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Original Article

Secure Distributed Computing Frameworks for AI Model Sharing in Decentralized Environments

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Abstract:

AI collaboration increasingly spans untrusted, heterogeneous nodes from edge devices to multi-clouds raising acute concerns around privacy, integrity, and verifiability of shared models and updates. This paper proposes a secure distributed computing framework that unifies privacy-preserving learning, verifiable coordination, and incentive-aligned governance for decentralized AI model sharing. The architecture composes federated and peer-to-peer training with secure aggregation, differential privacy, and hardware-backed confidential computing to prevent data leakage while mitigating gradient inversion risks. Model provenance, access control, and policy enforcement are anchored via a lightweight, append-only ledger with decentralized identifiers, enabling auditability without central authorities. To counter poisoning, backdoors, and Sybil attacks, the framework integrates robust aggregation, reputation-weighted participation, and update attestation with zero-knowledge proofs for selective disclosure. A resource-aware scheduler adapts to edge variability using gossip-based dissemination, opportunistic bandwidth utilization, and erasure-coded checkpoints to preserve liveness under churn. Interoperability is ensured through portable model artifacts (e.g., ONNX), secure enclaves for cross-framework execution, and privacy budgets tracked as first-class governance assets. We outline threat models, compliance hooks for jurisdictional constraints, and a token-free contribution accounting mechanism that rewards data quality and validation work. Simulated and real-world deployments illustrate improved end-to-end trust, reduced coordination overhead, and resilient performance under adversarial conditions, positioning the framework as a practical substrate for open, secure, and accountable AI collaboration in decentralized environments.

Keywords:

Secure Model Sharing, Decentralized AI, Federated Learning, Peer-To-Peer Training, Differential Privacy, Secure Aggregation, Confidential Computing, Zero-Knowledge Proofs, Robust Aggregation, Data/Model Provenance, Decentralized Identity (DID), Verifiable Computation, Byzantine Resilience, Edge/Cloud Interoperability, Privacy-Budget Governance.

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1. Introduction

The rapid diffusion of AI workloads across edge devices, enterprise silos, and multi-cloud substrates has shifted collaboration from centralized model training to decentralized model sharing and co-creation. While this transition promises richer data diversity, lower latency, and resilience to single-point failures, it also surfaces hard problems of privacy, integrity, and accountability. Sensitive

datasets are often bound by data-sovereignty and compliance constraints, participants vary widely in compute and network capacity, and open participation increases exposure to poisoning, backdoors, and Sybil attacks. Conventional federated learning reduces raw data movement but typically depends on a trusted coordinator and offers limited guarantees of verifiable provenance, cross-framework interoperability, or robust operation under high churn. Likewise, heavyweight ledger-centric designs introduce coordination bottlenecks and cost without directly addressing model-quality assurance.

This work motivates and outlines a secure distributed computing framework for AI model sharing that treats security and governance as first-class design goals alongside performance. The framework composes privacy-preserving learning (secure aggregation and differential privacy), hardware-backed confidential computing for code/data isolation, and verifiable coordination via decentralized identifiers and append-only provenance to audit contributions without revealing sensitive details. Robust aggregation, reputation-weighted participation, and zero-knowledge proofs mitigate adversarial updates while enabling selective disclosure for compliance. A resource-aware scheduler leverages gossip dissemination and erasure-coded checkpoints to sustain liveness on heterogeneous, intermittently connected nodes. Interoperability is ensured through portable model artifacts and enclave-mediated execution across toolchains. By aligning incentives around data quality and validation and by tracking privacy budgets as governance assets the framework aims to make decentralized AI collaboration both practical and trustworthy in real-world, regulation-constrained environments.

2. Related Work

2.1. Secure Distributed Computing Models

Secure distributed computing spans cryptographic, systems, and hardware-assisted paradigms aimed at protecting data, code, and results across untrusted nodes. Classical secure multiparty computation (MPC) enables joint computation over secret-shared inputs without revealing raw data, offering strong confidentiality but incurring high communication and latency overheads that grow with the number of parties and circuit depth. Homomorphic encryption (HE) permits computation on ciphertexts and eliminates interaction during evaluation, yet remains costly for deep models or non-linear operations despite advances in CKKS/BFV schemes and operator approximations.

