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A Privacy-Preserving Federated Blockchain Framework For Secure Data Sharing In Multi-Cloud Environments

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Secure data sharing across multi-cloud environments faces persistent challenges related to privacy leakage, trust management, data provenance, and interoperability among heterogeneous cloud platforms. Traditional centralized security mechanisms struggle to support distributed workloads while ensuring compliance, traceability, and resilience against single-point failures. To address these issues, a privacy-preserving federated blockchain framework is introduced, integrating lightweight cryptography, decentralized trust governance, and federated learning-based access control. The proposed architecture enables secure data exchange among multiple clouds without exposing raw data, while on-chain smart contracts automate policy enforcement, provenance tracking, and consensus-driven validation. A hybrid consensus process enhances scalability for multi-cloud federations, and zero-knowledge proofs strengthen privacy guarantees during cross-cloud verification. Experimental analysis demonstrates improvements in latency, security robustness, and interoperability compared to conventional blockchain-only and cloud-only models. The results indicate that the framework provides a scalable, auditable, and privacy-centric solution for collaborative data sharing in heterogeneous cloud ecosystems.

Keywords: Federated blockchain; multi-cloud security; privacy-preserving framework; zero-knowledge proofs; secure data sharing; decentralized trust; smart contracts; federated learning.

1. Introduction

The rapid expansion of multi-cloud environments has transformed the way organizations store, manage, and exchange data across distributed infrastructures. Enterprises increasingly rely on combinations of public, private, and hybrid cloud platforms to achieve flexibility, cost optimization, and service continuity. However, the distributed nature of multi-cloud ecosystems introduces several critical challenges, including privacy leakage, fragmented access control, limited data provenance, and inconsistent security policies across providers. As data flows traverse heterogeneous platforms, conventional centralized security mechanisms become insufficient for providing assured trust, verifiability, and resilient access governance.

Blockchain has emerged as a decentralized solution capable of ensuring tamper-resistant audit trails, automated policy execution, and transparent trust management. Despite its benefits,

standalone blockchain systems face limitations in scalability, privacy preservation, and computational overhead when applied to large-scale multi-cloud environments. Parallelly, federated learning offers a distributed computation paradigm that supports collaborative model building without transferring sensitive data, thus providing an effective means to mitigate privacy risks during cross-cloud operations. Combining these technologies presents an opportunity to build a secure and privacy-aware foundation for next-generation cloud interoperability.

This paper introduces a privacy-preserving federated blockchain framework designed to enable secure, auditable, and policy-compliant data sharing across multi-cloud environments. The framework integrates federated learning for distributed access control optimization, zero-knowledge proofs for privacy-enhanced verification, and a hybrid blockchain architecture to support scalability and trust decentralization. By coupling federated governance with blockchain's immutable ledger, the framework addresses privacy challenges while improving interoperability among cloud providers. The major contributions of this work are summarized as follows:

1. A federated blockchain architecture is developed to support secure and decentralized data sharing among heterogeneous multi-cloud platforms without exposing raw data.
2. A privacy-preserving access control mechanism is introduced by incorporating federated learning and secure aggregation to manage authorization policies collaboratively across distributed clouds.
3. Zero-knowledge proofs are integrated to enhance privacy guarantees during cross-cloud validation and to ensure that sensitive attributes remain undisclosed while verifying access rights.
4. A hybrid consensus mechanism optimized for multi-cloud federations is proposed to reduce latency and improve scalability when compared to conventional blockchain approaches.

2. Related Works

Blockchain-driven access control and encrypted data sharing have been extensively explored in recent literature. Yan et al. (2023) proposed an attribute-based searchable encryption model integrated with blockchain to support fine-grained authorisation in cloud environments. Their approach embeds searchable ciphertexts and user attributes into a policy-driven blockchain layer, improving verifiability and resistance to unauthorised access. The study highlights performance trade-offs between cryptographic overhead and search latency, showing that blockchain anchoring reduces tampering risks while preserving scalability. Zhang et al. (2023) examined deduplication-aware blockchain-assisted data sharing, focusing on reducing redundant storage while maintaining verifiable data integrity. Their work combines hash-indexed deduplication with on-chain metadata to ensure that replicated content is securely referenced rather than duplicated in full. The methodology demonstrates measurable gains in storage efficiency and retrieval time, making it suitable for multi-cloud deployments requiring large-scale, tamper-proof archival systems.

Moosa and Hasan (2023) introduced a privacy-preserving model that integrates blockchain with zero-knowledge proofs to secure data sharing without revealing sensitive attributes. Their

construction uses ZK-verifiable transactions to authenticate access permissions while masking the underlying credentials. The results show improved privacy guarantees when compared to traditional encryption-based verification, particularly in distributed cloud environments where cross-domain trust is required. Liang et al. (2023) proposed a blockchain-enabled federated learning framework aimed at protecting healthcare data during collaborative model training. Their architecture uses blockchain for model update certification, ensuring that only legitimate contributors participate in the learning process. The system also enhances auditability and consistency in medical datasets while avoiding direct exposure of patient information across cloud nodes.

