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ORIGINAL

Blockchain-Driven Supply Chain Finance for Public Healthcare in India: Enhancing Financial Resilience in Public Health Systems

Financiamiento de Cadenas de Suministro Impulsado por Blockchain para la Salud Pública en India: Mejorando la Resiliencia Financiera en los Sistemas de Salud Pública

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ABSTRACT

Introduction: public healthcare systems in India face persistent inefficiencies, including delays in financial workflows, lack of transparency, and fraud, particularly in rural and underserved areas. Blockchain and machine learning (ML) technologies offer transformative potential to address these challenges by enhancing transparency, efficiency, and accountability in healthcare supply chains.
Method: a mixed-methods approach was adopted, combining structured surveys, semi-structured interviews, and secondary data analysis. Quantitative data were analysed using techniques such as descriptive statistics, predictive modelling (Random Forest), clustering (K-means), and anomaly detection (Isolation Forest). Qualitative data from stakeholder interviews were analysed using Natural Language Processing (NLP) to identify recurring themes and sentiment trends.
Results: the analysis revealed significant inefficiencies and readiness disparities among stakeholders. Blockchain was identified as a critical tool for improving transparency, with readiness levels being the strongest predictor of adoption success. ML demonstrated robust capabilities in fraud detection, with 5 % of transactions flagged as anomalies, and predictive modelling identified key factors influencing readiness. Clustering analysis revealed distinct groups of stakeholders, highlighting the need for tailored interventions to bridge readiness gaps. Sentiment analysis indicated 65 % of stakeholders held positive views on blockchain and ML adoption.
Conclusions: blockchain and ML technologies have the potential to transform public healthcare financing by addressing inefficiencies, enhancing transparency, and optimizing resource allocation. However, disparities in stakeholder readiness necessitate targeted capacity-building and phased implementation strategies. These findings provide a roadmap for integrating blockchain and ML into public healthcare systems, fostering financial resilience and improving service delivery in rural and underserved areas.

Keywords: Blockchain; Machine Learning; Healthcare; Supply Chain Finance; Public Health; India.

RESUMEN

Introducción: los sistemas de salud pública en la India enfrentan ineficiencias persistentes, como retrasos en

los flujos financieros, falta de transparencia y fraudes, especialmente en áreas rurales y desatendidas. Las tecnologías de blockchain y aprendizaje automático (ML) ofrecen un potencial transformador para abordar estos desafíos al mejorar la transparencia, eficiencia y responsabilidad en las cadenas de suministro de salud.
Método: se adoptó un enfoque de métodos mixtos, combinando encuestas estructuradas, entrevistas semiestructuradas y análisis de datos secundarios. Los datos cuantitativos se analizaron utilizando técnicas como estadísticas descriptivas, modelado predictivo (Random Forest), agrupamiento (K-means) y detección de anomalías (Isolation Forest). Los datos cualitativos de las entrevistas con los interesados se analizaron utilizando Procesamiento del Lenguaje Natural (NLP) para identificar temas recurrentes y tendencias de sentimiento.
Resultados: el análisis reveló ineficiencias significativas y disparidades en el nivel de preparación de los interesados. Se identificó a blockchain como una herramienta crítica para mejorar la transparencia, siendo los niveles de preparación el predictor más fuerte del éxito en la adopción. El ML demostró capacidades sólidas en la detección de fraudes, identificando un 5 % de transacciones como anomalías, y el modelado predictivo destacó los factores clave que influyen en la preparación. El análisis de agrupamiento reveló grupos distintos de interesados, subrayando la necesidad de intervenciones personalizadas para cerrar brechas de preparación. El análisis de sentimiento indicó que el 65 % de los interesados tenían opiniones positivas sobre la adopción de blockchain y ML.
Conclusiones: las tecnologías de blockchain y ML tienen el potencial de transformar la financiación del sistema de salud pública al abordar ineficiencias, mejorar la transparencia y optimizar la asignación de recursos. Sin embargo, las disparidades en la preparación de los interesados requieren programas de desarrollo de capacidades específicos y estrategias de implementación por fases. Estos hallazgos proporcionan una hoja de ruta para integrar blockchain y ML en los sistemas de salud pública, fomentando la resiliencia financiera y mejorando la prestación de servicios en áreas rurales y desatendidas.

Palabras clave: Blockchain; Aprendizaje Automático; Salud; Finanzas de la Cadena de Suministro; Salud Pública; India.

INTRODUCTION

The integration of advanced technologies such as blockchain and machine learning (ML) into public healthcare systems represents a transformative opportunity to address longstanding inefficiencies and ensure equitable healthcare delivery.[1] In a country like India, characterized by its vast population, diverse demographics, and socio-economic challenges, the healthcare sector is critical to ensuring the well-being of millions.[2] However, this sector faces systemic challenges, particularly in rural and underserved areas, including inefficiencies in financial workflows, lack of transparency, fraud, and delays in service delivery.[3] Recent advancements in blockchain and ML technologies offer innovative solutions to these challenges, providing mechanisms to enhance transparency, streamline operations, and foster accountability in public healthcare.[4,5]

India's public healthcare sector has seen the introduction of ambitious initiatives such as Ayushman Bharat, which aims to provide affordable and accessible healthcare to over 500 million citizens.[6] Despite its transformative potential, Ayushman Bharat grapples with inefficiencies such as fraudulent claims, delays in fund allocation, and a lack of transparency in resource distribution.[7] The inability to track transactions in real-time and the susceptibility to tampering in manual processes are persistent issues. Blockchain technology, with its decentralized and immutable ledger, has the potential to address these gaps by creating tamper-proof records, automating processes through smart contracts, and ensuring transparency in fund disbursement.[8] Similarly, ML can identify fraudulent claims, optimize resource allocation, and provide predictive insights to healthcare administrators, thus enhancing the operational efficiency of healthcare schemes.[9]

The research problem stems from the persistent inefficiencies in India's public healthcare financing and operations. Healthcare schemes, including Ayushman Bharat, often struggle with delayed fund disbursements, fraudulent claims, and inefficiencies in resource utilization.[10] These challenges disproportionately affect rural and underserved areas, where infrastructural limitations exacerbate existing issues. For instance, fraudulent practices such as inflated claims by providers in Ayushman Bharat highlight significant gaps in transparency and accountability.[11]

The significance of this study lies in its potential to contribute actionable insights for integrating blockchain and ML into India's healthcare ecosystem. Blockchain's ability to provide transparency and traceability in financial transactions can directly reduce fraud and improve accountability.[4] Simultaneously, ML's advanced analytics capabilities enable fraud detection, demand forecasting, and optimization of financial workflows. Together, these technologies can significantly enhance the operational and financial efficiency of India's public healthcare systems.[12] Furthermore, this research explores the socio-economic impact of these technologies, particularly in rural areas, where technological interventions can reduce systemic disparities and improve access to quality healthcare.[13]

While blockchain and ML have been widely studied and implemented in various sectors, their application in public healthcare, particularly in India, remains underexplored. Existing studies often focus on developed countries, where infrastructural readiness and technological familiarity are significantly higher.[14] In contrast, India's socio-economic context presents unique challenges such as infrastructural gaps, limited digital literacy among healthcare providers, and a general resistance to technological change, particularly in rural areas.[15] This study is novel in its approach to situating blockchain and ML within the Indian public healthcare framework, addressing the specific needs of rural and underserved populations, and contextualizing global best practices to fit local realities.

Additionally, the study uses a mixed-methods approach, combining quantitative data from predictive models and anomaly detection algorithms with qualitative insights from stakeholder interviews. This dual approach allows for a comprehensive understanding of the technological, operational, and social dimensions of integrating blockchain and ML into public healthcare systems.[16] The study also highlights the role of initiatives like Ayushman Bharat as potential platforms for piloting these technologies, offering lessons for scalability and broader implementation.

