

A Novel Blockchain Proof of Validation Scheme Based on Explainable AI for Healthcare Workload

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Abstract

These days, the usage of blockchain with machine learning to optimise data validation in terms of transparency, validity, and immutability has been increasing daily. Therefore, many complex applications, such as healthcare and related disease processes, have recently required the implementation of many remote resources in a transparent form. The blockchain provides real-time security validation based on proof of work validation schemes. To understand the dynamic situation of blockchain, mainly machine learning implemented for the decision and improve the efficiency of the security. However, there are many limitations when using blockchain technology with machine learning. Therefore, to cope with this issue, a novel blockchain proof of validation scheme based on explainable AI for healthcare applications is needed to process the decision of blockchain with machine learning in a more explainable way. We present the blockchain proof of work validation explainable AI (PoWV-XAI) to control the delay, energy, cost and security dynamic issues compared to existing blockchains with machine learning algorithms. The proposed PoWV-XAI algorithm suggested different metaheuristic schemes and supported the explainability of healthcare workload execution on other nodes, such as local and server. Simulation results show that the proposed PoWV-XAI is more explainable, and all decisions, such as processing delay, validation, security, energy, and cost, are explainable compared to existing blockchain methods.

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1 Introduction

The usage of blockchain technologies in different industrial applications, such as healthcare, intelligent transport, and smart homes, has been increasing daily [1]. The blockchain is composed of several features, which include hash algorithms, which are built on the principles of SHA-256, hash schemes, time-based stamps, roots, and consensus verifications, including proof of work, validation, and proof of stake [2]. Other applications use different forms of blockchain like private, public, and hybrid in addition to consortium type. The use of blockchain such as private, public and hybrid as well as consortium type. Adoption of blockchain technologies in industrial application has been growing at a rapid rate in the recent past. Some of the sectors that are increasingly implementing blockchain to enhance the security, transparency, and efficiency of their operations include healthcare, intelligent transportation systems (ITS), and smart home automation. Healthcare, intelligent transportation systems (ITS), and smart home automation are just but a few sectors that are increasingly implementing blockchain to enhance the security, transparency and efficiency of their operations and processes [1]. As business and service organisations continue to digitise, blockchain has become a key technology in the management of data in a safe and decentralised form. Its de-centralised registry system offers the storage of data without tampering, data integrity and non-use of a central authority by parties involved in the process without a central authority [3].

The healthcare sector is significantly focused on the aspect of strengthening security and medical information interoperability through blockchain. Patient records, the history of their treatment, diagnostic outcome, and prescriptions can be saved in a ledger that is based on blockchain to ensure they can be accessed only by the required authorities. This eliminates the risks of data breaches and manipulations, which are typical of the traditional centralised healthcare data systems. Moreover, blockchain will allow sharing medical data in real-time between healthcare providers, insurance companies, and patients, which will result in increased collaboration, less administrative delay, and, eventually, better patient outcomes. The pharmaceutical supply chain management is also facilitated by the immutability and traceability of blockchain that allows determining the authenticity of drugs and preventing the distribution of counterfeit medicine. Blockchain is transforming the mobility solutions in intelligent transport systems, making it possible to conduct vehicle-to-everything (V2X) communication and share secure vehicular data, and manage traffic dynamically. The blockchain provides the possibility of providing a safe and transparent vehicle data tracking, i.e. of driving behavior, fuel consumption, and maintenance history, which may be utilized by manufacturers, insurance companies and regulatory authorities. It is also helpful in introducing smart contracts to ride-sharing apps and AV networks, which would make payments automated and trustless agreements between service providers and clients. Moreover, creating better transportation infrastructure should also be supported by blockchain as it allows managing it through decentralisation and providing real-time data analysis to optimise traffic flow, minimize congestion, and improve road safety [4].

Another section that is experiencing the growth in blockchain technology integration is smart homes. Due to the attachment of multiple devices in a home, e.g. lighting, HVAC, security cameras, and smart locks, secure and efficient communication is essential. Blockchain facilitates decentralised control of smart home devices and secure communication, which will not depend on centralised servers, which are susceptible to cyber attacks. Home-owners will be able to manage access controls, record user actions, and integrity of devices using blockchain. Moreover, blockchain may enable peer-to-peer energy trading in smart grids whereby people with solar panels have the ability to sell excess electricity to neighbours through secure smart contracts. Blockchain technology has a number of key building blocks which guarantee its strength and safety. The hashing algorithm is one of the most important aspects and usually, it is the SHA-256 (Secure Hash Algorithm 256-bit) that is used to convert input data into a fixed size string of characters and that is the representation of it. Hashing is used to protect the integrity of the blocks by ensuring cryptographic hashing between the block and the previous block, and so on, creating an insecure chain of custody. Another application of timestamps in block chain is the ability to specify

