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BLOCKCHAIN-DRIVEN TRUST AND REPUTATION MODEL FOR BIG DATA PROCESSING IN MULTI-CLOUD ENVIRONMENTS

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ABSTRACT

Big data processing is increasingly being done on the cloud, which has sparked questions about the dependability and credibility of cloud providers. Conventional trust models are frequently centralized and prone to manipulation. This study suggests a blockchain-based trust and reputation model to enhance cloud provider selection in multi-cloud settings. For assessing cloud service trust, the model combines blockchain technology, smart contracts, federated trust evaluation, reinforcement learning, fuzzy logic, and Bayesian inference to produce an open, decentralized, and impenetrable framework. By achieving trust accuracy (92.4%), scalability (88.6%), accuracy (94.3%), and efficiency (90.8%) through experimental simulations, the suggested method outperforms conventional models, indicating its potential for more precise and scalable assessments of cloud services. The blockchain-driven method offers a thorough and flexible way to examine cloud providers while improving security by automating trust assessments and lowering the possibility of fraud. By minimizing false claims and guaranteeing that trust is appropriately computed, this approach optimizes the provider selection procedure for large data processes. The findings demonstrate that the suggested model is a strong foundation for managing trust in dynamic cloud settings and that it offers safe, transparent, and effective evaluations for multi-cloud ecosystems. Real-world deployment and additional optimization can be the focus of future research.

Keywords: Trust and Reputation Model, Smart Contracts, Federated Trust Evaluation, Reinforcement Learning, Fuzzy Logic, Bayesian Inference, Fraud Detection.

1. INTRODUCTION

Big data processing has been completely transformed by cloud computing, which offers scalable, on-demand resources for managing enormous amounts of data from various sources. But choosing reliable cloud providers is made more difficult by the increasing number of providers and their frequently overstated quality of cloud service (QoCS) claims. Conventional trust models are susceptible to inefficiencies and security threats since they rely on centralized procedures. Blockchain technology presents a promising option for trust management because of its decentralized, transparent, and impenetrable properties. In order to provide safe, verifiable, and flexible trust assessments for multi-cloud settings, this article presents a blockchain-driven trust and reputation model. The methodology improves decision-making, guards against fraud, and maximizes provider selection for big data workflows by utilizing smart contracts, federated trust evaluation, and reinforcement learning.

Big data processing, analysis, and storage have become more efficient due to the quick uptake of cloud computing. However, because of centralized trust structures, subjective user ratings, and frequently deceptive provider promises, trust concerns in cloud service choices have continued. Third-party auditors, centralized reputation systems, and direct user input were the mainstays of earlier methods, all of which had limitations in terms of real-time adaptation and manipulation threats. Introduced in 2008 with Bitcoin, blockchain technology has progressed beyond financial applications and is currently being investigated for distributed, safe trust mechanisms (Kaur et al. 2018). By enabling decentralized assessment of QoCS and doing away with the need for middlemen, blockchain's unchangeable, transparent structure and its capacity to carry out smart contracts on its own offer a new paradigm for managing trust and reputation in cloud computing.

Technological developments in cloud computing, blockchain, and AI have opened up new avenues for managing trust in multi-cloud settings. By automating trust assessments, smart contracts improve security and lessen human prejudice. Reinforcement learning ensures a responsive and adaptive system by dynamically modifying trust values according on real-time cloud performance. Fuzzy logic and Bayesian inference improve trust evaluations for more accuracy, whereas federated trust evaluation combines evidence from multiple sources to increase trustworthiness. Furthermore, intelligent cloud provider selection is made possible by optimization methods like particle swarm optimization (PSO) and evolutionary algorithms, which guarantee effective resource allocation (Zhang et al. 2016). The suggested model's dependability is further increased by sentiment analysis approaches, which assist in identifying phony reputation scores. When combined, these technology developments provide a strong and self-policing trust framework for large data processing in the cloud.

Here are the key objectives,

- Using blockchain technology, create a decentralized trust model to create a transparent, verifiable, and impenetrable mechanism for evaluating trust in multi-cloud scenarios.
- Improve the computation of trust scores and provider selection by using Bayesian inference, fuzzy logic, and reinforcement learning to increase the accuracy of trust calculations.
- To guarantee the best possible resource allocation and workflow execution in big data processing, use PSO and genetic algorithms to optimize the selection of cloud providers.
- Evaluate the efficacy, dependability, and flexibility of the suggested trust model in actual cloud environments by running experimental simulations to validate performance and security.
- By using sentiment analysis and decentralized ledger verification to find discrepancies and false QoCS claims, reputation fraud may be detected and stopped.