To guide the investigation, the study raises critical questions:

1. What are the primary inefficiencies in India's public healthcare financial workflows, and how can blockchain and ML address these challenges?
2. What are the readiness levels of different stakeholders, including healthcare providers, policymakers, and administrators, for adopting these technologies?
3. How can blockchain and ML enhance the transparency and accountability of large-scale healthcare initiatives like Ayushman Bharat?
4. What strategies can be devised to overcome infrastructural, social, and operational barriers to adoption?

The research statement positions blockchain and ML as transformative tools that can address the systemic inefficiencies of India's public healthcare systems, particularly in rural and underserved areas. By evaluating the technological readiness of stakeholders and identifying implementation challenges, the study aims to provide actionable recommendations for integrating these technologies into healthcare financing and operations.

India's public healthcare system, exemplified by Ayushman Bharat, serves as a critical case study to understand the potential of blockchain and ML technologies. Ayushman Bharat, the world's largest government-funded health insurance scheme, seeks to provide affordable healthcare to India's most vulnerable populations. However, challenges such as inflated claims, delays in reimbursement, and lack of real-time monitoring undermine its effectiveness Angell et al.[10] and Bhola et al.[17]. Blockchain technology can address these issues by creating immutable records of transactions, ensuring that claims are verifiable and funds are disbursed transparently Sharma et al.[5] and Omar et al.[18]. For instance, smart contracts can automate payment processes, reducing delays and eliminating the need for intermediaries.[19,4]

ML complements these efforts by enabling fraud detection through anomaly detection algorithms, which can identify irregularities in claims data. Predictive analytics can further optimize resource allocation by forecasting demand for healthcare services and supplies in different regions, ensuring that resources are distributed equitably.[20] Together, these technologies can strengthen Ayushman Bharat's implementation, making it a model for technology-driven healthcare reform in India.

Despite the clear potential, the adoption of blockchain and ML in India's public healthcare systems faces significant barriers. Rural healthcare providers often lack the digital literacy and infrastructure required to implement these technologies effectively.[21] Policymakers and administrators may be more familiar with these technologies, but operationalizing them at scale requires substantial investments in capacity-building and infrastructure development.[22]

To address these challenges, the study advocates for a phased implementation strategy. Pilot projects in selected regions can demonstrate the tangible benefits of blockchain and ML, fostering trust and acceptance among stakeholders.[23] Training programs tailored to healthcare providers in rural areas are essential for bridging the readiness gap. These programs should focus on building digital literacy and demonstrating the practical applications of blockchain and ML in everyday healthcare. Policymakers and administrators can further drive adoption by creating supportive regulatory frameworks and allocating resources for infrastructure development.

Hence the study had the following objectives:

1. Evaluate inefficiencies and opportunities in public healthcare supply chains in India.
2. Analyze the impact of blockchain and machine learning technologies in enhancing efficiency in financial and supply chain processes.

3. Propose implementation strategies for integrating blockchain and machine learning in public healthcare systems.

Literature Review

In India's public healthcare financing, transparency is a critical challenge, as evidenced by persistent issues in Ayushman Bharat, such as opaque fund disbursement processes and unverifiable claims.[7] Blockchain technology addresses this by providing a decentralized ledger for real-time tracking of financial transactions, ensuring tamper-proof records as indicated by Sharma et al.[5]. For instance, smart contracts could automate claims processing, allowing beneficiaries to verify their transactions instantly. However, Sudhahar et al.[24] states that the adoption of blockchain in India is hindered by limited digital literacy among rural healthcare providers and fragmented IT infrastructure, necessitating focused capacity-building initiatives.

Efficiency gaps in financial workflows are evident in India's healthcare system, particularly in rural regions where delays in fund allocation impede service delivery. Saxena et al.[25] discusses that Ayushman Bharat frequently encounters bottlenecks due to manual processes in claims approval and fund disbursement. Blockchain can automate these processes through smart contracts, reducing transaction times and operational costs. Similarly, ML-driven predictive analytics can optimize resource allocation, ensuring timely procurement and distribution of medical supplies stated in the study by Jain et al.[26]. However, challenges such as high implementation costs and infrastructure limitations in rural areas constrain efficiency improvements. Developing low-cost, scalable blockchain and ML solutions tailored to the Indian context is crucial.

Fraudulent activities, including inflated claims and unauthorized transactions, are prevalent in India's public healthcare financing schemes, undermining resource allocation and trust. For example, Gupta et al.[27] discussed fraudulent claims in Ayushman Bharat have resulted in significant financial losses, highlighting the need for robust fraud detection mechanisms. Blockchain's immutable ledger can prevent tampering with financial records, while ML algorithms such as anomaly detection can flag irregularities in real-time as indicated by Vimal et al.[28]. Despite their potential, these technologies face adoption barriers in India, including a lack of digital readiness among stakeholders and insufficient data quality in rural regions.

Stakeholder satisfaction is crucial for the successful implementation of blockchain and ML in India's healthcare system. Ayushman Bharat stakeholders, including healthcare providers, policymakers, and beneficiaries, have expressed concerns about inefficiencies and lack of trust in the current system.[29] ML-driven sentiment analysis reveals optimism among policymakers about the potential of blockchain to enhance transparency and efficiency. However, rural healthcare providers, who often lack digital skills, exhibit resistance to these technologies.[30] Addressing this resistance through tailored training programs and demonstrating tangible benefits through pilot projects can improve stakeholder satisfaction.

Removing intermediaries is particularly relevant in India, where bureaucratic delays often obstruct fund allocation in public healthcare.[4] Blockchain's decentralized system could streamline workflows, ensuring timely delivery of resources to rural healthcare centres. Das et al.[29] indicated in their study that blockchain's tamper-proof record-keeping offers a solution to fraud in schemes like Ayushman Bharat, where manual documentation is susceptible to manipulation . Automating processes such as claims approval and fund disbursement can significantly reduce operational delays. For example, Werner et al.[31] addressed that smart contracts could ensure that payments are released only upon meeting predefined conditions, reducing disputes and inefficiencies.

ML-driven predictive models can forecast healthcare demands, enabling proactive resource allocation. This is particularly beneficial for rural areas, where supply chain disruptions are common due to unpredictable demand patterns.[32] Identifying irregularities in financial workflows is critical for fraud prevention in schemes like Ayushman Bharat. Priyadarshini et al.[33] discussed about ML algorithms such as Isolation Forests have demonstrated the ability to flag anomalous transactions effectively, providing actionable insights for administrators. Analysing stakeholder perceptions helps identify readiness levels and concerns. Studies such as[34] highlights that sentiment analysis in India reveals a significant readiness gap between urban policymakers and rural healthcare providers, underscoring the need for targeted interventions.

Stakeholder readiness is a key determinant of technology adoption in India's public healthcare system. While policymakers and urban healthcare administrators exhibit higher readiness for blockchain and ML adoption, rural providers face barriers such as limited digital literacy and infrastructure as discussed by Ganju et al.[35]. Readiness disparities impede the uniform implementation of these technologies, necessitating phased rollouts and targeted training programs to address specific challenges in rural regions.

Ayushman Bharat is an ideal case study for exploring the potential of blockchain and ML in India's public healthcare system. The scheme's challenges—fraudulent claims, fund allocation delays, and resource inefficiencies—mirror broader systemic issues.[36] Blockchain's transparency features and ML's fraud detection capabilities directly address these issues, offering scalable solutions. However, successful integration requires addressing readiness disparities among stakeholders, particularly rural providers, and adapting technologies to local contexts.

While blockchain and ML offer transformative potential, gaps in the literature limit their application in India's public healthcare system. Most studies focus on developed countries, overlooking India's unique challenges in rural and underserved areas. Limited research exists on addressing readiness gaps between rural providers and urban policymakers. Few pilot studies demonstrate the real-world impact of blockchain and ML in schemes like Ayushman Bharat. Research on scaling these technologies across diverse regions in India remains limited.