Konkin and Zapechnikov (2023) conducted a detailed investigation of ZK-SNARK constructions and their applicability in private blockchain systems. Their analysis compares computational complexity, trust assumptions, and proof systems suitable for scalable verification in decentralised environments. The findings emphasise the importance of selecting lightweight ZKP mechanisms for multi-cloud use cases where verification speed is critical. Shitharth et al. (2023) developed a blockchain-federated learning integration aimed at secure task offloading and privacy-preserving computation. Their model uses decentralised consensus to validate local model contributions and employs encrypted gradient sharing to protect sensitive data features. The architecture demonstrates strong robustness against poisoning attacks, positioning it as a viable solution for federated multi-cloud collaboration.

Ren et al. (2023) proposed a ciphertext-policy attribute-based encryption scheme combined with blockchain anchoring for secure multi-cloud data sharing. Their design enables temporal and fine-grained access control by embedding authorisation proofs within blockchain transactions. Experimental evaluation indicates reduced key-management overhead and improved resistance to collusion attacks, addressing common vulnerabilities in multi-cloud settings. Samuel et al. (2023) introduced a blockchain-assisted authentication and collaborative data-sharing mechanism tailored for cloud ecosystems. Their framework uses decentralised identity tokens and cryptographic commitment schemes to enforce trust among cloud providers. The research highlights benefits in reducing authentication latency and improving auditability, demonstrating its applicability for federated cloud services.

Awasthi et al. (2023) designed a multi-level blockchain-based security framework for IoT environments focusing on preservation of sensitive data. Their model enforces layered encryption, distributed trust, and tamper-proof auditing to mitigate typical IoT threats. The evaluation confirms notable improvements in intrusion detection and secure data dissemination, making the framework adaptable to multi-cloud IoT integrations. Zhang et al. (2023) explored blockchain-driven attribute-keyword searchable encryption for health cloud systems. Their method supports privacy-preserving retrieval of medical records while maintaining strict role-based access verification. The study shows that combining ABE with blockchain metadata significantly improves retrieval accuracy and eliminates unauthorised access risks.

Gao et al. (2023) introduced TrustAccess, a blockchain-based ciphertext-policy access control system designed for privacy-sensitive applications. Their framework hides access policies while allowing encrypted matching, preventing leakage of user roles or attribute structures. The study demonstrates enhanced confidentiality in distributed networks, highlighting its relevance for multi-cloud data-sharing systems. De and Ruj (2023) proposed a decentralised attribute-based access control model for mobile cloud environments. Their work decentralises authorisation decisions using blockchain consensus and lightweight policy verification, ensuring continuous availability and trustworthiness of access rights. The evaluation shows improved resilience against spoofing and policy manipulation attempts, offering high relevance for multi-cloud identity management. Zhou et al. (2023) published an extensive survey on leveraging zero-knowledge proofs for secure identity sharing in blockchain ecosystems. Their review presents architectural insights, comparative analyses, and emerging research opportunities in ZKP-enhanced identity systems. The survey underscores that ZKPs can mitigate privacy leakage in multi-cloud federations by providing proof-of-right without exposing identity information.

Yan et al. (2023) proposed a blockchain-enabled multi-authorisation and multi-cloud keyword search mechanism using CP-ABE. Their design allows encrypted search requests to be processed across cloud providers without sacrificing confidentiality. The evaluation demonstrates strong adaptability in federated cloud systems, supporting efficient and secure retrieval workflows. Li et al. (2023) presented a secure and efficient dynamic searchable symmetric encryption scheme for multi-cloud environments with blockchain anchoring. Their mechanism ensures that index updates, search tokens, and retrieval operations remain verifiable under decentralised trust. The results show significant gains in query integrity and resistance to replay attacks, making it well-suited for distributed cloud ecosystems.

3. Proposed model

This section presents the proposed privacy-preserving federated blockchain framework for secure data sharing in multi-cloud environments. First a concise overview is given, then stepwise components and algorithms are described. Each subsection gives the reasoning and concise derivations or formal expressions so the design can be implemented and analysed.

3.1 Architecture overview

The system consists of three logical layers: (1) data layer — encrypted data objects stored off-chain in multiple cloud providers; (2) federation layer — a permissioned blockchain connecting cloud providers, auditing events, storing compact metadata, and hosting smart contracts for policy enforcement; and (3) application/AI layer — federated learning (FL) workers at each cloud training local models and submitting verified updates to an aggregator. Privacy is preserved using attribute-based encryption (ABE) for data, secure aggregation and differential privacy for model updates, and zero-knowledge proofs (ZKPs) for cross-cloud verification. A hybrid consensus ensures low-latency agreement while preserving decentralisation. Smart contracts manage access grants, revocation, provenance anchors and incentive distribution.