the time at which a transaction was actually handled in order to ensure that the chronology of events can be restored and verified. Another concept that is mandatory in this field is the merkle roots, which enable effective and safe validation of the content in large data sets, making it easier to detect any alteration to the data. Consensus mechanisms such as Proof of Work (PoW), Proof of Stake (PoS), and other validation schemes ensure that all blockchain network nodes agree on the current ledger. PoW, for example, requires participants to solve complex mathematical problems to validate transactions and add new blocks, which helps deter malicious actors. PoS, on the other hand, assigns validation rights based on the stake held by a user, making it more energy-efficient than PoW [5].

However, many issues exist with existing blockchain technologies and artificial intelligence methods for industrial applications. (i) The existing blockchain proof of work (PoW) only identified the hashing, and AI methods optimise it more than optimal forms. However, it is a heavy process and takes too much time. (ii) The existing explainable AI methods, such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (Shapley Additive explanations) and other methods, are not adaptive and always face scalability issues.

To cope with the above challenge, we present a novel blockchain proof of validation scheme based on explainable AI for healthcare workloads. We will solve the above issues with the following solutions and contributions.

- We present a blockchain proof of work validation and an explainable AI-enabled algorithm (PoWV-XAI) consisting of different workloads, nodes, and attributes to process healthcare workloads on distributed nodes.
- We present the new scalable and lightweight XAI, which are more scalable and efficient than existing XAI while using blockchain technologies and schemes to run healthcare workloads.

The rest of the paper is organised as follows: Section 2 concerns related work. Section 3 is about the proposed work. Section 4 is about methodology. Section 5 is about performance evaluation, and Section 6 is about the conclusion and future work.

2 Related Work

To enhance the detection of cyber threats in smart healthcare systems, *et al.* [1] presented an XAI-based blockchain framework to enhance network security frameworks. They have used Clique Proof-of-Authority (C-PoA) to communicate safely in the clouds. They presented a threat-hunting model, that is, deep learning-based, which combines Parallel Stacked LSTM (PSLSTM) and multi-head attention to enhance detection performance. Initially, the involved entities securely communicate via a blockchain-based AKA mechanism. SHapley Additive exPlanations (SHAP) explained and interpreted the key features influencing the decision-making process.

Muneer and Fatima [2] A bibliometric review of XAI and blockchain integration in smart agriculture was introduced by Chen and colleagues. They highlighted the process of blockchain improvement of transparency by the inability to alter the cycle of production and better efficiency and sustainability of the entire agricultural supply chain.

Sachan and Liu [3] proposed the BXAI-IDCUCS model, an intrusion detection model that uses blockchain and XAI to work with clustered IoT settings. It applies energy-conscious duck swarm optimization algorithm to cluster nodes, deep neural networks to classify intrusions, and blockchain to establish safe inter-cluster communications, and with high accuracy and efficiency along various measures.

Kumar *et al.* [4] introduced an XAI-enabled blockchain framework to improve cyber threat detection in smart healthcare systems. They utilized Clique Proof-of-Authority (C-PoA) for secure cloud communication. They proposed a deep learning-based threat-hunting model integrating Parallel Stacked LSTM (PSLSTM) with multi-head attention to boost detection capabilities.

Chen *et al.* [5] presented a bibliometric review of integrating XAI and blockchain in smart agriculture. They emphasized how blockchain enhances transparency through immutable tracking of production processes and improves efficiency and sustainability across the agricultural supply chain.

Salama and Ragab [6] developed the BXAI-IDCUCS framework- an intrusion detection system which uses blockchain and XAI to use in clustering IoT devices. It utilizes an energy-aware duck swarm optimization algorithm for node clustering, deep neural networks for intrusion classification, and blockchain for secure inter-cluster communication, achieving high accuracy and efficiency across multiple metrics.

Houda *et al.* [7] proposed FedIoT, a federated learning (FL) system that incorporates blockchain and XAI to improve the detection of intrusions in IoT networks on the basis of federated learning (FL). The strategy relies on lightweight blockchain implemented reputation management and XAI stimulated manipulation detection to ensure collaborative model training and demonstrated successful outcomes on the UNSW-NB15 dataset.

Sharma and Shambharkar [8] suggested a multi-attention DeepCRNN-based hybrid security architecture to detect intrusions in Internet of Medical Things (IoMT) environments. The solution is a combination of blockchain-based decentralized storage with the enhanced accuracy of detecting a performance and real-time work performance and a decrease in the likelihood of a transaction reversal, which fits the healthcare setting.

