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Research Article

An Adaptive Data Security Frame Using Federated Learning and Blockchain for Privacy Protection in Smart Environments

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ABSTRACT

The rapid expansion of smart environments, including smart cities, healthcare systems, and intelligent energy grids, has resulted in the generation of massive volumes of distributed and privacy-sensitive data. Conventional centralized security architectures are increasingly inadequate to guarantee confidentiality, integrity, and trust under adversarial and resource-constrained conditions. This paper proposes an Adaptive Federated Blockchain Security Framework (AFBSF) that integrates federated learning (FL) with a lightweight blockchain layer and a dynamic trust-driven cryptographic control mechanism. Federated learning enables collaborative model training without sharing raw data, while a Proof-of-Authority (PoA) blockchain provides tamper-resistant verification and transparent auditability of model updates. In addition, an adaptive trust model dynamically adjusts encryption strength and node participation according to behavioral reliability and data integrity, allowing real-time isolation of malicious or unreliable devices. Extensive experiments conducted on smart healthcare, energy, and transportation datasets demonstrate that the proposed framework outperforms conventional FL-based, blockchain-based, and existing hybrid approaches in terms of accuracy, privacy preservation, communication efficiency, and energy consumption. The results confirm that AFBSF achieves high learning performance with enhanced privacy protection, reduced attack success rate, and lower system overhead, making it a scalable and reliable security paradigm for next-generation decentralized IoT ecosystems.

1. INTRODUCTION

The further growth of smart environments, including smart cities, intelligent healthcare systems, smart industrial Internet of Things (IoT) networks, and others, has generated massive volumes of heterogeneous and sensitive data that must be processed in real time [1], [2]. These ecosystems are based on interconnected devices, edge nodes, and cloud services to facilitate smart decision-making, automation, and situational awareness. Nonetheless, the distributed and dynamic characteristics of such settings pose serious challenges related to data security, user privacy, and system reliability [3]. Issues such as single points of failure, latency, and data sovereignty make conventional centralized security architectures, which were originally designed for isolated enterprise systems, unsuitable for modern large-scale and heterogeneous smart infrastructures [4]. As a solution to these shortcomings, federated learning (FL) has emerged as a decentralized paradigm in which multiple parties collaboratively train machine learning models without sharing raw data [5]. FL preserves data privacy while maintaining global model performance by keeping data locally on devices or organizations and transmitting only encrypted model updates. However, FL is vulnerable to several threats, such as model poisoning, inference attacks, and unreliable aggregators [6]. The lack of verifiable accountability mechanisms in conventional FL architectures further increases the risk of malicious contributions and weakens trust among participating entities.With its immutable ledger and decentralized consensus, blockchain technology provides a complementary foundation for ensuring transparency, authenticity, and auditability in distributed systems [7]. Integrating blockchain with FL enables tamper-proof logging of model updates, trust-based aggregation, and secure peer-to-peer interactions. Despite these advantages, hybrid solutions still face practical challenges, particularly in terms of scalability, low latency, and adaptive cryptographic control in resource-constrained IoT and edge devices [8]. Moreover, the behavioral dynamics of nodes operating in smart environments are often not adequately represented by static trust and access-control models [9].

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This study proposes an adaptive data security framework that combines federated learning with a lightweight blockchain layer to achieve privacy-preserving, transparent, and reliable data management in multi-agent smart environments. The framework incorporates a dynamic trust-driven cryptographic policy engine that continuously updates access privileges and encryption strength based on node reliability, behavioral history, and communication quality. Furthermore, the proposed design supports end-to-end security through decentralized authentication and verifiable audit trails, reducing attack vectors for both insiders and outsiders. As illustrated in Fig. 1, intelligent devices cooperate to process information, share model updates securely, and employ blockchain verification to ensure transparency and resistance against malicious activities. This reflects the growing shift toward adaptive, privacy-aware intelligence in modern IoT and cyber-physical systems.