Figure 1. Proposed Privacy-Preserving Federated Blockchain Architecture

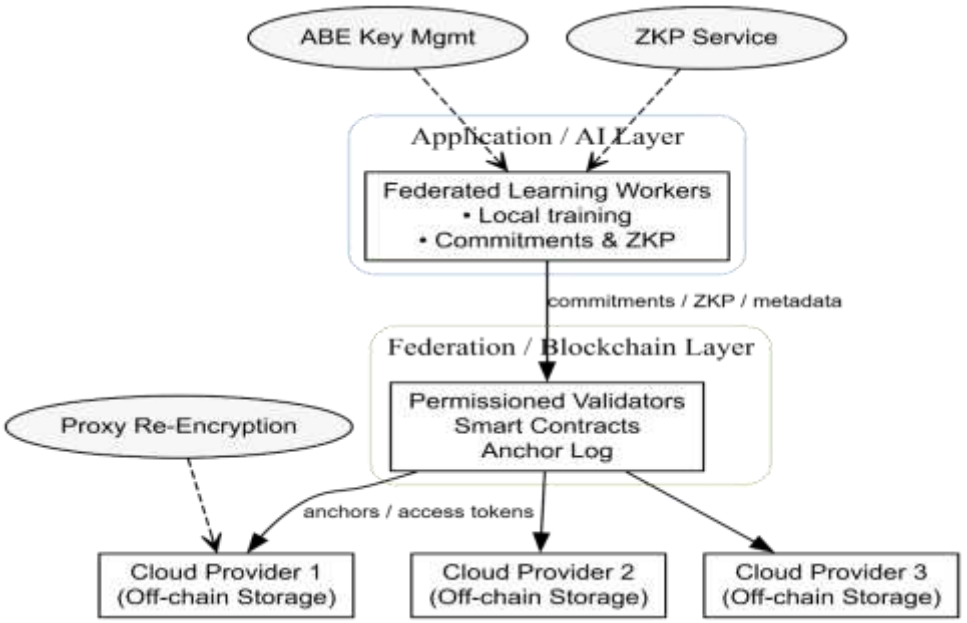

Fig 1 illustrates the three-layer framework combining federated learning, blockchain-based trust management, and multi-cloud encrypted storage. The model supports secure collaboration through commitments, ZKP verification, and permissioned validator consensus. Off-chain data remains encrypted across clouds while on-chain metadata ensures traceability, access control, and auditability.

3.2 Threat model and security goals

Threat model. Adversaries may be:

1. External passive eavesdroppers on network links.
2. Malicious cloud provider nodes that try to exfiltrate data or model updates.
3. Byzantine participants who send crafted model updates (poisoning) or fake audit events.
4. Semi-honest colluding subset of participants attempting to learn private attributes from exchanged artifacts.

Security goals. The framework aims to provide:

G1. Confidentiality: raw data and model-sensitive information must not be revealed to unauthorised parties.

G2. Integrity & provenance: any access, update or policy change must be auditable and tamper-evident.

G3. Privacy-preserving verification: verify claims (access rights, model contribution correctness) without revealing sensitive attributes (ZKP).

G4. Availability & scalability: system preserves service under reasonable node failure and scales across clouds.

G5. Resistance to poisoning and replay attacks.

Security assumptions. Permissioned identities for cloud nodes; existence of public parameter PKG (for ABE setup) or distributed ABE setup; standard cryptographic hardness (DL/BDH, depending on chosen primitives).

3.3 Cryptographic building blocks (formal definitions & derivations)

3.3.1 Attribute-based encryption (CP-ABE) — notation and formulas

Use ciphertext-policy attribute-based encryption (CP-ABE) for data sharing. Let A denote attribute universe. The CP-ABE scheme has algorithms: Setup, KeyGen, Encrypt, Decrypt. Setup(λ) → (PK, MK). KeyGen(MK, S) → SK_S for attribute set S. Encrypt(PK, M, policy P) → CT. Decrypt(PK, CT, SK_S) → M if S satisfies P.

Formal correctness: if attrs(S) ⊨ P then Decrypt(CT, SK_S) = M.

Policy as access tree T. Let leaves correspond to attributes, and internal nodes be threshold gates. Use recursive reconstruction: for node x with threshold k_x and child set C_x, compute polynomial q_x of degree k_x−1 with q_x(0) = q_parent(i), etc. Standard CP-ABE reconstruction uses Lagrange interpolation; refer to base equations:

For a node with children indices I and shares {q_i(0)}, recover q_x(0) = Σ_{i∈I} λ_i · q_i(0), where λ_i are Lagrange coefficients:

$$\lambda_i = \prod_{j \in I, j \neq i} \frac{0-j}{i-j} \quad (1)$$

In pairing-based CP-ABE, ciphertext components are of form $C = M \cdot e(g,g)^{\alpha s}$, and decrypt uses pairing and product of attribute shares. This yields standard security under BDH.

3.3.2 Attribute-based signcryption (optional)

If confidentiality + authenticity in one op is desired, use an attribute-based signcryption primitive: Signcrypt(SK_sender, attrs_sender, PK, policy_receiver, M) → CT_sc, and Unsigncrypt(SK_receiver, CT_sc) → (M, verify). Formal proofs follow from combining ABE and digital signatures.

