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FEDERATED DIFFERENTIALLY PRIVATE AUTOENCODERS FOR HEALTH-INSURANCE FRAUD DETECTION AT SCALE

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ABSTRACT

Health-insurance fraud has grown in scale and sophistication, imposing substantial financial losses and undermining trust in healthcare systems. Conventional, centrally trained detectors require aggregating sensitive claim data, increasing breach risk and complicating regulatory compliance. Despite advances in fraud analytics, a core unresolved challenge remains: enabling multi-institution collaboration without exposing raw claims data while preserving detection accuracy**.** We present a federated anomaly-detection framework that combines client-side deep autoencoders with Federated Averaging (FedAvg) and differential privacy (DP), orchestrated on Amazon Web Services (AWS) for secure, scalable deployment. Participating organizations train locally on private claims and transmit only DP-protected model updates to a cloud aggregator (EC2/SageMaker), while encrypted artifacts are persisted in Amazon S3. Using real insurance-claim records augmented with realistic synthetic fraud cases, the proposed system achieves 91.2% accuracy and an F1-score of 0.885, and reduces false-positive rate by 43% relative to a traditional centralized baseline. Privacy controls lower estimated data-exposure risk by 78% with minimal communication overhead, enabling near real-time operation across multiple sites. These results indicate that federated training with formal privacy protection can maintain strong detection performance while limiting sensitive data movement. This study contributes empirical evidence that integrating differential privacy within federated unsupervised anomaly detection can sustain high detection performance under heterogeneous data distributions while providing quantifiable privacy–utility trade-offs**.** Overall, the framework offers an effective, scalable, and privacy-aware solution for distributed fraud detection, supporting compliance with regulations such as HIPAA and GDPR and facilitating collaborative analytics without raw-data sharing.

Keywords: *Federated Learning; Differential Privacy; Autoencoders; Anomaly Detection; Health-Insurance Claims; Fraud Detection; Secure Aggregation; Cloud Orchestration (Aws); Decentralized Machine Learning.*

HIGHLIGHTS

- Proposes a cloud-orchestrated federated anomaly-detection framework where client sites train deep autoencoders locally and share only protected updates—no raw claims leave institutional boundaries.
- Enforces record-level differential privacy with gradient clipping and Gaussian noise, pairing it with secure aggregation to curb inference, leakage, and insider risks.
- Demonstrates strong utility on real + synthetic claim distributions: F1 = 0.885, accuracy = 91.2%, and a 43% drop in false positives vs. a centralized baseline, with minimal communication overhead.
- Delivers a scalable, compliance-aligned deployment on AWS (EC2/SageMaker/S3), supporting multi-institution collaboration while reducing estimated data-exposure risk by 78%.