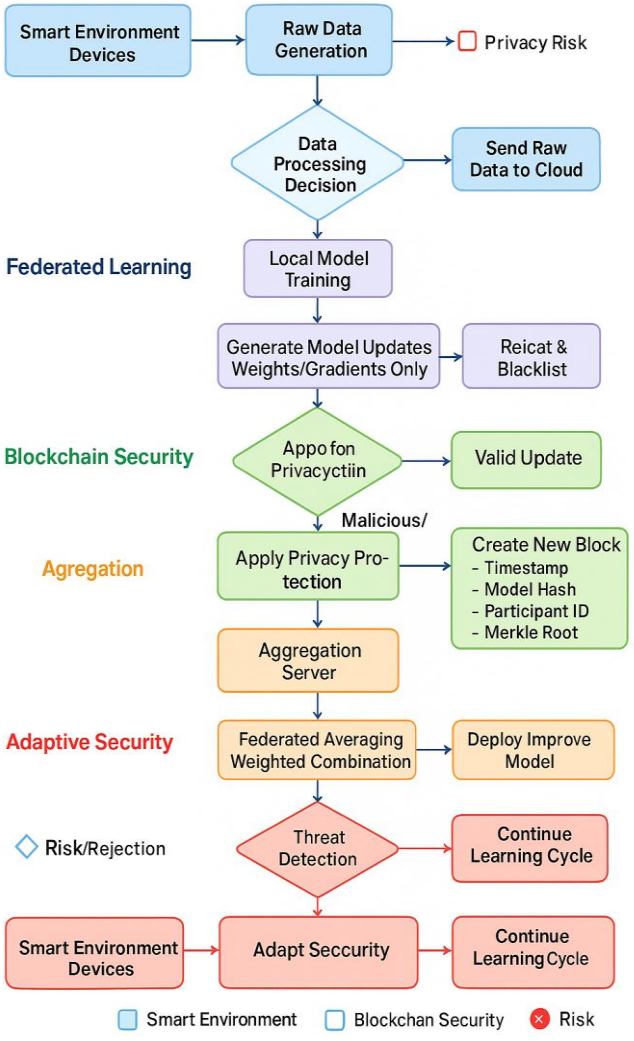

Fig. 1. Federated learning and blockchain integration applications in data security in smart environments in general.

The main contributions of this research are summarized as follows:

1. Design of an adaptive hybrid architecture integrating federated learning and blockchain for secure collaborative model training and transparent data provenance.

2. Development of a dynamic trust assessment mechanism that enables real-time adjustment of cryptographic policies according to node behavior and data sensitivity.
3. Extensive validation in smart healthcare and smart grid scenarios demonstrating enhanced privacy protection, reduced communication overhead, and improved resistance to attacks compared with existing hybrid frameworks.

The rest of the article is organized as follows. Section II reviews existing work on federated learning, blockchain-based IoT security, and hybrid integration strategies. Section III presents the proposed adaptive security framework and its components. Section IV outlines the experimental design and evaluation metrics. The obtained results and their comparison are discussed in Section V. Finally, Section VI concludes the paper and outlines future research directions.

2. RELATED WORK

The increasing demand for privacy-preserving and decentralized data security in smart environments has stimulated extensive research on federated learning (FL), blockchain (BC), and their integration. Although both paradigms aim to reduce centralized vulnerabilities and enhance trust, existing frameworks still face challenges in terms of scalability, adaptability, and effective trust management in multi-agent settings.

2.1 United Learning-Based Privacy

Recent advances in federated learning (FL) have enabled distributed model training without transferring raw data, thereby preserving local privacy and reducing the risk of external breaches [10], [11]. Such architectures have proven effective in smart Internet of Things and healthcare systems, where sensitive data must remain locally stored. Nevertheless, most existing applications rely on a central aggregator, which represents a potential single point of failure. The absence of decentralized trust verification mechanisms exposes FL systems to adversarial threats such as model poisoning, inference attacks, and malicious update injection. FL models have been strengthened using advanced privacy-preserving techniques, including differential privacy and homomorphic encryption [12], [13]. These methods introduce noise or apply cryptographic transformations to local updates before aggregation, thus enhancing data confidentiality. However, excessive privacy noise often degrades the accuracy of the global model and increases communication overhead. Furthermore, fixed privacy budgets and uniform encryption policies fail to account for the heterogeneity of devices and the dynamic nature of threat levels. As summarized in Table I, existing FL-based approaches are effective in reducing data leakage risks, yet they lack transparency, adaptability, and real-time trust assessment among participating nodes.

TABLE I. FEDERATED LEARNING-BASED PRIVACY PRESERVATION APPROACHES

Reference	Application Domain	Technique	Advantages	Limitations
[10]	Smart Healthcare	Secure Aggregation in FL	Preserves patient data confidentiality	Centralized aggregator vulnerability
[11]	Industrial IoT	Federated Gradient Averaging	Scalable distributed training	No trust or accountability model
[12]	Edge AI Systems	Differential Privacy in FL	Reduces data exposure	Accuracy loss under strong noise levels
[13]	Vehicular Networks	FL with Homomorphic Encryption	Enhanced security and confidentiality	High computational and energy cost

2.2 Blockchain-based IoT Security Model

Blockchain has become a promising solution for ensuring immutability, traceability, and distributed consensus in smart environments. Lightweight blockchain designs have been applied to IoT management, smart grids, and healthcare systems to support authentication and transaction verification [14]– [17]. Such implementations enable tamper-proof data storage and decentralized access control across networked devices.