Hasan *et al.* [9] presented an anomaly detection system of blockchain transactions using machine learning techniques; it was called detecting, not predicting, as prediction is typically the goal of such systems (hasan2024detecting). The researchers relied on multiple classifiers with the XAI methods to obtain insights into transaction patterns, which offers transparency and interpretability in the monitoring of financial transactions and fraud detection. tability in financial data monitoring and fraud detection.

Dutta *et al.* [10] addresses the topic of secure eHealth systems with XAI and blockchain. They proposed an adaptive authentication method with AI-enhanced block sensitivity, where the safety and explainability of personal health information are guaranteed. This indicates high applicability of user privacy and protection of medical data.

Brohi and Mastoi (2025) write about the cybersecurity threats of deep learning models applied in health care. They conduct a metric-based assessment by evaluating the possible risks and vulnerabilities of AI systems in the healthcare sector in their paper, highlighting the need to address security issue in deep learning models mitigation [11].

Mastoi *et al.* (2025) present an interpretable and collaborative federated learning framework to analyze brain tumour in medical imaging. They improve the explainability of AI models, which means that medical professionals are more likely to comprehend the logic behind the predictions, and address data privacy preservation using federated learning systems that leverage federated learning [12]. Their solution makes AI models easier to explain and understand their logic, and benefit data privacy through federated learning systems leveraging federated learning.

Lakhan *et al.* (2024) suggest a Meta-Verse-based operating healthcare body sensor network architecture. This article considers the combination of the Metaverse and the body sensor network to enhance healthcare monitoring and data analytics, which introduces a new framework to optimize the entire healthcar system on the whole [13].

Van Leersum and Maathuis [14] offer a vivid discussion of explainable AI decision-making in the healthcare sector, which is human-centered. Their paper posits that AIs should focus on human values, including trust, transparency and ethical responsibility. The opaque AI approach tends to hamper trust and clinical adoption. The authors note that the explainability introduced at the design stage may largely enhance the capacity of the clinicians to interpret and justify AI results, resulting in more responsible and acceptable clinical practices. leading to more responsible and acceptable clinical practices.

M et al. [15] take a new direction and combines explainable AI and federated learning to classify brain tumors. Their interpretable and collaborative architecture honors privacy of the data by decentralized training and improves the transparency of the model by visual representations like attention heatmap and feature importance score. This two-fold approach guarantees proper diagnostics with no impairment of data security, which makes the system appropriate in the real-life clinical applications.

3 Proposed Methodology

We presented different components in the proposed framework, as shown in Figure 1.

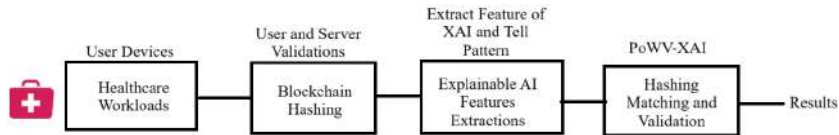


Figure 1. Proposed Blockchain XAI Architecture for Healthcare Workload.

The framework consisted of different workload parts, such as input healthcare data, where user devices collect and process the data on the local machine before offloading it to the server for further analysis. The workload is the patient bio-data, medicine, disease information, and more, which must be encrypted based on the blockchain hashing mechanism, SHA-256. To understand the hashing pattern and data behaviour, we have used explainable artificial intelligence (XAI), which is more scalable and efficient than existing XAI methods.

The explainable AI extracts the features based on generated blockchain hashing and patterns, and validation decisions are more explainable than existing blockchain consensus methods.

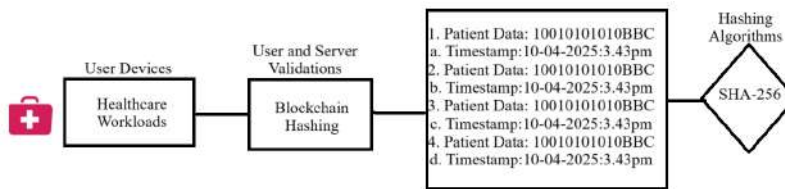


Figure 2. Proof of Work Validation based on Explainable AI.

As shown in Figure 2, we have SHA-256 convert plaintext into hashing with different features such as timestamps in a particular block into an immutable format. The hashing has 256 bits and is validated among other nodes.

