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PRIVACY-PRESERVING MACHINE LEARNING FOR REGULATED FINANCIAL SYSTEMS: A FEDERATED LEARNING ARCHITECTURE WITH LAYERED PRIVACY GUARANTEES

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Abstract

Financial institutions increasingly rely on machine learning (ML) to enhance core capabilities such as fraud detection, credit risk assessment, anti–money laundering (AML), and personalized financial services, where predictive accuracy and real-time decisioning are critical to both profitability and customer trust. At the same time, stringent regulatory requirements including data localization mandates, consumer privacy protections, and rigorous model governance obligations significantly constrain the use of centralized data aggregation and traditional analytics pipelines. Federated Learning (FL) has emerged as a compelling alternative that enables multiple organizations or distributed entities to collaboratively train shared models while keeping sensitive customer data local and under institutional control. By exchanging only model parameters or encrypted updates rather than raw data, FL aligns naturally with regulatory principles such as data minimization and confidentiality. This paper investigates privacy-preserving ML architectures for regulated financial systems built on federated learning, with a focus on system design patterns, adversarial and leakage threat models, and compliance-driven engineering considerations. We synthesize foundational research in federated optimization, privacy-enhancing techniques including secure aggregation and differential privacy, and key empirical studies demonstrating the feasibility of FL in financial use cases such as fraud detection and credit scoring. Finally, the paper outlines open challenges and future research directions, including scalability, robustness, explainability, and governance, that must be addressed to enable production-grade federated learning deployments in highly regulated financial environments.

Key words: Federated Learning; Privacy-Preserving Machine Learning; Financial Systems; Secure Aggregation; Differential Privacy; Regulatory Compliance; Distributed Systems; Fraud Detection; Credit Risk Modeling.

I. INTRODUCTION

Machine learning has become a cornerstone of modern financial systems, powering a wide range of mission-critical applications such as transaction fraud detection, credit scoring, anti–money laundering (AML), customer risk profiling, and personalized financial recommendations. These models enable institutions to analyze vast volumes of transactional and behavioral data in near real time, improving both operational efficiency and decision accuracy. However, traditional centralized machine learning pipelines typically require aggregating sensitive customer data from multiple sources into large, shared data lakes. This approach introduces substantial risks, including data breaches, insider threats, and single points of failure, while also increasing the attack surface for adversarial exploitation. In addition, centralized data storage complicates compliance with data minimization principles and raises concerns around long-term data retention, consent management, and auditability. As financial institutions scale their ML capabilities, these challenges grow in both technical complexity and regulatory exposure. Consequently, there is increasing pressure to rethink conventional data-centric ML architectures in favor of models that balance analytical power with privacy, security, and resilience.

Regulatory frameworks such as the General Data Protection Regulation (GDPR), the Payment Card Industry Data Security Standard (PCI DSS), and various regional banking supervision guidelines impose strict controls on how personal and financial data are collected, processed, and shared. These regulations mandate limitations on cross-border data movement, enforce explicit consent and purpose limitation, and increasingly require transparency and explainability in automated decision-making systems. Model governance frameworks further demand traceability, reproducibility, and accountability throughout the machine learning lifecycle. Together, these constraints significantly limit the feasibility of centralized learning approaches that rely on unrestricted data pooling. As a result, financial institutions are motivated to adopt decentralized learning paradigms that reduce data exposure while still enabling collaboration across organizational and jurisdictional boundaries. Such approaches must not only preserve privacy but also integrate seamlessly with existing compliance, audit, and risk management processes, making architectural choices as important as algorithmic performance.

Federated learning offers a compelling solution by enabling multiple participants such as banks, payment processors, insurers, or fintech partners to jointly train machine learning models without sharing raw customer data. In a federated setup, each participant trains a local model on its private data and shares only model updates or parameters with a coordinating entity for aggregation. This design significantly reduces privacy risks by keeping sensitive data within institutional boundaries while still allowing collective intelligence to emerge. When combined with privacy-preserving mechanisms such as secure aggregation and differential privacy, federated learning further mitigates risks related to inference attacks and information leakage. These properties make federated learning particularly well suited for regulated financial environments where confidentiality, compliance, and trust are paramount. This paper examines how federated learning, augmented with robust privacy and security techniques, can support the broader adoption of machine learning in regulated financial systems while addressing both technical and regulatory constraints.