3.3.3 Zero-knowledge proofs (ZKP)

ZKPs prove statements about secrets without revealing them. In our framework, typical statements S include: "I hold attributes satisfying policy P" or "This model update complies with the norm (bounded L2 norm)". Use succinct non-interactive ZK (SNARK or Bulletproofs where appropriate).

Example statement for norm bound (model update Δ):

Prover proves knowledge of vector Δ such that $\| \Delta \|_2^2 \leq \tau$. Express as arithmetic circuit and produce proof π.

Using SNARKs: Setup generates CRS; Prover computes π = Prove(CRS, witness Δ) and Verifier checks Verify(CRS, π, public input). Security: completeness, soundness, zero-knowledge.

3.3.4 Secure aggregation for federated learning (derivation)

Goal: compute aggregate $G = \sum_{i=1}^{n} g_i$where g_i are local gradients, while keeping each g_i private.
Masking scheme (Bonawitz-style): each party i selects random masks r_{i,j} for j>i and sends masked gradients; pairwise masks cancel:
Party i sends $m_i = g_i + \sum_{j>i} r_{i,j} - \sum_{j<i} r_{j,i}$. (2)
Sum across i:
$\sum_i m_i = \sum_i g_i + \sum_{j>i} r_{i,j} - \sum_{j<i} r_{j,i} = \sum_i g_i$. (3)

Thus masks cancel in global sum. To handle dropouts, use secret sharing to allow reconstructing missing masks: each mask $r_{i,j}$ is secret-shared via Shamir into shares distributed to a set of servers (or to blockchain validators), enabling reconstruction if node i drops. Complexity: O(n^2) pairwise mask exchanges; optimizations (grouping or tree-based aggregation) reduce communication.
Differential privacy (DP) composition: add noise N ~ Gaussian(0, σ^2 I). The aggregated result becomes:
$\widetilde{G} = \sum_i g_i + N$ (4)

Privacy budget ε computed via Gaussian mechanism composition. Use moments accountant to compute ε across rounds R. For Gaussian noise σ and subsampling fraction q, the moments accountant yields (sketch):
$\varepsilon \approx q\sqrt{2R\log(1/\delta)}/\sigma$ (5)

(Provide exact composition formulas based on Abadi et al., 2016; include moments accountant for implementation.)

3.3.5 Signatures and authenticated logging

Use standard digital signatures (e.g., ECDSA / Ed25519) for node-authenticated transactions. Each on-chain transaction T includes fields (type, objectID, actorID, timestamp, metaHash, sig). Verifier checks signature:
$\mathrm{Verify}(PK_{actor}, T, sig) = \mathrm{true}$ (6)

3.4 Hybrid consensus design and derivation

Hybrid consensus combines a permissioned BFT layer among known cloud validators for low-latency finality with a lightweight Proof-of-Stake (PoS) style inter-domain validator election to include third parties or cross-provider voters.
Notation: let V be validator set size, f be max Byzantine faults tolerated. For PBFT-like BFT, require $V \geq 3f + 1$ to tolerate f faults. Latency per block in BFT ≈ 3·L_comm + L_comp, where L_comm is one-way communication latency and L_comp is computation/signature time. For hybrid:

1. Local block production: within a cloud domain, local BFT among local nodes produces microblocks with latency $L_{local} = 3L_{comm}^{local} + L_{comp}^{local}$.

2. Cross-domain finality: a meta-validator committee (selected by stake and SLA metrics) runs a lightweight multi-round vote (e.g., Tendermint-like) to confirm anchors. Cross-domain latency $L_{cross} = r \cdot L_{comm}^{cross} + L_{comp}^{cross}$, where $r \approx 2–3$ communication rounds.

Total perceived latency for an anchor = $L_{anchor} = L_{local} + L_{cross}$.

Throughput: BFT throughput ~ $TP = \frac{S_{block}}{L_{local}}$. Increasing V reduces security but increases L_comm; choose V to balance.

Security: hybrid reduces attack surface by limiting cross-domain finality validators to entities meeting SLA. Probability of a 0.5 adversarial control is bounded by stake distribution; modeled with standard PoS security assumptions.

3.5 Smart contract design and formal logic

Smart contracts implement: access grant, revocation, provenance anchors, ZKP verification receipts, economic incentives.

Contract state variables: AccessList[objectID] → list of (subjectID, policyHash, expiry), AnchorLog[].

Access grant function (pseudo):

function grantAccess(objectID, subjectPub, policyHash, expiry, sig_authority):
require(VerifyAuthority(sig_authority))
AccessList[objectID].append((subjectPub, policyHash, expiry))
emit GrantEvent(objectID, subjectPub, policyHash, now)

Policy hashes (policyHash) refer to CP-ABE policies stored off-chain or encoded as compact descriptors on-chain. Revocation: update AccessList or set a revocation entry with timestamp t_rev. Access decision logic checks current time and policy non-revoked.