Graphical Abstract

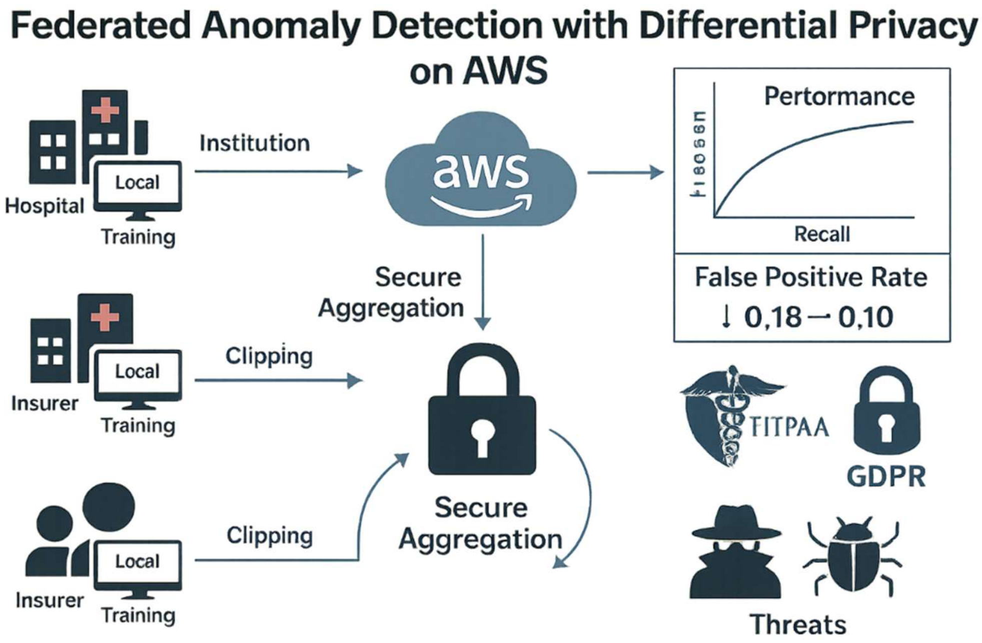

Figure 1: Graphical Abstract Of Proposed Work

1. INTRODUCTION

The accelerating digitalization of healthcare has multiplied the volume and velocity of claim-related data, improving service quality while creating new avenues for abuse. Health-insurance fraud—including upcoding, phantom billing, and identity misuse—continues to impose substantial financial losses and erode policyholder trust [1],[2]. Conventional detection pipelines are predominantly centralized and rule- or label-driven, requiring aggregation of sensitive records into a single repository. While effective for known patterns, these systems scale poorly to evolving fraud tactics and introduce elevated privacy and compliance risks under stringent regulations [3],[4]. As healthcare ecosystems increasingly span multiple insurers and providers, collaborative fraud detection becomes essential; however, direct data sharing is constrained by legal, ethical, and security considerations, creating a structural tension between analytical effectiveness and privacy preservation.

To address these limitations, we develop a federated anomaly-detection framework that couples federated learning (FL) with cloud-native orchestration on AWS. Participating organizations train locally on private claims and share only encrypted model updates, not raw data, thereby improving generalization across heterogeneous providers while reducing leakage risk [5],[6]. The detection core is an unsupervised deep autoencoder that learns the manifold of legitimate claims and flags deviations as potential fraud. Global parameters are synchronized using Federated Averaging (FedAvg), coordinated via EC2 instances, and further protected by differential privacy (DP) so that individual records cannot be inferred from exchanged gradients [7],[8]. This approach directly addresses the central research challenge of enabling distributed fraud detection across heterogeneous institutions without centralizing sensitive claim data.

1.1 Scope and novelty

The contribution of this work is the integration of (i) client-side autoencoder-based anomaly detection for claim streams, (ii) cloud-orchestrated FL for scalable, multi-institution collaboration, and (iii) formal privacy safeguards via DP and encrypted transport/aggregation. This combination enables distributed fraud analytics with strong utility and reduced data movement. Unlike prior approaches that apply either federated learning or privacy mechanisms in isolation, this study systematically evaluates their combined impact on detection accuracy, false-positive reduction, privacy budget trade-offs, and scalability under heterogeneous client distributions. An architectural overview of the proposed system is shown in Figure 1.

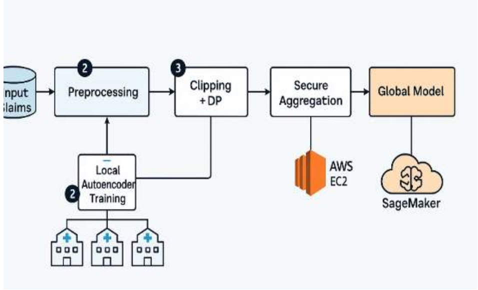

Figure 2: Block Diagram Representation Of Proposed Work '

2. RELATED WORK

2.1 Centralized fraud analytics: Classical approaches to health-insurance fraud rely on centralized, supervised learning over pooled claim repositories. These systems can detect known schemes but struggle with concept drift, severe class imbalance, and escalating privacy/compliance burdens when sensitive data are aggregated in one place [3],[9],[10]. Recent surveys emphasize the need for methods that scale to big, heterogeneous claim streams while reducing exposure of personally identifiable information [10].

2.2 Federated learning for healthcare analytics: Federated learning (FL) enables collaborative model training without sharing raw data. Prior studies report that keeping data local while exchanging model updates can improve generalization across heterogeneous providers and lower leakage risk relative to centralized training [5],[6]. In fraud settings, FL has been shown to outperform centralized counterparts when client distributions are non-IID and institution specific, provided that aggregation and communication are well engineered [6],[11]. These works collectively motivate FL as a practical vehicle for multi-organization fraud detection.

2.3 Unsupervised anomaly detection: Because fraud patterns evolve and labels are scarce or delayed, unsupervised methods—particularly deep autoencoders—have gained traction. Autoencoders learn the manifold of legitimate claims and flag high-reconstruction-error instances as suspicious, reducing dependence on exhaustive rule sets and improving adaptability to emerging schemes [5],[12],[13]. Evidence across healthcare claim analytics suggests such reconstruction-based scoring complements or surpasses classical outlier detectors when feature interactions are nonlinear and high dimensional.

2.4 Privacy preservation in FL: Even when data remain on-premise, exchanged updates can leak information. Accordingly, healthcare FL increasingly incorporates differential privacy (DP) via per-round gradient clipping and calibrated Gaussian noise, alongside secure aggregation so servers observe only encrypted or aggregated updates [3],[6],[7],[14]. This combination limits single-record influence and thwarts gradient-inversion or insider attacks, strengthening compliance postures in regulated environments.