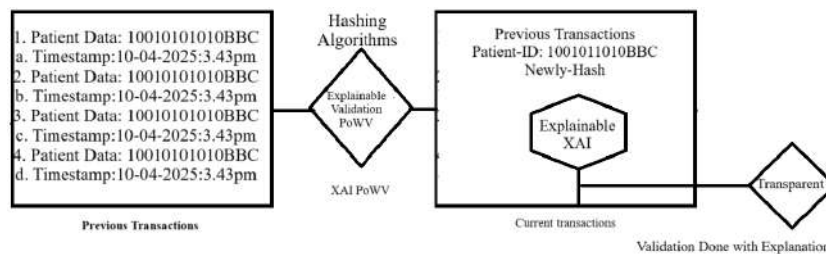


Figure 3. Transparency in PoWV-XAI.

In this study, the experimenter intends to create a safe and transparent blockchain-based healthcare validation architecture based on the Proof of Work (PoW) consensus and Explainable Artificial Intelligence (XAI). The goal

of this framework is to guarantee the integrity, authenticity and traceability of health in decentralised networks and improve trust and accountability by being interpretable through AI-driven decision making. The proposed system has the ability to validate robust data with transparency of XAI, reduce fraudulent transactions, and allow healthcare professionals to make ethically sound and informed decisions in medical diagnoses, treatment prescriptions, and data sharing in healthcare ecosystems.

3.1 Mathematical Model

We defined the mathematics of the considered problem in the following way.

- N : Total number of participating nodes (local devices, edge, cloud servers).
- $i = 1, \dots, N$
- W_i : Healthcare workload assigned to node i (e.g., diagnosis, monitoring, prediction tasks).
- $E_i(W_i)$: Energy consumption of node i based on workload W_i .
- $C_i(W_i)$: Cost (computation + communication) at node i for workload W_i .
- $D_i(W_i)$: Delay (latency) at node i for workload W_i .
- T : System-wide transparency enabled via Explainable AI (XAI).
- A : Attack resilience factor (trust/security score).
- $X_i(W_i)$: Explainability score of workload W_i on node i .
- \mathcal{V}_i : Validation score for node i used in Proof of Validation (PoV).

The objective is to minimize energy, cost, and delay for all healthcare workloads while maximizing transparency and security:

$$\min_{W_i, \mathcal{V}_i} \sum_{i=1}^N (\alpha_1 E_i(W_i) + \alpha_2 C_i(W_i) + \alpha_3 D_i(W_i)) - \beta_1 T - \beta_2 A \quad (1)$$

Where:

- $\alpha_1, \alpha_2, \alpha_3$ are the weight coefficients for energy, cost, and delay, respectively.
- β_1, β_2 are the weight coefficients for transparency (T) and attack resilience (A).
- The goal is to balance energy efficiency, cost minimization, delay reduction, and maximizing transparency and security.

$$(a) \text{ Explainability constraint: } X_i(W_i) \geq \theta_X, \quad \forall i \quad (2)$$

$$(b) \text{ Delay constraint: } D_i(W_i) \leq \delta, \quad \forall i \quad (3)$$

$$(c) \text{ Energy constraint: } E_i(W_i) \leq E_{\max}, \quad \forall i \quad (4)$$

$$(d) \text{ Workload capacity: } 0 \leq W_i \leq W_{\max}^i, \quad \forall i \quad (5)$$

$$(e) \text{ Validation score: } \mathcal{V}_i = f(X_i(W_i), A, D_i(W_i), E_i(W_i)) \quad (6)$$

$$(f) \text{ Consensus requirement: } \sum_{i=1}^N \mathbb{I}[\mathcal{V}_i \geq \theta_V] \geq M \quad (7)$$

Where:

- θ_X is the minimum explainability threshold.
- δ is the maximum allowed delay.
- E_{\max} is the maximum allowed energy consumption for each node.
- W_{\max}^i is the maximum allowed workload for node i .

- $f(\cdot)$ is a function that computes the validation score ν_j based on explainability, attack resilience, delay, and energy.
- $\mathbb{I}[\cdot]$ is an indicator function which evaluates if the validation score exceeds a certain threshold θ_V .
- M is the minimum number of nodes required for consensus in order to validate a healthcare block.

The explainability score for workload W_i on node i is computed using various Explainable AI techniques such as SHAP, LIME, and Attention mechanisms:

$$X_i(W_i) = g(\text{SHAP}_i(W_i), \text{LIME}_i(W_i), \text{Attention}_i(W_i)) \quad (8)$$

Where:

- $g(\cdot)$ is a function that aggregates the explainability contributions from SHAP, LIME, and Attention.
- $\text{SHAP}_i(W_i)$, $\text{LIME}_i(W_i)$, and $\text{Attention}_i(W_i)$ are the scores generated from SHAP, LIME, and Attention methods for workload W_i on node i .