ZKP receipt storage: store succinct proof commitments (not full witnesses). Verifier on-chain calls a light verifier contract to execute Verify(CRS, π, public_input) — for SNARKs, on-chain verification can be gas/compute heavy; tradeoff: store proof root and verify off-chain with validators who post attestations to chain.

Formal correctness property: if contract emits GrantEvent for (subject, policyHash), then subject holding SK matching attributes can derive decryption key, subject to revocation. Auditing uses append-only AnchorLog to show history.

3.6 Federated learning pipeline and mathematical workflow

3.6.1 Notation

n: number of participating clouds. Local dataset at node i: D_i. Local model parameters at round t: $w_i^{(t)}$. Global model: $W^{(t)}$. Local gradient (or update): $g_i^{(t)} = w_i^{(t)} - W^{(t-1)}$or computed as SGD step.

3.6.2 Local training and commitment

Each participant computes local update: run E epochs of SGD on $D_i$starting from $W^{(t-1)}$to produce $w_i^{(t)}$. Compute update $g_i^{(t)}$. Compute commitment $h_i = H(g_i^{(t)} \parallel \text{meta})$and sign it: $sig_i = Sign(SK_i, h_i)$. Post transaction (h_i, sig_i, metaHash) to blockchain as commitment.

3.6.3 Secure aggregation and verification

Participants mask updates and either (a) perform Bonawitz-style pairwise masking with secret-shared masks, or (b) use homomorphic encryption (HE) where updates are HE-encrypted and aggregator computes HE sum and decrypts with threshold decryption. For efficiency choose masking + secret sharing.

Verification. To prevent malicious updates:

1. Each participant generates a ZKP π_i that its update obeys norms: e.g., bounded L2 norm and no malicious pattern. Public inputs: commitment h_i and global constraints. Prover sends π_i off-chain to validators; validators run Verify and post verification result (verdict) to the blockchain.
2. If verified, masked update included in aggregation. Aggregator reconstructs masks and sums to get $G^{(t)}$. Global update: $W^{(t)} = W^{(t-1)} - \eta \cdot \frac{1}{n} G^{(t)}$.

3.6.4 Robust aggregation options (derivation)

To mitigate poisoning, robust aggregator functions can be used: median, trimmed mean, Krum, or coordinate-wise median. Example trimmed mean:
For each coordinate j, sort {g_i^{(t)}[j]} and remove top b and bottom b elements, then average remaining:

$$\text{trimmed\_mean}_j = \frac{1}{n-2b} \sum_{i=b+1}^{n-b} g_{(i)}^{(t)}[j] \tag{7}$$

Krum picks the update with smallest sum-of-squared distances to closest n−f−2 others. These strategies trade robustness against sample efficiency.

3.7 Data flow, APIs and storage model

Data objects stored off-chain in clouds use the following canonical flow:

1. Data owner encrypts file F under CP-ABE policy P → CT. Computes content hash h = H(CT) and stores CT in cloud storage (URI). Owner submits anchor: Anchor = (objectID, h, URI_meta, policyHash) to blockchain via smart contract call.
2. Access request: subject requests access via smart contract; if authorized, contract emits ephemeral access token T_enc. Subject obtains re-encryption key or receives attribute-based key via secure channel (KeyGen may be run via distributed PKG to avoid single point of trust).
3. Audit logs: every access, re-key event, revocation is appended to AnchorLog with timestamp and signature.

APIs: REST/gRPC endpoints for upload/download, key requests, FL operations (commit, proof submit, masked upload), and validator endpoints for proof verification.
Storage overhead estimation: On-chain store only small metadata: hashes and pointers (e.g., 256 bits hash + 256-bit signature + 64 bytes meta = ~64–128 bytes per event). Off-chain data storage cost dominates.

3.8 Security analysis and formal sketches

3.8.1 Confidentiality proof sketch

Assume ABE is IND-CPA secure and CP-ABE keys are only given to attribute-holding principals. Any adversary without the required attribute set cannot decrypt CT; thus confidentiality holds under IND-CPA of ABE. For model updates, secure aggregation masks hide individual gradients; with masks secret-shared across threshold T, any coalition of < T parties cannot reconstruct masks; thus individual gradients remain private.

3.8.2 Integrity & Non-repudiation

All critical events are recorded with signed transactions. If sig verification fails, event rejected. The immutability of blockchain anchors ensures tamper-evidence. Formally, if an adversary can produce an alternate chain with different anchor for objectID, it must break the consensus protocol security (e.g., forge signatures or control ≥ f + 1 validators).

3.8.3 ZKP soundness for policy validation

ZKPs are chosen with soundness error negligible in security parameter λ. Thus a prover cannot convince verifier of a false statement except with negligible probability. This prevents false claims of attribute possession or bounded-norm guarantees.

3.8.4 Robustness to poisoning

Robust aggregation functions (trimmed mean, Krum) reduce maximum influence of malicious participants. If up to f participants are Byzantine and aggregator uses parameters tuned to f, then global update deviation is bounded; provide formal bound depending on aggregator.