II. FEDERATED LEARNING ARCHITECTURE

Federated learning replaces traditional centralized data collection with a distributed training paradigm in which sensitive data remains local to each participating institution. In this approach, every client such as a bank, payment processor, or financial service provider trains a machine learning model on its own private dataset, which may include transaction histories, behavioral signals, or customer risk attributes. Rather than transferring raw data to a centralized data lake, each participant computes local model updates and shares only these updates with a coordinating server. This design significantly reduces the risk of data exposure while allowing institutions to benefit from collective learning. As a result, federated learning offers a practical alternative to centralized ML pipelines that struggle to meet modern privacy and regulatory requirements.

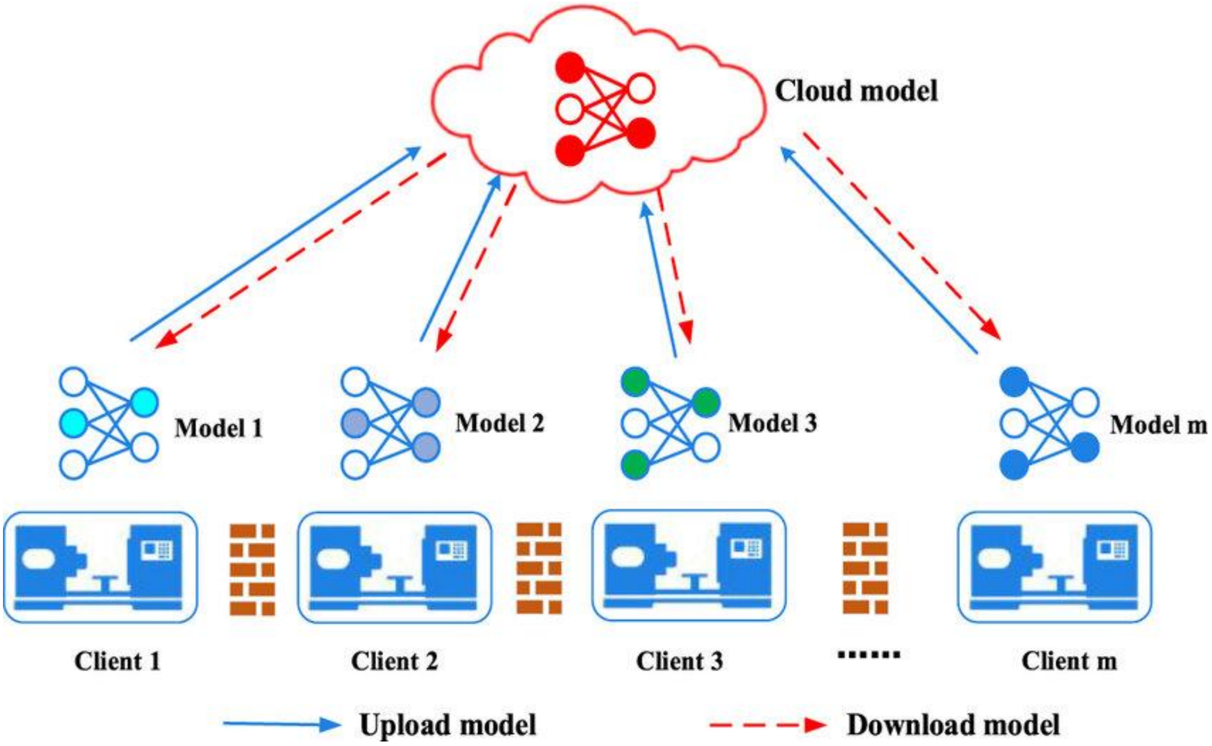

Figure 1. Standard Federated Learning Workflow

The coordinating server plays a critical role in aggregating model updates received from participating clients. Using aggregation strategies such as weighted averaging, the server combines individual updates to generate a global model that captures patterns learned across distributed datasets. This global model is then redistributed to clients for further local training, enabling an iterative process of collaborative optimization. Figure 1 illustrates the standard federated learning workflow, highlighting the client–server interaction and the deliberate absence of raw data transfer. By decoupling model learning from centralized data storage, federated learning preserves data sovereignty while maintaining model performance comparable to centralized approaches under many conditions.