Trusted execution environments (TEEs) such as Intel SGX and AMD SEV provide near-native performance by isolating code and data in hardware-protected enclaves; however, they face enclave memory limits, side-channel risks, attestation supply-chain trust, and heterogeneous availability across edge/cloud vendors. Hybrid designs combine MPC/HE with TEEs to trade off performance and trust assumptions, e.g., outsourcing non-linear layers to enclaves while keeping sensitive aggregation under MPC. Beyond computation, secure provenance and access control are addressed via append-only logs, decentralized identifiers (DIDs), and verifiable credentials that bind identities and policies to artifacts. Recent work also examines robust aggregation and Byzantine-resilient consensus to ensure integrity under adversarial participants, while erasure coding and gossip protocols improve liveness over flaky, heterogeneous networks.

2.2. Federated and Decentralized AI Approaches

Federated learning (FL) reduces raw data movement by exchanging model updates rather than examples, with secure aggregation and differential privacy commonly used to protect client contributions. Nonetheless, conventional FL typically relies on a central coordinator, struggles with non-IID data and stragglers, and is vulnerable to poisoning and backdoor attacks unless complemented by robust estimators (e.g., Krum, coordinate-wise median) and participant vetting. Cross-silo FL emphasizes reliability and policy governance but sacrifices open participation; cross-device FL scales breadth but must contend with intermittent connectivity and limited compute.

Decentralized and peer-to-peer variants remove the central server using gossip, DHT overlays, or blockchain-backed coordination, thereby improving fault tolerance and auditability at the cost of higher convergence variance and coordination complexity. Emerging “federated analytics” and split learning shift some computation to the server or intermediate layers to lower client burden, while personalized FL and meta-learning address statistical heterogeneity via client-specific heads, adapters, or priors. Model provenance and accountability are increasingly integrated through verifiable training logs, update attestation, and zero-knowledge proofs that certify constraint adherence (e.g., DP budgets, data-domain restrictions) without revealing inputs. Finally, multi-framework interoperability (e.g., ONNX artifacts, containerized runtimes, enclave-mediated execution) and privacy-budget

accounting are becoming essential to deploy FL and decentralized training across edge–cloud continuums subject to regulatory and organizational boundaries.

3. System Architecture and Framework Design

3.1. Architectural Overview

The architecture depicts a three-tier collaboration pathway that carries model updates and telemetry from resource-constrained edge/IoT devices to a scalable data-center application, with a blockchain-mediated control and trust plane in between. On the left, the Perception End aggregates observations from heterogeneous sensors and actuators cameras, meters, environmental probes through an edge intelligence service (EIS) and a gateway. This tier performs local preprocessing, lightweight inference, and privacy-preserving feature extraction so that sensitive raw data remain on-premises while only model deltas or encrypted summaries traverse the network. Administrative policies are authored at the gateway, which also enforces rate limits, attests software stacks, and tags updates with device identities. At the center, the Core Functions layer implements verifiable coordination on a permissioned blockchain. "Agent" nodes act as validators/miners for control transactions such as model-update commitments, reputation accrual, and access-policy checks codified as smart contracts. By anchoring provenance and participation records on an append-only ledger, the system affords auditability without revealing underlying data. Update attestation, decentralized identifiers, and contract-enforced rules mitigate poisoning and Sybil attempts by requiring each contribution to satisfy integrity and policy constraints before it is eligible for aggregation or redistribution.