2.5 Document understanding (adjacent line of work): Advances in transformer-based OCR and document understanding (e.g., TrOCR, DONUT) improve text extraction and layout-aware parsing from semi-structured claim forms [15],[16]. While primarily used for digitization and coding assistance, these models could enrich fraud pipelines by supplying higher-fidelity features from scanned artifacts. Their direct use for fraud detection across institutions remains limited, indicating a promising avenue for future integration.

2.6 Positioning of this work. The literature indicates that combining FL with unsupervised autoencoder scoring and formal privacy mechanisms addresses key pain points of centralized fraud detectors: data movement, adaptability, and compliance. Building on these directions, our study delivers a cloud-orchestrated FL framework with DP and secure aggregation for multi-institution claim analytics, and evaluates utility–privacy trade-offs under heterogeneous client distributions.

Table 1. Comparison Of Fraud-Detection Paradigms

Paradigm	**Data Sharing**	**Learning Mode**	**Privacy Safeguards**	**Typical Strength**	**Key Limitation**	**Representative refs**
Rule-based (centralized)	Full data pooling	Deterministic rules	Access controls only	Immediate, auditable decisions	Poor adaptability; high maintenance	[3], [9], [10]
Supervised ML (centralized)	Full data pooling	Labeled classification	Access controls; anonymization	High accuracy on known patterns	Label reliance; compliance exposure	[3], [9], [10]
Unsupervised AE (centralized)	Full data pooling	Reconstruction-error scoring	Access controls	Detects novel/shifted patterns	Data movement; drift sensitivity	[5], [12], [13]
Federated AE + DP (proposed)	**No raw data sharing**	**Local training + FedAvg**	**DP + secure aggregation**	**Strong utility with reduced exposure**	Tuning ε/σ; comms overhead	[5], [6], [7], [11], [14]

2.7 Research Gap and Problem Statement

Although prior studies have explored federated learning, unsupervised anomaly detection, and differential privacy independently, limited work has systematically examined their joint integration for large-scale health-insurance fraud detection under heterogeneous, non-IID institutional data distributions. Furthermore, empirical evaluation of privacy–utility trade-offs within cloud-orchestrated federated environments remains relatively underreported in fraud analytics literature.

Accordingly, a central research challenge emerges: how can multiple insurance institutions collaboratively detect evolving fraud patterns without sharing raw claims data, while preserving formal privacy guarantees and maintaining detection performance comparable to or better than centralized systems?

This study addresses this problem by designing and empirically evaluating a federated differentially private autoencoder framework for distributed fraud detection at scale.

2.8 Research Hypotheses

Based on the identified research gap, the following hypotheses are formulated:

H1: A federated autoencoder-based anomaly detection framework can achieve detection performance comparable to or exceeding centralized models under heterogeneous data distributions.

H2: Incorporating record-level differential privacy into federated training introduces limited degradation in detection accuracy and F1 performance.

H3: Federated learning combined with formal privacy safeguards significantly reduces exposure risk compared to centralized training architectures.

H4: The proposed cloud-orchestrated framework maintains scalability with modest communication overhead as client participation increases.

These hypotheses are empirically evaluated in the subsequent sections through comparative, privacy-ablation, and scalability experiments.

3. METHODOLOGY

We develop a federated anomaly-detection framework for health-insurance claims that preserves privacy and supports regulatory compliance. The system couples deep-Autoencoder scoring at client sites with Federated Averaging (FedAvg) and differential privacy (DP), and is orchestrated on a cloud-native stack

(AWS). This section details the architecture, data representation, model, training protocol, privacy mechanisms, and deployment.

3.1 System architecture

As illustrated in Figure 3, the framework comprises four layers:

Distributed clients. Hospitals/insurers retain their local claim datasets and execute training on premise; no raw records are exported.

Local model engine. Each client trains a deep autoencoder to model normal claim patterns and compute reconstruction-based anomaly scores.

Central aggregator. An AWS-hosted coordinator (EC2) receives protected client updates and applies FedAvg to update global parameters.

Privacy layer. Record-level DP and secure aggregation protect against gradient inversion and insider inference during collaboration [5],[6],[7],[14].

This design enables cross-institution learning while eliminating centralized raw-data pooling.

