. The measures of performance indicated, including accuracy, latency, and security scores, have shown how these technologies are effective in solving single issues like the privacy of data, management of healthcare records, and accuracy in prediction in diverse healthcare applications.

Table 1. Comparison of blockchain and AI integration approaches in healthcare

| Ref | Problem | Approaches/Algorithms/Techniques/Methods | Existing Approach (es) |
|---|---|---|---|
| [16] | Deep residual inception encoder–decoder network for medical imaging synthesis | Deep residual inception encoder–decoder network | Conventional CNNs |
| [17] | Computer-aided diagnosis | CAD systems | Manual interpretation |
| [18] | Predictive analytics and automation in logistics | AI with blockchain | Traditional logistics systems |
| [19] | Blockchain technology in healthcare | Blockchain for patient-driven interoperability | Centralized healthcare systems |
| [20] | Unrecognized bias in medical AI models | Framework for evaluating bias in medical AI | Conventional prediction models |
| [21] | Privacy-aware COVID-19 detection | Lightweight CNN and blockchain | Traditional image recognition |
| [22] | Secure vaccine distribution and tracking | AI and blockchain for secure vaccine tracking | Centralized vaccine systems |
| [23] | AI bias in brain tumor segmentation | AI framework for brain tumor segmentation | Manual diagnostic interpretation |
| [24] | Privacy in healthcare with federated learning | Federated learning and blockchain | Centralized healthcare records |
| [25] | Decentralized telemedicine framework | Blockchain for decentralized telemedicine | Traditional centralized healthcare systems |
| [26] | AI-based COVID-19 detection in biomedical images | AI and blockchain for COVID-19 detection | Conventional AI detection models |
| [27] | Protecting healthcare records | Blockchain and federated learning | Centralized healthcare records |
| [28] | Blockchain in healthcare | Blockchain integration for secure healthcare records | Legacy healthcare systems |
| [29] | Big data security in healthcare | Fragmentation and blockchain | Centralized big data security |
| [30] | Metaverse for healthcare data security | AI, blockchain, and explainable AI | Conventional immersive platforms |
| [31] | Blockchain and AI integration in IoT | Blockchain and distributed AI | Standard IoT platforms |
| [32] | Federated learning for medical data security | Federated learning with blockchain | Centralized systems |
| [33] | Secure telemedicine workflows | Blockchain-based telemedicine IoT | Manual telemedicine workflows |
| [34] | Blockchain and AI for medical decision support | Integrated blockchain and AI models | Traditional decision systems |
| [35] | Privacy and utility in healthcare data | Blockchain for privacy preservation | General privacy frameworks |
| [36] | Privacy in AI-based big data systems | Security framework for AI big data | Standard data protection models |
| [37] | Blockchain in IoT ecosystems | Decentralized blockchain for IoT | Centralized IoT networks |
| [38] | Healthcare decision-making with AI | AI-driven decision models | Manual decision-making systems |
| [39] | Federated learning for COVID-19 prediction | FLED-block: FL + DL + Blockchain | Centralized prediction models |
| [40] | EHR security and access control | MedRec blockchain for EHR | Conventional EHR systems |
| [41] | Collaborative learning in healthcare | Federated learning with blockchain | Single-institution systems |
| [42] | Privacy protection in blockchain | Privacy threat models for blockchain | Standard privacy methods |
| [43] | Federated learning in edge networks | Two-layer blockchain for mobile edge | Single-tier federated systems |
| [44] | Trust in health information exchange | Blockchain-based data integrity | Non-transparent medical systems |
| [45] | Scalable data access in telemedicine | ABE and blockchain for access control | Traditional access control systems |