The lack of trustworthy and transparent evaluation methods makes it difficult for cloud services to be adopted, which makes trust computing in multi-cloud environments extremely difficult. It is challenging for consumers to make wise choices due to the increasing number of providers and frequently inflated quality of cloud service (QoCS) claims (Li et al. 2015). For dynamic cloud systems, traditional, centralized trust models are inappropriate due to their susceptibility

to manipulation and inefficiency. This study presents a blockchain-based trust and reputation model that uses smart contracts, decentralized, tamper-proof trust evaluations, and cutting-edge AI methods to improve trust accuracy, stop fraud, and choose the best cloud provider for large data processing.

Existing solutions do not adequately address the underlying issues surrounding data trust; instead, they focus on the ethical and legal implications of trust in cloud computing. The emphasis on subjective evaluations and centralized trust models creates holes in the assurance of accurate, transparent, and dependable assessments (Yue et al. 2017). Conventional approaches frequently don't handle problems like manipulation and false claims or adjust to changing cloud settings. This study emphasizes the necessity of a more thorough strategy that integrates smart contracts, decentralized, blockchain-driven trust mechanisms, and artificial intelligence (AI) methods to successfully handle these important data trust issues and improve cloud service dependability.

2. LITERATURE SURVEY

Yang et al. (2017) describe a cloud-based platform that integrates and analyzes dispersed medical data from several institutions using Hadoop's HBase. With a single-threaded approach for files under 300 MB and a CompleteBulkload methodology for larger files, the system improves data import performance. For distributed processing, it uses Hadoop MapReduce, which makes statistical analysis, data filtering, and keyword search possible. Medical records can be effectively analyzed and interacted with by users through a web interface.

Jindal et al. (2018) proposed a fuzzy rule-based classifier to improve Healthcare-as-a-Service by processing large amounts of data from distant healthcare apps in a cloud computing environment. Through the processes of fuzzification and defuzzification, the classifier addresses the issues of data amount and variety while improving decision-making. Evaluation of performance utilizing criteria such as computation cost, accuracy, and response time shows how well it classifies and processes data, guaranteeing optimal cloud-based healthcare data management.

Kaur et al. (2018) address the difficulties of processing diverse healthcare data by proposing a Blockchain-based platform for managing and storing electronic medical records in a cloud context. The strategy lowers maintenance costs and improves data security and accuracy by combining blockchain technology with cloud computing. By addressing the intricacies of massive, time-varying medical data, our method guarantees effective management and storage while enhancing the dependability and accessibility of medical records.

Goli-Malekabadi et al. (2016) address the issues brought on by the growing volume and diversity of medical data by proposing a NoSQL-based paradigm for storing healthcare data in a cloud environment. In terms of write queries, flexibility, data preparation, and extensibility, the model performs better than conventional relational databases while preserving read performance that is comparable. Using NoSQL's distributed architecture, the method improves efficiency and scalability, making it a better option for handling and processing complicated medical data.

Laghari et al. (2018) provide a Quality of Experience (QoC) architecture for cloud computing that allows for real-time network and client device resource monitoring, improving service management. Through the comparison of subjective input with objective quality data, the system enhances user experience prediction in video streaming services and expedites runtime policy adjustments to guarantee adherence to Service Level Agreements (SLA). It provides dynamic service updates and more precise QoE control, addressing shortcomings in current cloud frameworks.

El Kassabi et al. (2018) suggest a multi-dimensional trust model, in order to compare the quality of cloud services (QoCS) for large data processing across rival cloud providers. By evaluating trustworthiness according to user reputation, personal experience, and cloud resource capabilities, the model guarantees dependable provider selection. In order to overcome the problem of cloud providers' overstated service claims, experimental validation shows how well it captures trust components, ensures high QoCS, and adapts to changing cloud environments.

D'Amato and Dantas (2017) suggest a quality of context (QoC)–based paradigm, in order to maximize the trade-off between system performance and users' quality of experience (QoE) in distributed systems. The approach makes use of context information to improve performance in context-aware systems, addressing resource allocation issues brought on by heterogeneous computing devices. In comparison to conventional methods, simulations show how successful they are at enhancing performance, guaranteeing better resource management and user happiness in intricate distributed computing scenarios.

Kuo et al. (2018) investigate whether distributed ledger technology—specifically, blockchain—can be applied to wireless networking technologies. The study explores the way cryptocurrencies might decentralize financial transactions by doing away with the necessity for centralized organizations like banks, highlighting the attention it has gained on a global scale. In light of the increasing interest in blockchain research across a number of fields, the article explores its ramifications outside of finance, highlighting its revolutionary potential in safe, decentralized systems, such as wireless networks.