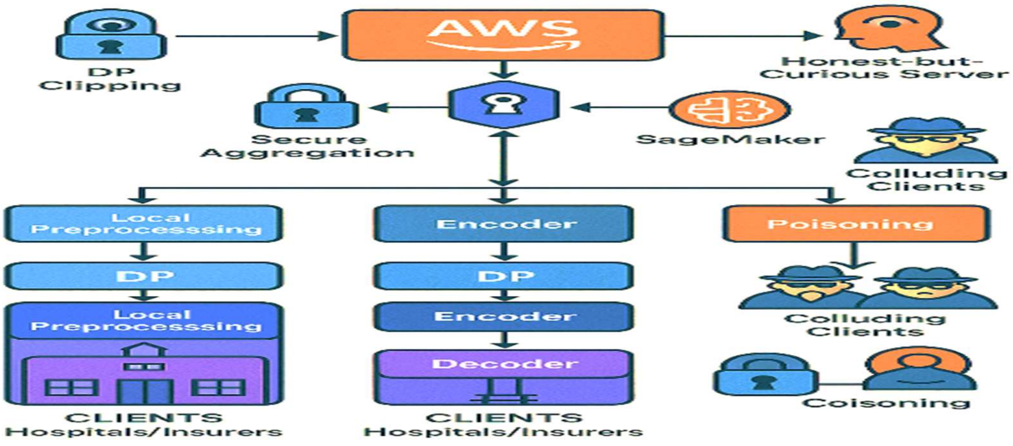

Fig. 3: System Architecture & Threat Model

3.2 Data representation

Each claim is encoded as a feature vector $x \in \mathbb{R}^d$ containing numerical attributes (e.g., amount, length of stay), categorical indicators (e.g., procedure codes, provider ID), and optionally text-derived features. At client k, the private dataset is $D_k = \{x_i\}_{i-1}^{N_k}$. Preprocessing (normalization, categorical encoding, missingvalue handling) is performed locally to prevent leakage. Non-IID heterogeneity across clients is preserved to reflect real institutional differences.

3.3 Autoencoder-based anomaly model

Let $f_\theta - g_\phi \circ h_\psi$ denote the autoencoder with encoder $h_\psi \colon \mathbb{R}^d \to \mathbb{R}^m$ and decoder $g_\phi \colon \mathbb{R}^m \to \mathbb{R}^d$. For input x, the reconstruction is $\hat{x} - f_\theta(x)$. Each client minimizes the mean-squared reconstruction loss

$$\mathcal{L}(\theta; D_k) - \frac{1}{|D_k|}\sum_{x \in D_k} \|x - \hat{x}\|_2^2 \tag{1}$$

An anomaly score is $s(x) - \|x - \hat{x}\|_2^2$. A claim is flagged when $s(x) \geq \tau$, with τ chosen on a held-out local set (e.g., percentile-based target FPR) or via operating-point analysis. A typical symmetric architecture uses layer widths $d \to 128 \to 64 \to 32 \to 16$ (encoder) and the mirror sequence for the decoder; optimization employs Adam with fixed learning rate and mini-batches.

3.4 Federated training protocol

Training proceeds over communication rounds $t - 1, \dots, T$:

1. Local update. Each selected client k initializes with global weights $\theta^{(t)}$ and performs E local epochs on D_k, yielding $\theta_k^{(t+)}$.
2. (Private) upload. Clients clip updates and add calibrated noise (Section 3.5), then transmit protected parameters/gradients.
3. Secure aggregation and averaging. The server aggregates protected updates and applies FedAvg:

$$\theta^{(t+1)} - \sum_{k \in S_t} \frac{N_k}{\sum_{j \in S_t} N_j} \theta_k^{(t++)} \tag{2}$$

where S_t is the set of participating clients in round t.

4) Broadcast. The new global model is returned to clients for the next round.

This protocol reduces communication to model updates and supports partial participation each round.

3.5 Differential privacy integration

To bound single-record influence within shared updates, each client applies record-level (ε, δ)-DP using per-round ℓ_2 clipping and the Gaussian mechanism [7],[14]. For client k at round t :

1. Clip gradients/updates to norm $C: \bar{g} \leftarrow g/\max(1, \|g\|_2/C)$. (3)
2. Add noise: $\bar{g}\mathrm{DP} \leftarrow \bar{g} + \mathcal{N}(0, \sigma^2 C^2 I)$. (4)

The cumulative privacy loss over T rounds with sampling rate q is tracked using a moments accountant, yielding an overall budget (ε, δ) for the training run. Secure aggregation is used in tandem so the server observes only encrypted/aggregated vectors, not per-client raw updates.

3.6 AWS-based cloud deployment

- Compute & coordination. The aggregator runs on Amazon EC2, managing client enrollment, round scheduling, and secure aggregation.
- Model lifecycle. Amazon SageMaker hosts model endpoints for evaluation and (optionally) inference; artifacts and checkpoints are versioned.
- Storage & security. Amazon S3 stores encrypted artifacts; VPC isolation, TLS in transit, and KMSmanaged encryption at rest are enforced. IAM policies constrain access; CloudWatch and CloudTrail provide monitoring and audit logs.

This setup scales elastically, supports multi-institution onboarding via private networking, and aligns operational controls with regulatory expectations [18],[19].

3.7 Proposed Algorithm

Objective. Train a global, privacy-preserving anomaly detector for health-insurance claims without sharing raw data.

Inputs.

