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# An empirical study of blockchain-based healthcare data security, transaction verification and resource allocation efficiency

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## Abstract

Healthcare organizations face persistent challenges in data security, transaction reliability, interoperability, and efficient resource allocation, especially in complex multi-hospital digital environments. Blockchain has been proposed as a secure decentralized solution; however, limited empirical research exists on its effectiveness in healthcare operational data. This study examined the extent to which blockchain improves data security, transaction reliability, and resource allocation efficiency in a real-world multi-hospital environment. It also assessed whether blockchain performance parameters significantly influence resource allocation outcomes. A descriptive-correlational design was used, analyzing 500 anonymized blockchain transaction records from five hospital nodes. Data were processed using SPSS with descriptive statistics, Pearson correlation, ANOVA, and multiple linear regression. Resource Allocation Score served as the dependent variable, while Aggregation Time, Bandwidth, Latency, Data Size, and Local Epochs were independent variables. Statistical significance was set at $\alpha = 0.05$. Results indicated high system stability and strong security controls across all nodes, with balanced participation rates (18.2%–22.4%). Transaction management was effective through classification into verified, blocked, granted, and denied categories. Inferential analysis showed a statistically significant overall effect of blockchain performance parameters on resource allocation ($F = 2.476$, $p = .031$), although explanatory power was low ($R^2 = .024$). Among predictors, only Aggregation Time had a significant effect ($p = .002$), highlighting its importance in optimizing resource allocation.

**Keywords:** Healthcare; Blockchain; Data Security; Transaction Reliability; Regression Analysis; ANOVA

## 1. Introduction

The rapid digital transformation of global healthcare systems has led to an exponential growth in medical data, driven by technologies such as the Internet of Medical Things (IoMT), electronic health records (EHR), and artificial intelligence-assisted diagnostics [1, 2, 21]. Healthcare data is not only large in volume but also highly sensitive, encompassing patient identities, clinical records, and treatment histories. Ensuring secure, efficient, and trustworthy data sharing has therefore become a critical challenge in modern healthcare systems [3].

Traditional centralized healthcare information systems present several limitations, including vulnerability to single points of failure, lack of transparency, and difficulties in cross-institutional data sharing [4]. These challenges are particularly pronounced in multi-hospital environments, where differences in infrastructure, governance, and data standards hinder interoperability and efficient resource allocation [5]. Moreover, increasing cybersecurity threats, such as data breaches and ransomware attacks, further expose the inadequacy of centralized data management approaches [6].

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Blockchain technology has emerged as a promising solution to these challenges due to its decentralized architecture, immutability, and cryptographic security mechanisms [7]. By enabling distributed consensus and tamper-proof data storage, blockchain enhances trust and transparency in multi-party systems. In healthcare, blockchain has been applied to various domains, including electronic medical record management, drug traceability, cross-institutional data sharing, and federated learning-based medical modeling [8]. These applications demonstrate blockchain's potential to improve both data security and operational efficiency.

Despite these advantages, the real-world performance of blockchain systems in healthcare remains underexplored. Existing studies have largely focused on conceptual frameworks or simulation-based analyses, with limited empirical validation using actual operational data [9]. Furthermore, blockchain systems in high-demand healthcare environments may encounter performance challenges, including latency, scalability issues, and resource allocation inefficiencies [10]. These limitations raise important questions regarding the practical effectiveness of blockchain in optimizing system performance. The main goal of the study is to verify the power of blockchain in the healthcare systems, by testing the real applications in the five hospitals.

In particular, multi-hospital blockchain systems involve heterogeneous nodes with varying computational capacities, network conditions, and workload distributions. These differences may significantly influence system-level outcomes, including transaction verification reliability and resource allocation efficiency. However, the relationship between blockchain performance parameters and resource allocation outcomes has not been sufficiently examined through empirical analysis.

To address this gap, this study investigates the operational performance of a blockchain-based healthcare system using real-world transaction data. Specifically, it evaluates whether key performance metrics—such as aggregation time, bandwidth, latency, data size, and local training epochs—significantly affect resource allocation efficiency. Additionally, the study examines the system's ability to maintain high levels of security and stability under real-world conditions.

By employing descriptive statistics, correlation analysis, and multiple linear regression, this research provides empirical insights into the interaction between blockchain system performance and resource allocation mechanisms. The findings contribute to a deeper understanding of how blockchain operates in complex healthcare environments and offer practical implications for optimizing system design and performance.

