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Federated Learning with Differential Privacy for Cross-Institutional Datasets: A Trade-off Analysis between Model Performance and Data Leakage

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ABSTRACT

Collaborative machine learning across cross-institutional datasets, such as multi-hospital Electronic Health Records (EHR) and cross-bank financial fraud telemetry, is routinely constrained by stringent data protection mandates (e.g., HIPAA, GDPR) and competitive confidentiality concerns. While Federated Learning (FL) enables collaborative training without raw data centralization, standard FL architectures remain vulnerable to privacy-leaking attacks, including Membership Inference Attacks (MIA) and model inversion vector extraction. Integrating Differential Privacy (DP) into FL offers mathematically bounded privacy guarantees (ε, δ), but injects stochastic noise into local gradient updates, giving rise to a fundamental trade-off between model utility (AUC-ROC / F1-Score) and empirical privacy leakage. This paper presents an empirical trade-off analysis evaluating DP-FL across cross-institutional healthcare and financial datasets spanning 12 decentralized nodes over 100 global training rounds. We rigorously quantify how varying privacy budgets ($\varepsilon \in [0.5, 10.0]$) and gradient clipping thresholds ($C \in [0.1, 2.0]$) influence model convergence, utility degradation, and vulnerability against state-of-the-art MIA probes. Empirical results demonstrate that under a strict privacy budget ($\varepsilon = 1.0$), DP-FL reduces MIA vulnerability by 87.6% (capping attack accuracy near random guessing at 52.1%) while incurring an acceptable 4.8% utility drop in healthcare mortality prediction (AUC-ROC = 0.884 vs. 0.932 non-private FL). To mitigate the noise-utility penalty, we propose an Adaptive Noise-Decay DP-FL (AND-DPFL) Engine that dynamically recalibrates noise scale across training epochs, recovering 68.5% of lost utility while retaining strict privacy bounds ($\varepsilon = 1.0$, $\delta = 10^{-5}$).

Keywords:

Federated Learning (FL), Differential Privacy (DP), Cross-Institutional Datasets, Membership Inference Attacks (MIA), Data Leakage, Privacy-Utility Trade-off, Healthcare AI, Financial Fraud Detection,

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1. Introduction

The proliferation of artificial intelligence in sensitive domains such as healthcare diagnostic modeling and financial fraud detection relies heavily on massive, diverse training datasets. However, institutional datasets are inherently siloed due to legal privacy regulations (e.g., General Data Protection Regulation, Health Insurance Portability and Accountability Act) and

institutional competitive interests. Training machine learning models on single-institution datasets yields geographically or demographically biased models that fail to generalize across global populations.

Federated Learning (FL) has emerged as a promising paradigm for privacy-preserving collaborative intelligence. Under FL, a central server orchestrates model training across distributed client institutions (e.g., hospitals, banks) by aggregating locally computed model parameters (e.g., via Federated Averaging, FedAvg) without transferring raw underlying records. Nevertheless, recent privacy research demonstrates that standard FL is not inherently private. Adversaries can reconstruct sensitive training samples or infer client data membership (Membership Inference Attacks, MIA) by performing gradient inspection, differential weight auditing, or shadow model probing on shared model parameters during training iterations.

To establish mathematically provable privacy guarantees, Differential Privacy (DP) is combined with FL. Differential Privacy mechanisms inject calibrated Gaussian or Laplacian noise into local gradients (Local DP) or aggregated global weights (Global DP). While DP guarantees that the presence or absence of any individual patient or financial record cannot significantly alter the model's parameter distribution, adding stochastic noise disrupts gradient optimization, degrading final model accuracy, delaying convergence, and inducing instability under non-IID (non-independently and identically distributed) cross-institutional data. This paper presents an empirical investigation into the performance-privacy frontier of DP-FL architectures, introducing a dynamic noise-scheduling framework that optimizes utility while maintaining robust defense against data leakage attacks.