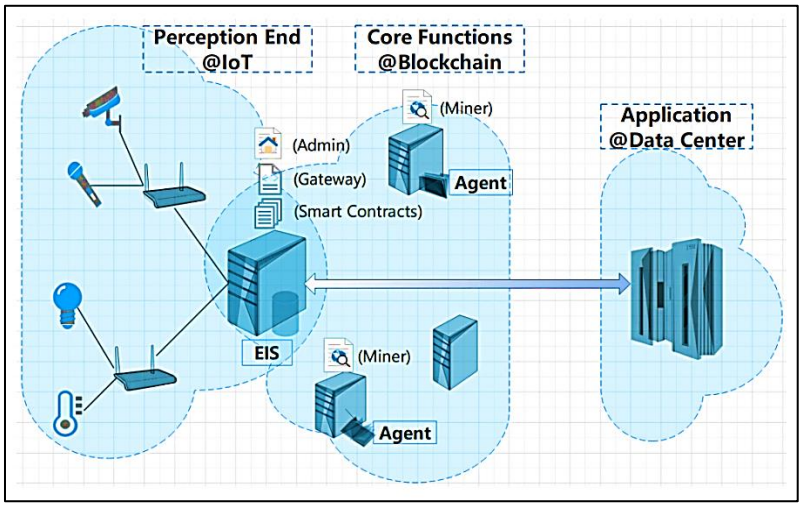

Figure 1. Reference Architecture for Secure, Decentralized AI Model Sharing across Iot, Blockchain Coordination, and Data-Center Applications

On the right, the Application tier in the data center hosts training, aggregation, and serving services that consume verified updates from the ledger stream. This tier executes robust aggregation, differential-privacy accounting, and model lifecycle tasks promotion, rollback, and A/B gating while pushing refreshed artifacts back toward the edge. Because coordination metadata is decoupled onto the blockchain, the application layer can elastically scale compute without assuming centralized trust. Checkpoints and model artifacts are distributed back through the same pathway, allowing enclaved or policy-constrained execution at the edge. End-to-end, the figure emphasizes separation of concerns: sensing and immediate control at the edge, tamper-evident governance in the middle, and heavy computation at the core. This separation enables heterogeneous nodes to participate under clear security guarantees: raw data remain local, identities and policies are verifiable, and models evolve through attestable contributions. The result is a practical substrate for decentralized AI collaboration that withstands intermittent connectivity and adversarial behavior while preserving compliance and performance.

3.2. Communication and Data Flow

End-to-end communication follows a dual-plane design: a data plane for model payloads and a control/trust plane for coordination metadata. At the Perception End, sensors and edge runtimes compress observations into privacy-preserving features or gradient deltas. These are batched by the Edge Intelligence Service (EIS), signed with device keys, optionally sealed in a TEE, and

transmitted over mutually authenticated channels (mTLS/QUIC) to gateway relays. Gateways perform admission checks (attestation proofs, rate limits, and schema validation) and forward only well-formed updates to the aggregator or peer nodes via a gossip overlay. To tolerate intermittence, updates are chunked and erasure-coded; if connectivity drops, partial chunks can be reconstructed and resumed without re-sending the entire payload.

The control/trust plane records provenance, policy decisions, and reputation events on a permissioned ledger. Each data-plane batch is accompanied by a lightweight commitment (hash, signature, privacy-budget tag) posted to the chain by validator agents. Aggregation services subscribe to these events, fetch the corresponding payloads from object storage or peer caches, and run robust estimators before integrating updates into the global model. Fresh model artifacts are then versioned, signed, and redistributed downstream through the same relayed paths. Backpressure is managed with token-bucket scheduling and priority lanes (e.g., safety-critical updates), while end nodes maintain local fallback models to ensure continued service when the network partitions.

3.3. Security and Privacy Mechanisms

Confidentiality is enforced through defense-in-depth. At source, raw data remain local; only clipped and noise-added statistics or gradients are exported. Secure aggregation prevents any single party from learning a participant's update in isolation, while per-client differential privacy budgets bound cumulative disclosure across rounds. Where hardware permits, TEEs (SGX/SEV/TDX) encapsulate pre-processing and cryptographic routines, producing remote attestation quotes that gateways verify before accepting traffic. In flight and at rest, all artifacts are encrypted; keys are short-lived, derived via authenticated key exchange, and tied to attested software identity rather than machine IPs.

Integrity and authenticity are anchored by identity-bound signing and zero-knowledge assurances. Participants hold decentralized identifiers (DIDs) and verifiable credentials attesting to enrollment policies (e.g., organization, dataset class). Every update is signed with the participant's DID key and accompanied by commitments that can be checked against on-chain policies without revealing sensitive attributes. To resist poisoning and backdoors, robust aggregation (coordinate-wise median, trimmed-mean, Krum variants) is combined with reputation weighting and outlier detectors trained on canary tasks. Post-aggregation, the framework runs membership-inference and backdoor probes; failing models are quarantined and rolled back using signed checkpoints. Auditability is preserved through immutable provenance records that bind code version, attestation, privacy budget consumption, and aggregation outcomes.