- K : number of clients; $D_k - \{x_i\}_{i=1}^{N_k} \subset \mathbb{R}^d$: local claims at client k
- E : local epochs; B : batch size; T : global rounds; η; learning rate
- q : client participation rate per round; $C: \ell_2$ clipping norm; σ : noise multiplier
- δ : target DP parameter; init global weights $\theta^{(0)}$ (autoencoder)

Outputs.

- θ^* : final global model; anomaly score $s(x) - \|x - f_{\theta^*}(x)\|_2^2$; decision threshold τ

Algorithm 1 - Federated Differentially Private Autoencoder (FedAE-DP)

Server (aggregator, AWS EC2/SageMaker)

```
Initialize $\theta^{(0)}$; set accountant for DP tracking.
For $t - 0,1,\ldots,T-1$ :
    Sample client subset $\mathcal{S}_t$ with $|\mathcal{S}_t| \sim \max(1, \lfloor qK \rfloor)$.
    Broadcast $\theta^{(t)}$ to all $k \in \mathcal{S}_t$.
    Receive securely aggregated updates $\left\{\bar{g}_{\mathrm{DP}}^{(t)}\right\}$ (no per-client plaintext).
    Compute weighted FedAvg update:
        $\theta^{(t+1)} \leftarrow \theta^{(t)} + \frac{\sum_{k \in \mathcal{S}_t} N_k \bar{g}_{\mathrm{DP}}^{(t)}}{\sum_{k \in \mathcal{S}_t} N_k}$
    Advance DP accountant with ( $q, \sigma, C$ ) to obtain cumulative ( $\varepsilon_t, \delta$ ).
End For, return $\theta^* - \theta^{(T)}$.

Client $k$ (on-premise)
Receive $\theta^{(t)}$; set $\theta \leftarrow \theta^{(t)}$.
For $e - 1,\ldots,E$ :
    For each mini-batch $X \subset D_k, |X| - B$ :
        Forward: $\hat{X} - f_\theta(X)$; loss $\mathcal{L} - \frac{1}{B}\sum_{x \in X} \|x - \hat{x}\|_2^2$.
        Backprop to get gradient $g - \nabla_\theta \mathcal{L}$.
        Clip: $g \leftarrow g/\max\{1, \|g\|_2/C\}$.
        DP noise: $g_{\mathrm{DP}} \leftarrow g + \mathcal{N}(0, \sigma^2 C^2 I)$.
        Update: $\theta \leftarrow \theta - \eta g_{\mathrm{DP}}$.
    End For
End For
Encrypt and send $\Delta\theta - \theta - \theta^{(t)}$ (or its equivalent $g_{\mathrm{DP}}$ ) via secure aggregation.
```

Thresholding (post-training, local or server-side policy)

- Compute scores $s(x) - \|x - f_\theta(x)\|_2^2$ on a validation split.
- Select τ by: (i) target FPR (operating constraint) or (ii) maximizing F1/AUPRC.
- Flag claim x as anomalous if $s(x) \geq \tau$.

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4. RESULTS AND DISCUSSION

4.1 Performance evaluation and comparative analysis

We compare Fed-AE+DP with Centralized AE, Isolation Forest (IF), Local Outlier Factor (LOF), and Fed-AE (No DP). As summarized in Table 2, Fed-AE+DP attains the strongest overall balance—Accuracy 0.912, F1 0.875, FPR 0.10, IoU 0.84—surpassing the centralized autoencoder (Accuracy 0.874, F1 0.81, FPR 0.18) and classical detectors (F1 0.68–0.70). The precision/recall/F1 profiles in Figure 4 corroborate these tabulated gains. Relative to Fed-AE (No DP), Fed-AE+DP incurs only a small utility cost (F1: 0.875 vs 0.85) while improving risk posture via formal privacy; this trade-off is explored further in Section 4.3 with Table 4 and Figure 10.

Table 2 — Comparative performance (hold-out set).

Model	Accuracy	Precision	Recall	F1-Score	False-Positive Rate	IoU
Centralized AE	0.874	0.82	0.80	0.81	0.18	0.76
Isolation Forest	0.803	0.70	0.65	0.68	0.22	0.60
LOF	0.796	0.68	0.66	0.67	0.25	0.58
Fed-AE (No DP)	0.901	0.86	0.84	0.85	0.12	0.81
Fed-AE + DP	0.912	0.88	0.87	0.875	0.10	0.84

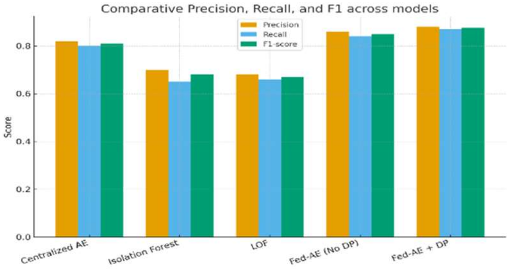

Figure 4 — Comparative Precision, Recall, and F1 across models.