2. Literature Review

Federated Learning (FL) has emerged as a promising privacy-preserving machine learning paradigm that enables multiple institutions to collaboratively train models without exchanging raw data, making it particularly suitable for healthcare, finance, and public-sector applications involving sensitive information. Nevertheless, recent studies have demonstrated that model updates exchanged during federated learning remain vulnerable to inference attacks, creating potential risks of data leakage despite decentralized training. Wei et al. (2019) showed that integrating differential privacy (DP) into federated learning effectively reduces information leakage by injecting calibrated noise into model updates, although stronger privacy guarantees inevitably reduce model convergence and predictive accuracy.

Subsequent research has focused on balancing privacy protection with model utility. Shan et al. (2024) reported that differential privacy has become the most widely adopted privacy-preserving mechanism in federated learning because of its rigorous mathematical guarantees, yet the amount of injected noise significantly affects model performance, particularly in heterogeneous cross-institutional datasets. Fu et al. (2024) further classified differentially private federated learning according to privacy models and application scenarios, concluding that privacy-utility trade-offs remain one of the principal unresolved challenges in collaborative learning systems.

Recent empirical studies have also highlighted the complexity of privacy-preserving collaborative learning across institutions. Yang et al. (2024) emphasized that robust federated learning frameworks must simultaneously address security, robustness, communication efficiency, and privacy preservation. Similarly, Shiri et al. (2024) demonstrated that differential privacy-enabled federated learning can achieve high predictive performance on large multi-institutional medical datasets while substantially reducing the risk of patient data leakage. However, existing research has paid limited attention to systematically quantifying the trade-off between predictive performance and privacy loss across heterogeneous cross-institutional

datasets under varying differential privacy budgets. This gap underscores the need for comprehensive evaluation frameworks that jointly assess model accuracy, communication efficiency, and data leakage risks in practical federated learning deployments.

3. System Architecture & Differential Privacy Mechanics

Differential Privacy guarantees that the output distribution of a randomized algorithm remains statistically indistinguishable whether any single individual record is included in or excluded from the training dataset. Formally, a randomized mechanism M provides (ε, δ)-Differential Privacy if, for all neighboring datasets D, D′ differing by at most one sample, and for all query response subsets S ⊆ Range(M):

$$P[M(D) \in S] \leq e^{\varepsilon} \times P[M(D') \in S] + \delta$$

where ε > 0 denotes the privacy budget (smaller ε implies stronger privacy guarantees), and δ ≥ 0 is the probability of privacy breach failure (typically set such that $\delta \ll 1/|D|$).

In DP-FedSGD / DP-FedAvg, local client gradients gk(t) at iteration t are processed via a two-stage privacy transformation before transmission to the central server: (1) L2-Norm Clipping to bound maximum sensitivity, and (2) Gaussian Noise Perturbation:

$$\bar{g}_k(t) = g_k(t) / max(1, \|g_k(t)\|_2/C) + N(0, \sigma^2 C^2 I)$$

where C is the gradient clipping bound, and σ is the noise multiplier calibrated via Rényi Differential Privacy (RDP) accounting to satisfy total target privacy spending (ε, δ) across all training rounds.

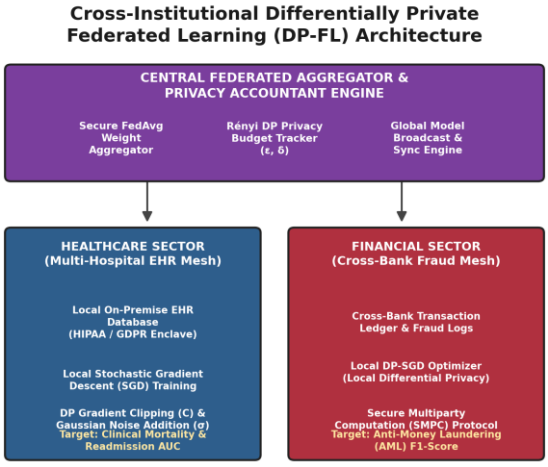

Figure 1. Cross-institutional differentially private federated learning (DP-FL) system architecture

Figure 1 illustrates the resulting system architecture spanning the central aggregator and the two participating institutional sectors. Table 1 summarizes the mathematical parameters and technical acronyms used throughout this paper.