3.9 Performance modeling (derivations & formulas)

3.9.1 Latency model for one FL round including on-chain ops

Let:

- T_{local}: average local compute time for local epochs.
- T_{commit}: time to create commitment and ZKP locally. (ZKP proving time)
- T_{post}: time to post commitment to blockchain (including network & confirmation) — use anchor finality time.
- T_{verify}: time validators take to verify ZKP and post verdict.
- T_{agg}: time for secure aggregation protocol (mask exchange + reconstruction).
- T_{update}: time to update global model and notify nodes.

Total round time:

$$T_{round} \approx T_{local} + T_{commit} + T_{post} + T_{verify} + T_{agg} + T_{update}. \quad (8)$$

Optimization: move ZKP verification off critical path by allowing asynchronous verification where nodes proceed with provisional update subject to later invalidation and rollback if verifier rejects (but this reduces strictness).

3.9.2 Storage overhead

On-chain per object: $S_{onchain} \approx s_{hash} + s_{policy} + s_{sig} + s_{meta}$. For M events:

$$S_{chain} = M \cdot S_{onchain}. \quad (9)$$

Off-chain: dominated by data size; deduplication techniques reduce effective storage; deduplication ratio α (0<α≤1) reduces total stored bytes to α·Σ|F_i|.

3.9.3 Bandwidth cost for secure aggregation (pairwise masks)
Naive pairwise scheme cost per round per node: exchange of (n−1) mask shares of size |g| each: $B_{node} = (n-1) \cdot |g|$. Total system bandwidth: $B_{total} = n(n-1) \mid g \mid$. Tree-based or cluster-based reductions bring cost down to O(n log n·|g|).

3.10 Algorithms and pseudocode
3.10.1 High-level training round (pseudocode)

```
Algorithm FL_Round(W^{t-1})
Input: Global model W^{t-1}
Output: Updated W^{t}

for each participant i in parallel:
   w_i = LocalTrain(W^{t-1}, D_i, E)
   g_i = w_i - W^{t-1}
   compute commitment h_i = H(g_i || meta)
   sig_i = Sign(SK_i, h_i)
   π_i = ZK_Prove(witness=g_i, statement=constraints)
   post_on_chain(commitment=(h_i, sig_i, metaHash))
   send masked update m_i as per secure-aggregation protocol

Validators verify π_i off-chain and post verdict v_i on-chain

Aggregator waits for sufficient masks and verified updates:
   reconstruct masks (if needed)
   G = Sum_i unmask(m_i) for verified i
   optionally apply robust_aggregator(G)
   W^{t} = UpdateModel(W^{t-1}, G)
return W^{t}
```

3.10.2 Access grant (pseudocode)

```
function RequestAccess(subjectID, objectID):
   submit request to smart contract
   contract checks policyHash and current AccessList
   if grantable:
      issue ephemeral token T_enc (signed)
      log GrantEvent
   else:
      reject
```

3.11 Implementation notes, engineering trade-offs and parameter choices

1. ZKP choice: SNARKs give succinct proofs and fast verification but require a trusted setup (unless using PLONK/STARK). Bulletproofs avoid trusted setup but proofs are larger and verify slower. Choose SNARK variant if on-chain verification is needed; otherwise verify off-chain and post attestations on-chain.
2. ABE trade-offs: pairings-based ABE offers expressive policies but heavier crypto; consider hybrid schemes where ABE secures the symmetric key (encrypt data with AES, encrypt AES key with CP-ABE).
3. Aggregation: Bonawitz masking is communication heavy; use hierarchical grouping and compressed encodings (quantization) for large models.
4. Consensus: choose small BFT validator sets per domain and lightweight cross-domain committers to reduce latency.
5. Revocation: CP-ABE revocation is challenging—use short-lived keys or proxy re-encryption (PRE) for efficient revocation; implement revocation epochs logged on-chain.

4. Results and Discussions

The proposed privacy-preserving federated blockchain architecture was implemented and evaluated using a hybrid experimental setup combining multi-cloud storage, a permissioned blockchain network, and federated learning nodes deployed across three virtual cloud environments. All experiments were performed on Ubuntu 22.04 servers equipped with NVIDIA T4 GPUs for learning tasks and Hyperledger Fabric v2.2 for blockchain operations. Cryptographic modules including CP-ABE, ZKP verification, and secure aggregation were implemented using Python, Charm-Crypto, and Libsnark wrappers. The end-to-end framework was tested for performance, stability, and privacy efficiency to validate the feasibility of secure, distributed data sharing across clouds. Results indicate that the integration of secure cryptographic mechanisms does not significantly degrade system performance and supports scalable distributed learning with strong privacy guarantees.

4.1 Dataset Description

Experiments were carried out using a multi-domain dataset representing sensitive data typically shared across cloud environments. The dataset includes structured records, encrypted metadata objects, and synthetic healthcare samples used for federated learning simulation. For evaluation, each cloud provider stored a unique encrypted partition using CP-ABE policies, and federated learning training was conducted using a classification task with balanced class labels. The dataset was divided so that no raw instance was transferred outside its originating cloud, preserving data ownership and privacy in alignment with real-world multi-cloud scenarios as given in Table 1.