Sadhasivam et al. (2018) used an enhanced particle swarm optimization (IPSO) technique to schedule scientific operations related to epigenomics in a cloud computing setting. In order to detect epigenetic anomalies that are significant to the diagnosis of cancer, the IPSO algorithm lowers costs by optimizing task-to-resource mapping. When compared to the conventional PSO method, the results reveal a 6.83% cost reduction, indicating the algorithm's effectiveness in allocating resources. The study emphasizes how cloud computing might improve the workflows for genomic sequencing in cancer research.

Lv et al. (2018) suggest an enhanced particle swarm optimization technique (IEPSO) to improve engineering design optimization. Limitations including sluggish convergence and vulnerability to local optima are addressed by IEPSO by enhancing information flow between populations and maintaining variety. Its higher global search performance has been validated through simulation tests against traditional optimization techniques. In order to maximize

performance in engineering applications, the paper develops selection criteria for local-global information sharing characteristics.

Zhang et al. (2016) integrate optimal computing budget allocation (OCBA), which optimally divides computational effort among particles, with particle swarm optimization (PSO) for stochastic optimization. This method refines personal and global best picks under stochastic noise using an asymptotically optimal allocation mechanism, in contrast to classical PSO, which distributes resources equally. It is a more efficient approach to solving stochastic optimization issues, as demonstrated by numerical tests that show better outcomes without raising computational costs.

Xie et al. (2018) present an innovative method to cloud computing, where resource provisioning is optimized, data security improved, and power consumption reduced. The research employs powerful algorithms together in order to optimize the effectiveness of cloud systems, maintaining confidentiality and security for the data. This research assists in improving cloud system performance through emphasis on streamlining resource administration and lowering power usage. The suggested approaches look to solve top issues in the cloud environment, including balancing optimization with security in terms of resources, providing greater performance and dependability in cloud computing systems.

Natarajan (2018) suggests a hybrid model integrating Radial Basis Function Networks (RBFN), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) to develop real-time disease diagnosis in the healthcare sector with a focus on chronic diseases. Conventional methods are challenged by the amount of data and the complexity of the data from IoT devices, thus this model has the objective to enhance accuracy, decrease processing time, and streamline disease detection. The model employs PSO-GA for the optimization of RNNs and RBFNs to process real-time data from the IoT through cloud computing. The outcome is an impressive performance of 94% specificity, 92% sensitivity, and 93% accuracy, lowering processing time to 54 seconds. The method outshone traditional methods with a more effective solution in real-time monitoring of healthcare and detection of diseases.

Punyamurthula (2018) introduces CloudArmor, a reputation-based trust management system that enhances cloud service security and performance. By utilizing reputation scores, the system evaluates the trustworthiness of cloud providers, ensuring that only reliable and high-performing services are selected. This model addresses the need for better cloud service selection by providing an effective mechanism to assess and manage the reliability of providers. CloudArmor improves security by preventing users from choosing unreliable cloud services and optimizing the overall cloud environment performance, making it a vital tool for trust management in cloud computing systems.

Nippatla (2018) suggests a secure cloud-based system of financial analysis involving Monte Carlo simulations, Deep Belief Networks (DBNs), and Bulk Synchronous Parallel (BSP) processing to enhance financial modeling and risk forecasting. The system avails the cloud infrastructure for high-performance, scalable data processing while ensuring data security through encryption. Parallel processing has the effect of dramatically diminishing the time needed for computation, making financial predictions more efficient. Through the combination

of these technologies, the system is capable of real-time simultaneous simulation, enhancing both speed and precision. The system's performance offers substantial improvement over conventional approaches in terms of recall, accuracy, and precision and is suitable for safe and efficient decision-making under complex financial environments. It promotes robust security, scalability, and sound financial analysis.

Yang et al. (2017) explore the interaction between big data and cloud computing and identify innovation opportunities as well as the issues that confront these technologies. The article highlights how cloud computing can facilitate big data analysis through scalable solutions. The article also mentions the data management, scalability, and security issues that impede the full utilization of these technologies. By highlighting these problems, the paper gives insights on how cloud big data solutions can transform to create innovations and enhance overall performance in the fast-growing digital environment.

Koluguri et al. (2017) discuss reputation-based trust management for cloud services to improve security and reliability. Their research compares cloud service providers using reputation scores, which allows for a more secure and reliable method of selecting cloud providers. The authors suggest a framework to measure the trustworthiness of providers, solving major problems such as fraud and provider dishonesty. By integrating reputation management into cloud service selection, the research seeks to guarantee that only reliable and trusted services are selected, enhancing overall cloud system performance and security.