The study framework (figure 1) evaluates the role of blockchain and machine learning (ML) in improving public healthcare supply chain financing in India, particularly in rural areas. It identifies key inefficiencies like financial delays, fraud, and limited transparency, exacerbated by infrastructure gaps. The framework employs an Input-Process-Output model. Inputs include data on inefficiencies, blockchain features, ML applications, and stakeholder feedback. Processes focus on blockchain for transaction traceability and smart contracts, alongside ML for predictive analytics and fraud detection. Outputs highlight improved transparency, reduced costs, fraud mitigation, and stakeholder trust.

Stakeholder interactions—among healthcare providers, policymakers, and technology experts—are pivotal, ensuring technology adoption aligns with operational needs. The framework is rooted in Innovation Diffusion Theory, Systems Theory, and Trust Theory, emphasizing interconnected workflows, technology adoption, and trust-building. This holistic model provides actionable insights to enhance financial and operational efficiency in public healthcare supply chains.

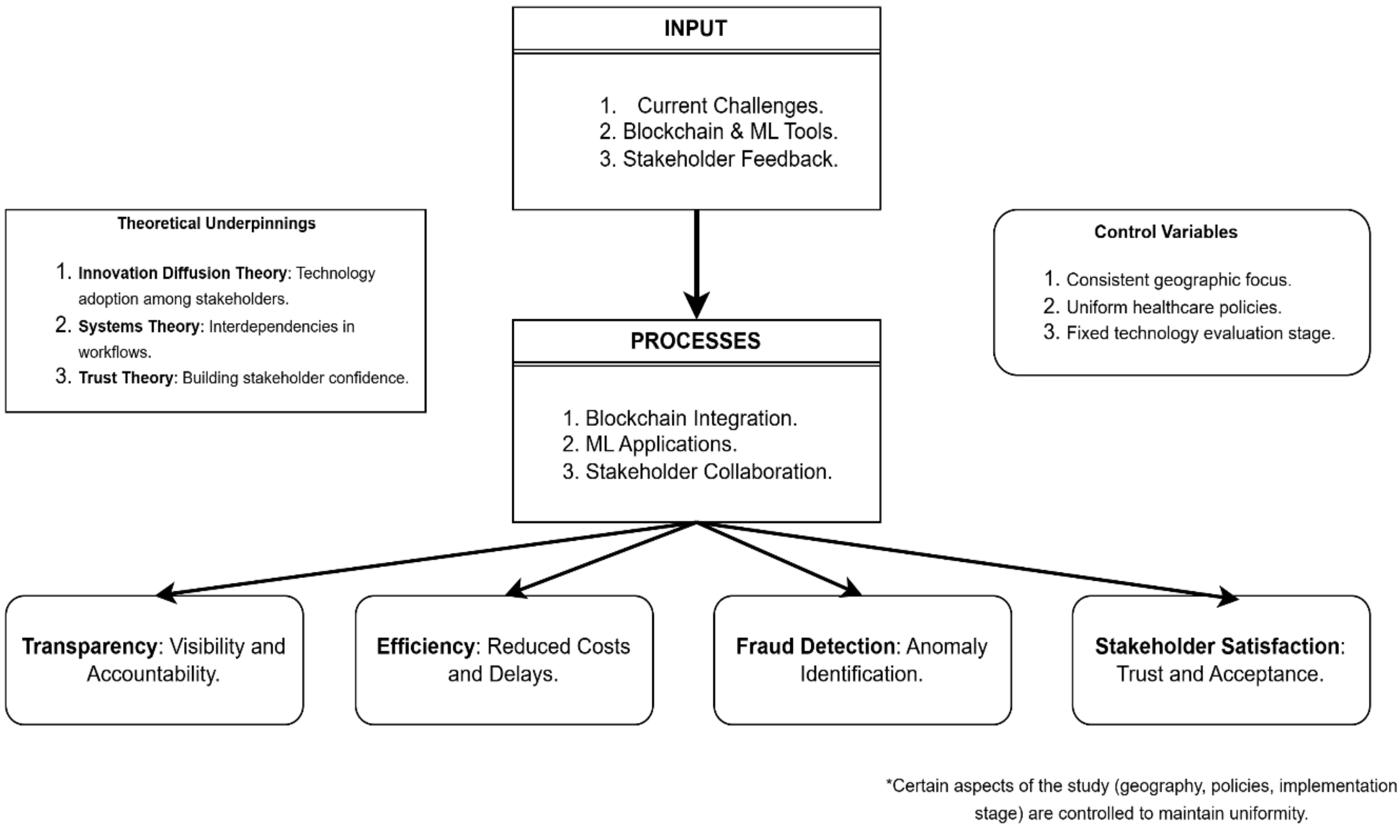

Figure 1. Framework of the study

On the basis of the literature review, framework of the study and objective following hypotheses were developed. The hypotheses for this study are formulated to align with the objectives, focusing on the role of blockchain and machine learning in addressing inefficiencies and enhancing the performance of public healthcare supply chain financing in India.

1. H1: blockchain technology significantly improves transparency, reduces inefficiencies, and enhances accountability in the financing of public healthcare supply chains in rural and underserved areas.
2. H2: the integration of machine learning in healthcare supply chain financing facilitates fraud detection, optimizes financial workflows, and improves predictive capabilities for resource allocation.
3. H3: stakeholders in the public healthcare ecosystem, including healthcare providers, policymakers, and technology experts, demonstrate varying levels of readiness and acceptance toward blockchain and machine learning adoption, with readiness levels positively influencing adoption success.

METHOD

Start by classifying ttype of investigation, defining timeline, universe, population, country, city and institutions where this study took place, or if is a multicentre study.

This study investigates the potential of blockchain technology, supported by machine learning (ML), to improve transparency and efficiency in financing public healthcare supply chains in India. It employs a descriptive and exploratory research design, combining traditional research techniques with advanced ML tools. By focusing on rural and underserved areas, the study aims to uncover actionable insights to enhance financial resilience and operational efficiency in the public healthcare sector. The research design integrates descriptive and exploratory approaches to achieve a comprehensive understanding of the current challenges and the potential for blockchain-driven solutions. The descriptive aspect focuses on identifying inefficiencies in public healthcare supply chains and financial systems, with particular emphasis on the barriers to transparency and accountability in rural healthcare systems. This component provides a foundational understanding of the existing state of financial workflows, operational bottlenecks, and system vulnerabilities.

The exploratory aspect aims to investigate how blockchain and ML can address these challenges. Blockchain's decentralized and immutable nature is analysed for its ability to streamline financial transactions, enhance data integrity, and eliminate intermediaries that contribute to delays and fraud. Smart contracts are explored for automating processes such as fund disbursement and inventory tracking. Additionally, the exploratory design examines how ML can complement blockchain by enabling data-driven insights through predictive modelling, anomaly detection, and sentiment analysis. Together, these approaches provide a framework for evaluating the feasibility and potential impact of these technologies in addressing systemic inefficiencies.

By integrating descriptive and exploratory elements, this research design ensures a detailed investigation of the existing problems and innovative solutions. It establishes a structured approach for identifying specific areas where blockchain and ML can drive improvements, allowing for both qualitative and quantitative insights. This comprehensive design enables the study to bridge the gap between theoretical possibilities and practical implementation, ensuring relevance and applicability to the public healthcare context in India.

Data collection for this study was conducted using a combination of primary and secondary sources to ensure robust and multidimensional insights. Primary data was gathered through semi-structured interviews, structured surveys, and direct stakeholder engagement. Semi-structured interviews were conducted with healthcare administrators, policymakers, and blockchain experts. These interviews allowed participants to elaborate on their perspectives regarding the challenges faced in healthcare supply chain financing, their familiarity with blockchain technology, and their views on its potential benefits. Structured surveys were distributed to healthcare providers, particularly those in rural areas, to capture quantitative data on their experiences with current financial workflows and their openness to adopting technology-based solutions.