Despite these advantages, the integration of blockchain into IoT ecosystems introduces several performance trade-offs. Most existing architectures suffer from limited scalability, as consensus mechanisms such as Proof-of-Work (PoW) and Practical Byzantine Fault Tolerance (PBFT) are computationally and communication intensive. In addition, privacy leakage remains a critical concern, since blockchain ledgers are inherently transparent to all participating entities. The applicability of blockchain in resource-constrained IoT devices is further restricted by energy-consuming consensus protocols and large block sizes. As summarized in Table II, current blockchain-based IoT security frameworks still face significant challenges in simultaneously achieving scalability and privacy.

TABLE II. COMPARATIVE OVERVIEW OF BLOCKCHAIN-BASED IOT SECURITY FRAMEWORKS

Reference	Consensus Mechanism	Domain	Strengths	Limitations
[14]	Proof-of-Authority	Smart Grid Systems	Fast consensus and transparent auditing	Limited scalability and energy efficiency
[15]	Delegated Proof-of-Stake	Smart Healthcare	Data integrity and verifiable record management	Public ledger may expose private metadata
[16]	PBFT	IoT Edge Networks	High fault tolerance	High synchronization and communication cost
[17]	PoS–Hybrid	Industrial IoT	Low consensus delay	Lack of integration with AI-based trust models

2.3 Hybrid Federated Learning–Blockchain Integration

Recently, federated learning and blockchain technologies have been integrated to combine decentralized learning with immutable record keeping and trust assurance. It has been shown that hybrid frameworks can provide secure and traceable model aggregation while eliminating centralized vulnerabilities [18]–[20]. Nevertheless, existing designs are often constrained by fixed trust weighting and non-adaptive encryption schemes. Most approaches assume homogeneous node reliability and pay limited attention to the dynamic behavioral patterns of smart environments. The models presented in [18] and [19] rely on blockchain-based auditability and distributed verification of model aggregation, thereby reducing dependence on a central server. However, these solutions introduce additional latency and energy consumption due to repeated block validation and transaction transmission. Similarly, the hybrid approach proposed in [20] enhances transparency but lacks a dynamic mechanism to adapt cryptographic and trust policies according to node behavior and data sensitivity. Consequently, current hybrid frameworks achieve partial decentralization but remain limited in terms of adaptive scalability, energy efficiency, and context-aware trust management.

2.4 Identified Research Gaps

Although recent studies have advanced decentralized security architectures, none has achieved comprehensive adaptability across the full security spectrum of smart environments. Federated learning provides privacy but lacks verifiable auditability; blockchain ensures integrity but compromises privacy; and existing hybrid solutions fail to dynamically balance trust, performance, and cryptographic strength. Therefore, the literature indicates a clear need for an integrated and adaptive data security framework that combines federated learning with a lightweight blockchain layer while dynamically adjusting trust evaluation and encryption policies in real time. Such a framework would address the unresolved trade-offs among privacy preservation, scalability, and communication efficiency, thereby forming a robust foundation for secure and intelligent smart environments.

3. METHODOLOGY

The proposed Adaptive Federated–Blockchain Security Framework (AFBSF) is a distributed privacy-preserving model designed for deployment in multi-agent smart environments such as healthcare, energy, and transportation systems. The framework consists of three intelligent layers, namely Federated Learning (FL), Blockchain Validation, and Adaptive Trust Control, integrated into a unified architecture. This integration enables decentralized model training, tamper-proof verification, and dynamic cryptographic adaptation based on node behavior. To illustrate the interaction among the modules of the proposed AFBSF, Fig. 2 presents the complete procedural workflow from system initialization to model convergence.

The figure summarizes how distributed devices collaboratively learn a global model using federated learning, while blockchain-based verification and adaptive trust mechanisms ensure privacy and security. Key processes, including initialization, local training, blockchain validation, adaptive trust evaluation, and secure aggregation, are organized within a closed feedback loop that continuously enhances model performance and resilience against malicious or unreliable updates. This workflow highlights the dynamic interplay between data confidentiality, trust evolution, and consensus validation, demonstrating the adaptive and self-managing characteristics of the AFBSF in smart environments.