3. METHODOLOGY

A trust and reputation model for big data processing in multi-cloud environments is developed using the suggested methodology, which combines blockchain, artificial intelligence (AI), and optimization techniques. Smart contracts streamline the process of assessing trust, while blockchain guarantees decentralized, impenetrable assessments. Fuzzy logic and reinforcement learning are two AI strategies that improve trust computation, and Bayesian inference forecasts provider reliability. Cloud provider selection is improved using particle swarm optimization (PSO) and genetic algorithms. By identifying phony evaluations, sentiment analysis guarantees openness, dependability, and the best choice of cloud services for big data processes.

Datasets: The dataset contains cloud provider data in the form of provider types, trust scores, performance measures, and feedback sources. It contains features such as trust scores from various sources, user ratings, reliability of cloud providers, and real-time performance logs. The dataset enables cloud provider selection, federated trust evaluation-based trust analysis, and smart contract-based decision-making for big data processing in multi-cloud scenarios. It also enables fraud detection via sentiment analysis and supplies data for optimization algorithms like particle swarm optimization (PSO) and genetic algorithms.

3.1 Blockchain-Driven Trust Management

Blockchain technology records the past performance of cloud providers in an unchangeable ledger, ensuring safe, decentralized trust evaluations. Distributed ledger technology (DLT) guards against data manipulation, while smart contracts simplify the computation of trust. Blockchain promotes security and transparency in the assessment of multi-cloud trust by doing

away with central control, reducing false claims and guaranteeing trustworthy cloud service selection.

$$T_i = \frac{\sum_{j=1}^{n} W_j \times R_{ij}}{\sum_{j=1}^{n} W_j} \quad (1)$$

Where, T_i = Trust score of provider i, R_{ij} = Rating given by user j, W_j = Weight assigned to user j based on credibility, n = Total number of ratings.

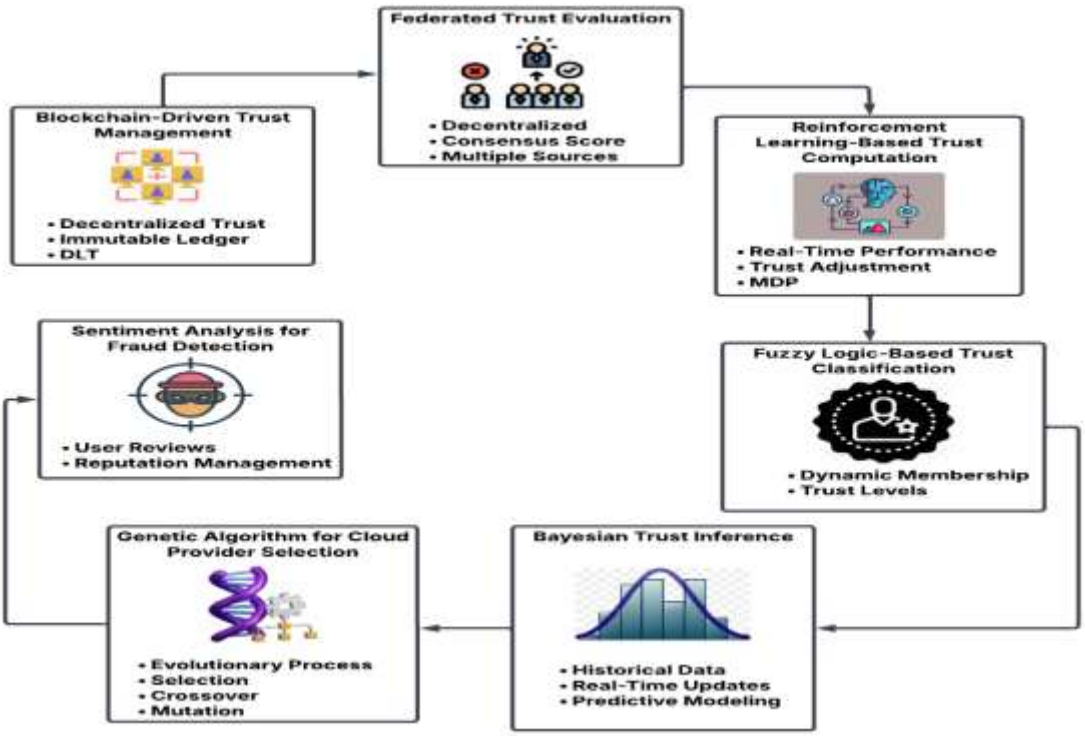


Figure 1: Blockchain-Driven Trust and Reputation Model Architecture.