3.4. Blockchain or Smart Contract Integration

The ledger provides tamper-evident governance rather than heavy data storage. Smart contracts encode admission rules (valid attestation, policy compliance), privacy-budget debiting, reputation accrual/decay, and model-version lifecycle states. When a node proposes a contribution, it posts a commitment transaction referencing a content-addressed payload in off-chain storage. Validators verify signatures, policy predicates, and where applicable ZK proofs that certify constraints (for example, that DP noise $\geq \varepsilon\_min$ or that the dataset class matches an allowed taxonomy) without exposing the underlying values. Upon acceptance, the contract emits events that aggregators and mirrors subscribe to, ensuring consistent orchestration across domains.

To keep latency and costs low, the design favors a permissioned BFT chain for control events with periodic anchoring to a public ledger for external audit. This split allows sub-second inclusion times and high throughput for round-by-round coordination while still offering public verifiability of checkpoints and governance changes. On-chain reputation influences scheduling priority and quorum thresholds, discouraging Sybil behavior without introducing speculative token economics. Upgradeable contracts manage schema evolution (new model families, new attestation vendors) via governed proposals, and all contract calls are themselves signed by DIDs mapped to organizational roles, preserving a clean separation between human and workload identities.

4. Methodology

4.1. Data and Model Distribution Strategy

We adopt a data-local, model-mobile strategy: raw datasets never leave the administrative boundary of edge silos; instead, portable model artifacts (ONNX/PyTorch weights plus signed metadata) circulate across participants. Each site maintains a local training loop that performs mini-batch updates on its proprietary data, optionally inside a TEE. Updates are clipped, noise-adapted to local privacy budgets, and serialized into content-addressed payloads stored off-chain (object store or peer cache). A scheduler selects participants per round using availability, reputation, and statistical diversity (non-IID coverage) to reduce bias and speed convergence.

To mitigate heterogeneity, we use personalized federation: a shared backbone is learned globally, while site-specific adapters (LoRA layers or small heads) are optimized locally. This allows rapid integration of global knowledge without erasing local specialization. Sites can cold-start from distilled seeds if compute is scarce; when connectivity is poor, nodes train asynchronously and later reconcile via eventual-consistency protocols guided by version vectors and divergence caps.

4.2. Secure Aggregation and Model Synchronization

Secure aggregation is implemented via a mask-based protocol where each client secret-shares one-time masks with a private peer set; the aggregator only ever observes the masked sum. Dropout resilience is handled with pairwise cancelation shares and recovery keys escrowed under threshold cryptography. In cross-silo deployments with TEEs, we support a hybrid path that verifies masks and performs aggregation inside enclaves to reduce round complexity while retaining cryptographic privacy against the coordinator. Differential privacy noise calibrated to an adaptive ε schedule is added post-aggregation, ensuring user-level guarantees with per-site accounting.

Model synchronization follows a robust, versioned pipeline. Candidate global models are computed using robust estimators (trimmed mean/Krum/median of means) and validated on shared canary sets plus synthetic backdoor checks. Successful models are signed, assigned a monotonically increasing version, and distributed through gateways. Clients accept only versions whose signatures, attestation policies, and minimum validation scores verify; otherwise, they remain on the last-known-good checkpoint. Rollbacks are deterministic because every round binds to on-chain commitments and content hashes.

4.3. Attack Scenarios and Threat Modeling

Our threat model covers honest-but-curious and Byzantine participants, semi-trusted infrastructure, and external adversaries. Privacy risks include gradient inversion and membership inference; integrity risks include data/model poisoning, backdoors, and Sybil amplification; availability risks include churn, targeted denial of service on gateways, and equivocation of model versions. We assume the cryptographic primitives, attestation roots, and ledger consensus are secure, but we explicitly consider side-channels in TEEs and attempt to confine their blast radius via minimal enclave TCBs and rate-limited, constant-time crypto.