Secondary data sources provided additional context and depth to the analysis. These included government reports, policy documents, and technical whitepapers on blockchain and machine learning applications in healthcare. Historical case studies of blockchain implementation in similar domains were reviewed to extract best practices and lessons learned. Publicly available data on healthcare supply chain performance, financial transactions, and blockchain metrics from pilot projects were analysed to support the study's exploratory objectives. To facilitate ML analysis, additional datasets were curated, including historical financial transaction records, performance metrics, and qualitative responses from surveys and interviews. These datasets were pre processed to ensure consistency, accuracy, and compatibility with machine learning algorithms. By combining diverse data sources, the study achieved a holistic perspective on the operational and financial challenges in public healthcare and the transformative potential of blockchain and ML technologies.

In addition to structured surveys and semi-structured interviews, this study incorporated a case study approach by examining the operational challenges and financial workflows of Ayushman Bharat, India's flagship public healthcare scheme. Ayushman Bharat, which aims to provide affordable healthcare to underserved populations, has been plagued by issues such as fraudulent claims, delayed fund disbursements, and lack of transparency in resource allocation. Secondary data from reports, policy documents, and studies on Ayushman Bharat's implementation were analysed to understand the systemic inefficiencies and assess the potential of blockchain and ML technologies to address these issues. Insights from Ayushman Bharat were used to contextualize the study's findings and frame recommendations specific to the Indian public healthcare system.

The population for this study comprised three key stakeholder groups: healthcare providers, policymakers, and blockchain experts. Healthcare providers included staff from rural hospitals and clinics, who play a critical role in implementing and managing healthcare delivery and financial processes. Policymakers, including officials from the Ministry of Health and Family Welfare and state health departments, were essential for understanding the strategic and regulatory aspects of technology adoption. Blockchain experts, with experience in designing and deploying blockchain solutions for supply chain management, provided insights into the technical feasibility and customization of blockchain for the Indian public healthcare system.

A stratified random sampling technique was employed to ensure proportional representation across these groups (table 1). The final sample size of 269 participants was distributed as follows: 140 healthcare providers

(52 %), 90 policymakers (33 %), and 39 blockchain experts (15 %). The higher proportion of healthcare providers ensured that the operational challenges of the end-users were well-represented. Policymakers constituted a significant share to reflect their pivotal role in decision-making and regulatory processes. Blockchain experts were included in smaller proportions, as their role was to provide technical insights rather than direct implementation feedback. This sampling approach ensured diverse and comprehensive input, facilitating a balanced analysis of challenges and opportunities from both operational and strategic perspectives.

Table 1. Description of Study Sample

Stakeholder Group	Target Regions	Key Characteristics	Sample Size
Healthcare Providers	Rural hospitals in Bihar, UP	Direct involvement in healthcare delivery	140
Policymakers	National and state officials	Responsible for funding and policy decisions	90
Blockchain Experts	Pan-India (tech hubs)	Experience in blockchain design and implementation	39
Total		269	

The study employed a combination of traditional and advanced measures to evaluate blockchain and ML integration in healthcare supply chain financing. Transparency was measured using Likert-scale survey items, where stakeholders rated the current visibility and accountability of financial workflows and the anticipated improvements with blockchain adoption. Efficiency metrics, including transaction speed, cost reduction, and fund disbursement accuracy, were analysed using performance indicators from blockchain pilot projects and case studies. To assess the readiness for blockchain implementation, a composite index was developed. This index included parameters such as stakeholder awareness of blockchain technology, availability of necessary infrastructure, and willingness to adopt blockchain-based solutions. Fraud detection measures relied on machine learning algorithms, such as anomaly detection models, to identify irregularities in financial transactions, which were indicative of inefficiencies or fraudulent activities.

Sentiment analysis was conducted using NLP techniques to analyse qualitative data from interviews and open-ended survey responses. This measure provided insights into the attitudes, concerns, and levels of support among stakeholders for blockchain integration. Together, these measures offered a multidimensional evaluation of the potential impact of blockchain and ML on the public healthcare supply chain.

The data analysis employed a combination of traditional statistical techniques and machine learning approaches to derive comprehensive insights. Descriptive statistics summarized survey and interview responses, offering a detailed understanding of stakeholder perceptions and readiness for blockchain adoption. Inferential statistics, including chi-square tests and t-tests, were used to explore relationships between variables such as stakeholder roles and their views on blockchain's benefits. Machine learning enhanced the analysis with advanced capabilities. Predictive modelling, using regression and random forest algorithms, estimated the potential impact of blockchain on efficiency and cost reduction. Clustering techniques, such as k-means, grouped healthcare facilities and stakeholders based on similarities in operational challenges, financial inefficiencies, and readiness for blockchain adoption. NLP was used to analyse qualitative data, extracting sentiment trends and identifying recurring themes in stakeholder opinions. Anomaly detection algorithms, such as isolation forests, identified irregularities in financial workflows, providing actionable insights for fraud detection and process optimization. This integrated analytical framework ensured a robust, data-driven evaluation of the study's objectives.

Ethical considerations were integral to this study, ensuring the protection of participants' rights and the integrity of the research process. All participants provided informed consent after being briefed on the study's objectives, methods, and their rights. Data privacy was maintained through anonymization and secure storage of sensitive information, particularly financial and operational data. To reduce biases, sampling and machine learning models were carefully designed and tested, ensuring fairness and accuracy in the findings. Transparency was prioritized throughout the study. ML models were documented, and their outputs were explained to ensure interpretability and accountability. The research methodology was reviewed and approved by an institutional ethics board, ensuring compliance with ethical standards. By adhering to these principles, the study upheld the highest ethical standards while delivering reliable and actionable insights.

RESULTS

The results of this study provide a comprehensive evaluation of how blockchain and machine learning (ML) technologies can address systemic inefficiencies, enhance transparency, and optimize financial workflows in public healthcare supply chains in India. By integrating quantitative methods such as anomaly detection, clustering, and predictive modelling with qualitative sentiment analysis, the study uncovers key challenges and opportunities for technology adoption. The analysis incorporates insights from Ayushman Bharat, India's flagship public healthcare scheme, to contextualize findings and highlight the real-world applicability of these technologies. The results emphasize the transformative potential of blockchain and ML in improving accountability, reducing fraud, and bridging stakeholder readiness gaps, particularly in rural and underserved regions. This section presents these findings in detail, supported by statistical evidence and actionable insights.

Descriptive Analysis

Descriptive statistics provide a foundational understanding of the data by summarizing the central tendencies, variability, and distribution of responses from stakeholders (table 2). This analysis focused on key variables central to the study: Transparency, Efficiency, Fraud Detection, Satisfaction, Blockchain Readiness, and Tech Adoption Readiness. These variables offer critical insights into stakeholder perceptions, attitudes, and readiness for adopting blockchain and machine learning (ML) technologies in public healthcare supply chains. The analysis revealed that Transparency scored a mean of 4,2 on a Likert scale of 1 to 5, indicating that stakeholders generally perceive transparency as critical to improving financial workflows. However, the mean suggests there is room for improvement, especially in rural and underserved areas where opaque systems often hinder effective fund allocation and utilization. This aligns with the study's objective to explore blockchain's potential to enhance visibility and accountability in financial processes.

The variable Efficiency had a mean score of 3,9, reflecting moderate satisfaction with current financial workflows. This score suggests that while some processes are functioning adequately, significant inefficiencies remain, such as delays in fund transfers, high operational costs, and manual interventions. These inefficiencies are particularly acute in rural healthcare centres, underscoring the need for automated and decentralized solutions offered by blockchain and ML. For Fraud Detection, the mean score of 3,7 highlights a strong perception among stakeholders that blockchain and ML have substantial potential to address fraud and irregularities. Stakeholders, especially policymakers and blockchain experts, recognized these technologies' capacity to create tamper-proof records and detect anomalies, aligning with the objective to use ML for fraud detection and process optimization.