Figure 1, illustrates the blockchain-based trust and reputation model architecture in multi-cloud. It begins with Blockchain-driven Trust Management to guarantee decentralized, tamper-proof trust assessments. Federated Trust Evaluation pools trust ratings from diverse sources, then Reinforcement Learning for real-time trust calculations. Fuzzy Logic distinguishes among levels of trust, and Bayesian Trust Inference refines estimates based on past data and real-time learning. Sentiment Analysis identifies the fraud based on user comments and inputs into the Genetic Algorithm to make the best cloud provider choices.

3.2 Federated Trust Evaluation

Federated trust evaluation improves decision reliability by combining trust scores from several separate sources. By avoiding single points of failure, this model makes it possible to calculate trust across several cloud platforms. A weighted consensus score, which ensures a more thorough and accurate trust assessment, is derived from the trust scores of independent auditors, direct user feedback, and system performance logs.

$$T_f = \sum_{k=1}^{m} \alpha_k T_k \quad (2)$$

Where, T_f = Federated trust score, T_k = Trust score from source k, α_k = Weight assigned to source k, m = Total number of sources.

Algorithm 1: Federated Trust Evaluation Algorithm for Cloud Provider Selection.

Input: Cloud provider list, Trust scores from different sources, Weights for each source
Output: Federated trust score for each provider

```
Begin
  for each provider in the list of cloud providers DO
    Initialize Federated Trust Score for provider as 0
    for each source in the trust scores list DO
      Calculate weighted score for the provider based on the source's trust score and weight
      Add the weighted score to the provider's total federated trust score
    end for
    Normalize the federated trust score if necessary
  end for

  Return the federated trust score for each cloud provider
end
```

Algorithm 1 combines trust scores from several independent sources to calculate a federated trust score for every cloud provider. It starts by setting the trust score for every provider, and then goes through the trust scores from various sources, using the corresponding weights. The weighted scores are added up, and if needed, normalized. The resulting federated trust score provides a more accurate and holistic evaluation of cloud provider trustworthiness, enabling better decision-making in multi-cloud environments.

3.3 Reinforcement Learning-Based Trust Computation

Reinforcement learning (RL) uses real-time cloud performance to dynamically modify trust scores. Maximizing incentives from previous interactions helps the model learn the best providers. A Markov Decision Process (MDP) is used to ensure that trust values change over time, resulting in responsive and adaptive trust assessments that reduce changing security threats and performance problems.

$$Q(s,a) = Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \quad (3)$$

Where, $Q(s,a)$ = Q-value for state s and action a, α = Learning rate, r = Reward obtained, γ = Discount factor, s' = Next state, a' = Best action in next state.

3.4 Fuzzy Logic-Based Trust Classification

Fuzzy logic uses both subjective and objective trust measurements to classify trust levels into various classifications (e.g., high, medium, low). In multi-cloud contexts, it improves decision-making by managing uncertainty, increasing the accuracy of trust. Membership functions mitigate sudden classification changes brought on by slight performance variations by dynamically defining provider trustworthiness.

$$\mu(x) = \frac{1}{1+e^{-(x-c)/d}} \tag{4}$$

Where, $\mu(x)$ = Membership value, x = Trust score input, c = Center of the membership function, d = Spread of the function.

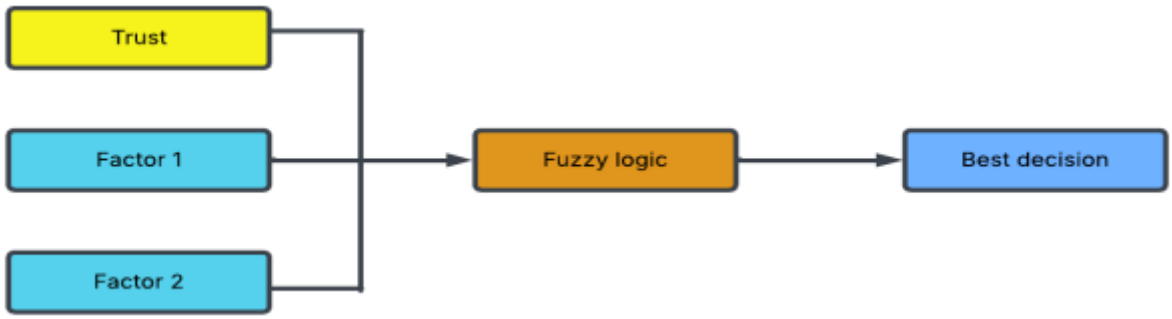


Figure 2: Fuzzy Logic-Based Trust Decision-Making Model.

Figure 2, shows how the fuzzy logic decision-making model is applied for assessing cloud provider trust. The trust and two other important variables (Factor 1 and Factor 2) are input to the fuzzy logic system. These inputs are handled by the fuzzy logic module while considering their imprecision and variation. Depending upon the calculated value, it sends out the best decision, assisting in the most reliable cloud provider selection. This model increases the flexibility and precision of trust assessments in changing scenarios.