The PoV score for node i is computed as:

$$\nu_i = \lambda_1 \cdot X_i(W_i) + \lambda_2 \cdot A - \lambda_3 \cdot E_i(W_i) - \lambda_4 \cdot D_i(W_i) \quad (9)$$

Where:

- $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the weight coefficients for explainability, attack resilience, energy consumption, and delay, respectively.
- The PoV score integrates these factors to determine whether the healthcare workload processing on node i is valid within the system.

The final validation decision for a healthcare transaction block is based on the aggregated validation scores from all nodes:

$$\sum_{i=1}^N \mathbb{I}[\nu_i \geq \theta_V] \geq M \quad (10)$$

Where:

- $\mathbb{I}[\cdot]$ is the indicator function that checks if the validation score for node i exceeds the threshold θ_V .
- If the sum of valid nodes is greater than or equal to M , the block is validated:

$$\sum_{i=1}^N \mathbb{I}[\text{score}_i \geq \theta_V] \geq M.$$

Data Initialization: Initialize all parameters and constraints (such as energy, cost, delay, transparency, attack resilience, etc.) for N nodes.

Workload Assignment: For each node i , assign a workload W_i and evaluate its energy $E_i(W_i)$, cost $C_i(W_i)$, and delay $D_i(W_i)$.

Validation Constraints: Check if the energy consumption $E_i(W_i)$, delay $D_i(W_i)$, and workload limits W_i are within allowable constraints:

$$E_i(W_i) \leq E_{\max}, \quad D_i(W_i) \leq \delta, \quad 0 \leq W_i \leq W_{\max}^i$$

where E_{\max} is the maximum allowed energy, δ is the maximum delay, and W_{\max}^i is the maximum allowed workload for node i .

Algorithm 1. Optimized Healthcare Workload Distribution and Validation

Input: $N, W_{\max}^i, \alpha_1, \alpha_2, \alpha_3, \beta_1, \beta_2, \theta_X, \delta, E_{\max}, M$ Output: Optimized Workload Distribution and Validation Results
Data Initialization: Initialize all parameters and constraints for N nodes

$i = 1$ to N **Workload Assignment:** Assign initial workload W_i **Energy, Cost, and Delay Evaluation:** Calculate $E_i(W_i), C_i(W_i), D_i(W_i)$

Validation Constraints:

if $E_i(W_i) \leq E_{\max}$ and $D_i(W_i) \leq \delta$ and $W_i \leq W_{\max}^i$ **then Explainability Score:** Compute $X_i(W_i)$ using Explainable AI techniques (SHAP, LIME, Attention) **Validation Score:** Compute $\mathcal{V}_i = \lambda_1 X_i(W_i) + \lambda_2 A - \lambda_3 E_i(W_i) - \lambda_4 D_i(W_i)$

if $X_i(W_i) \geq \theta_X$ **then Update Consensus:** Check $\mathcal{V}_i \geq \theta_V$ and update consensus requirement

else Reject Workload Assignment: Reject W_i and reassign

Reject Workload Assignment: Reject W_i and reassign

Optimization Objective: Solve the following optimization problem to minimize energy, cost, and delay, and maximize transparency and security:

$$\min_{W_i, \mathcal{V}_i} \sum_{i=1}^N (\alpha_1 E_i(W_i) + \alpha_2 C_i(W_i) + \alpha_3 D_i(W_i)) - \beta_1 T - \beta_2 A$$

Optimization Process: Use Genetic Algorithm, Gradient Descent, or other suitable methods to solve the above optimization problem

Consensus Check: Ensure that at least M nodes satisfy $\mathcal{V}_i \geq \theta_V$ for block validation

Final Decision: If consensus is reached, validate healthcare transaction block

if Consensus Reached **then Healthcare Block Validation:** Validate healthcare block and propagate across the system

else Retry Validation: Re-assign workloads and re-compute for consensus

Explainability Score Calculation: Compute the explainability score $X_i(W_i)$ using Explainable AI methods such as SHAP, LIME, and Attention:

$$X_i(W_i) = g(\text{SHAP}_i(W_i), \text{LIME}_i(W_i), \text{Attention}_i(W_i))$$

where $g(\cdot)$ aggregates the explainability contributions from SHAP, LIME, and Attention.

Validation Score: Compute the validation score \mathcal{V}_i for node i considering the following factors:

$$\mathcal{V}_i = \lambda_1 \cdot X_i(W_i) + \lambda_2 \cdot A - \lambda_3 \cdot E_i(W_i) - \lambda_4 \cdot D_i(W_i)$$

where $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the weight coefficients for explainability, attack resilience, energy consumption, and delay, respectively.