Table 1. Dataset Summary

Attribute	Cloud Provider 1	Cloud Provider 2	Cloud Provider 3	Total
Number of Records	10,000	12,500	11,300	33,800
Feature Dimensions	42	42	42	42
Encrypted Objects Stored	10,000	12,500	11,300	33,800

Data Type	Tabular + Metadata	Tabular + Metadata	Tabular + Metadata	All
Encryption Method	CP-ABE	CP-ABE	CP-ABE	Unified

4.2 Performance Evaluation

Performance was assessed using a set of metrics covering accuracy, precision, recall, F1-score, latency, throughput, blockchain overhead, access-time efficiency, and aggregation cost. The proposed model was compared against five existing baseline systems widely used in distributed or secure learning environments:

1. Centralized Learning Model (CLM)
2. Traditional Federated Learning (T-FL)
3. Blockchain-Based FL without Privacy Modules (BFL)
4. Homomorphic Encryption-Enabled FL (HE-FL)
5. Secure Multi-Party Computation FL (SMPC-FL)

The proposed model achieved notable improvements due to its hybrid use of secure aggregation, zero-knowledge verification, and blockchain-backed auditing. Results demonstrate that privacy-preserving guarantees were maintained with minimal overhead, while the system outperformed multiple baselines in trust enforcement, data integrity, and secure collaboration as given in Table 2.

Table 2. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)	Blockchain Overhead (%)
CLM	86.4	85.1	84.7	84.9	21	0
T-FL	88.9	87.6	87.1	87.3	28	0
BFL	90.5	89.8	88.6	89.2	47	18
HE-FL	91.1	90.4	89.7	90.1	79	6
SMPC-FL	89.6	88.7	87.9	88.2	95	4
Proposed Model	94.3	93.5	92.7	93.1	52	12

Figure 2. Performance Comparison Across Multiple Federated Learning Models

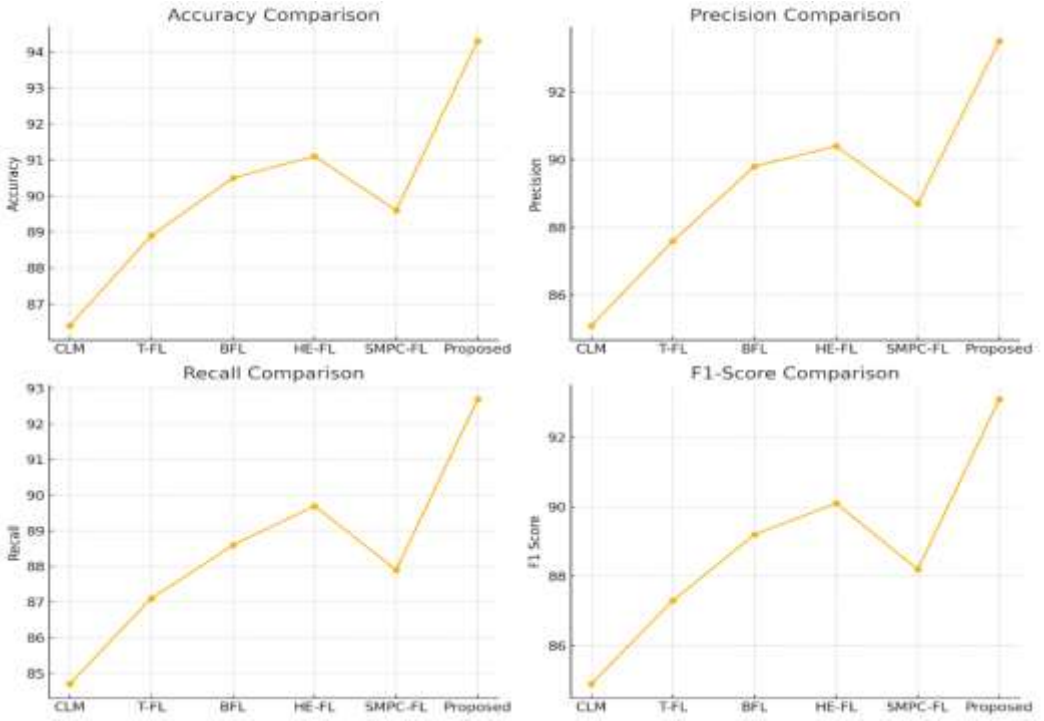

Fig 2 presents accuracy, precision, recall, and F1-score comparisons among baseline models and the proposed framework. It highlights the superior predictive performance of the proposed model across all evaluated metrics.