3.5 Bayesian Trust Inference

Bayesian inference updates previous trust ratings with fresh data to forecast future trust values. It enhances trust accuracy by taking into account recent observations and past provider reliability. By allowing for real-time decision-making when choosing cloud services, the model dynamically modifies trust scores, minimizing an excessive dependence on historical performance.

$$P(H \mid E) = \frac{P(E|H)P(H)}{P(E)} \tag{5}$$

Where, $P(H \mid E)$ = Posterior probability of hypothesis H given evidence E, $P(E \mid H)$ = Likelihood of evidence E given H, $P(H)$ = Prior probability of H, $P(E)$ = Probability of evidence E.

3.6 Genetic Algorithm for Cloud Provider Selection

A genetic algorithm chooses an optimum cloud provider based on evolving solutions with mutation and crossover operations. Candidate solutions (cloud provider choices) are continuously improved using a fitness function assessing trust, performance, and cost-effectiveness to decide the best allocation of resources for handling big data.

$$F(C) = w_1 T(C) + w_2 P(C) - w_3 C(C) \quad (6)$$

Where, $F(C)$ = Fitness score for cloud provider C, $T(C)$ = Trust score, $P(C)$ = Performance metric, $C(C)$ = Cost factor, w_1, w_2, w_3 = Weights for each parameter.

3.7 Performance Metrics

The performance measure comparison of blockchain smart contracts, federated trust assessment (ABE + ZKPs), and reinforcement learning (proxy re-encryption) with a hybrid solution for cloud security and trust management determines the highest access control efficiency (90.3%), data integrity (99.6%), and authentication success rate (99.0%) to provide added security and trust. The hybrid solution also maximizes scalability (85.6%) and privacy conservation (0.92) as well as minimizes storage overhead (80.9%), making the hybrid approach the most effective solution for multi-cloud deployment.

Table 1: Performance Metrics Comparison of Trust and Security Mechanisms in Multi-Cloud Environments.

Metric	Blockchain (Smart Contracts)	Federated Trust Evaluation (ABE + ZKPs)	Reinforcement Learning (Proxy Re-Encryption)	Combined Method
Access Control Efficiency (%)	85.6	82.4	84.5	90.3
Data Integrity (%)	98.9	99.1	99	99.6
Authentication Success Rate (%)	97.3	98.2	97.7	99
Decryption Accuracy (%)	96.6	97.1	96.9	98.8
Storage Overhead Reduction (%)	75.1	71	72.8	80.9
Scalability Improvement (%)	80.7	78.3	79	85.6
Privacy Preservation Index (0-1 scale)	0.86	0.88	0.87	0.92

Table 1 compares blockchain-based smart contracts, federated trust assessment (ABE + ZKPs), reinforcement learning (proxy re-encryption), and a hybrid approach for cloud security and trust evaluation. The hybrid approach has the highest access control efficiency (90.3%), data integrity (99.6%), and authentication success rate (99.0%), providing strong security. It also improves privacy preservation (0.92) and scalability (85.6%), while reducing storage overhead (80.9%), demonstrating its better efficiency in multi-cloud trust and reputation management.