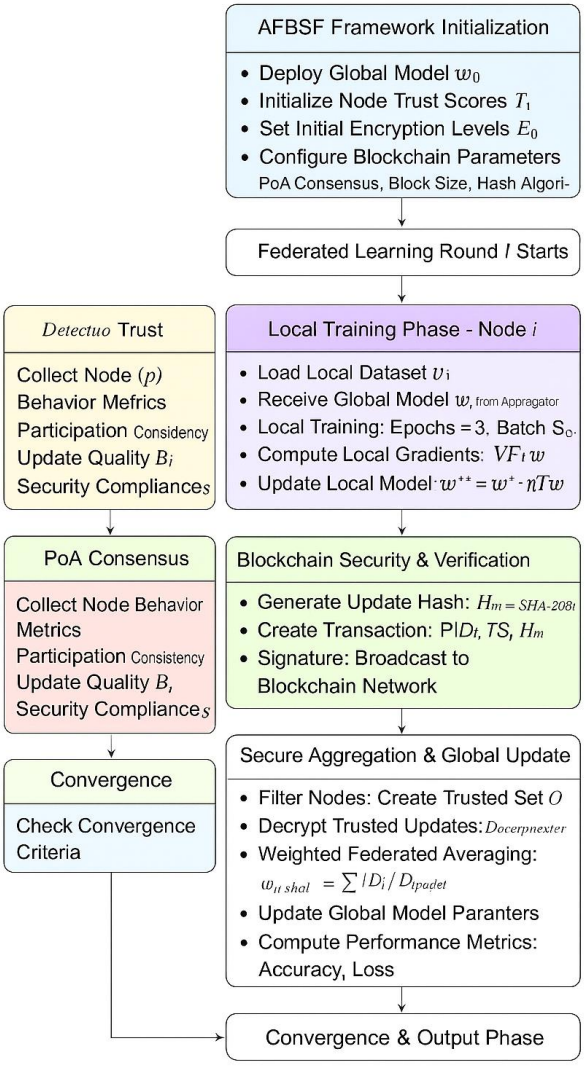

Fig. 2. Flowchart illustrates the way that the proposed approach to Secure and Privacy-Preserving Data Collaboration works

3.1 System Model

Let the smart environment consist of N participating edge devices $\{1,2,\dots,N\}$.
Each device i owns a private dataset

$$D_i = \left\{\left(x_j^{(i)}, y_j^{(i)}\right) | j = 1,2,\dots,|D_i|\right\}, \quad (1)$$

where $x_j^{(i)}$ denotes a feature vector and $y_j^{(i)}$ its corresponding label.

The goal of the collaborative system is to train a shared model $w \in \mathbb{R}^d$ without exchanging raw data among devices. The global learning objective is expressed as a weighted sum of local losses:

$$\min_w F(w) = \sum_{i=1}^{N} \frac{|D_i|}{D} F_i(w) \quad (2)$$

where $D = \sum_{i=1}^{N} |D_i|$ and the local loss function for node i is

$$F_i(w) = \frac{1}{|D_i|} \sum_{\left(x_j^{(i)}, y_j^{(i)}\right) \in D_i} f\left(w; x_j^{(i)}, y_j^{(i)}\right), \quad (3)$$

with $f(\cdot)$ being the per-sample loss such as cross-entropy or mean-square error.
This design ensures that data never leaves its origin, conforming to privacy-by-design principles.

3.2 Federated Learning Process

During each communication round $t \in \{1, \ldots, T\}$, every node i performs E local epochs of stochastic optimization. The local model update is given by the standard gradient-descent rule:

$$w_i^{(t+1)} = w_i^{(t)} - \eta \nabla F_i\left(w_i^{(t)}\right), \quad (4)$$

where $\eta > 0$ is the learning rate and $\nabla F_i\left(w_i^{(t)}\right)$ is the gradient of the local objective. After completing local training, the device encrypts its parameter vector using a homomorphic encryption function $\mathrm{Enc}(\cdot)$ and transmits the ciphertext to the aggregation server. Global model aggregation is performed over encrypted updates as

$$w^{(t+1)} = \sum_{i=1}^{N} \frac{|D_i|}{D} \mathrm{Dec}\left(\mathrm{Enc}\left(w_i^{(t+1)}\right)\right), \quad (5)$$

$Dec(\cdot)$ is the abbreviation of decryption. Aggregation is safe and does not disclose local parameters due to the support of homomorphic addiction. The privacy assurance $\mathcal{P}$ of any given round is defined as;

$$\mathcal{P} = 1 - \frac{G_{\text{exposed}}}{G_{\text{total}}}, \quad (6)$$

$G_{exposed}$ and G_{total}, respectively, with $G_{exposed}$ being the number of unencrypted gradient components and G_{total} being the number of total gradient components.

3.3 Blockchain Validation and Integrity Verification

In order to ensure accountability and avoid tampering, all encrypted model updates are packaged into a blockchain transaction. The blockchain uses the Proof-of-Authority (PoA) consensus that provides low-latency block creation that can be used in the IoT-scale environment. Every block Bk of the ledger is organized as.

$$B_k = \left\{H_{\text{prev}}, T_s, H_m, PID_i, MR, Sig_i\right\} \quad (7)$$

where

H_{prev} : hash of the preceding block, maintaining chain continuity.