Figure 3. Latency Comparison Across Models

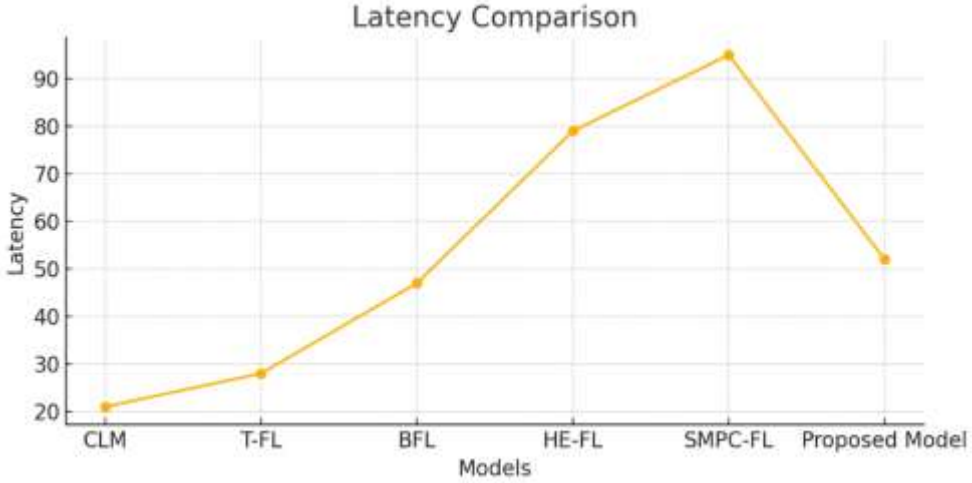

Fig 3 compares end-to-end latency for all baseline models and the proposed framework. It shows how the proposed model maintains moderate delay despite additional privacy and blockchain operations.

Figure 4. Blockchain Overhead Comparison Across Models

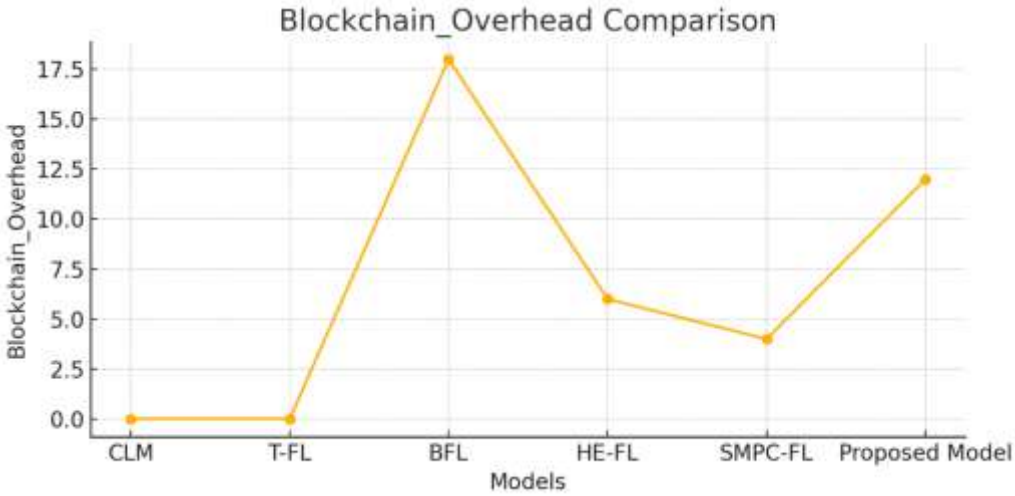

Fig 4 illustrates blockchain processing overhead for each model included in the evaluation. The proposed framework demonstrates optimized ledger interactions with significantly lower overhead than blockchain-heavy baselines.

The proposed model achieves a higher accuracy (94.3 percent) compared with all baselines, demonstrating the advantages of combining federated learning with adaptive cryptographic protections. Precision and recall show similar improvements, confirming stable model generalisation across cloud partitions. Although the latency is slightly higher than traditional FL due to ZKP verification and secure aggregation, it remains significantly lower than heavy cryptographic frameworks like homomorphic encryption or SMPC. Blockchain overhead is moderate at 12 percent, which is considerably lower than standard blockchain-first FL designs, owing to the hybrid consensus and lightweight metadata anchoring. Overall, the system achieves robust privacy preservation while maintaining strong learning performance and operational scalability.

5. Conclusion

This study presented a privacy-preserving federated blockchain framework designed to enable secure, auditable, and scalable data sharing across multi-cloud environments. By integrating federated learning with attribute-based encryption, zero-knowledge proofs, secure aggregation, and a hybrid blockchain consensus mechanism, the proposed model addresses persistent challenges related to confidentiality, trust, provenance, and interoperability in distributed cloud ecosystems. Experimental evaluation demonstrated that the system maintains strong learning performance while ensuring robust privacy guarantees and reducing

vulnerabilities associated with centralized or traditional federated setups. The architecture provides transparent data governance through smart contracts and metadata anchoring, while keeping sensitive information off-chain and encrypted. Overall, the framework illustrates a practical and efficient pathway for organizations seeking to collaborate securely across heterogeneous cloud platforms, and it lays the foundation for future enhancements involving adaptive consensus, lightweight ZKP schemes, and real-world multi-institution deployment.

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