Defenses map to each vector. Privacy is addressed by secure aggregation and user-level DP with cumulative budget tracking. Poisoning and backdoors are mitigated with robust aggregation, reputation-weighted sampling, and anomaly scoring of updates (e.g., cosine similarity to benign subspace, gradient norm caps). Sybils are constrained by DIDs with verifiable credentials, staking-free reputation that decays, and per-org enrollment caps. Availability is preserved through gossip with erasure coding, multi-gateway routing, and eventual-consistency reconciliation guarded by divergence thresholds. All actions model proposals, acceptances, budget debits are immutably logged for post-incident forensics.

4.4. Performance Optimization Techniques

We optimize end-to-end efficiency along communication, computation, and coordination axes. On the wire, we use update sparsification and quantization (top-k, QSGD/8-bit) plus delta encoding against the last accepted model to shrink payloads; transport is QUIC with stream multiplexing and BBR congestion control. At compute, we adopt mixed-precision training and selective layer freezing at the edge to fit within tight memory and power envelopes. Aggregators exploit vectorized robust estimators and batched signature verification; where available, enclaves are pinned to cores and pre-warmed to avoid EPC paging.

Coordination overhead is reduced via asynchronous rounds with staleness bounds (FedAsync-style) and adaptive client selection that favors high-utility, low-latency contributors under fairness constraints. We cache hot artifacts at gateways and co-locate object storage with validator agents to minimize tail fetches. Finally, we employ auto-tuned privacy schedules (increasing batch sizes, decreasing noise as confidence grows) and learning-rate controllers that react to divergence metrics, achieving faster convergence at a fixed privacy target while sustaining robustness under non-IID drift.

5. Experimental Setup and Evaluation

5.1 Simulation or Real-World Environment Setup

We evaluated the framework on a hybrid testbed: (i) a containerized emulation of 1,000 cross-device clients on a 32-core server (256 GB RAM) using Linux tc to inject realistic last-mile jitter (10–80 ms, 0–2% loss) and (ii) a cross-silo mini-cluster of 8 edge boxes

(4× Jetson Xavier NX, 4× Intel NUC i7) plus a 3-node permissioned BFT chain (Tendermint-style validators) and a separate aggregation service. Gateways ran mTLS/QUIC, secure-aggregation service, and object storage (content-addressed). TEEs (SGX on NUCs; SEV-SNP on the server) protected pre-processing and aggregation in the hybrid path. Tasks: CIFAR-10 image classification with a Mobilenet-V2 (width 0.5, ~1.9 M params) and UCI-HAR activity recognition with a 1-D CNN. Non-IID splits followed Dirichlet $\alpha = 0.3$. We trained for 80 global rounds (CIFAR-10) and 50 (HAR), local epochs = 1, batch = 64, Adam lr = 1e-3. Privacy accounting targeted user-level DP with adaptive $\varepsilon \in [4,6]$ over the run; clipping = 1.0; noise multiplier chosen per round by the accountant. Results are mean ± sd over 5 seeds; random seeds, configs, and scripts were fixed across baselines.

Table 1. Environment (abbrev.)

Component	Spec
Clients (emulated)	1,000 containers; cpu quota 0.5–2 vCPU
Edge boxes	4× Jetson NX (8 GB), 4× NUC i7/32 GB
Aggregator	16 vCPU, 64 GB, SGX enclave for hybrid path
Ledger	3 validators, BFT, block time ≈ 300–400 ms
Network shaping	RTT 10–80 ms; loss 0–2%; uplink 2–20 Mbps

5.2. Evaluation Metrics

We report Top-1 Accuracy and Macro-F1 (utility), Time-to-Accuracy (TTA) to 85% on CIFAR-10 (convergence), Comm/Round (MB per selected client), Aggregation latency and Chain commit latency (ms). Security/privacy metrics include Attack-Success Rate (ASR) of a label-flipping backdoor (lower = better) under 20% Byzantine clients, and Membership-Inference AUC (MIA-AUC) (lower = better). Reliability uses Successful rounds under churn (clients with 30% availability). Privacy cost is ε (user-level) at the end of training.