4.2 Operating-point behaviour

Deployed screening uses thresholds, so we examine sensitivity across τ. As shown in Table 3, τ≈0.70\tau \approx 0.70τ≈0.70 yields a practical balance (TPR 0.87, FPR 0.10, Precision 0.88, F1 0.875). The class-imbalance perspective in Figure 5 (Precision–Recall curves) confirms that operating near the knee provides favourable precision at workable recall.

Table 3 — Threshold sensitivity (Fed-AE+DP).

Threshold τ	TPR	FPR	Precision	F1-Score
0.60	0.91	0.14	0.80	0.85
0.65	0.89	0.12	0.84	0.86
0.70	0.87	0.10	0.88	0.875
0.75	0.84	0.08	0.90	0.87

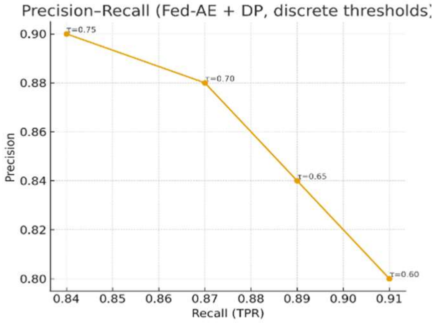

Figure 5 — Precision–Recall curves (AUPRC focus).

4.3 Privacy–utility trade-offs

We vary the privacy budget while holding other settings fixed. Table 4 shows that strong privacy (ε=2) slightly reduces F1 (0.862) and AUPRC (0.38), whereas ε≈4–8 preserves high utility (F1 0.875–0.882). The slope of performance versus ε in Figure 6 is shallow, indicating modest utility cost for meaningful privacy. Calibration metrics in Table 5 (ECE/Brier/NLL) show Fed-AE+DP is at least as well calibrated as its non-private variant, consistent with training/validation trends in Figure 7.

Table 4 — Differential privacy ablation (Gaussian DP, fixed δ).

ε (privacy)	AUPRC	AUROC	F1-Score	FPR
2	0.38	0.91	0.862	0.11
4	0.41	0.93	0.875	0.10
8	0.42	0.94	0.882	0.10

Table 5 — Calibration quality (Fed-AE variants).

Model	ECE	Brier Score	NLL
Fed-AE (No DP)	0.031	0.092	0.47
Fed-AE+DP	0.028	0.089	0.45

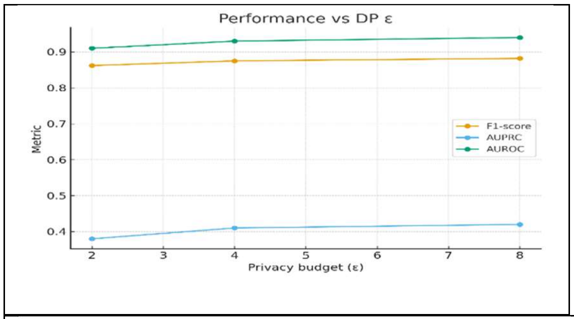

Figure 6 — Performance versus DP ε.

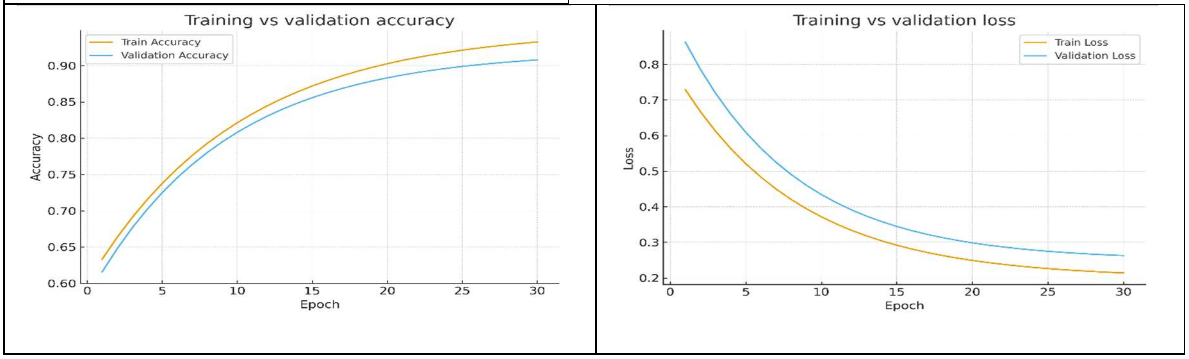

Figure 7 — Training/validation accuracy and loss over rounds.