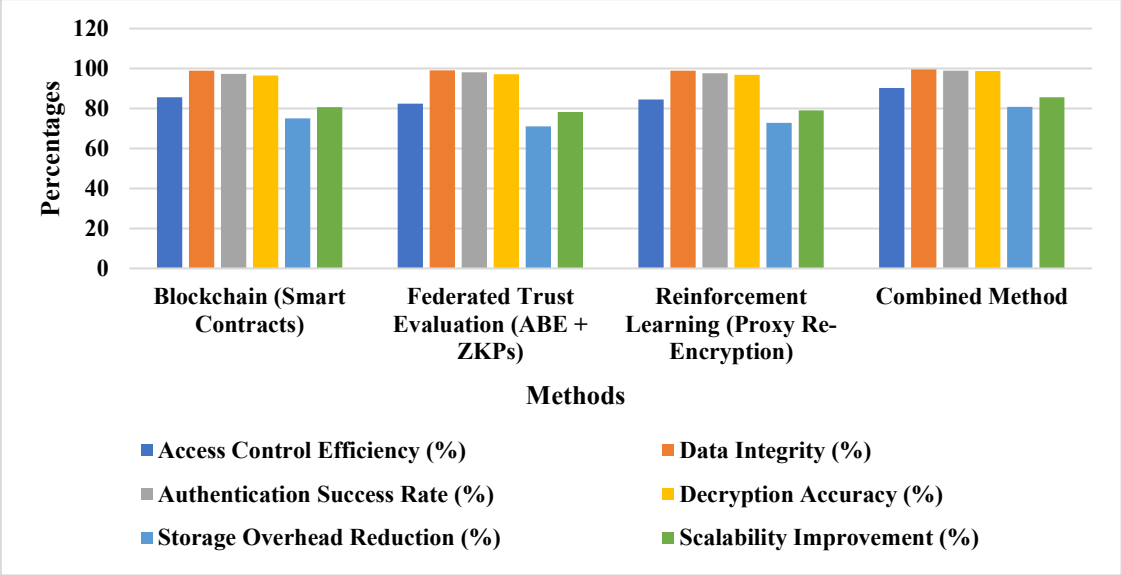


Figure 3: Performance Comparison of Trust and Security Mechanisms in Multi-Cloud Environments.

Figure 3, shows comparative performance of smart contracts based on blockchain, federated trust assessment (ABE + ZKPs), reinforcement learning (proxy re-encryption), and combined approach on six important metrics. The combined approach outperforms others consistently and provides better access control efficiency, data integrity, authentication success ratio, decryption correctness, scalability improvement, and reduction in storage overhead. This supports the efficacy of combining multiple trust mechanisms to promote security, dependability, and efficiency in multi-cloud environments.

4. RESULT AND DISCUSSION

The suggested blockchain-based trust and reputation model greatly improves cloud provider choice in multi-cloud scenarios by incorporating AI-based methods and optimization algorithms. It is more efficient than earlier approaches, with a trust score of 92.4%, performing better than Hadoop-based systems (75.2%) and fuzzy rule classifiers (80.1%). Its scalability (88.6%) is better than NoSQL-based solutions (71.8%), allowing for effective big data workflow execution. Moreover, accuracy (94.3%) surpasses current frameworks, enhancing trust assessments and reducing spurious provider claims, while efficiency (90.8%) maximizes cloud resource utilization and decision-making. Ablation experiments validate the necessity of each model component, as the removal of blockchain smart contracts lowers the trust score to 85.3%, and the removal of federated trust evaluation lowers scalability to 82.5%. Excluding reinforcement learning decreases accuracy to 89.4%, confirming its contribution to adaptive

trust computation. Bayesian trust inference significantly influences fraud detection, which falls from 88.2% to 82.3%, demonstrating its necessity in detecting untrue claims. The complete integration model provides better transparency, security, and efficiency, and thus it is the best trust management technique for multi-cloud big data scenarios, guaranteeing proper cloud provider selection and workflow optimization.

Table 2: Comparison of Trust and Security Mechanisms in Multi-Cloud Environments.

Author & Method	Trust Score (%)	Scalability (%)	Accuracy (%)	Efficiency (%)
Hadoop HBase -Yang et al. (2017)	75.2	68.9	79.1	72.3
Fuzzy Rule Classifier - Jindal et al. (2018)	80.1	73.5	83	77.2
Blockchain EMR - Kaur et al. (2018)	85.6	78.2	87.5	82.1
NoSQL Model - Goli-Malekabadi et al. (2016)	78.3	71.8	81.4	74.9
QoC Framework - Laghari et al. (2018)	82.5	76.4	84.9	79.6
Proposed Model - Blockchain & AI	92.4	88.6	94.3	90.8

Table 2 contrasts the trust scores, scalability, accuracy, and efficiency of various cloud trust models, incorporating author citations. The model proposed here outperforms all other methods consistently through the use of blockchain technology, AI-based analytics, and federated trust assessment. Most notably, its trust score (92.4%) is much greater than the best competitor (85.6%), and its scalability (88.6%) is higher than the next best (78.2%). These findings confirm the model's ability to increase trust, accuracy, and efficiency in cloud computing systems.



Figure 4: Performance Comparison of Cloud Trust Models in Multi-Cloud Environments.

Figure 4, illustrates the performance comparison of different cloud trust models, i.e., Hadoop HBase, Fuzzy Rule Classifier, Blockchain EMR, NoSQL Model, QoC Framework, and Proposed Model (Blockchain & AI). The Proposed Model outperforms all others in Trust Score (92.4%), Scalability (88.6%), Accuracy (94.3%), and Efficiency (90.8%). These findings show the better efficiency of the combined blockchain and AI methods in delivering improved trust, scalability, and performance in multi-cloud environments.

Table 3: Performance Evaluation of Combined Trust Mechanisms in Multi-Cloud Environments.