Optimization Process: Solve the optimization problem to minimize the weighted sum of energy, cost, and delay while maximizing transparency and security:

$$\min_{W_i, \mathcal{V}_i} \sum_{i=1}^N (\alpha_1 E_i(W_i) + \alpha_2 C_i(W_i) + \alpha_3 D_i(W_i)) - \beta_1 T - \beta_2 A$$

where $\alpha_1, \alpha_2, \alpha_3$ are the weight coefficients for energy, cost, and delay, and β_1, β_2 are the weight coefficients for transparency and attack resilience.

Consensus Check: Ensure that at least M nodes satisfy the following condition for the validation of the healthcare transaction block:

$$\sum_{i=1}^N \mathbb{I}[\mathcal{V}_i \geq \theta_V] \geq M$$

where $\mathbb{I}[\cdot]$ is an indicator function and θ_V is the validation threshold. If consensus is reached, the healthcare block is validated; otherwise, the process retries with updated workloads.

4 Performance Evaluation

This system integrates blockchain technology with edge cloud and mobile computing resources to optimize healthcare applications. The system uses the Proof of Work (PoW) blockchain algorithm, where miners solve cryptographic puzzles to achieve consensus. Each blockchain block is mined approximately every 10 minutes, with a block size of 1 MB and a PoW difficulty level of 15-20. The transaction throughput is around 7 transactions per second (TPS).

Parameter	Value
Blockchain Algorithm	Proof of Work (PoW)
Blockchain Consensus Method	Miners Solving Cryptographic Puzzles
Block Time	10 minutes
Block Size	1 MB
PoW Difficulty Level	15-20
Transaction Throughput	7 transactions per second (TPS)
Mobile Device Computational Power	1.8 GHz Quad-Core CPU
Edge Cloud Computational Power	3.2 GHz Octa-Core CPU
Energy Efficiency (Mobile)	10 W
Energy Efficiency (Edge Cloud)	100 W
Explainable AI Model	XAI with Local Interpretable Model-agnostic Explanations (LIME)
Healthcare Workload	Medical Imaging Analysis, Disease Diagnosis
Security Level	High (end-to-end encryption)
Data Storage Location	Distributed across mobile and edge cloud nodes
Smart Contract Integration	For managing patient records and transaction validation
Latency in Validation	100 ms for mobile, 30 ms for edge cloud
Blockchain Block Interval	10 minutes

A 1.8 GHz Quad-Core CPU powers the system's mobile devices, while the edge cloud utilizes a 3.2 GHz Octa-Core CPU. The mobile devices consume 10 W of energy, while the edge cloud consumes 100 W. The system employs an Explainable AI (XAI) model using Local Interpretable Model-agnostic Explanations (LIME) to ensure transparency in decision-making.

In terms of workload, the system manages the tasks of medical imaging analysis and diagnosis of diseases. Security is a priority and the data protection is ensured with end-to-end encryption. Information is spread in mobile and edge cloud nodes. Patient records are managed and transactions are validated by the use of smart contracts.

Latency has been optimised to 100 ms and 30 ms in mobile validation and edge cloud validation respectively. Lastly, the block interval of the blockchain is about 10 minutes, which guarantees the consistency of the transac-

tion processing environment.

4.1 Healthcare Workload

ID	Name	Disease	Doctor	Hospital
1	Farhan	Diabetes	Dr. Smith	General Hospital
2	Raheem	Hypertension	Dr. Adams	City Hospital
3	Uzura	Cancer	Dr. Brown	State Hospital
4	Emily White	Asthma	Dr. Green	City Hospital
5	Michael Black	Heart Disease	Dr. Blue	General Hospital
6	Sara Lee	Kidney Disease	Dr. White	State Hospital
7	David Kim	Tuberculosis	Dr. Gray	City Hospital
8	Jessica Davis	Pneumonia	Dr. Silver	General Hospital
9	James Wilson	Stroke	Dr. Gold	City Hospital
10	Patricia Clark	Arthritis	Dr. Red	State Hospital
11	Robert Lewis	Hepatitis	Dr. Pink	General Hospital
12	Laura Hall	Influenza	Dr. Violet	City Hospital
13	William Allen	Parkinson's	Dr. Brown	State Hospital
14	Elizabeth Harris	COVID-19	Dr. Green	General Hospital
15	Joseph Martin	Obesity	Dr. Yellow	City Hospital
16	Karen Thompson	Epilepsy	Dr. Black	General Hospital
17	Charles Moore	Anemia	Dr. Blue	State Hospital
18	Linda Robinson	Migraine	Dr. Orange	City Hospital
19	Steven Lewis	Malaria	Dr. White	General Hospital
20	Susan Walker	Depression	Dr. Silver	State Hospital

The table represents the detailed data about 20 patients with their ID, name, disease, treating doctor, and hospital. The entries also represent a distinct patient with different medical conditions. An example of this is Farhan with ID 1 who is a Diabetes patient who is under the care of Dr. Smith at General Hospital. Raheem, who is 2 and has ID 2, has Hypertension and he is taken care of by Dr. Adams at the City Hospital. ID 3 is Uzura who is diagnosed with Cancer and is under the care of Dr. Brown at the State Hospital. Emily White with an ID number of 4 is also a patient with Asthma under the care of Dr. Green in City Hospital.