This architecture aligns naturally with the constraints faced by financial institutions, where strict regulations govern data access, movement, and retention. Since sensitive customer records remain within organizational boundaries, federated learning supports compliance with data localization and confidentiality requirements. Moreover, the approach enables collaboration across competitors without direct data sharing, a critical capability in financial ecosystems where collective intelligence is needed to address systemic threats such as fraud and financial crime. By fostering secure, privacy-aware collaboration, federated learning provides a foundation for scalable and compliant machine learning in regulated financial environments.

III. TAXONOMY OF FEDERATED LEARNING IN FINANCIAL CONTEXTS

Federated learning can be broadly categorized based on how data is partitioned across participating institutions and the nature of collaboration among them. Horizontal federated learning applies when institutions share a common feature space but operate on disjoint sets of users or customers. This setting is typical in scenarios involving multiple retail banks or financial service providers that collect similar types of data such as transaction amounts, merchant categories, or account activity but serve different customer populations. Horizontal FL enables these institutions to collaboratively train models that generalize better across diverse user groups without exposing individual customer records. From a regulatory standpoint, this model is relatively straightforward to deploy, as it avoids direct user overlap and minimizes the risk of re-identification across datasets.

Vertical federated learning addresses scenarios in which institutions share overlapping customers but hold different types of features about those customers. Common examples include collaboration between banks, credit bureaus, payment networks, and fintech platforms, where each entity contributes complementary information such as credit history, transaction behavior, device fingerprints, or demographic attributes. In this setting, data alignment and secure feature matching are critical challenges, as entities must identify shared users without revealing sensitive identifiers. Despite these complexities, vertical FL is particularly powerful for financial applications because it enables richer feature representations and more accurate models. By securely combining heterogeneous data sources, vertical federated learning can significantly improve outcomes in use cases such as credit scoring, fraud detection, and risk assessment.