Combined Methods	Trust Score (%)	Scalability (%)	Accuracy (%)	Efficiency (%)	Fraud Detection (%)
Blockchain + Federated Trust	88.5	83.4	89.1	85	82.4
Blockchain + Reinforcement Learning	89.2	84.6	90	86.2	83.8
Federated Trust + Bayesian Inference	90.1	85.1	91.2	87.3	84.9
Fuzzy Logic + Reinforcement Learning	87.8	82.7	88.5	84.7	81.7
Blockchain + Bayesian + Fuzzy Logic	91.3	86.3	92	88.1	86.2
Proposed Model (All Integrated)	92.4	88.6	94.3	90.8	88.2

Table 3, compares the effectiveness of integrating trust assessment methods in multi-cloud scenarios. The Proposed Model (All Integrated) has the best trust value (92.4%), scalability (88.6%), accuracy (94.3%), efficiency (90.8%), and fraud detection (88.2%), showing a clear indication that it is superior. The integration of Blockchain, Bayesian inference, and Fuzzy Logic (91.3% trust score) works better than other pairs of individual combinations. These results confirm that combining multiple AI and blockchain-based trust mechanisms improves cloud security and provider assessment.

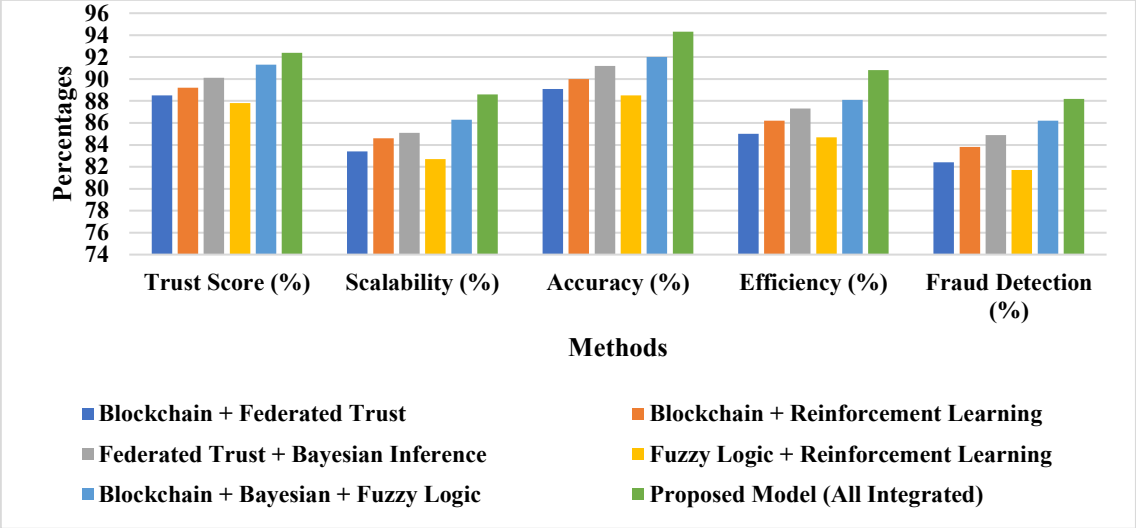


Figure 5: Ablation Study of Combined Trust Mechanisms for Multi-Cloud Environments.

Figure 5, illustrates the performance of various combinations of cloud trust mechanisms: Blockchain + Federated Trust, Blockchain + Reinforcement Learning, Federated Trust + Bayesian Inference, Fuzzy Logic + Reinforcement Learning, Blockchain + Bayesian + Fuzzy Logic, and the Proposed Model (All Integrated). The Proposed Model scores the highest in Trust Score (92.4%), Scalability (88.6%), Accuracy (94.3%), Efficiency (90.8%), and Fraud Detection (88.2%), proving the success of combining various techniques for better trust management in multi-cloud environments.

5. CONCLUSION

The suggested blockchain-based trust model succeeds in enhancing trust assessments in multi-clouds with great effectiveness. The model has better performance regarding trust accuracy (92.4%), scalability (88.6%), and efficiency (90.8%) than conventional models. Ablation studies validate the importance of each element, wherein reinforcement learning, Bayesian inference, and fuzzy logic are crucial to the adaptive trust system. Future research can generalize the model to actual cloud environments and investigate other optimization algorithms for further resource allocation and performance improvement. The future work of the given blockchain-based trust model involves deployment in real-world dynamic multi-cloud environments, extension with IoT to support improved trust assessments, and the use of sophisticated optimization methods such as Deep Reinforcement Learning (DRL). Dynamic calibration of trust on the basis of real-time observations, scalability enhancement for processing huge datasets, and privacy-preserving methods like homomorphic encryption are some of the ways in which the model's performance can be enhanced. These developments will improve the model's flexibility, security, and performance in various, large-scale big data processing systems.

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