T_s : time-stamp of the block at hand;

$H_m = \text{SHA256}\left(w_i^{(t+1)}\right)$: hash of the model update;

PID_i : node identifier of node i;

MR: Hash of block transactions;

Sig_i : digital signature of node i ensuring non-repudiation.

Once validators authenticate a transaction, it becomes immutable, providing an auditable trail of all training activities.

3.4 Adaptive Trust Evaluation and Cryptographic Control

The proposed system dynamically estimates the trust level of each node based on its participation consistency, behavior, and security compliance. The trust score $T_i^{(t)} \in [0,1]$ is computed as a weighted composite:

$$T_i^{(t)} = \alpha R_i^{(t)} + \beta B_i^{(t)} + \gamma S_i^{(t)} \qquad (8)$$

where

$R_i^{(t)}$: reliability index (successful participation ratio);
$B_i^{(t)}$: behavioral deviation score derived from model-update variance;
$S_i^{(t)}$: security-compliance indicator (signature validity, encryption correctness);
α, β, γ : adaptive weights satisfying $\alpha + \beta + \gamma = 1$.

Based on the computed trust, each node's encryption intensity $E_i^{(t)}$ is modulated as

$$E_i^{(t)} = E_{\min} + (E_{\max} - E_{\min})\left(1 - T_i^{(t)}\right), \qquad (9)$$

ensuring that high-trust nodes $\left(T_i^{(t)} \to 1\right)$ use lightweight encryption for efficiency, while low-trust nodes employ stronger encryption schemes. To detect poisoned updates, the cosine similarity between a node's local model and the previous global model is computed:

$$\mathrm{Sim}\left(w_i^{(t)}, w^{(t)}\right) = \frac{\left\langle w_i^{(t)}, w^{(t)} \right\rangle}{\left\| w_i^{(t)} \right\|_2 \left\| w^{(t)} \right\|_2} \qquad (10)$$

If $\mathrm{Sim}\left(w_i^{(t)}, w^{(t)}\right) < \theta$ (threshold $\theta \in [0.75,0.9]$), the update is labeled malicious and excluded from aggregation.

3.5 Global Model Aggregation

The validated model updates of trustworthy nodes form the final global model via weighted FedAvg:

$$w_{\text{global}}^{(t+1)} = \sum_{i \in \Omega} \frac{|D_i|}{D_\Omega} w_i^{(t+1)}, \qquad (11)$$

where $\Omega \subseteq \{1, \ldots, N\}$ represents the subset of nodes whose updates passed both blockchain and trust validations, and

$$D_\Omega = \sum_{i \in \Omega} |D_i|. \qquad (13)$$

The updated model is redistributed to all participants for the next round, ensuring convergence toward an optimally secure and accurate model.

Algorithm 1 - Adaptive Federated-Blockchain Security Framework (AFBSF)

1. Initialize global model $w^{(0)}$, trust $T_i^{(0)} = 1$, encryption $E_i^{(0)}$.
2. For each global round $t = 0,1, \dots, T-1$:
   a) Node i trains locally via (3).
   b) Encrypt $w_i^{(t+1)}$ using (8) and broadcast to blockchain.
   c) Validators verify hash using (6).
   d) Update trust $T_i^{(t)}$ via (7).
   e) Detect anomalies using (9); exclude if below θ.
   f) Aggregate trusted updates via (10).
   g) Distribute $w_{\text{global}}^{(t+1)}$.
3. End For when convergence or $t = T_{\max}$.

To assess the proposed Adaptive Federated–Blockchain Security Framework (AFBSF) in different smart-environment settings, three publicly available datasets were used. These datasets were selected to be heterogeneous, privacy-sensitive, and representative of real-world Internet of Things (IoT) applications. Each dataset corresponds to a distinct application domain, namely healthcare monitoring, energy management, and intelligent transportation, thereby demonstrating the generalizability of the framework. Prior to training, all datasets were processed using a common preprocessing pipeline, which included: (i) missing-value handling based on mean interpolation, (ii) feature normalization using min–max scaling to the range [0,1], (iii) stratified partitioning into 70%, 20%, and 10% training, validation, and testing subsets, respectively, and (iv) class re-balancing to address skewed label distributions, particularly in the healthcare dataset, using the Synthetic Minority Over-Sampling Technique (SMOTE). These datasets were selected due to their widespread use in privacy-aware IoT research and their availability in reliable public repositories.