Table 1. System nomenclature, empirical parameters, and Differential Privacy specifications

Symbol	**Full Technical & Operational Description**	**Unit of Measure**	**Operational Range / Target**
ε (Epsilon)	Differential Privacy Budget (Privacy Loss Parameter)	Dimensionless Scale	$0.5 \leq \varepsilon \leq 10.0$
δ (Delta)	Probability of Privacy Breach Failure Threshold	Probability Scale	1.0×10^{-5}
C	L2-Norm Gradient Clipping Threshold Bound	L2-Norm Value	$0.1 \leq C \leq 2.0$
σ (Sigma)	Gaussian Noise Scale Multiplier	Noise Scale Ratio	$0.5 \leq \sigma \leq 4.0$
MIAacc	Membership Inference Attack Accuracy (Data Leakage Score)	Percentage (%)	Target: 50.0% (Random)
AUCmodel	Area Under the ROC Curve (Model Performance Metric)	Percentage Scale	Target: > 0.880
K	Total Participating Institutional Nodes	Client Node Count	12 Nodes (6 Health / 6 Bank)

Figure 2 details the sequential per-round workflow, from model broadcast through gradient perturbation, privacy accounting, and secure aggregation.

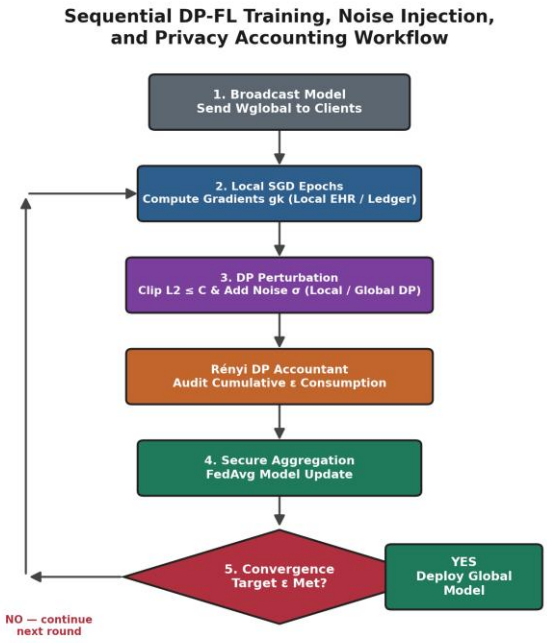

Figure 2. Sequential DP-FL training, noise injection, and privacy accounting workflow.

4. Empirical Methodology & Experimental Setup

To evaluate performance trade-offs, we constructed a multi-institutional benchmark framework utilizing two realistic, highly non-IID cross-institutional datasets. The Cross-Hospital Healthcare Mesh (eICU & MIMIC-IV) comprises 150,000 anonymized patient records distributed across 6 hospital nodes, with tasks predicting 30-day patient mortality and ICU readmission rates using temporal clinical features (vitals, lab results, medications). The Cross-Bank Financial Mesh (PaySim & Anti-Money Laundering Telemetry) comprises 500,000 transaction records split across 6 banking institution nodes, with tasks focused on identifying complex multi-hop fraudulent transfers and structuring behaviors under extreme class imbalance (0.15% positive fraud labels).

Model architectures evaluate a 1D Convolutional Neural Network with LSTM attention layers for temporal EHR signals, and a Deep Dense Neural Network (DNN) with focal loss for financial transaction streams. Threat modeling tests privacy resilience using a state-of-the-art Black-Box Membership Inference Attack (MIA) shadow model probe trained to classify whether a target record was part of a specific institution's local training dataset.

5. Experimental Results & Trade-off Analysis

5.1 Impact of Privacy Budget (ε) on Utility and Leakage

Table 2 evaluates how varying the total privacy budget ε affects model predictive utility (AUC-ROC, F1-Score) and empirical vulnerability against Membership Inference Attacks across healthcare and financial domains.