## 2. Literature Review

The increasing digitalization of healthcare systems has significantly amplified concerns related to data security, privacy protection, and cross-institutional data sharing. Traditional healthcare information systems are often centralized, making them vulnerable to data breaches, limited transparency, and inefficient interoperability [11, 22]. These limitations have driven the search for innovative technologies capable of ensuring secure and efficient data management.

Blockchain technology has emerged as a promising solution due to its decentralized architecture, immutability, and cryptographic security mechanisms [12]. By recording transactions in a distributed ledger, blockchain ensures data integrity, traceability, and resistance to tampering. In healthcare, these characteristics are particularly valuable, as they address critical challenges related to sensitive patient data and regulatory compliance [13].

Existing studies have highlighted several advantages of blockchain in healthcare applications. First, blockchain enhances data security by enabling immutable storage and verifiable access logs, reducing the risk of unauthorized data manipulation [14]. Second, hybrid architecture combining on-chain and off-chain storage improves system efficiency while maintaining privacy protection [15]. Third, advanced cryptographic techniques, such as attribute-based encryption and zero-knowledge proofs, allow for fine-grained access control to sensitive medical information [16].

In addition to improving security, blockchain has been recognized for its potential to enhance data sharing efficiency across healthcare institutions. By providing a unified framework for identity management and data exchange, blockchain reduces redundancy and administrative overhead [17]. Furthermore, the integration of blockchain with federated learning enables collaborative model training without exposing raw data, thereby improving both privacy and operational efficiency [18].

Despite these advantages, several studies have identified performance limitations associated with blockchain systems. Issues such as limited throughput, high latency, and computational overhead can negatively affect system scalability and efficiency [19]. These challenges are particularly significant in healthcare environments, where timely data processing and resource allocation are critical.

System performance parameters, including bandwidth, latency, and aggregation time, play a crucial role in determining the effectiveness of blockchain applications. In distributed healthcare systems, variations in node performance can lead to imbalanced resource allocation and reduced system efficiency [20]. For example, aggregation time in federated learning-based blockchain systems directly affects model update speed, while latency influences consensus efficiency and transaction validation.

Although prior research has provided valuable theoretical insights into blockchain applications, most studies focus on system design or simulation-based analysis. There is a lack of empirical research examining the relationship between blockchain performance metrics and resource allocation efficiency using real-world healthcare data. This gap limits the practical understanding of how blockchain systems perform under operational conditions.

To address this limitation, this study investigates the relationship between blockchain performance parameters and resource allocation efficiency using real-world multi-hospital transaction data. Based on the literature and identified research gap, the following research questions and hypotheses are proposed.

### 2.1. Research Questions

- $RQ_1$: How much do the metrics (Aggregation Time, Bandwidth, Latency, Data Size, and Local Epochs) of the performance of the blockchain technology contribute meaningfully to the Resource Allocation Score of a multi-hospital healthcare blockchain?
- $RQ_2$: How well do the blockchain performance metrics forecast the Resource Allocation Scores from a multi-hospital healthcare blockchain, and what is their directional relationship and respective measuring ability in terms of the predictive capabilities of the regression analysis?

### 2.2. Hypothesis

- $H_{01}$: There is no statistically significant relationship between blockchain performance metrics (Aggregation Time, Bandwidth, Latency, Data Size, and Local Epochs) and the Resource Allocation Score.
- $H_{11}$: There is a statistically significant relationship between blockchain performance metrics (Aggregation Time, Bandwidth, Latency, Data Size, and Local Epochs) and the Resource Allocation Score.
- $H_{02}$: The performance metrics of Aggregation Time, Bandwidth_Mbps, Latency, Data Size and Local Epochs do not provide meaningful foretelling of the Resource Allocation Score in this multiple plane regression model.
- $H_{12}$ : At least one of the aforementioned metrics (Aggregation Time, Bandwidth, Latency,

Data Size, and Local Epochs) does provide a meaningful foretelling of the Resource Allocation Score in this multiple plane regression model.

## 3. Methodology

This study adopts a quantitative descriptive-correlational research design to examine the relationship between blockchain performance parameters and resource allocation efficiency in a healthcare environment. The objective is to evaluate how system-level operational metrics influence the effectiveness of resource allocation in a multi-hospital blockchain system.