The other ones would be Michael Black, whom Dr. Blue of General Hospital treated and had Heart Disease, and Sara Lee, whose Kidney Disease is being treated under Dr. White of State Hospital. David Kim, ID 7, is a patient who has contracted Tuberculosis and is under treatment of Dr. Gray at City Hospital whereas Jessica Davis was diagnosed with Pneumonia and is under the treatment of Dr. Silver at General Hospital.

James Wilson (ID 9) is recovering from a Stroke, treated by Dr. Gold at City Hospital. Patricia Clark, diagnosed with Arthritis, is under Dr. Red's care at State Hospital. Robert Lewis, with Hepatitis, is treated by Dr. Pink at General Hospital, and Laura Hall, diagnosed with Influenza, is under the care of Dr. Violet at City Hospital.

Other entries include William Allen (ID 13) with Parkinson's, treated by Dr Brown at State Hospital, and Elizabeth Harris (ID 14), diagnosed with COVID-19 and treated by Dr Green at General Hospital. Joseph Martin (ID 15) suffers from obesity. He is treated by Dr Yellow at City Hospital, and Karen Thompson (ID 16) has epilepsy and is under the care of Dr. Black at General Hospital.

Charles Moore, diagnosed with anaemia (ID 17), is treated by Dr Blue at State Hospital, while Linda Robinson,

diagnosed with Migraine (ID 18), is under the care of Dr Orange at City Hospital. Steven Lewis (ID 19) has Malaria, treated by Dr. White at General Hospital, and Susan Walker (ID 20), suffering from Depression, is treated by Dr. Silver at State Hospital.

The table helps track these patients' conditions, their treating doctors, and the hospitals where they are being treated.

4.2 Result Analysis

In the result analysis, we integrated the different baseline approaches such as proof of work (PoW), and proof of stake (PoS) and compared them with the proposed scheme.

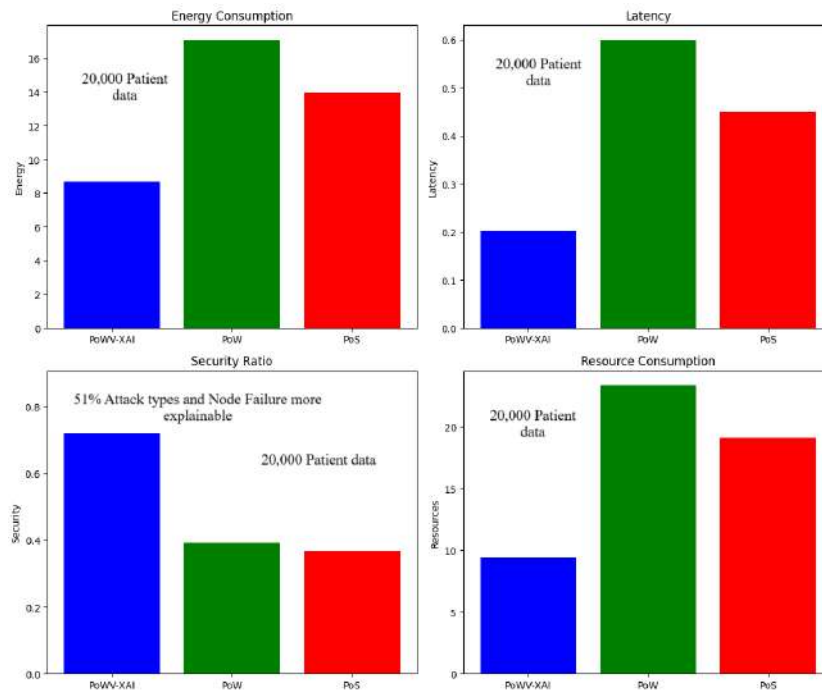


Figure 4. Result Analysis of Proposed (PoS) schemes for Healthcare Workload.