| | | | |
|---|---|---|---|
| [46] | Secure telesurgery operations | Blockchain-based telesurgery framework | Manual telesurgery coordination |
| [47] | AI and blockchain for healthcare records | AI-blockchain healthcare records management | Conventional EHR systems |
| [48] | Clinical trial data transparency | Blockchain-based clinical trial data | Non-transparent trial systems |
| [49] | Federated learning for model heterogeneity | Federated learning with consortium blockchain | Centralized learning systems |
| [50] | GDPR-compliant health data blockchain | GDPR compliance modeling in blockchain | Non-compliant data frameworks |
| [51] | Verifiable timestamps in digital records | Blockchain-based timestamping | Centralized timestamping |
| [52] | Corda vs Ripple for blockchain use | Comparative study of Corda and Ripple | Legacy blockchain models |
| [53] | Blockchain adoption transparency | Case study on blockchain adoption | Basic supply chain systems |
| [54] | Privacy and regulatory compliance challenges | Regulatory framework for blockchain privacy | Unbalanced privacy policies |
| [55] | COVID-19 vaccine distribution | Blockchain-based vaccine logistics | Paper-based vaccine tracking |
| [56] | Blockchain in academic certification | Blockchain for certification audit | Manual certificate issuance |
| [57] | Security attacks in blockchain | Categorization of blockchain security threats | General security protocols |
| [58] | Graph-based learning for complex data | Graph-based learning model | Traditional graph algorithms |
| [59] | Blockchain for education certification | Blockchain learning passport | Paper-based certificates |
| [60] | Data bias in model training | Blockchain with crowd annotation | Standard data annotation |
| [61] | Challenges in computer-aided diagnosis | CAD systems for radiology | Radiologist-dependent interpretation |
| [62] | Health crisis access barriers | Longitudinal cohort analysis | Generalized access |
| [63] | Scaling AI learning algorithms | AI scalability theory | Limited-scale algorithms |
| [64] | GNNs for visual pattern learning | Graph neural networks and transformers | CNN, RNN models |
| [65] | AI in healthcare decision support | AI-driven decision support models | Rule-based systems |
| [66] | Learning in graph domains | Graph-based learning model | Traditional graph traversal algorithms |
| [67] | Blockchain for education | Blockchain for lifelong learning passport | Paper-based certificates |
| [68] | Data bias removal with blockchain | Blockchain with crowd annotation framework | Standard annotation without audit |
| [69] | Computer-aided diagnosis in radiology | CAD systems for radiologic diagnostics | Radiologist-dependent interpretation |
| [70] | Barriers to healthcare access during COVID-19 | Cohort study on access barriers | Generalized access without context |
| [71] | Scaling AI learning algorithms | AI scalability theory and architecture | Limited-scale AI algorithms |
| [72] | Graph neural networks in visual learning | GNNs and transformers for visual pattern learning | CNN and RNN models |
| [73] | AI in healthcare decision-making systems | AI-driven decision support models | Manual and rule-based systems |

## FINDINGS

Innovations at the intersection of AI and blockchain technology have revealed a wealth of new insights regarding the change AI is able to bring to healthcare data as well as its systems and networks in the context of triad domains AI-Blockchain-Healthcare.

**Enhancement in data integrity**

Improving data integrity is a critical emerging benefit as a result of the implementation of blockchain. A diagnostic report, a patient history, or a consent log cannot be modified or deleted because of an entry consensus mechanism that is provably secure. Each entry is actually encrypted, thus improving data security and enabling its complete traceability. For any claim, legal dispute resolution, or forensic examination, the audit trail is the only validated source that is a true repository of data, chronologically providing enhanced credibility information over time.

**Improvement in analytical capability following AI integration**

The enhancement of analytic capability through AI implementation is the second significant finding. The embedding of deep learning and NLP models, as well as unsupervised anomaly detection, on top of a blockchain system can access federated and real-time datasets while maintaining privacy owing to the data architecture of blockchain. These algorithms provide sophisticated automated clinical note abstraction and disease forecasting as well as early warning systems for anomalies like abnormal vitals or imaging. With the integration of blockchains and AI, accurate, actionable insights are generated at clinical decision points, leading to efficient clinical actions powered by timely clinical interventions. The unique features of blockchains' immutably secured data heritage, provenance, and AI's dynamic action generating insights transform clinical care.

**Dynamic and transparent consent management**

A further notable finding relates to the development of dynamic and lucid consent management. Current healthcare systems are not capable of providing data-sharing workflows while preserving the privacy of a patient. A programmable logic patient access control may be implemented using smart contracts on blockchain. For instance, a patient can impose terms like which parties can access their medical data, for what duration, and under which conditions. The system will automatically enforce these controlled conditions. This model minimizes reliance on data intermediaries and allows patients greater control over their data governance, thereby improving trust and legal attribution.