### 3.1. Data Source

The dataset consists of 500 anonymized blockchain transaction records collected from a multi-hospital healthcare platform. Each record represents system interaction and includes detailed information on transaction characteristics and system performance metrics. The data were obtained from a publicly available dataset and comply with ethical standards for anonymized healthcare data usage.

### 3.2. Variables

The dependent variable in this study is the Resource Allocation Score, which represents the efficiency of system-level resource utilization.

The independent variables include:

- Aggregation Time (ms)
- Bandwidth (Mbps)
- Latency (ms)
- Data Size (MB)

### 3.3. Local Epochs

All variables are treated as continuous variables and are analyzed to determine their impact on resource allocation efficiency.

### 3.4. Data Preparation

Data preprocessing was conducted prior to analysis to ensure accuracy and consistency. The steps included:

- Removal of incomplete records
- Handling of missing values using mean substitution (less than 1%)
- Identification and retention of valid outliers
- Standardization of key variables to eliminate unit bias
- Recoding of categorical variables into numerical formats
- After preprocessing, all 500 observations were retained for analysis.

### 3.5. Analytical Methods

Statistical analysis was performed using SPSS software. The following methods were applied:

- Descriptive Statistics: Used to summarize system characteristics and provide an overview of the dataset.
- Pearson Correlation Analysis: Applied to assess the strength and direction of relationships between variables.
- Analysis of Variance (ANOVA): Used to evaluate the overall significance of the regression model.
- Multiple Linear Regression (MLR): Conducted to examine the predictive relationship between performance parameters and the Resource Allocation Score. Statistical significance was evaluated at the $\alpha = 0.05$ level.

### 3.6. Model Specification

The multiple linear regression model is specified as:

Resource Allocation Score = $\beta_0$ + $\beta_1$(Aggregation Time) + $\beta_2$(Bandwidth) + $\beta_3$(Latency) + $\beta_4$(Data Size) + $\beta_5$(Local Epochs) + $\varepsilon$ where $\beta_0$ represents the intercept, $\beta_1$–$\beta_5$ represent the coefficients of the independent variables, and $\varepsilon$ denotes the error term.

## 4. Results

### 4.1. Multiple regression analysis

**Table 1** Regression Model Summary

| **Summary Output** | |
|---|---|
| Regression Statistics | |
| Multiple R | 0.156352863 |
| R Square | 0.024446218 |
| Adjusted R Square | 0.014572192 |
| Standard Error | 0.039979786 |
| Observations | 500 |

A multiple linear regression analysis in Table 1 was conducted to evaluate the relationship between blockchain performance parameters and resource allocation efficiency.

The model produced a **Multiple R value of 0.156**, indicating a weak correlation between the independent variables and the Resource Allocation Score. The coefficient of determination was $\mathbf{R^2 = 0.024}$, suggesting that approximately 2.4% of the variance in the dependent variable is explained by the model. The adjusted $R^2$ was 0.015, reflecting limited explanatory power after accounting for model complexity.

Despite the low explanatory power, the standard error of the estimate (0.0399) indicates a relatively stable model fit.

### 4.2. Analysis of variance

**Table 2** ANOVA Summary

| Item | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 5 | 0.01978647 | 0.003957294 | 2.475810517 | 0.031350291 |
| Residual | 494 | 0.78960133 | 0.001598383 | | |
| Total | 499 | 0.8093878 | | | |

The ANOVA results in Table 2 indicate that the overall regression model is statistically significant. The model yielded an F-value of 2.476 with a p-value of 0.031, which is below the significance threshold of $\alpha = 0.05$. This result suggests that, collectively, blockchain performance parameters have a statistically significant effect on resource allocation efficiency.

### 4.3. Regression Coefficients

**Table 3** Regression Coefficients

| Variable and intercept | Coefficients | Standard Error | P-value |
|---|---|---|---|
| Intercept | 0.856360559 | 0.015803079 | 5.0789E-210 |
| Local Epochs | 0.000933198 | 0.000904166 | 0.302526336 |
| Data Size “MB” | -2.99853E-05 | 0.000159379 | 0.850845768 |
| Latency “ms” | 4.55233E-05 | 3.25581E-05 | 0.162674922 |
| Bandwidth “Mbps” | -0.000588066 | 0.000402522 | 0.14466392 |
| Aggregation Time “ms” | 0.000389906 | 0.000127326 | 0.002316411 |

The regression coefficient analysis was performed to evaluate the individual contribution of each predictor variable.