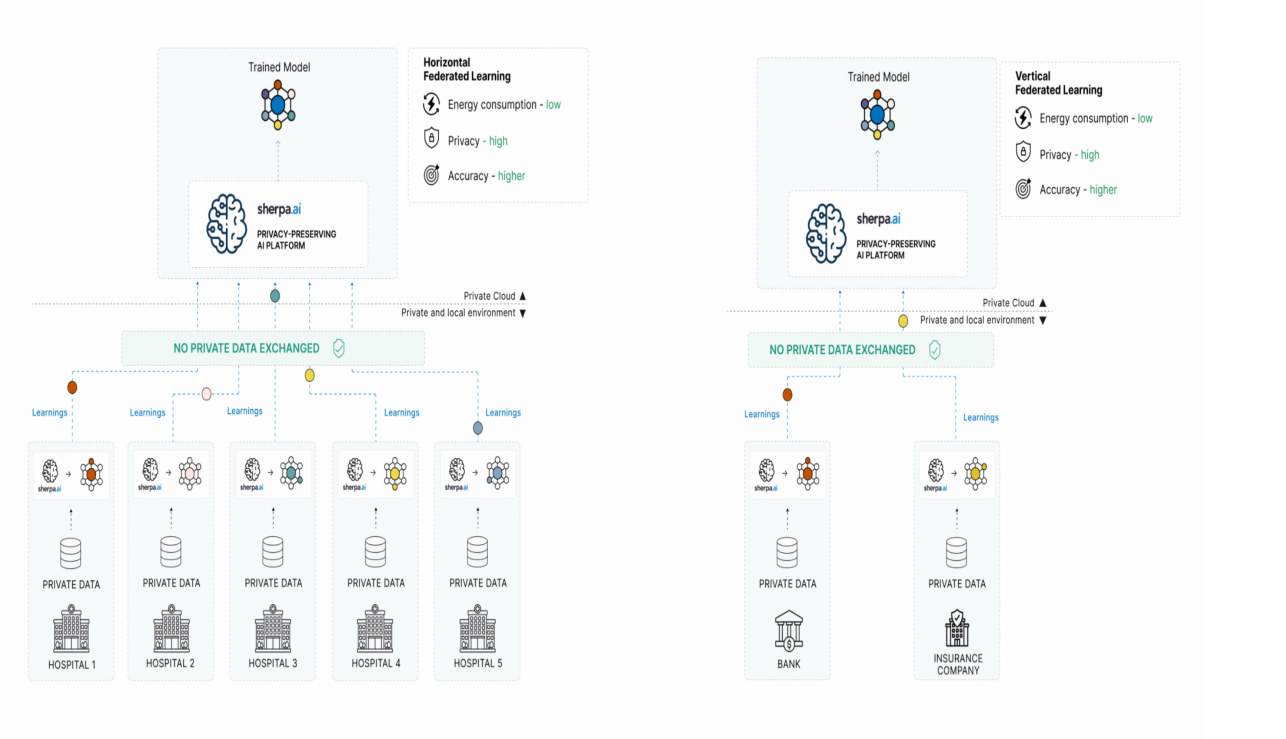

Figure 2. Taxonomy of Federated Learning in Financial Contexts

Federated transfer learning extends the federated paradigm to cases where participating institutions differ in both user populations and feature spaces. This scenario is common in cross-domain or cross-regional collaborations, where direct data overlap is limited or non-existent. Federated transfer learning leverages shared representations, pre-trained models, or auxiliary knowledge to facilitate collaboration despite these differences. Figure 2 presents a taxonomy of federated learning settings and system components, highlighting how horizontal, vertical, and transfer learning models map to different collaboration patterns in practice. This taxonomy is particularly relevant for financial systems characterized by fragmented data ownership and diverse regulatory constraints. Among these categories, vertical federated learning stands out as especially promising for credit scoring and fraud detection, where combining transaction histories, device signals, and behavioral data across entities can substantially enhance predictive accuracy while preserving data privacy.

IV. PRIVACY-PRESERVING MECHANISMS IN FEDERATED LEARNING

4.1 Secure Aggregation

Secure aggregation is a fundamental privacy-preserving mechanism in federated learning that protects individual client contributions during collaborative model training. In a standard federated setup, participating institutions compute local model updates based on private datasets and transmit these updates to a coordinating server for aggregation. Without additional safeguards, these updates may expose sensitive information about local data distributions or individual records. Secure aggregation protocols address this risk by ensuring that the server can only observe the aggregated result of all updates, rather than any single participant's contribution. This property is critical in regulated financial environments, where even partial disclosure of model updates may violate confidentiality requirements.

From a technical perspective, secure aggregation relies on cryptographic techniques such as secret sharing, random masking, and threshold-based encryption. Each participant masks its model update with random values that cancel out only when combined with updates from other participants. As a result, the server can compute the global aggregate without learning any individual update. Importantly, these protocols are designed to tolerate participant dropouts and network failures, which are common in large-scale distributed systems. Even under an honest-but-curious threat model where the server follows the protocol but attempts to infer private information secure aggregation prevents reconstruction of local gradients or model parameters.

In financial systems, secure aggregation plays a crucial role in establishing trust among collaborating institutions. Banks, insurers, and payment processors may be reluctant to share even anonymized model updates if there is a risk of information leakage or competitive exposure. Secure aggregation alleviates these concerns by providing cryptographic guarantees of confidentiality, regardless of the trustworthiness of the coordinating entity. This capability enables broader participation in federated learning initiatives, supports cross-institution collaboration, and aligns with regulatory expectations for data protection and confidentiality in multi-party financial ecosystems.