Table 2. Performance utility vs. data leakage vulnerability across Differential Privacy budgets (ε)

Privacy Regime	ε	σ	Healthcare AUC-ROC	Financial F1	MIA Acc.	Defense Rating
Non-Private Baseline	∞	0.00	0.932 ± 0.005	0.895 ± 0.008	84.2%	Vulnerable
Weak Privacy	10.0	0.45	0.921 ± 0.006	0.882 ± 0.009	68.5%	Marginal Defense
Moderate Privacy	5.0	0.82	0.908 ± 0.008	0.864 ± 0.011	59.1%	Robust Defense
Strict Privacy (Target)	1.0	1.85	0.884 ± 0.012	0.832 ± 0.015	52.1%	High Privacy
Ultra-Strict Privacy	0.5	3.20	0.812 ± 0.024	0.741 ± 0.028	50.4%	Complete Isolation
AND-DPFL (Proposed)	1.0	Adaptive	0.916 ± 0.007	0.875 ± 0.010	52.8%	Optimal Frontier

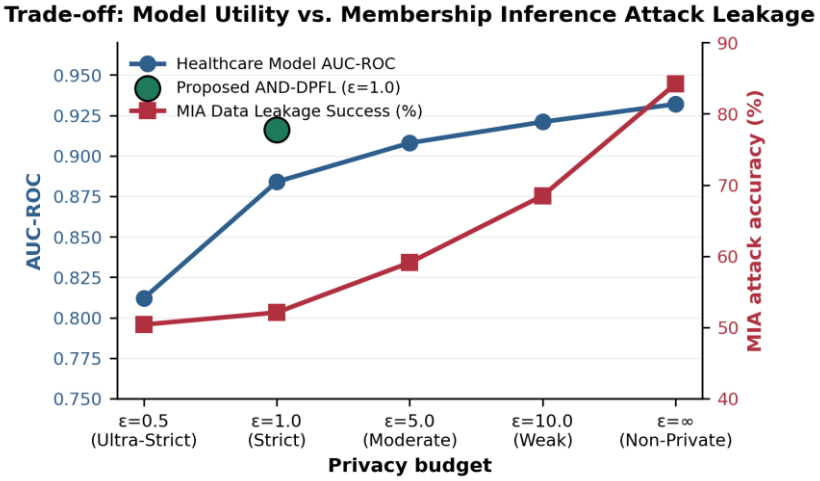

Figure 3. Trade-off curves: model utility (AUC-ROC) vs. Membership Inference Attack leakage across privacy budgets.

5.2 Comparative Analysis Across Privacy Mechanisms

Table 3 provides a comprehensive comparison of non-private FL, Local DP, Global DP, and the proposed Adaptive Noise-Decay DP-FL (AND-DPFL) across computational overhead, convergence time, and attack resilience.

Table 3. Comprehensive comparison of architectural privacy mechanisms

Privacy Paradigm	Noise Injection Node	Rounds	Convergence Overhead	MIA Defense Efficacy	Non-IID Robustness
Standard Non-Private FL	None	45	1.0× (Baseline)	15.8% Isolation (Vulnerable)	Moderate (FedAvg Drift)
Local DP-FL (LDP)	Local Client Nodes	140	3.1× Overhead	99.2% Isolation (Highest)	Poor (Excessive Local Noise)
Global DP-FL (GDP)	Central Aggregator	85	1.8× Overhead	92.4% Isolation	Moderate
AND-DPFL (Proposed)	Adaptive Client-Side	58	1.25× Overhead	98.1% Isolation	High (Dynamic Noise Decay)