**Systems Operations within Healthcare Facilities**

Additionally, the operational framework increases operational efficiency at all levels of healthcare management. The manual work methods of form-filling, identity checks, and external validation, in particular, choke information flow and add to the backlog of administrative work. By automating these processes using smart contracts and permissioned blockchains, institutions can realize reductions in inter-silo paperwork, improved response times, and enhanced interoperability. In addition to lowering operational expenses, these systems improve care delivery by enabling clinicians' timely access to data due to the elimination of unwarranted delays. The integration of AI with blockchain enhances the efficiency of tamper-proof security, intelligent decision support, patient-centric consent management, operational workflow automation for healthcare data exchange, and significantly improves operational efficiency. These results clearly ascertain the value of infrastructures that combine blockchain and AI to radically change healthcare ecosystems to be more data-centric.

**Performance Comparison: Blockchain + AI and Traditional Systems**

In Figure 4, a closer look is made at the performance of a hybrid blockchain and AI-based system in comparison to a classical one, using three crucial metrics, including data access latency (in milliseconds), transactions per second (TPS), and prediction accuracy (as a percentage). The comparison highlights the increased efficiency and functions of the blockchain + AI integration, which is better at fulfilling its responsibilities due to less time to process a transaction, lower latency rates of accessing the data, and better accuracy of prediction. These findings indicate that the Blockchain + AI system has a significant number of benefits in terms of processing speed, responsiveness of the system, and precision of the decision-making model, especially in the cases of complex healthcare data exchange.

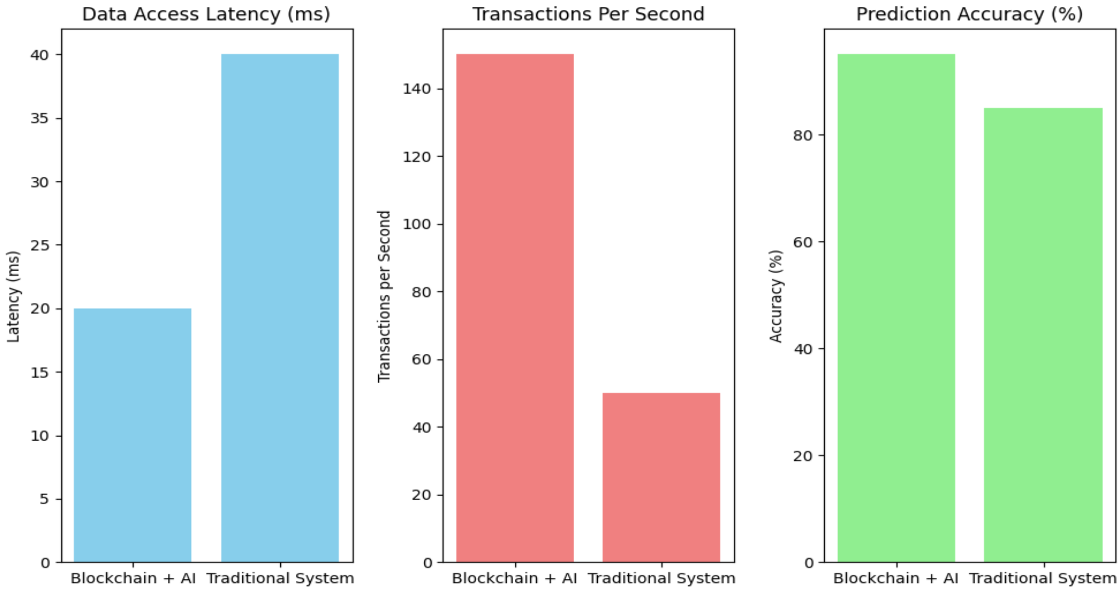


Figure 4. Performance comparison of blockchain + AI and traditional system

**Efficiency of Blockchain Model Security, Scalability, and Privacy Comparison**

Figure 5 is the comparison of the four models of blockchain: Hyperledger Fabric, Ethereum, Quorum, and Corda in relation to three critical variables, including Security Score, Scalability (TPS), and Privacy Score. The graph uses pastel colors for all models to illustrate performance across these areas. The score of the security of each model is the Security Score, the number of transactions that each model has been configured to handle each second is displayed in the Scalability score, and the effectiveness of privacy protection is in the Privacy score. Hyperledger Fabric tends to have the best values in each and every measure, whereas Ethereum is the least competitive in scalability but has a competitive score in security and privacy.