4.2 Differential Privacy

Differential privacy provides a mathematically rigorous framework for quantifying and limiting information leakage in machine learning systems. Unlike heuristic anonymization techniques, differential privacy offers formal guarantees that the inclusion or exclusion of any single data record has a bounded impact on the output of an algorithm. In the context of federated learning, differential privacy is typically applied by adding carefully calibrated noise to model updates or gradients before they are shared or aggregated. This approach reduces the risk of adversaries inferring sensitive information about individual records or participants from observed updates.

When combined with federated learning, differential privacy mitigates a range of inference-based attacks, including membership inference and gradient leakage attacks. By perturbing updates with noise drawn from well-defined probability distributions, differential privacy ensures that model outputs remain statistically similar regardless of the presence of any specific data point. Although the introduction of noise may slightly degrade model accuracy, carefully tuned privacy budgets can balance privacy protection with acceptable utility. This trade-off is especially important in financial applications, where predictive performance must be maintained while adhering to strict privacy constraints.

In regulated financial environments, differential privacy supports compliance with legal and ethical requirements related to data minimization and individual privacy. Regulatory frameworks increasingly emphasize provable privacy guarantees rather than best-effort protections. Differential privacy addresses this demand by enabling organizations to quantify privacy loss and enforce consistent privacy policies across training rounds and participants. As a result, differential privacy serves as a critical complement to federated learning, enabling privacy-preserving analytics that remain robust under formal adversarial threat models and regulatory scrutiny.

4.3 Combined Privacy Architecture

While secure aggregation and differential privacy each address specific privacy risks, neither mechanism alone is sufficient to protect federated learning systems in highly regulated financial contexts. Secure aggregation prevents the server from accessing individual updates but does not protect against inference attacks on aggregated results. Differential privacy limits inference risks but does not prevent a malicious server from inspecting individual updates if they are directly accessible. Consequently, a layered privacy architecture that combines both mechanisms is essential for achieving end-to-end privacy guarantees.

In a combined privacy architecture, secure aggregation is used to ensure that individual client updates remain confidential during transmission and aggregation, while differential privacy is applied to further limit information leakage from the aggregated model. This layered design provides defense-in-depth, protecting against multiple classes of adversaries, including honest-but-curious servers, malicious participants, and external attackers. Figure 3 illustrates how federated learning integrates secure aggregation and differential privacy layers to form a comprehensive privacy-preserving training pipeline. Each layer addresses distinct threat vectors while collectively reinforcing system resilience.