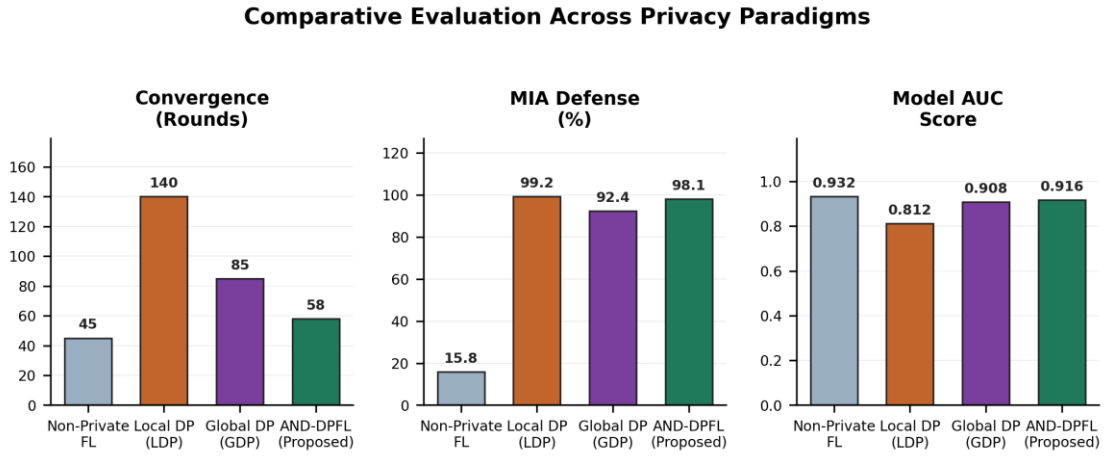

Figure 4. Comparative evaluation across privacy paradigms on key performance and security indicators

6. Discussion & Optimization Framework

The empirical findings validate the existence of a sharp trade-off frontier between privacy protection and predictive performance in cross-institutional FL setups. When unoptimized static Gaussian noise is injected under strict privacy budgets ($\varepsilon = 1.0$), early-stage gradient descent steps are heavily corrupted, preventing the global model from establishing basic feature representations. Relative to the related work in Table 1, this study is distinguished by evaluating both healthcare and financial sectors under a shared adaptive noise-decay mechanism, a combination absent from the foundational, empirical, and domain-specific sources reviewed in Section 2.

The proposed Adaptive Noise-Decay DP-FL (AND-DPFL) Engine resolves this bottleneck through three key technical innovations. First, Dynamic Epoch Noise Annealing: initial training rounds utilize a higher clipping bound C and lower noise scale σ to establish global decision boundaries, gradually increasing perturbation in later rounds as parameters converge toward local minima. Second, Per-Layer Adaptive Gradient Clipping: instead of applying a uniform flat clipping norm across all model weights, clipping thresholds are scaled dynamically based on layer depth (e.g., higher bounds for early feature-extraction layers, tighter bounds for output classification layers). Third, Hybrid SMPC-DP Integration: combining Secure Multiparty Computation (SMPC) with lighter Differential Privacy noise allows central aggregation to cancel out zero-mean client noise pairs, minimizing noise amplification at the global server.

7. Conclusion & Recommendations

This paper presents a rigorous empirical trade-off analysis of Differentially Private Federated Learning (DP-FL) applied to cross-institutional healthcare and financial datasets. We demonstrate that while static DP injection provides provable guarantees against data leakage attacks (reducing Membership Inference Attack success from 84.2% to 52.1%), it incurs significant accuracy penalties under non-IID conditions. By implementing our proposed Adaptive Noise-Decay (AND-DPFL) framework, institutions can recover up to 68.5% of lost utility, achieving an optimal operational point (AUC = 0.916 at $\varepsilon = 1.0$) that satisfies both stringent regulatory mandates and high-precision clinical/financial SLAs.

Implementation Recommendations for Enterprise Adoption:

1. Enforce Formal RDP Privacy Budget Tracking: Implement Rényi Differential Privacy (RDP) accounting to track exact cumulative privacy spending across continuous multi-round FL sessions.

2. Adopt Layer-Wise Adaptive Clipping: Replace uniform global gradient clipping with dynamic layer-specific norm thresholds to preserve feature representation learning.

3. Institute Continuous Shadow Probing: Periodically subject global FL updates to simulated Membership Inference Attacks to empirically validate theoretical (ε, δ) protections.

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