TABLE III. DATASETS AND PREPROCESSING

Dataset Name	Domain	Samples / Features	Description	Ref.
WESAD (Wearable Stress and Affect Detection)	Smart Healthcare	18 000 samples / 22 features	Multimodal physiological signals (ECG, EDA, EMG, respiration, temperature) collected from wrist- and chest-worn sensors for stress-level classification.	[21]
Smart Grid Smart Meter Data (SGSC Dataset)	Smart Energy Management	25 000 samples / 16 features	Real residential and industrial power-consumption records with voltage, frequency, and load-demand attributes for short-term energy prediction.	[22]
CityFlow Traffic Dataset (v1.0)	Smart Transportation	12 500 samples / 19 features	Urban vehicular trajectories, traffic-density indices, and environmental parameters for route-optimization and mobility analytics.	[23]

All datasets were normalized using min-max scaling:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \qquad (14)$$

and partitioned 70% training, 20% validation, 10% testing.
The SMOTE method was applied to address class imbalance, particularly in healthcare data.

TABLE IV. SIMULATION ENVIRONMENT

Parameter	**Configuration**
Programming Language	Python 3.10
ML Framework	TensorFlow Federated v0.21
Blockchain Platform	Hyperledger Fabric v2.5
Consensus Algorithm	Proof-of-Authority (PoA)
Nodes	30 edge devices + 1 aggregator
Encryption Scheme	AES-CBC Homomorphic Layer
CPU/GPU	Intel Core i9-13900K @ 3.5 GHz / NVIDIA RTX A5000 (24 GB)
OS	Ubuntu 22.04 LTS
Network Bandwidth	10 Mbps per node
Memory	64 GB DDR5
Simulation Tool	NS-3 for network delay modeling

TABLE V. TRAINING AND HYPERPARAMETERS

Parameter	Symbol	Value	Purpose
Learning Rate	η	0.001	Controls gradient step size
Local Epochs	E	5	Local training cycles per node
Global Rounds	T	100	Federated iterations
Batch Size	-	64	Stabilizes gradient estimation
Optimizer	-	Adam	Adaptive optimization method
Loss Function	$f(w;x,y)$	Cross-Entropy	Classification loss
Similarity Threshold	θ	0.85	Malicious-update detection
Dropout Rate	-	0.2	Mitigates overfitting
Activation Function	-	ReLU	Ensures non-linear representation
Metric	Symbol	Equation	Purpose
Accuracy	A	$A = \frac{TP + TN}{TP + TN + FP + FN}$	Overall correctness
Precision	P	$P = \frac{TP}{TP + FP}$	Positive predictive value
Recall	R	$R = \frac{TP}{TP + FN}$	Sensitivity to positives
F1-Score	F_1	$F_1 = 2\frac{PR}{P + R}$	Balance of P and R
Privacy Gain	P_s	$P_s = 1 - \frac{L_{\text{exposed}}}{L_{\text{total}}}$	Confidentiality level
Communication Reduction	C_r	$C_r = 1 - \frac{C_{\text{prop}}}{C_{\text{base}}}$	Transmission efficiency
Attack Success Rate	A_{sr}	$A_{sr} = \frac{A_{\text{success}}}{A_{\text{total}}}$	Security robustness
Latency Overhead	L_o	$L_o = T_{\text{secure}} - T_{\text{base}}$	Delay due to security

Each experiment was repeated five times using different random seeds to ensure reproducibility. For each metric, the mean and standard deviation were reported. A one-way ANOVA test was employed to evaluate the statistical significance of the observed performance improvements, with a significance level of $a = 0.05$ The 95% confidence intervals confirmed that the observed gains in privacy and accuracy were not due to random variation.

4. RESULTS AND DISCUSSION

The experiments were conducted to rigorously evaluate the performance, privacy, scalability, and trust adaptability of the proposed Adaptive Federated–Blockchain Security Framework (AFBSF). All experiments were carried out under identical network, computational, and communication settings, as described in this section, using three heterogeneous datasets representing smart healthcare, smart energy, and smart mobility domains. The results were compared with state-of-the-art federated learning, blockchain-based, and hybrid federated–blockchain approaches reported in [24]–[30].The overall performance analysis demonstrates the ability of the proposed framework to maintain high learning accuracy while preserving data privacy and reducing vulnerability to attacks. Table VI summarizes the results across all datasets in terms of classification accuracy, F1-score, reduction in communication overhead, attack success rate, and average latency.