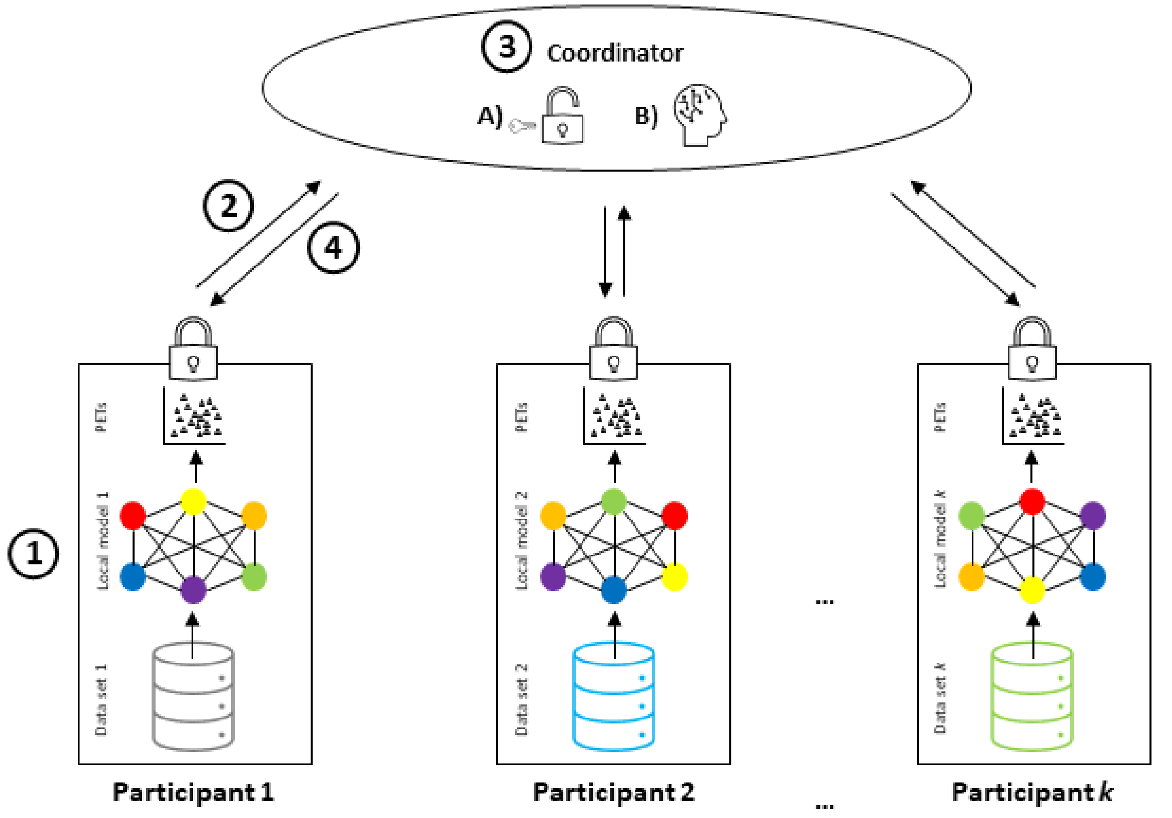

Figure 3. Combined Privacy Architecture

This combined approach aligns closely with regulatory expectations in financial systems, where privacy, confidentiality, and risk management must be addressed holistically. Regulators increasingly expect organizations to demonstrate not only technical safeguards but also systematic risk mitigation strategies across the entire machine learning lifecycle. By integrating secure aggregation and differential privacy into federated learning workflows, financial institutions can reduce data exposure, strengthen governance controls, and enable compliant collaboration at scale. Such layered privacy architectures are therefore essential for deploying federated learning in production-grade, regulated financial environments.

V. KEY STUDIES AND EMPIRICAL EVIDENCE

Several pre-2022 studies provide strong empirical and theoretical evidence supporting the feasibility of federated learning for financial applications. McMahan et al. (2016) introduced the Federated Averaging (FedAvg) algorithm, demonstrating that decentralized training across distributed clients can achieve performance comparable to centralized learning while significantly reducing data movement. This work established the core optimization foundation of federated learning and showed that collaborative model training is possible even under constrained communication and heterogeneous data distributions conditions that closely mirror real-world financial environments. By proving that accuracy need not be sacrificed for decentralization, FedAvg laid the groundwork for adopting federated learning in privacy-sensitive domains such as banking and payments.

Building on this foundation, Bonawitz et al. (2017, 2019) addressed one of the most critical barriers to real-world adoption: privacy and system scalability. Their work introduced practical secure aggregation protocols and demonstrated how federated learning could be deployed at production scale while preserving confidentiality of individual client updates. These system-level contributions were instrumental in moving federated learning from a theoretical construct to an operationally viable approach. In parallel, Abadi et al. (2016) established differentially private training techniques, providing formal guarantees against data re-identification. Differential privacy has since become a cornerstone of privacy-preserving machine learning and is frequently combined with federated learning to meet regulatory and ethical requirements in sensitive domains.

More application-focused studies further validated the relevance of federated learning in finance. Zheng et al. (2020) demonstrated the effectiveness of federated meta-learning for credit card fraud detection, showing that collaborative models trained without centralized data pooling can outperform locally trained models while maintaining privacy. Meanwhile, Kairouz et al. (2019) provided a comprehensive survey of federated learning, identifying open challenges related to robustness, communication efficiency, system heterogeneity, and privacy–utility trade-offs. Collectively, these studies indicate that federated learning can satisfy both performance and privacy requirements for financial systems. However, they also highlight that operational complexity spanning system orchestration, security, governance, and compliance remain a significant challenge that must be addressed for large-scale, production-grade deployments.