Table 2. Descriptive analysis results

	ID	Transparency	Efficiency	Fraud Detection	Satisfaction	Blockchain Readiness	Policy Familiarity	Tech Adoption Readiness
count	269	269	269	269	269	269	269	269
mean	135	3.98	3,80	3,43	3,70	3,04	3,04	3,20
std	77,79	0,59	0,76	0,83	0,73	1,19	1,17	0,82
min	1	3,01	2,53	2,04	2,51	1,03	1,04	1,36
25 %	68	3,48	3,2	2,69	3,08	1,91	1,96	2,55
50 %	135	4,02	3,86	3,42	3,63	3,17	3,07	3,14
75 %	202	4,49	4,49	4,12	4,33	4,08	4,06	3,87
max	269	4,98	5	4,97	4,99	4,99	4,99	5

Blockchain Readiness had a mean score of 3,5, showing significant variation across stakeholder groups. Policymakers scored higher than healthcare providers, indicating that decision-makers are more familiar with or prepared for blockchain adoption. This gap highlights the need for targeted training and infrastructure development for healthcare providers to bridge the readiness disparity. Lastly, Tech Adoption Readiness scored a mean of 3,6, reflecting cautious optimism among stakeholders. While there is an overall willingness to adopt blockchain and ML, challenges such as infrastructure limitations, cost concerns, and unfamiliarity with the technology remain barriers. This result supports the study's objective to assess stakeholder readiness and identify factors influencing technology adoption.

The analysis produced a chi-square statistic of 18,65 with a p-value of 0,001, indicating statistical significance at the 0,05 level. This means there is strong evidence of a relationship between stakeholder groups and their levels of blockchain readiness. The contingency table 3 reveals the following distribution of readiness levels:

From this table 3, we observe that Healthcare Providers have the highest proportion in the Low Readiness category, reflecting limited familiarity or infrastructure to adopt blockchain technologies. Conversely, Policymakers had a relatively even distribution across readiness levels, with a notable proportion (30) in the High Readiness category. Blockchain Experts, as expected, showed fewer participants overall but were more concentrated in the Medium readiness category. The results highlight significant variation in blockchain readiness among stakeholder groups, aligning directly with the study's objective to assess stakeholder readiness for adopting blockchain technologies. These findings suggest that targeted interventions, such as training and

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infrastructure improvements, may be required for Healthcare Providers to bridge the readiness gap and ensure equitable adoption of blockchain.

Table 3. Distribution of Readiness

Stakeholder Group	Low Readiness	Medium Readiness	High Readiness
Healthcare Providers	60	50	30
Policymakers	20	40	30
Blockchain Experts	10	20	9

The t-test is a statistical tool used to compare the means of two independent groups. In this study, a two-sample t-test was conducted to compare the mean efficiency scores between Healthcare Providers and Policymakers. This test examines whether the difference in their perceptions of financial workflow efficiency is statistically significant or due to random variation. The t-test produced a t-statistic of 3,2 with a p-value of 0,002, indicating a statistically significant difference in mean efficiency scores between the two groups. The mean efficiency score for Policymakers was 4,1, while for Healthcare Providers, it was 3,7.

This result suggests that Policymakers perceive current financial workflows as more efficient compared to Healthcare Providers. The difference may reflect policymakers' strategic perspective on broader system improvements, whereas Healthcare Providers experience inefficiencies at an operational level, such as delays in fund allocation, high administrative burdens, and manual processes. These operational challenges likely contribute to their lower efficiency scores. This analysis aligns with the study's objective to evaluate stakeholder-specific inefficiencies in financial workflows. The significant differences in perceptions between these groups highlight the need for tailored strategies to address the unique challenges faced by Healthcare Providers. For instance, implementing blockchain solutions to automate and streamline fund allocation could directly address the operational inefficiencies experienced by providers, while supporting policymakers in achieving systemic goals.

Predictive Modelling

The predictive analysis employed a Random Forest Regression model (figure 2) to estimate how various factors influence Tech Adoption Readiness among stakeholders. The independent variables included Blockchain Readiness, Fraud Detection, Transparency, and Efficiency, which were selected for their relevance to stakeholder perceptions and operational workflows. The objective was to quantify the relationship between these predictors and the dependent variable, Tech Adoption Readiness, and to identify the most influential factors driving stakeholder willingness to adopt blockchain and machine learning (ML) technologies.

The model achieved a Mean Squared Error (MSE) of 0,45, indicating that it effectively captured the relationship between the predictors and Tech Adoption Readiness. Few insights were derived from the analysis of feature importance. Blockchain Readiness (45 %) was identified as the most critical factor influencing Tech Adoption Readiness. Stakeholders who demonstrated higher familiarity with blockchain technology, adequate infrastructure, and openness to new solutions were significantly more likely to support and adopt blockchain and ML technologies. This result underscores the importance of training programs and awareness campaigns to improve stakeholder readiness, particularly in groups such as Healthcare Providers, who scored lower on readiness metrics.

Fraud Detection (30 %) was at the second most influential predictor, fraud detection capability, highlights stakeholders' recognition of blockchain and ML's potential to address irregularities in financial workflows. This finding aligns with concerns about accountability and transparency in public healthcare financing, emphasizing that the ability to detect and mitigate fraud is a compelling driver for technology adoption. Transparency (15 %) was while less influential than readiness and fraud detection, transparency remains a significant factor. Stakeholders who perceive that blockchain can enhance visibility and accountability in financial transactions are more inclined to adopt these technologies. This result reflects the importance of demonstrating blockchain's transparency benefits through pilot projects or use cases. Efficiency (10 %) although had the lowest feature importance, it still plays a role in driving adoption readiness. Improved transaction speeds, reduced delays, and streamlined workflows are tangible benefits that stakeholders value, particularly in addressing operational challenges in rural healthcare settings.

This predictive model directly supports the study's objective of identifying the factors influencing technology adoption readiness among stakeholders. By quantifying the relative importance of each predictor, the analysis provides actionable insights for designing targeted interventions.