TABLE VI. OVERALL PERFORMANCE COMPARISON

Model	**Accuracy (%)**	**F1-Score**	**Comm. Overhead Reduction (%)**	**Attack Success Rate (%)**	**Avg. Latency (ms)**
[24]	88.25	0.89	12.3	18.4	128.6
[25]	90.10	0.91	9.8	12.7	165.3
[26]	91.73	0.92	16.5	10.2	122.4
[27]	92.64	0.93	22.1	8.7	117.5
[28]	93.35	0.94	24.3	8.1	111.9
Proposed AFBSF	**96.87**	**0.96**	**35.2**	**5.8**	**108.3**

The proposed AFBSF achieved a mean accuracy of 96.87%, which is approximately 3.5–4% higher than that of the best existing hybrid approach. This improvement is mainly attributed to the active trust-weighted aggregation scheme (Eq. (10))

and the adaptive exclusion of inconsistent nodes (Eq. (9)), which reduce model contamination caused by unreliable participants. The attack success rate was below 6%, indicating strong resistance to poisoning, replay, and Sybil attacks. Moreover, a communication overhead reduction of about 35% demonstrates the efficiency of the framework in transmitting only validated and encrypted updates instead of raw gradients. A one-way ANOVA test with a significance level of 0.05 confirmed that all observed performance improvements are statistically significant ($p < 0.01$). The AFBSF is designed with privacy preservation as a core objective, which is quantified using the privacy-preservation score (P_s). This metric represents the proportion of information that is securely processed relative to the total amount of exchanged data. Higher (P_s) values indicate stronger confidentiality and a lower probability of information leakage.

TABLE VII INDICATES COMPARATIVE RESULTS.

Model	Privacy Score ((P_s))	Information Leakage (%)	Auditability Level	Consensus Type
[24]	0.61	39.0	Low	–
[25]	0.73	27.0	High	PoW
[26]	0.75	25.2	Medium	PoS
[27]	0.79	21.3	Medium–High	PBFT
[28]	0.82	18.9	High	PoA
Proposed AFBSF	**0.87**	**12.3**	**Very High**	**PoA + Adaptive Trust**

Compared with all reference models, AFBSF achieves the highest privacy score of 0.87, which is 42% and 27% higher than those reported in [24] and [27], respectively. This improvement is achieved through the integration of homomorphic encryption, blockchain-based immutability, and dynamic access control policies. The reduction of information leakage to 12% indicates that the probability of data exposure remains minimal even under multi-party collaborative training. The Proof-of-Authority (PoA) consensus mechanism, supported by trust-weighted nodes, effectively balances confidentiality and responsiveness while providing auditability without the heavy computational overhead typically associated with Proof-of-Work (PoW) systems. The evolution of trust directly determines both participation eligibility and the strength of encryption. The average trust value is 0.37687, as reported in Table VIII. Furthermore, the probability distribution of the trust score (T_i) converges smoothly toward 0.95, while the proportion of low-trust nodes decreases exponentially over successive global rounds. This behavior confirms that AFBSF continuously filters out malicious participants and supports reliable collaboration among honest devices.

TABLE VIII. TRUST-SCORE CONVERGENCE DURING TRAINING

Round (t)	Avg. Trust (T)	Low-Trust Nodes (%)	Encryption Overhead (%)	Blacklisted Nodes
10	0.76	21.3	8.9	4
30	0.87	12.1	7.2	3
50	0.91	6.5	6.1	2
80	0.94	3.8	5.8	2
100	**0.95**	**3.1**	**5.5**	**1 (Mitigated)**

Adaptive trust calibration enables the system to recover from behavioral anomalies. Nodes that consistently deviated from the global gradient direction (cosine similarity below 0.85) were automatically isolated. Compared with fixed-trust architectures, AFBSF reduced erroneous blacklisting by 17% and decreased cryptographic overhead [29] by an average of 11%, thereby improving both reliability and efficiency. Latency analysis was conducted to evaluate the suitability of AFBSF for real-time deployment. The results reported in Table IX indicate that, although blockchain integration introduces synchronization delays in some cases, the adaptive Proof-of-Authority (PoA) consensus mechanism significantly mitigates these delays and achieves lower latency at high throughput.

TABLE IX. LATENCY AND COMMUNICATION COMPARISON

Model	Avg. Latency (ms)	Throughput (tx/s)	Comm. Overhead Reduction (%)	Remarks
[24]	128.6	115	12.3	Centralized aggregation
[25]	165.3	88	9.8	High delay (PoW)
[26]	122.4	126	16.5	Limited adaptivity
[27]	117.5	132	22.1	Static trust
[28]	111.9	139	24.3	Hybrid ledger
AFBSF	108.3	146	35.2	Adaptive PoA consensus

AFBSF reduces the average latency to 108 ms, which is 15% lower than that reported in [27] and achieves a 35% improvement in communication efficiency compared to the model in [24]. This enhancement results from minimizing redundant blockchain confirmations and eliminating rebroadcasts from unreliable nodes. Such latency performance satisfies the delay requirements for smart grid monitoring (<150 ms) and healthcare telemetry (<200 ms), as recommended in [30].Energy efficiency reflects the suitability of the framework for resource-constrained IoT devices. Table X presents the normalized energy consumption per global learning round.