VI. REGULATORY AND GOVERNANCE CONSIDERATIONS

For financial institutions, the adoption of federated learning must be carefully aligned with existing regulatory and governance frameworks to ensure compliance, accountability, and operational resilience. Data residency is a primary concern, as many regulations require sensitive financial and personal data to remain within specific geographic or jurisdictional boundaries. Federated learning inherently supports these requirements by enabling local model training on institution-controlled infrastructure, ensuring that raw data never leaves its origin. This property simplifies compliance with cross-border data transfer restrictions and reduces the legal risks associated with centralized data storage, particularly in multinational financial organizations.

Auditability and transparency are equally critical in regulated financial environments, where institutions must demonstrate control over data processing and decision-making pipelines. Federated learning systems can support auditability through secure aggregation protocols, comprehensive logging, and versioned model updates that allow regulators and internal auditors to trace training processes without exposing sensitive data. These mechanisms enable institutions to reconstruct training histories, verify compliance with internal policies, and investigate anomalies while maintaining confidentiality. In parallel, explainability requirements imposed by regulators necessitate that federated models either be inherently interpretable or supplemented with robust post-hoc explanation techniques. This is especially important for high-stakes decisions such as credit approvals, fraud alerts, and risk scoring, where institutions must justify automated outcomes to regulators and affected customers.

Risk management remains a central governance challenge for federated learning deployments. Financial institutions must account for adversarial threats such as poisoning attacks, collusion among participants, and systemic failures arising from unreliable or malicious contributors. Effective threat modeling should encompass both technical risks such as compromised clients or aggregation servers and organizational risks related to trust, incentives, and accountability among participants. Consequently, governance frameworks for federated learning must integrate legal, technical, and organizational controls, including clearly defined participation policies, security standards, monitoring procedures, and escalation mechanisms. Only through such integrated governance can financial institutions ensure the responsible, secure, and compliant deployment of federated learning in production environments.

VII. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite its promise, federated learning continues to face several unresolved challenges that limit its widespread adoption in regulated financial systems. Communication overhead and system scalability remain significant concerns, as federated learning typically involves frequent exchanges of model updates between participants and coordinating servers. In large-scale financial deployments with hundreds or thousands of participants, these communication costs can introduce latency, increase infrastructure expenses, and complicate system orchestration. Heterogeneous network conditions, intermittent client availability, and varying computational capabilities further exacerbate these challenges, requiring sophisticated scheduling, compression, and aggregation strategies to maintain efficiency without degrading model performance.

Robustness and security present another critical set of challenges, particularly in adversarial or partially trusted environments. Federated learning systems must contend with malicious participants who may attempt poisoning attacks, model manipulation, or collusion to influence the global model. Detecting and mitigating such behavior is especially complex in privacy-preserving settings, where limited visibility into individual updates is a design goal rather than a flaw. At the same time, model explainability under privacy constraints remains an open problem, as the use of secure aggregation and differential privacy can obscure the internal behavior of models and complicate interpretability. Financial regulators increasingly require transparent and explainable decision-making, creating tension between strong privacy guarantees and the need for model introspection.

Finally, the lack of standardized federated learning protocols poses challenges for cross-institution collaboration and regulatory acceptance. Differences in data schemas, training workflows, privacy configurations, and governance practices can hinder interoperability and slow adoption. Integrating federated learning into existing model risk management (MRM) processes such as validation, stress testing, and ongoing performance monitoring also remains non-trivial, as traditional MRM frameworks were designed for centralized models. Future research should therefore explore hybrid human–AI oversight models, adaptive privacy budgets that respond to risk and context, and regulatory-aware federated learning frameworks that embed compliance requirements directly into system design. Addressing these challenges will be essential for realizing the full potential of federated learning in regulated financial environments.

VIII. CASE STUDY: PRIVACY-PRESERVING FRAUD DETECTION USING FEDERATED LEARNING IN A MULTI-BANK ECOSYSTEM

8.1 Background and Problem Context

A consortium of mid-to-large financial institutions operating across multiple jurisdictions sought to improve credit card fraud detection while complying with strict regulatory constraints on data sharing. Each institution independently maintained transaction datasets containing sensitive customer information, including payment histories, merchant metadata, and behavioral signals. Regulatory requirements related to data residency, customer privacy, and competitive confidentiality prevented the creation of a centralized data lake for joint model training. As a result, individual institutions relied on locally trained models, which suffered from limited exposure to diverse fraud patterns and reduced detection accuracy for emerging cross-bank fraud schemes.