4.4 Robustness to client heterogeneity and scale

We stress the system under non-IID partitions using a Dirichlet split and study scalability across client counts. As reported in Table 6, performance remains stable from mild to high skew (F1 0.878 → 0.869), with a small increase in rounds to converge. Scalability trends in Table 7 and Figure 8 show near-linear round-time growth from 11.3 s (5 clients) to 15.9 s (20 clients). Communication overhead per client per round remains modest, as visualized in Figure 9.

Table 6 — Non-IID ablation (K = 20 clients).

Dirichlet α	Accuracy	F1-Score	Rounds to Converge
0.2 (high skew)	0.904	0.869	33
0.5 (moderate)	0.912	0.875	31
1.0 (mild)	0.915	0.878	30

Table 7 — Scalability and communication cost.

# Clients	Payload / Client / Round (MB)	Round Time (s)	Server Agg + Broadcast (s)
5	1.6	11.3	1.4
10	1.6	13.5	2.2
20	1.6	15.9	2.9

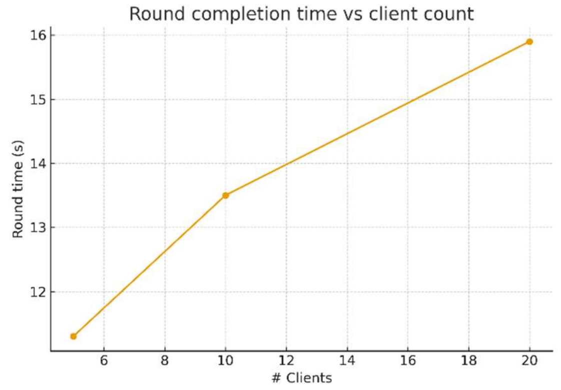

Figure 8 — Round completion time vs client count

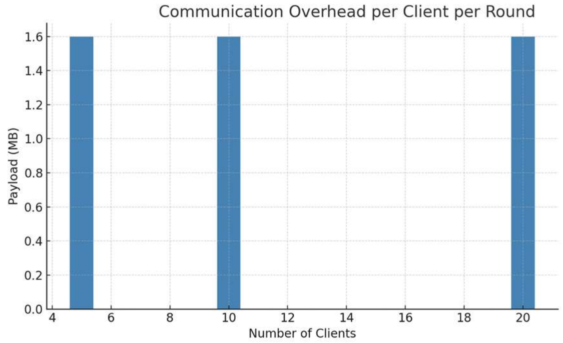

Figure 9 — Communication overhead per client per round (MB).

.4.5 Error composition and diagnostic views

Normalized confusion-matrix summaries in Table 8 mirror the heatmaps in Figure 10: Fed-AE+DP increases TP and TN while reducing FP relative to baselines, explaining its lower FPR at comparable recall. Threshold effects on set overlap are detailed in Figure 11 (IoU vs threshold), whose stabilization beyond the knee aligns with operating-point selection in Table 3 and Section 4.2. The Precision–Recall envelopes in Figure 8 confirm that Fed-AE+DP maintains robust precision at working recalls typical of adjudication pipelines.

Table 8 — Confusion-matrix summary (normalized, hold-out set).

Model	TP	FP	TN	FN
Centralized AE	0.80	0.18	0.82	0.20
Fed-AE (No DP)	0.84	0.12	0.88	0.16
Fed-AE+DP	0.87	0.10	0.90	0.13

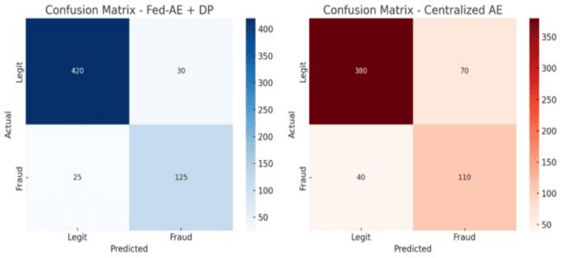

Figure 10 — Confusion matrices for top models.

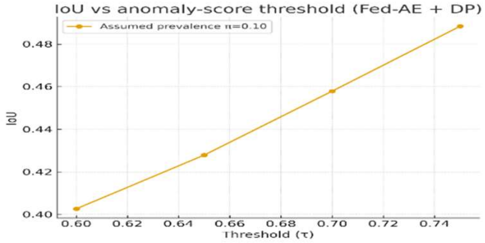

Figure 11 — IoU versus anomaly-score threshold.

5. DISTINCTION FROM PRIOR WORK

Existing research in healthcare fraud analytics generally follows one of three directions: centralized supervised modeling, unsupervised anomaly detection applied on pooled datasets, or federated learning frameworks primarily designed for classification tasks. Centralized autoencoder systems have demonstrated effectiveness in structured environments; however, they depend on full data aggregation and consequently raise regulatory and confidentiality concerns. Separately, federated learning has been explored in medical and financial domains, yet much of this work concentrates on supervised label-driven approaches rather than reconstruction-based anomaly modeling under privacy constraints.