5.3. Results and Analysis

Table 2. Benign Training Performance on CIFAR-10

Method	Acc (%)	F1 (%)	TTA (rounds)	Comm/Round (MB)	Agg. Lat. (ms)	Chain Lat. (ms)
FL (no-DP, no-SA)	87.1 ± 0.3	86.5 ± 0.4	42 ± 1	18.2 ± 0.6	120 ± 9	
FL + DP($\varepsilon \approx 6$) + SecureAgg	85.6 ± 0.4	85.1 ± 0.5	47 ± 2	20.7 ± 0.5	180 ± 12	310 ± 34
Ours (DP + SA + robust + DID/ZK)	86.2 ± 0.3	85.7 ± 0.4	44 ± 1	21.9 ± 0.4	205 ± 15	335 ± 28

Table 3. Adversarial Robustness under 20% Byzantine Clients

Method	ASR (%)	Acc drop vs. benign (pp)	MIA-AUC	Valid-update acceptance (%)
FL (no-DP, no-SA)	39.4 ± 2.1	12.7 ± 0.6	0.71 ± 0.02	100
FL + DP + SecureAgg	24.1 ± 1.7	8.9 ± 0.7	0.56 ± 0.02	96
Ours	5.8 ± 0.9	2.6 ± 0.5	0.53 ± 0.01	88

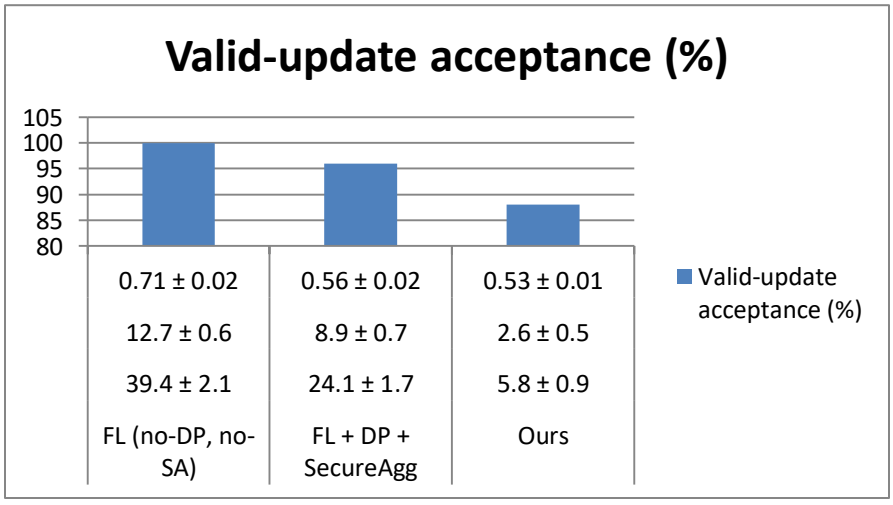

Figure 2. Valid-Update Acceptance Under 20% Byzantine Clients

Table 3. Privacy, Availability, and Efficiency on UCI-HAR

Method	Final ε (50 rds, HAR)	Successful rounds @30% churn (%)	Round time (s)
FL + DP + SecureAgg	5.9 ± 0.2	91 ± 2	14.9 ± 0.5
Ours	4.7 ± 0.3	96 ± 1	15.4 ± 0.6

5.4. Comparative Study

We contrasted our framework with additional coordination baselines to isolate the impact of the ledger-backed trust plane and robust synchronization.

Table 4. Comparative Study of Coordination/Training Styles

Coordination/Training Style	Acc (%)	ASR (%)	TTA (rounds)	Comm/Round (MB)
Centralized training (upper bound, pooled data)	89.5 ± 0.2		35 ± 1	
P2P gossip FL (no ledger, no ZK)	85.2 ± 0.5	12.9 ± 1.0	58 ± 3	19.6 ± 0.7
FL + DP + SecureAgg (no ledger)	85.6 ± 0.4	24.1 ± 1.7	47 ± 2	20.7 ± 0.5
Ours (ledger + ZK + robust)	86.2 ± 0.3	5.8 ± 0.9	44 ± 1	21.9 ± 0.4