8.2 Federated Learning Architecture and Deployment

To address these challenges, the consortium adopted a horizontal federated learning architecture, where each participating bank trained a local fraud detection model on its internal transaction data. A coordinating aggregation service orchestrated training rounds by distributing an initial global model, collecting encrypted model updates, and computing aggregated updates using secure aggregation protocols. No raw transaction data or institution-specific features were shared during the process. Differential privacy was applied to local model updates to mitigate inference risks, with privacy budgets calibrated to balance regulatory compliance and predictive performance. The system was deployed across geographically distributed infrastructure, ensuring that all data processing remained within jurisdictional boundaries.

8.3 Results and Operational Impact

The federated fraud detection model demonstrated a measurable improvement over locally trained baselines across participating institutions. On average, fraud detection recall improved by approximately 8–12%, particularly for low-frequency and emerging fraud patterns that were previously underrepresented in single-institution datasets. False-positive rates were reduced due to improved generalization, leading to fewer unnecessary transaction declines and enhanced customer experience. From a compliance perspective, internal audits confirmed that no sensitive customer data left institutional boundaries, and the federated training process met regulatory expectations for data minimization and confidentiality. The consortium also established shared governance procedures for model updates, monitoring, and incident response, enabling sustainable collaboration.

8.4 Key Lessons Learned

This case study highlights several important insights for deploying federated learning in regulated financial systems. First, federated learning can deliver tangible performance gains without violating data privacy or competitive boundaries. Second, privacy-preserving mechanisms such as secure aggregation and differential privacy are essential enablers rather than optional enhancements. Finally, successful deployment requires not only technical solutions but also coordinated governance, clear participation rules, and alignment with existing model risk management practices. Together, these lessons demonstrate that federated learning is a viable and effective approach for advancing fraud detection and financial intelligence in highly regulated environments.

IX. CONCLUSION

Federated learning represents a fundamental paradigm shift in the way machine learning systems are designed and deployed within regulated financial environments. By decoupling model training from centralized data collection, federated learning enables institutions to collaboratively extract value from distributed datasets while keeping sensitive customer information within organizational and jurisdictional boundaries. This architectural shift directly addresses long-standing regulatory concerns related to data localization, consent management, and breach exposure. Instead of concentrating risk in centralized data lakes, federated learning distributes computation to the data, significantly reducing the attack surface and improving overall system resilience. As financial institutions increasingly rely on advanced analytics for decision-making, this model offers a sustainable approach that balances innovation with regulatory responsibility.
When combined with privacy-enhancing technologies such as secure aggregation and differential privacy, federated learning provides robust, defense-in-depth protections suitable for high-stakes financial applications. Secure aggregation ensures that individual model updates remain confidential, even from coordinating servers, while differential privacy offers formal guarantees against data re-identification and inference attacks. Together, these mechanisms transform federated learning from a decentralized training technique into a comprehensive privacy-preserving framework. This layered approach allows institutions to collaborate across competitive and regulatory boundaries without exposing proprietary or customer-sensitive information. As a result, federated learning becomes a viable foundation for large-scale deployment in areas such as fraud detection, credit risk modeling, and anti–money laundering, where both accuracy and confidentiality are paramount.

Beyond technical safeguards, the success of federated learning in financial systems depends on robust governance and operational integration. Effective deployment requires alignment with model risk management processes, regulatory reporting obligations, and organizational accountability structures. Governance frameworks must define participation rules, audit mechanisms, and escalation procedures to ensure that federated models remain transparent, fair, and controllable throughout their lifecycle. By embedding compliance and oversight directly into system design, federated learning enables financial institutions to innovate responsibly while preserving customer trust and data sovereignty. In this sense, federated learning is not merely a technical advancement, but a strategic enabler for the next generation of compliant, collaborative financial intelligence.

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