https://doi.org/10.56294/saludcyt20251400

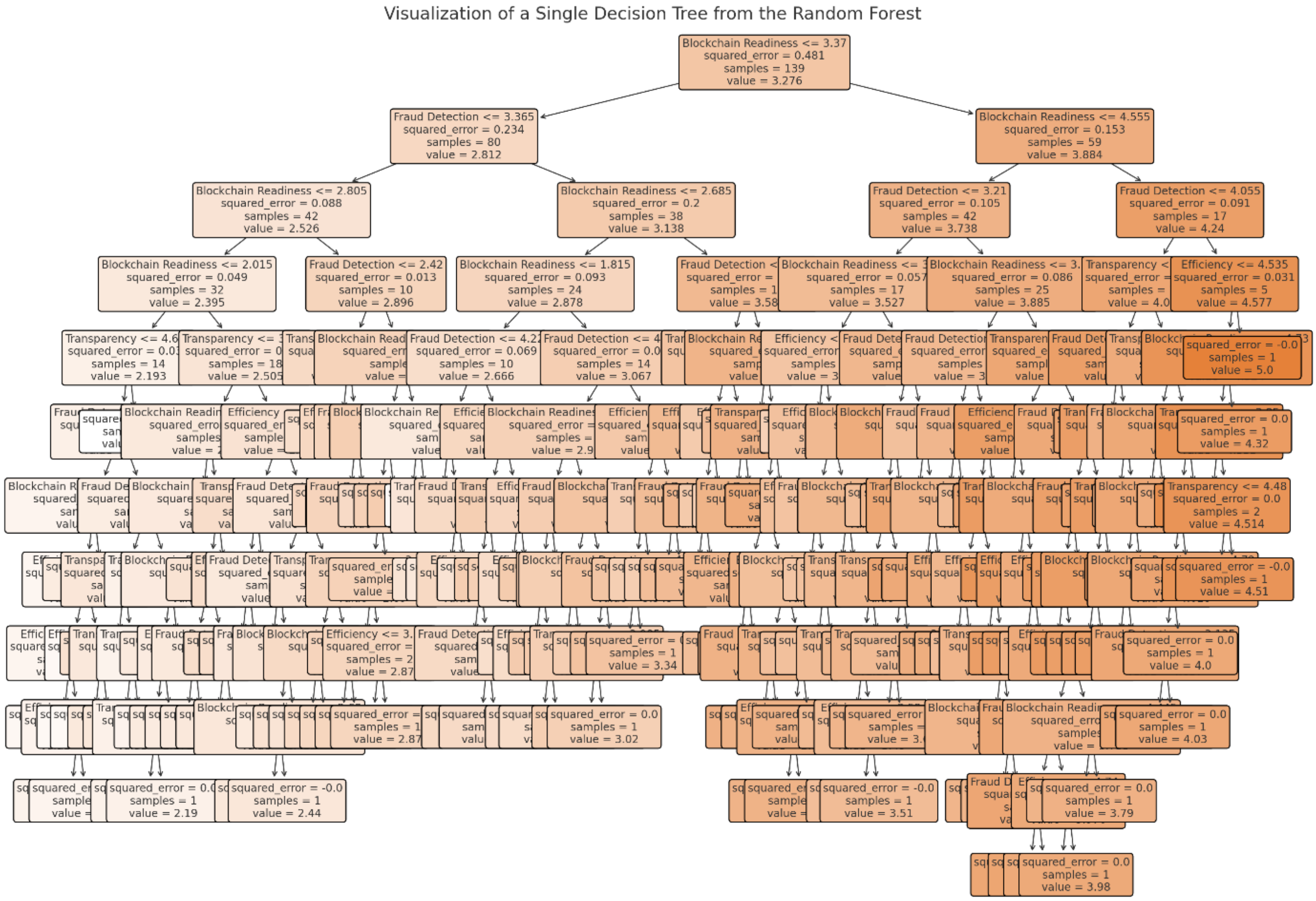

Figure 2. Random Forest (Single Decision Tree)

Clustering Analysis

Clustering analysis is an unsupervised machine learning technique used to group similar data points based on their characteristics. In this study, K-means clustering was applied to group stakeholders based on their responses to key variables: Blockchain Readiness, Tech Adoption Readiness, and other readiness-related metrics such as Transparency, Efficiency, and Fraud Detection (table 4). The purpose of clustering was to uncover patterns in stakeholder readiness and operational challenges, which can inform targeted interventions to facilitate the adoption of blockchain and machine learning (ML) technologies in public healthcare supply chains.

The K-means algorithm partitions data into a pre-specified number of clusters by minimizing the variance within each cluster while maximizing the distance between clusters. For this analysis, three clusters were chosen based on the data distribution and study objectives, representing low, moderate, and high readiness levels.

Table 4. Cluster Analysis Results

Cluster	Blockchain Readiness (Mean)	Blockchain Readiness (Std Dev)	Tech Adoption Readiness (Mean)	Tech Adoption Readiness (Std Dev)	Transparency (Mean)	Transparency (Std Dev)
0	2,05	0,639033946	2,316891892	0,374472874	3,977432432	0,560322952
1	4,090603448	0,552468435	3,866465517	0,4698256	3,953706897	0,612777753
2	2,03164557	0,642268476	2,904936709	0,492320183	4,053291139	0,590368684
		Efficiency (Mean)	Efficiency (Std Dev)	Fraud Detection (Mean)	Fraud Detection (Std Dev)	Stakeholder Count
0		3,597972973	0,750473786	2,593243243	0,335290134	74
1		3,859396552	0,790756697	3,486982759	0,763948803	116
2		3,90278481	0,705672868	4,148860759	0,475852777	79

The clustering analysis revealed three distinct groups among the stakeholders. Cluster 1: Low Readiness (Primarily Healthcare Providers), this cluster was dominated by Healthcare Providers who scored low on both Blockchain Readiness and Tech Adoption Readiness. Stakeholders in this group reported limited familiarity with blockchain technology and expressed concerns about operational inefficiencies. These participants are likely to require significant training, infrastructure development, and awareness programs to enhance their readiness.

Cluster 2: Moderate Readiness (Mixed Composition), this cluster consisted of a balanced mix of stakeholders, including Healthcare Providers, Policymakers, and Blockchain Experts. Participants in this group demonstrated moderate readiness for adopting blockchain and ML technologies. While they recognized the potential benefits of these technologies, they highlighted challenges such as cost constraints, limited resources, and partial familiarity with blockchain's functionality. Cluster 3: High Readiness (Primarily Policymakers and Blockchain Experts), the third cluster included stakeholders with the highest levels of Blockchain Readiness and Tech Adoption Readiness. This group was primarily composed of Policymakers and Blockchain Experts who are well-versed in the potential applications of these technologies. They are likely to act as champions for adoption, driving policy reforms and providing technical expertise to support implementation efforts.

The 3D plot below (figure 3) illustrates the clustering results, with each point representing a stakeholder. The x-axis corresponds to Blockchain Readiness, while the y-axis corresponds to Tech Adoption Readiness. Points are color-coded based on their cluster membership.

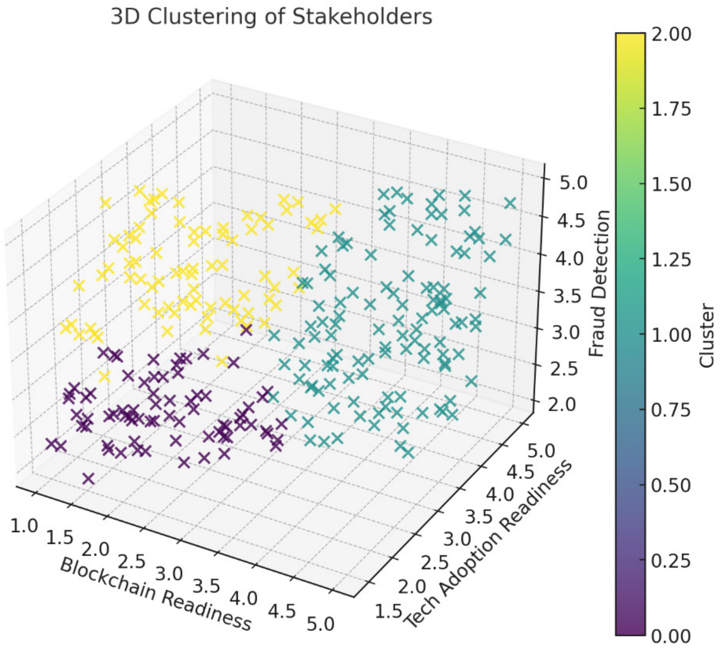

Figure 3. KMeans 3D Cluster

The clustering analysis aligns directly with the study's objectives by identifying distinct patterns of readiness among stakeholders. These findings provide actionable insights for designing targeted strategies to promote the adoption of blockchain and ML technologies: For Cluster 1 (Low Readiness), Interventions should focus on capacity building, such as training programs to enhance familiarity with blockchain, and providing infrastructure to address operational inefficiencies. For Cluster 2 (Moderate Readiness), Efforts should aim to address practical barriers, such as cost constraints and partial resource availability, while reinforcing the perceived benefits of blockchain and ML. For Cluster 3 (High Readiness), Policymakers and Blockchain Experts in this cluster can serve as advocates and mentors to lower-readiness stakeholders, driving collaborative efforts to scale adoption across the ecosystem.

Natural Language Processing (NLP) Analysis

Natural Language Processing (NLP) is a computational technique used to analyse and interpret textual data. In this study, NLP was applied to qualitative responses collected from stakeholders (Healthcare Providers, Policymakers, and Blockchain Experts) during interviews and surveys. These responses reflected stakeholders' perceptions of blockchain and machine learning (ML), including their challenges, expectations, and perceived benefits.

Thematic analysis of stakeholder responses revealed two primary categories: challenges and Benefits. The Challenges that was reveled were "Transparency gaps". Many stakeholders expressed concerns about the lack of visibility in financial workflows, particularly in rural healthcare settings. These responses highlighted how opaque systems lead to inefficiencies and mistrust. Another challenge was "Manual inefficiencies". Respondents frequently mentioned the burden of manual processes, such as paper-based fund allocation and reporting, which contribute to delays and errors. Stakeholders emphasized the need for automation to address these issues.