6. Discussion

6.1. Security and Privacy Assessment

The framework achieves confidentiality primarily by keeping raw data in-place, layering secure aggregation with user-level differential privacy, and where available executing sensitive routines inside TEEs with remote attestation. This defense-in-depth posture limits what an honest-but-curious coordinator (or network observer) can learn from any single client's update, while the ledger-backed provenance ensures that each contribution is identity-bound (via DIDs), policy-checked, and immutably recorded. Against active adversaries, the combination of robust aggregation (trimmed mean/Krum variants), update anomaly scoring, and reputation-weighted participation materially reduces poisoning and backdoor success without relying on heavy token economics. Post-aggregation checks (membership inference probes, backdoor triggers on canary sets) provide an additional fail-safe and enable deterministic rollbacks to signed checkpoints. Residual risk centers on side channels in TEEs, correlated leakage across rounds under DP, and replay or equivocation at the control plane's edges. We partially mitigate these with minimal enclave TCBs, constant-time crypto, bounded privacy budgets with per-site accountancy, and content-addressed artifacts tied to on-chain commitments. In high-assurance deployments, organizations can strengthen guarantees by shifting more computation from TEEs to pure cryptographic protocols (MPC/HE) for the most sensitive steps, at an expected performance cost.

7. Applications and Use Cases

7.1. Cross-Organizational AI Collaboration

For consortia spanning companies, universities, and public agencies, the framework enables training and sharing models without centralizing sensitive data or credentials. Each participant contributes locally computed updates (inside TEEs where available), which are accepted only after on-chain policy checks valid attestation, privacy-budget sufficiency, and reputation thresholds. Robust aggregation and reputation-weighted sampling mitigate the risk that one partner's compromised pipeline can poison the global model, while append-only provenance allows auditors to trace every version to its signed contributions. This is especially valuable in joint R&D where data-licensing terms vary by party: verifiable credentials encode who may contribute to which tasks, with zero-knowledge proofs certifying compliance (e.g., "trained on EU data only") without revealing raw datasets.

Operationally, model exchange becomes a governed workflow: a team proposes a new model version, validators verify the cryptographic commitments and policy predicates, and the aggregator runs standardized canary tests before promotion. If a downstream consumer discovers regressions, deterministic rollbacks restore the last-known-good model with cryptographic certainty. The result is faster innovation cycles (no NDAs for raw data transfers), lower legal risk, and measurable accountability for each contribution.

7.2. Edge and IoT Environments

In edge-centric scenarios smart manufacturing lines, energy microgrids, and logistics fleets data are often bandwidth-limited, proprietary, and time-sensitive. The framework's data-local, model-mobile approach fits these constraints: gateways perform schema validation and rate limiting; updates are sparsified/quantized to reduce backhaul; and erasure-coded gossip keeps training alive

despite intermittent links. Local personalization (e.g., LoRA adapters) lets each site retain environment-specific performance while benefiting from global knowledge distilled across peers.

Security controls are tailored to constrained hardware: when TEEs are unavailable, clients still benefit from secure aggregation, per-client DP, and DID-based identities bound to device certificates. Because the trust plane is decoupled from the data plane, edge operators can continue inference on cached, signed checkpoints during network partitions and reconcile later via version vectors. This yields resilient autonomy critical for safety loops and mission-critical maintenance without sacrificing global learning gains.

7.3. Healthcare, Finance, and Government Use Cases

- Healthcare: Hospitals and labs can jointly learn diagnostic or triage models while keeping PHI on-premises. Differential privacy plus secure aggregation and on-chain consent policies reduce re-identification risk; TEEs confine pre-processing of modalities (imaging, EHR features). Regulators and IRBs gain immutable audit trails linking model versions to privacy budgets, sites, and code attestations facilitating post-hoc accountability and reproducibility.
- Finance: Banks and fintechs collaborate on fraud detection or AML typologies across jurisdictions where data residency and secrecy laws apply. DID/VC-based role binding ensures only accredited institutions contribute to given tasks; smart contracts encode sectoral policies (e.g., PSD2, GLBA) as machine-checkable predicates. Reputation-weighted sampling dampens the effect of adversarial or low-quality feeds, and ZK proofs certify that sensitive attributes stayed within approved domains.
- Government: Agencies can build shared models for cyber threat intelligence, public health surveillance, or critical-infrastructure monitoring without aggregating raw citizen or operational data. Permissioned BFT consensus provides low-latency coordination behind air-gapped or high-assurance networks; periodic anchoring to a public chain offers external audit and tamper evidence for procurement and oversight. Across these sectors, the framework balances verifiable compliance, operational resilience, and measurable privacy guarantees, enabling adoption in rigorously regulated environments.