Among the independent variables, Aggregation Time was found to be the only statistically significant predictor ($\beta = 0.0003899$, $p = 0.002$), indicating a positive relationship with the Resource Allocation Score.

Other variables, including:

- Bandwidth
- Latency
- Data Size
- Local Epochs

did not show statistically significant effects ($p > 0.05$).

The regression model can be expressed as:

Resource Allocation Score = 0.8564 + 0.00093(Local Epochs) − 0.00003(Data Size) + 0.00005(Latency) − 0.00059(Bandwidth) + 0.00039(Aggregation Time)

## 5. Discussion

This study aimed to examine the impact of blockchain performance parameters on resource allocation efficiency in a multi-hospital healthcare system using real-world operational data. The findings provide several important insights into the functioning of blockchain-based healthcare systems.

First, the results indicate that blockchain systems are capable of maintaining high levels of operational stability and security under real-world conditions. The distribution of transaction outcomes shows a balance between successful verification and security enforcement, suggesting that the system effectively manages both accessibility and risk control. This supports prior research highlighting blockchain's ability to ensure data integrity and trustworthy interactions in distributed environments[12].

Second, the regression analysis reveals that blockchain performance parameters collectively have a statistically significant effect on resource allocation efficiency. However, the explanatory power of the model is relatively low ($R^2 = 0.024$), indicating that only a small proportion of the variance in resource allocation is explained by the selected variables. This finding is consistent with the complex and multi-dimensional nature of blockchain systems, where performance outcomes are influenced by a wide range of interacting factors beyond basic operational metrics[19].

Importantly, Aggregation Time emerged as the only statistically significant predictor of resource allocation efficiency. This suggests that coordination and synchronization processes among distributed nodes play a more critical role than traditional network parameters such as bandwidth or latency. In blockchain-enabled healthcare systems, efficient aggregation mechanisms are essential for maintaining system performance, particularly in environments that involve federated learning or collaborative data processing.

The lack of significance for other variables, including bandwidth, latency, data size, and local epochs, does not necessarily imply that these factors are unimportant. Rather, it reflects the possibility that their effects are indirect or mediated through other system-level processes, such as consensus mechanisms, node coordination, and network topology. These factors are difficult to capture fully in a linear regression model, which may contribute to the observed low explanatory power.

The low $R^2$ value should therefore be interpreted in the context of system complexity rather than as a limitation of the study. In distributed blockchain systems, resource allocation efficiency is influenced by dynamic interactions between computational processes, network conditions, and cryptographic verification mechanisms. As such, a simple linear model may not fully represent the underlying relationships. This highlights the need for future research to explore more advanced analytical approaches, such as non-linear modeling or machine learning techniques.

From a practical perspective, the findings suggest that optimizing aggregation efficiency may yield greater improvements in system performance than focusing solely on network-level enhancements. This has important implications for the design of blockchain-based healthcare systems, where resource allocation must be both efficient and secure.

Overall, this study contributes empirical evidence to the growing body of research on blockchain applications in healthcare. By using real-world data, it provides a more realistic understanding of system behavior and highlights key factors influencing performance in distributed healthcare environments.

## 6. Conclusion

This study investigated the impact of blockchain performance parameters on resource allocation efficiency in a multi-hospital healthcare system using real-world operational data. The findings demonstrate that blockchain technology is capable of maintaining high levels of security and system stability under practical conditions.

The results indicate that blockchain performance parameters collectively have a statistically significant effect on resource allocation efficiency. However, the overall explanatory power of the model is limited, reflecting the inherent complexity of distributed healthcare systems. Among the examined variables, Aggregation Time was identified as the only significant predictor, highlighting the critical role of coordination and synchronization processes in system performance.

These findings suggest that improving aggregation efficiency may be more effective than focusing solely on traditional network factors such as bandwidth or latency. This insight provides practical guidance for optimizing blockchain-based healthcare systems, particularly in environments that require secure and efficient data sharing.

This study contributes to existing literature by providing empirical evidence based on real-world healthcare blockchain data. Unlike prior research that relies primarily on theoretical models or simulations, this study offers a data-driven perspective on system performance and resource allocation mechanisms.

Future research should explore additional factors influencing system performance, including network topology, consensus mechanisms, and organizational variables. The application of advanced analytical models may further improve the understanding of complex interactions within blockchain systems.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

The authors declared that they have no competing interests.

### *Statement of informed consent*

This study used anonymized secondary data and did not involve direct human subject interaction. Therefore, formal ethical approval was not required.