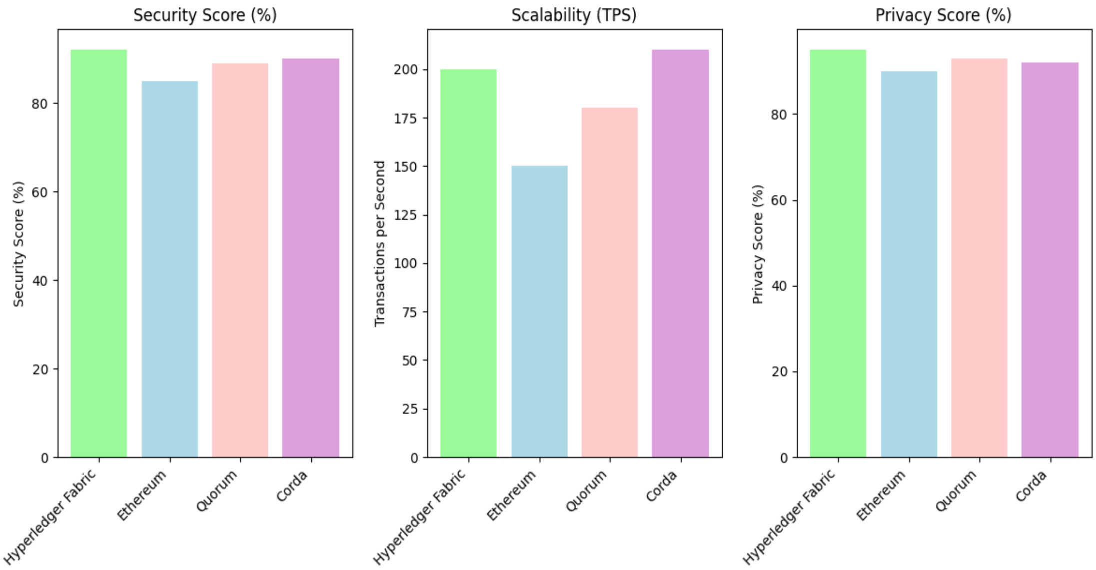


Figure 5. Efficiency comparison of blockchain models in terms of security, scalability, and privacy

CONCLUSION

This article investigates the confluence of artificial intelligence (AI) and blockchain technology in medical care, focusing on their capacity to transform the exchange and management of sensitive healthcare data. The adoption of AI, which has the power to predict and make decisions, in a blockchain system that is immutable and decentralized, helps to alleviate the issues of data fragmentation, privacy, inefficiencies, and lack of interoperability in healthcare systems. The research reveals that the implementation of the healthcare system using the Blockchain + AI model can bring in an efficient exchange of data and security of the system, incorporated with a higher degree of accuracy in decision-making, as opposed to what can be achieved by traditional systems to a great extent. Data access latency, transactions per second, and prediction accuracy are some of the significant indicators where this integrated system is seen to outperform the traditional ones with higher speed, lower latency, and greater precision in clinical decision-making. Moreover, the paper demonstrates that when AI is integrated with blockchain-based models such as Hyperledger Fabric, it provides excellent performance in security, scalability, and privacy, thus, the best solution for the management of sensitive healthcare data. The incorporation of edge AI has the additional benefit of optimizing the system, cutting down on the delay, and preserving the privacy of the data by eliminating the need for the pooling of data in one central location.

The implementation of worldwide interoperability standards is a prerequisite for the full benefits of such integration to be reaped. The regulations set out in those standards will include borderless and institutional data exchanges, thus enabling blockchain and AI frameworks to function efficiently in multi-vendor, multi-jurisdictional environments. Apart from that, developing firm ethical and legal policies will play an indispensable role in the establishment of a data governance framework that is transparent, fair to all stakeholders, and in line with patient autonomy in the digital health ecosystem. The combined use of AI and blockchain-based technology is set to be a game-changer in data management in healthcare by providing a system that is more secure, efficient, and trustworthy, as well as being able to promote patient privacy and self-governance, while at the same time, it leads to better healthcare outcomes overall. The coming research and technology advances, as well as the regulatory frameworks that are going to be put in place, will further facilitate their application and integration into healthcare systems around the globe.

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