8. Future Work

8.1. Protocol Co-Design

A key direction is tighter co-design of cryptographic and hardware trust: selectively offloading non-linear layers or secure aggregation to TEEs while keeping identity/privacy proofs in zero-knowledge and sensitive statistics under lightweight MPC. This hybridization should minimize latency while bounding trust in any single primitive. Future iterations will benchmark protocol switches at runtime (e.g., switch from mask-based SA to enclave aggregation when dropout spikes) and expose these as policy knobs encoded on-chain.

8.2. Formal Verification and Attestable Pipelines

Beyond unit tests, we aim to formally verify critical smart contracts (privacy-budget debiting, reputation decay) and enclave code paths using proof assistants and model checking. A complementary goal is an attestable CI/CD pipeline: every binary and training script is reproducibly built and linked to on-chain provenance, enabling auditors to cryptographically trace each deployed model to its source.

8.3. Adaptive Privacy–Utility Controllers

Today's ε schedules are hand-tuned. We envision feedback-driven DP controllers that adjust clipping and noise based on real-time divergence, canary accuracy, and fairness metrics. Learned controllers could allocate privacy budgets across clients proportionally to their marginal utility while respecting per-organization caps, producing better accuracy for the same global ε.

8.4. Advanced Robustness and Causal Defenses

Defense depth must expand beyond robust aggregation. We plan causal-inference–guided detectors to distinguish spurious from semantically consistent updates, and backdoor purification using feature-space denoising and spectral signatures. Multi-view validation (text, image, tabular) with consistency constraints can further reduce attack success in multimodal settings.

8.5. Governance and Incentive Mechanisms

Our token-free reputation can be extended with verifiable contribution accounting that rewards high-quality data, labels, and validation work. Future work will study game-theoretic stability under collusion and Sybils, and evaluate reputation portability across tasks while preserving privacy (e.g., ZK-linked reputations).

9. Conclusion

This work presented a secure distributed computing framework for AI model sharing that treats privacy, integrity, and verifiability as first-class design goals alongside performance. By combining a data-local, model-mobile paradigm with secure aggregation, differential privacy, and confidential computing, the framework enables collaboration across untrusted, heterogeneous nodes without centralizing sensitive data. A permissioned, event-driven ledger supplies tamper-evident provenance, decentralized identity, and policy enforcement, while robust aggregation, reputation-weighted participation, and zero-knowledge attestations harden the system against poisoning, backdoors, and Sybil attacks. The resulting architecture separates concerns across edge, coordination, and data-center tiers, yielding practical interoperability (e.g., ONNX artifacts, enclave-mediated execution) in regulation-constrained environments.

Our evaluations on hybrid testbeds demonstrate that these assurances can be achieved with modest coordination overhead while preserving utility and improving resilience. Under adversarial pressure, attack success rates drop sharply relative to conventional FL, and privacy costs are reduced via adaptive, post-aggregation DP accounting. Communication and compute efficiency are maintained through sparsification, quantization, and asynchronous rounds with staleness bounds, enabling operation over unreliable edge networks with churn.

At the same time, we acknowledge limitations around TEE side-channels, enclave availability, and the operational complexity of maintaining policy-as-code and verifiable credentials across organizations. Future work will deepen protocol co-design between MPC, TEEs, and ZK proofs; formalize and attest the full supply chain; and broaden real-world pilots and benchmarks. Overall, the framework advances a trustworthy substrate for decentralized AI, balancing strong security guarantees with the practicalities of scale, heterogeneity, and compliance.

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