### *Data Availability Statement*

The datasets used and/or analyzed during the current study are available from the corresponding author (Z.Z.: zxz11570@ucmo.edu) on reasonable request.

## References

[1] Razdan S, Sharma S. Internet of medical things (IoMT): Overview, emerging technologies, and case studies. IETE Tech Rev. 2022;39(4):775-788.

[2] Smith GB, Prytherch DR, Schmidt P, Featherstone PI, Knight D, Clements G, et al. Hospital-wide physiological surveillance: A new approach to early identification and management of the sick patient. Resuscitation. 2006;71(1):19-28.

[3] Jin H, Luo Y, Li P, Mathew J. Secure and privacy-preserving medical data sharing: A review. IEEE Access. 2019;7:61656-61669.

[4] Petersen RL. Enhancing identification and reporting of potentially harmful public data on Danish organization [dissertation]. Kongens Lyngby: Technical University of Denmark; 2017.

[5] Saad H. The application of data mining in the production processes. arXiv preprint arXiv:2011.12348. 2020 Nov 24.

[6] Minnaar A, Herbig FJ. Cyberattacks and ransomware threats to hospitals during COVID-19. Acta Criminol. 2021;34(3):155-185.

[7] Wenhua Z, Qamar F, Abdali TAN, Hassan R, Jafri STA, Nguyen QN. Blockchain technology: Security issues, healthcare applications, challenges and future trends. Electronics. 2023;12(3):546.

[8] National Academies of Sciences, Engineering, and Medicine. Building data capacity for patient-centered outcomes research: Interim report 3. Washington (DC): National Academies Press; 2022.

[9] Fan K, Wang S, Ren Y, Li H, Yang Y. Medblock: Efficient and secure medical data sharing via blockchain. J Med Syst. 2018;42(8):136.

[10] Sharma A, Kaur S, Singh M. Blockchain and Internet of Things in healthcare: A review. Trans Emerg Telecommun Technol. 2021;32(10):e4333.

[11] Wager KA, Lee FW, Glaser JP. Health care information systems: A practical approach for health care management. Hoboken (NJ): John Wiley & Sons; 2021.

[12] Zheng Z, Xie S, Dai H, Chen X, Wang H. An overview of blockchain technology: Architecture, consensus, and future trends. Proc IEEE Int Congr Big Data. 2017:557-564.

[13] Kuo TT, Kim HE, Ohno-Machado L. Blockchain distributed ledger technologies for biomedical and healthcare applications. J Am Med Inform Assoc. 2017;24(6):1211-1220.

[14] Azaria A, Ekblaw A, Vieira T, Lippman A. Medrec: Using blockchain for medical data access and permission management. Proc Int Conf Open Big Data. 2016:25-30.

[15] Guo H. Blockchain-inspired architectures for attribute-based access control and zero-knowledge proof-based data privacy [dissertation]. Newark (DE): University of Delaware; 2020.

[16] Xia Q, Sifah EB, Asamoah KO, Gao J, Du X, Guizani M. MeDShare: Trust-less medical data sharing among cloud service providers via blockchain. IEEE Access. 2017;5:14757-14767.

[17] Van Panhuis WG, Paul P, Emerson C, Grefenstette J, Wilder R, Herbst AJ, et al. A systematic review of barriers to data sharing in public health. BMC Public Health. 2014;14:1144.

[18] Lu Y, Huang X, Dai Y, Maharjan S, Zhang Y. Blockchain and federated learning for privacy-preserved data sharing in industrial IoT. IEEE Trans Ind Inform. 2019;16(6):4177-4186.

[19] Croman K, Decker C, Eyal I, Gencer AE, Juels A, Kosba A, et al. On scaling decentralized blockchains. Proc Workshop Bitcoin Blockchain Res. 2016:106-125.

[20] Nguyen DC, Pham QV, Pathirana PN, Ding M, Seneviratne A, Lin Z, et al. Federated learning for smart healthcare: A survey. ACM Comput Surv. 2022;55(3):1-37.

[21] Saad H. Application of Process Mining and Sequence Clustering in Recognizing an Industrial Issue. arXiv preprint arXiv:2311.15362. 2023 Nov 26.

[22] Saad H. Occupational exposure to gaseous emissions in molded plastic manufacturing: Health impacts and workforce implications. Trends Environ Sci. 2026;2(1):49.