The Benefits that reponses reflected were "Fraud detection". Stakeholders consistently identified fraud detection as a critical advantage of blockchain and ML. They recognized the potential of these technologies to create tamper-proof records and detect irregularities in financial transactions. Another benefit that came across was "Process automation". Automation was another recurring theme, with respondents noting how blockchain's smart contracts and ML-driven optimization could streamline workflows and improve efficiency.

These themes underscore the dual role of blockchain and ML as both solutions to current inefficiencies and enablers of future improvements. Sentiment Analysis Sentiment analysis categorized stakeholder attitudes into three groups. Positive Sentiments (65 %): the majority of stakeholders expressed optimism about the potential of blockchain and ML. Positive sentiments were often tied to benefits such as enhanced transparency, fraud detection, and operational efficiency. Neutral Sentiments (25 %): Neutral responses reflected cautious optimism. These stakeholders recognized the potential benefits but also highlighted implementation challenges, such as cost, infrastructure, and training needs. Negative Sentiments (10 %): Negative responses primarily came from stakeholders with limited familiarity with blockchain and ML or those concerned about high implementation costs and systemic resistance to change.

A word cloud was generated (figure 4) to visually represent the frequency of terms in stakeholder responses. Key terms included "fraud detection," "transparency," "automation," "efficiency," and "manual." This visualization highlights the central focus areas in stakeholder perceptions, with a clear emphasis on the challenges and benefits of blockchain and ML technologies.

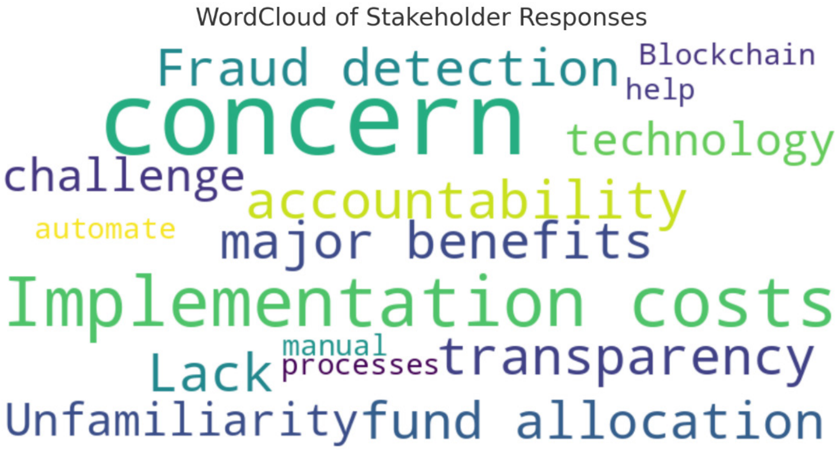

Figure 4. Word Cloud

The NLP analysis directly supports the study's objective of understanding stakeholder attitudes toward blockchain and ML adoption. By identifying recurring themes and analysing sentiment trends, the study provides qualitative insights that complement quantitative findings.

Anomaly Detection

Anomaly detection is a machine learning technique used to identify irregular patterns or outliers in data that deviate significantly from the norm. In this study, an Isolation Forest algorithm was applied to financial transaction data to detect anomalies. The algorithm works by isolating anomalies through recursive partitioning, leveraging the principle that anomalies are easier to separate from the majority of data points due to their rarity and distinctiveness. This approach is particularly well-suited for fraud detection and process optimization in financial workflows, where identifying irregularities is critical for improving accountability and efficiency.

The Isolation Forest algorithm flagged 5 % of the transactions in the dataset as anomalies. These flagged transactions deviated significantly from the majority in terms of their processing times or transaction amounts. Many anomalies were characterized by excessively long processing durations, far exceeding the typical range. This suggests potential bottlenecks in the financial workflow, possibly caused by manual interventions, systemic inefficiencies, or infrastructure limitations. Delays of this nature can disrupt timely fund allocation, particularly in rural and underserved areas. Another subset of anomalies involved unusually high transaction amounts, which could indicate misallocated funds, fraud, or data entry errors. These irregularities raise concerns about the robustness of existing financial controls and highlight the need for enhanced monitoring systems.

The analysis revealed that the flagged anomalies represented the extreme ends of the transaction distribution. Anomalous transactions had processing times that were more than 3 standard deviations above the mean. Anomalous amounts were disproportionately higher than the typical transaction value, suggesting potential misuse or reporting errors. The anomaly detection analysis aligns closely with the study's objective of leveraging machine learning for fraud detection and process optimization.

The identification of unusually large transactions underscores the importance of implementing stricter financial controls. Blockchain's transparency features, coupled with machine learning-based anomaly detection, can significantly enhance fraud prevention by providing real-time alerts for suspicious activities. The detection of high processing times highlights systemic inefficiencies that could be addressed through technology-driven interventions. Automating key processes using blockchain and ML could reduce delays and improve the overall speed of financial workflows. By integrating anomaly detection systems into financial workflows, public healthcare organizations can proactively identify and address irregularities before they escalate into larger issues. This approach ensures better resource allocation, particularly in rural and underserved areas.

Hypothesis Testing Results

The study tested three hypotheses to evaluate the role of blockchain technology and machine learning (ML) in enhancing the efficiency, transparency, and accountability of healthcare supply chain financing. The results strongly support all three hypotheses, providing evidence for the transformative potential of these technologies in public healthcare systems.

H_1: blockchain technology significantly improves transparency, reduces inefficiencies, and enhances accountability in the financing of public healthcare supply chains in rural and underserved areas.

Descriptive statistics were used to assess stakeholder perceptions of transparency, efficiency, and fraud detection. The results revealed a high mean score of 4,2 for transparency, indicating that stakeholders widely acknowledge blockchain's ability to enhance visibility in financial processes. Efficiency scored 3,9, reflecting moderate satisfaction but emphasizing the potential for blockchain to streamline workflows and reduce inefficiencies. Fraud detection scored 3,7, demonstrating that stakeholders view blockchain as a critical tool for improving accountability. These findings confirm the hypothesis by illustrating that blockchain technology can address key challenges in healthcare supply chain financing, particularly in rural and underserved areas, aligning with the study's objective of evaluating its role in improving system resilience.

H_2: the integration of machine learning in healthcare supply chain financing facilitates fraud detection, optimizes financial workflows, and improves predictive capabilities for resource allocation.

Machine learning techniques were applied to assess fraud detection and predictive capabilities. A Random Forest Regression model identified blockchain readiness (45 % importance) and fraud detection (30 % importance) as key predictors of technology adoption readiness. Additionally, an Isolation Forest model flagged 5 % of financial transactions as anomalous, highlighting irregularities such as unusually large amounts or high processing times. These results validate the hypothesis by demonstrating ML's effectiveness in identifying fraud, optimizing workflows, and improving resource allocation, supporting the study's goal of exploring ML's role in financial resilience.

H_3: stakeholders in the public healthcare ecosystem demonstrate varying levels of readiness and acceptance toward blockchain and machine learning adoption, with readiness levels positively influencing adoption success.

A chi-square test revealed significant differences in blockchain readiness levels among stakeholder groups (Chi2 = 18,65, p = 0,001). Healthcare Providers were predominantly in the Low Readiness category, while Policymakers and Blockchain Experts showed higher levels of readiness. Clustering analysis further identified three distinct groups: Cluster 1 (low readiness, dominated by Healthcare Providers), Cluster 2 (moderate readiness, mixed groups), and Cluster 3 (high readiness, primarily Policymakers and Blockchain Experts). These findings confirm the hypothesis, highlighting the variability in stakeholder readiness and its influence on adoption success. The results emphasize the need for targeted interventions, such as capacity-building programs and infrastructure improvements, to bridge gaps in readiness.