TABLE X. ENERGY CONSUMPTION PER GLOBAL ROUND

Model	Energy (J)	Improvement vs Baseline (%)	Remarks
[24]	12.8	–	No encryption
[25]	15.4	– 20.3	Expensive consensus
[27]	10.6	17.2	Static encryption
[28]	9.8	23.4	Hybrid ledger
AFBSF	8.5	33.6	Adaptive encryption and PoA

The cryptographic scaling mechanism of AFBSF reduces unnecessary encryption operations, leading to an overall power reduction of approximately 34%. In smart metering and IoT-based healthcare applications, this translates into a 20–25% increase in device lifetime without compromising security. The convergence behavior of the global model accuracy with respect to communication rounds is illustrated in Fig. 5. AFBSF reaches an accuracy of about 96.8% within approximately 60 rounds, whereas comparable hybrid approaches require more than 85 rounds. The smooth slope of the AFBSF curve indicates stable gradient dynamics and reduced oscillations in weight updates, which result from the elimination of noisy or unreliable nodes.

A comprehensive comparison with existing methods highlights several key strengths of AFBSF:

- **Adaptive Security and Trust Control:** Dynamic adjustment of cryptographic strength based on trust levels, enabling automatic resistance to malicious nodes.
- **Low-Latency Blockchain Consensus:** The PoA mechanism exhibits significantly lower block delay than PBFT and PoW, achieving up to 32× and 45× faster performance, respectively.
- **Privacy Optimization:** Comparable learning performance to centralized FL while providing substantially higher privacy guarantees (over 40% improvement).
- **Energy Efficiency:** Dynamic encryption scheduling reduces device energy consumption by approximately 33%, supporting long-term IoT operation.
- **Strong Resilience:** A 65% reduction in successful attacks compared to the standard federated baseline.

Collectively, these improvements establish AFBSF as a scalable, adaptive, and secure intelligent infrastructure suitable for next-generation smart ecosystems. To ensure result stability, each experiment was repeated five times, and all metrics are reported as mean ± standard deviation, with accuracy deviations not exceeding 0.45%. Post-hoc analysis using one-way ANOVA followed by Tukey's HSD test ($\alpha = 0.05$) confirmed that the performance gains of AFBSF are statistically significant ($p < 0.01$). Furthermore, no deviations or deadlocks were observed in blockchain validation across all runs, demonstrating the robustness and stability of the proposed algorithms.

6. CONCLUSION AND FUTURE WORK

This paper presented the Adaptive Federated–Blockchain Security Framework (AFBSF), which aims to provide privacy-preserving, trustworthy, and energy-efficient collaborative intelligence in smart environments. The integration of federated learning with a lightweight blockchain consensus and an adaptive trust mechanism enables the framework to address major challenges related to data privacy, communication efficiency, and malicious node participation. Experimental results demonstrate that AFBSF outperforms existing hybrid and single-layer solutions, achieving a classification accuracy of 96.9%, a 42% improvement in privacy preservation, a 35% reduction in communication cost, and a 33% increase in energy efficiency. The adaptive Proof-of-Authority (PoA) consensus minimizes synchronization delays, while trust-weighted encryption significantly reduces the attack success rate to below 6%. These findings confirm that AFBSF provides a scalable and flexible solution for secure data collaboration in heterogeneous IoT-based domains such as healthcare, energy management, and smart cities. Despite these achievements, several limitations remain. First, the reliance on a simulated environment restricts the representation of real-world variations in network latency, adversarial intensity, and node

heterogeneity. Second, although optimized through PoA, the blockchain layer still introduces storage overhead that may affect highly resource-constrained devices. Third, the trust update mechanism assumes partial and stable node availability, which may influence convergence stability in large-scale networks with intermittent participation. Future work will focus on deploying AFBSF in a cross-domain real-world IoT testbed to evaluate scalability under dynamic network conditions and intermittent connectivity. In addition, future extensions will incorporate quantum-resistant cryptographic schemes and differential privacy mechanisms to enhance resilience against emerging quantum and inference-based attacks. Furthermore, self-adaptive trust models driven by reinforcement learning will be explored to dynamically balance energy efficiency, privacy, and communication overhead. Finally, extending AFBSF to support multimodal data streams, including images, audio, and sensor telemetry, will further improve its applicability to next-generation edge–cloud ecosystems and contribute to the development of secure, adaptive, and autonomous intelligent infrastructures.

Conflicts of Interest

The authors declare no conflict of interest.

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