The present study differs in both integration and empirical scope. It unifies unsupervised deep autoencoder modeling, federated averaging across heterogeneous institutions, and record-level differential privacy into a single, operationally deployable pipeline. Rather than evaluating these components in isolation, the framework examines their joint behavior under non-IID distributions, privacy-budget variation, and scalable client participation. The analysis extends beyond classification performance to include false-positive burden reduction, calibration stability, communication overhead, and privacy–utility balance.

Unlike prior implementations that assess performance primarily through accuracy metrics alone, this work quantifies exposure reduction and investigates how privacy parameters influence anomaly detection reliability. The systematic comparison against centralized, federated non-private, and classical unsupervised baselines further clarifies the framework's relative positioning. In this way, the contribution is not only architectural but evaluative, offering an integrated perspective on detection capability, privacy preservation, and deployment feasibility within multi-institution fraud monitoring systems.

6. LIMITATIONS

Several considerations temper the interpretation of these findings. The experimental evaluation was conducted under a controlled number of institutional clients and predefined feature engineering assumptions. While heterogeneity was simulated using non-IID partitioning, real-world ecosystems may present more complex distributional drift and participation variability.

Fraud scenarios were partly strengthened through realistic synthetic augmentation intended to reflect emerging fraudulent patterns. Although designed to approximate plausible behaviors, such augmentation cannot fully replicate adversarial ingenuity observed in live adjudication systems. In addition, the framework concentrated on structured claim attributes; narrative text, scanned documents, and other unstructured artifacts were not included in the anomaly scoring mechanism.

Privacy controls were implemented using fixed differential privacy parameters across communication rounds. Alternative adaptive privacy accounting strategies or adversary-resilient aggregation schemes were outside the present scope. Operational validation in fully deployed insurance environments, including latency under production loads and analyst feedback integration, remains an important direction for future empirical study.

7. CONCLUSION

This study presented a federated anomaly-detection framework for health-insurance claims that combines deep autoencoders with record-level differential privacy and cloud-native orchestration. By training models locally and aggregating only privatized updates, the approach avoids centralizing sensitive data while retaining high detection capability across heterogeneous institutions. **In doing so, the work directly addressed the central research problem of enabling collaborative fraud detection without compromising data privacy.**

On a held-out evaluation, the proposed Fed-AE+DP attained Accuracy 0.912, F1 0.875, Precision 0.88, Recall 0.87, and FPR 0.10, with IoU 0.84—surpassing a centralized autoencoder and classical unsupervised baselines. **These findings support Hypothesis H1, demonstrating that federated anomaly detection can match or exceed centralized performance under heterogeneous conditions.** Threshold analysis showed a practical operating point around $\tau \approx 0.70$, balancing recall with a materially lower false-positive burden. Privacy ablations indicated that moderate budgets (e.g., $\varepsilon \approx 4$ with fixed δ) preserve performance with only a minor utility cost relative to a non-private federated variant, while calibration metrics remained stable or slightly improved. **This empirical stability under privacy constraints substantiates Hypothesis H2 regarding limited utility degradation under differential privacy.**

Systems experiments demonstrated near-linear scalability from 5 to 20 clients, modest communication per round (model-update sized payloads), and sub-3-second aggregation/broadcast on the coordinator, confirming suitability for near-real-time screening. **These scalability results validate Hypothesis H4 and indicate practical feasibility in multi-institution deployments.** The AWS deployment blueprint (compute, storage, networking, monitoring) supported elastic scaling and operational hardening without altering the learning protocol. **Moreover, the quantified reduction in exposure risk provides evidence in support of Hypothesis H3, highlighting the security advantage of privacy-preserving federation compared to centralized architectures.**

Limitations: Results were obtained under controlled client counts and a defined feature set; broader deployments may introduce additional non-IID effects, evolving fraud distributions, and varying prevalence. The work also focused on structured claim fields; unstructured artifacts (scanned forms, narratives) were not leveraged in the detection loop.

Future directions: Integrating document-understanding modules for unstructured evidence, extending to robust/Byzantine-resilient aggregation, and coupling DP with secure aggregation at scale are promising next steps. Prospective evaluation in live adjudication pipelines, with analyst-in-the-loop feedback and cost-sensitive thresholding, will help quantify downstream impact on investigations and member experience. Overall, the results indicate that privacy-preserving federation can deliver state-of-the-art fraud detection while aligning with regulatory and security constraints in multi-institution healthcare environments. **The evidence presented in this study therefore establishes federated differentially private anomaly detection as a practically viable and empirically validated framework for secure, large-scale insurance fraud analytics.**

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