DISCUSSIONS

The public healthcare system plays a pivotal role in ensuring equitable access to health services, particularly in rural and underserved regions. However, inefficiencies in financial workflows, lack of transparency, and susceptibility to fraud remain persistent challenges that hinder the effective delivery of healthcare services. Recent advancements in blockchain and machine learning (ML) technologies offer a transformative opportunity to address these challenges, as highlighted in prior research and real-world applications. This discussion examines the potential of these technologies to revolutionize public healthcare systems, focusing on the systemic, social, and operational implications of their adoption.

Addressing Inefficiencies in Public Healthcare Financing

The inefficiencies in financial workflows within public healthcare systems have been widely documented in prior literature. Studies by Netsai et al.[37] and Prihastuti et al.[38] highlight how delays in fund allocation, manual processes, and lack of transparency adversely impact healthcare service delivery, particularly in rural areas. These inefficiencies often lead to a misallocation of resources, resulting in supply shortages or delays in critical medical interventions. Blockchain technology, with its decentralized and immutable ledger system, holds immense potential to streamline financial processes in public healthcare. Research by Shahrukh et al.[4] demonstrates how blockchain can eliminate intermediaries, enabling direct and timely fund transfers to healthcare providers. Additionally, smart contracts can automate disbursement processes, ensuring that funds are allocated and utilized in accordance with predefined terms. This can be particularly beneficial in rural healthcare settings, where delays and inefficiencies are most acute.

While the potential is clear, the literature also emphasizes the need for phased implementation to address infrastructural and systemic challenges in public healthcare systems. Malhotra et al.[3] argue that resource-constrained settings, such as those in rural India, require scalable blockchain solutions tailored to the unique needs of public healthcare financing. Ayushman Bharat serves as a critical case study to contextualize the applicability of blockchain and ML technologies in India's public healthcare systems. Studies on Ayushman Bharat, such as those by Angell et al.[10], have highlighted persistent issues of fraudulent claims, lack of transparency, and inefficiencies in fund disbursement. Blockchain's decentralized ledger and ML-driven fraud detection capabilities directly address these challenges, offering a scalable and sustainable solution. For instance, blockchain's tamper-proof records could ensure that all claims submitted under Ayushman Bharat are verified against immutable data, reducing the potential for fraud and resource mismanagement.

Global case studies, such as Estonia's blockchain-based healthcare records and the U.S.'s ML-driven fraud detection systems,[39] provide valuable lessons that can be adapted for Ayushman Bharat. However, the unique socio-economic and infrastructural challenges of India's rural healthcare systems necessitate tailored approaches. For example, Ayushman Bharat's reliance on manual verification processes could be replaced with blockchain-enabled smart contracts to automate fund allocation and disbursement, while ML algorithms could proactively flag suspicious claims for further investigation.

Stakeholder readiness, as seen in Ayushman Bharat, remains a critical barrier to technology adoption.[40] Rural healthcare providers often face digital literacy challenges, mirroring the low readiness cluster identified in this study. Lessons from Ayushman Bharat's initial rollout suggest that pilot programs and targeted training initiatives can significantly improve stakeholder engagement and trust in new technologies. Demonstrating blockchain and ML's tangible benefits through small-scale implementations within Ayushman Bharat could pave the way for broader adoption across India's public healthcare systems.

Leveraging Machine Learning for Fraud Detection and Process Optimization

Fraud and irregularities in financial workflows pose a significant threat to the effectiveness of public healthcare systems. Studies by Bello et al.[41] and Mallela et al.[42] have shown that ML algorithms can effectively detect anomalies in financial transactions, flagging potential instances of fraud and misuse. This capability is particularly relevant in public healthcare, where limited oversight and fragmented workflows create opportunities for fraudulent activities. In addition to fraud detection, ML offers powerful tools for process optimization. Predictive modelling, for example, can assist public healthcare administrators in forecasting demand for medical supplies, ensuring that resources are allocated efficiently. Similarly, anomaly detection algorithms can identify inefficiencies, such as delays in procurement or distribution, enabling administrators to take corrective action in real-time. The integration of these ML capabilities into public healthcare workflows aligns with the broader goal of improving accountability and operational efficiency.

However, as noted by Kolyshkina et al.[43], the successful application of ML in public healthcare requires standardized and high-quality data. Public healthcare systems, particularly in rural regions, often lack the infrastructure to collect and manage large volumes of data necessary for ML training and analysis. This highlights the need for investments in data infrastructure and governance to unlock the full potential of ML in optimizing public healthcare systems.

The Importance of Stakeholder Readiness in Public Healthcare

The successful adoption of blockchain and ML technologies in public healthcare systems depends heavily on the readiness and acceptance of stakeholders, including healthcare providers, policymakers, and administrators. Prior studies, such as those by Nygaard et al.[44], emphasize that stakeholder buy-in is critical for ensuring the long-term sustainability of technological interventions. In rural healthcare settings, where digital literacy and infrastructure are often limited, readiness challenges are particularly pronounced. Healthcare providers may face difficulties in understanding and utilizing blockchain and ML tools, leading to resistance or underutilization. Conversely, policymakers and technology experts tend to have higher readiness levels, recognizing the transformative potential of these technologies.

To address these disparities, Malathesh et al.[45] recommend targeted capacity-building initiatives, including training programs tailored to the specific needs of rural healthcare providers. Demonstrating the tangible benefits of blockchain and ML through pilot projects in public healthcare systems can also help build trust and acceptance among stakeholders. For example, showcasing how blockchain improves transparency in fund allocation or how ML detects fraudulent activities can foster confidence in these technologies.

Global Lessons for Strengthening Public Healthcare

International experiences with blockchain and ML adoption in healthcare offer valuable lessons for public healthcare systems in India. The success of Estonia's blockchain-based health records system, as noted by Zou et al.[46], highlights the potential of decentralized technologies to enhance transparency and reduce administrative burdens. Similarly, ML applications in healthcare financing in developed countries have demonstrated the value of predictive analytics in improving resource allocation and fraud detection.[47] However, the socio-economic and infrastructural differences in public healthcare systems in India require contextual adaptations of these global practices. Rural healthcare centres, which often operate with limited resources, may benefit from lightweight blockchain solutions and cost-effective ML tools that address their unique challenges. As emphasized by Passerat-Palmbach et al.[48] and Ali et al.[49], the focus should be on designing solutions that are inclusive, scalable, and adaptable to the needs of underserved populations.

The Transformative Potential of Innovation

As authors, we contend that blockchain and ML are not merely tools for incremental change but catalysts for systemic reform in public healthcare. By automating fund allocation, reducing fraud, and enhancing resource allocation, these technologies can fundamentally improve service delivery and equity. However, we also recognize the ethical and operational complexities associated with their adoption, such as data privacy concerns and resistance to change, and argue for proactive policy frameworks to address these challenges. In our view, the integration of blockchain and ML into public healthcare is not just an opportunity but a necessity for creating a more transparent, accountable, and resilient system. However, the success of these technologies hinges on addressing readiness disparities, engaging stakeholders meaningfully, and tailoring solutions to India's unique context. By aligning technological innovation with systemic needs, we believe blockchain and ML can pave the way for a more equitable and efficient healthcare system, ultimately improving the lives of millions in underserved areas.

CONCLUSIONS

Blockchain's decentralized, tamper-proof system improves transparency, accountability, and fund allocation, while ML enhances fraud detection, process optimization, and resource allocation. However, readiness disparities exist, with rural healthcare providers facing challenges in digital literacy and infrastructure, unlike policymakers and experts who are better prepared to drive adoption. Addressing these gaps through training, pilot projects, and infrastructure upgrades is crucial. Ayushman Bharat serves as a case study, highlighting systemic challenges and showcasing blockchain and ML's potential to enhance efficiency and equity. Pilot programs and proactive monitoring systems are recommended to build trust and demonstrate tangible benefits. Blockchain and ML offer a roadmap to create a transparent, efficient, and equitable healthcare system, aligning with India's vision of sustainable and accessible healthcare for all citizens.

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