Figure 4 displays a comparative analysis of three consensus mechanisms: Proof-of-Work with Voting and Aggregation (PoWV-XAI), Proof-of-Work (PoW), and Proof-of-Stake (PoS), across four key performance metrics: Energy Consumption, Latency, Security Ratio, and Resource Consumption. The analysis is based on a dataset of 20,000 patient data points. Each metric is presented in a separate subplot as a bar chart, where the height of each bar represents the value of the metric for the corresponding consensus mechanism.

The top-left subplot in Figure 4 illustrates the energy consumption of the three consensus mechanisms.

- **PoWV-XAI** (Blue bar): Shows a relatively lower energy consumption.
- **PoW** (Green bar): Exhibits the highest energy consumption among the three.
- **PoS** (Red bar): Demonstrates an energy consumption level between PoWV-XAI and PoW.

The y-axis is labeled as "Energy". The text "20,000 Patient data" is overlaid on the PoW bar, indicating the dataset size used for this evaluation.

The top-right subplot in Figure 4 compares the latency of the three consensus mechanisms.

- **PoWV-XAI** (Blue bar): Shows the lowest latency.

- **PoW** (Green bar): Exhibits the highest latency.
- **PoS** (Red bar): Presents a latency value between PoWV-XAI and PoW.

The y-axis is labeled as "Latency". Similar to the energy consumption plot, "20,000 Patient data" is indicated on the PoW bar.

The bottom-left subplot in Figure 4 compares the security ratio achieved by each consensus mechanism.

- **PoWV-XAI** (Blue bar): Achieves the highest security ratio. The text "51% Attack types and Node Failure more explainable" is positioned above this bar, suggesting enhanced explainability in handling such scenarios.
- **PoW** (Green bar): Shows a lower security ratio compared to PoWV-XAI.
- **PoS** (Red bar): Exhibits the lowest security ratio among the three.

The y-axis is labeled "Security." Above the Pos bar, the text "20,000 Patient data" is placed.

The bottom-right subplot in Figure 4 illustrates the resource consumption of the three consensus mechanisms.

- **PoWV-XAI** (Blue bar): Shows the lowest resource consumption.
- **PoW** (Green bar): Exhibits the highest resource consumption.
- **PoS** (Red bar): Demonstrates a resource consumption level between PoWV-XAI and PoW.

The y-axis is marked as resources. The PoW bar is overlaid with the text "20,000 Patient data" marked on it.

According to the given numbers of 20,000 patient records, PoWV-XAI provides good trade-off, as it has less energy usage, latency, and security ratio than the conventional PoW and PoS. Also, PoWV-XAI consumes the least amount of resource. According to the annotation of the security ratio plot, PoWV-XAI offers a more appropriate explainability in the case of 51% of attack and node failures.

5 Discussion and conclusions

This section discusses the study's results and findings, emphasizing key ideas and drawing conclusions about the work. This section presents the discussion on the results and findings of the study and highlights the main points and provides the conclusions about the work. In this paper we have examined how blockchain and machine learning can be used to improve data validation in healthcare based applications with respect to enhancing transparency, validity and immutability. Although blockchain technologies, in the form of proof-of-work validation, have proven to provide real-time security validation, there are multiple associated challenges with their application into complex fields like healthcare, such as delays, energy usage, and inefficiencies in terms of cost. Our proposal was the blockchain Proof of Work Validation Explainable AI (PoWV-XAI), which integrates blockchain with machine learning and is able to explain the decision-making process in terms of processing delay, validation, security, energy and costs. Our findings show PoWV-XAI is better than available blockchain and machine learning integration strategies since it provides more transparent, understandable, and explainable decision-making, especially in dynamic healthcare settings.

6 Future Work

The further studies in the field will be aimed at several important directions, which will make the PoWV-XAI more effective and applicable. To test the scalability of the algorithm, first we intend to apply it to large and more challenging healthcare data, including multi-modal patient data. Moreover, we will have a goal of optimizing the metaheuristic optimization methods that are incorporated in the PoWV-XAI in order to attain even better results in terms of energy-consumption, cost-reduction, and real-time performance. Additional investigation on the hybrid consensus algorithms, involving the use of proof of work with alternative consensus algorithms such as proof of stake/delegated proof of stake, will be carried out to enhance energy efficiency and transaction speed.

Moreover, real-world deployment and testing in healthcare settings will help identify additional limitations and provide insights for further optimization. Finally, we intend to investigate the integration of PoWV-XAI with other emerging technologies, such as 5G networks and edge computing, to enhance healthcare systems' security and real-time capabilities, ensuring their robustness in critical applications.

Author Contributions

Muhammad Faisal Memon worked on data analysis. Mansoor Ali worked on methodology, and Aijaz Ahmed Siddiqui designed related work. Qurtual Ain Mastoi designed mathematical model and Abdullah Lakhan write paper, results and dataset.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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