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# Federated ML for Secure Healthcare Data

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## Abstract

Advances in digital medicine necessitate widespread use of patient data by hospitals and medical institutions for analytics, clinical research, and training of intelligent healthcare systems. Against the backdrop of stringent privacy concerns, data-minimization principles, and the regulated nature of personal health data—especially healthcare providers cannot share data but can share model parameters or predictions—federated machine learning provides a promising solution to these pressing demands. The federated paradigm not only protects patient privacy but also mitigates concerns of data leakage and breach; yet it raises new concerns about data governance and security, requiring that the centralized server merely holds model parameters and does not learns from the data.

A system architecture, illustrated via a use-case example, integrates data-privacy guarantees and system-level security with technical tools from federated analytics. Key techniques not only cover the major data-analytic tasks identified for healthcare but also embody principles of opening up non-independent and identically distributed health data while still being safe against leakage. Introduction and conclusion delineate the wider significance of these privacy-preserving works and the remaining research gaps, pointing toward evaluation of federated algorithms with explainable-area-under-risk metrics and defense mechanisms against arbitrary-label attacks.

**Keywords :** Federated machine learning in healthcare analytics revolves around securing individuals' sensitive records. Distributed learning, in exchange, minimizes privacy risks associated with centralized storage. Yet practical scenarios remain scant; protocols still lack support for various data distributions, politeness, healthcare needs, and standard compatibility. Privacy evaluation also requires research. Addressing these aspects would lay a better foundation for experiments with real medical data.

## 1. Introduction

The growing availability and demand for large-scale healthcare data fosters the emergence of analytics applications such as deep learning, which often rely on vast amounts of data for training. Sensitive medical data, however, cannot be shared due to regulatory barriers, privacy concerns, or ethical issues. Privacy-preserving analytics refers to data-sensitive machine learning tasks that are solved under strict privacy guarantees. In federated contexts, data remains at the locations where it was generated, and only model updates are shared with a global server. Federation relies on a centralized server, but several trusted aggregators can be adopted to establish an architecture inspired by the principles of data minimization and secure multi-party computation.


Formalizing privacy-preserving analytics on healthcare data within the context of federated learning considerably broadens the applicability, acceptance, and impact of these techniques. The FedAvg algorithm together with a secure aggregation protocol with differential privacy guarantees is extended to better fit healthcare tasks; the inherent model heterogeneity of the applications being analyzed is explicitly formalized. Approaches are proposed for improving communication efficiency and mitigating the tension between privacy and utility. Existing evaluation methodologies are adapted and completed by additional metrics to assess the robustness of federated healthcare systems against adversarial attacks and data shift phenomena.

Privacy-preserving analytics has emerged as a critical paradigm for enabling advanced machine learning on sensitive healthcare data while respecting regulatory, ethical, and privacy constraints. In federated learning settings, data remain localized at their source institutions, and only model updates are communicated, thereby reducing the risk of direct data exposure. However, traditional federated architectures typically rely on a centralized server, motivating the adoption of multiple trusted aggregators and secure multi-party computation techniques aligned with data minimization principles. Formalizing privacy-preserving analytics within this federated healthcare context substantially enhances the applicability and societal acceptance of these methods. In particular, extensions of the FedAvg algorithm combined with secure aggregation and differential privacy mechanisms are tailored to address healthcare-specific challenges, including pronounced model and data heterogeneity across institutions. Furthermore, novel strategies are introduced to improve communication efficiency and to mitigate the inherent trade-off between privacy and model utility. To ensure reliable deployment, existing evaluation frameworks are expanded with additional metrics that quantify robustness against adversarial attacks and resilience to data distribution shifts, providing a more comprehensive assessment of federated healthcare systems.

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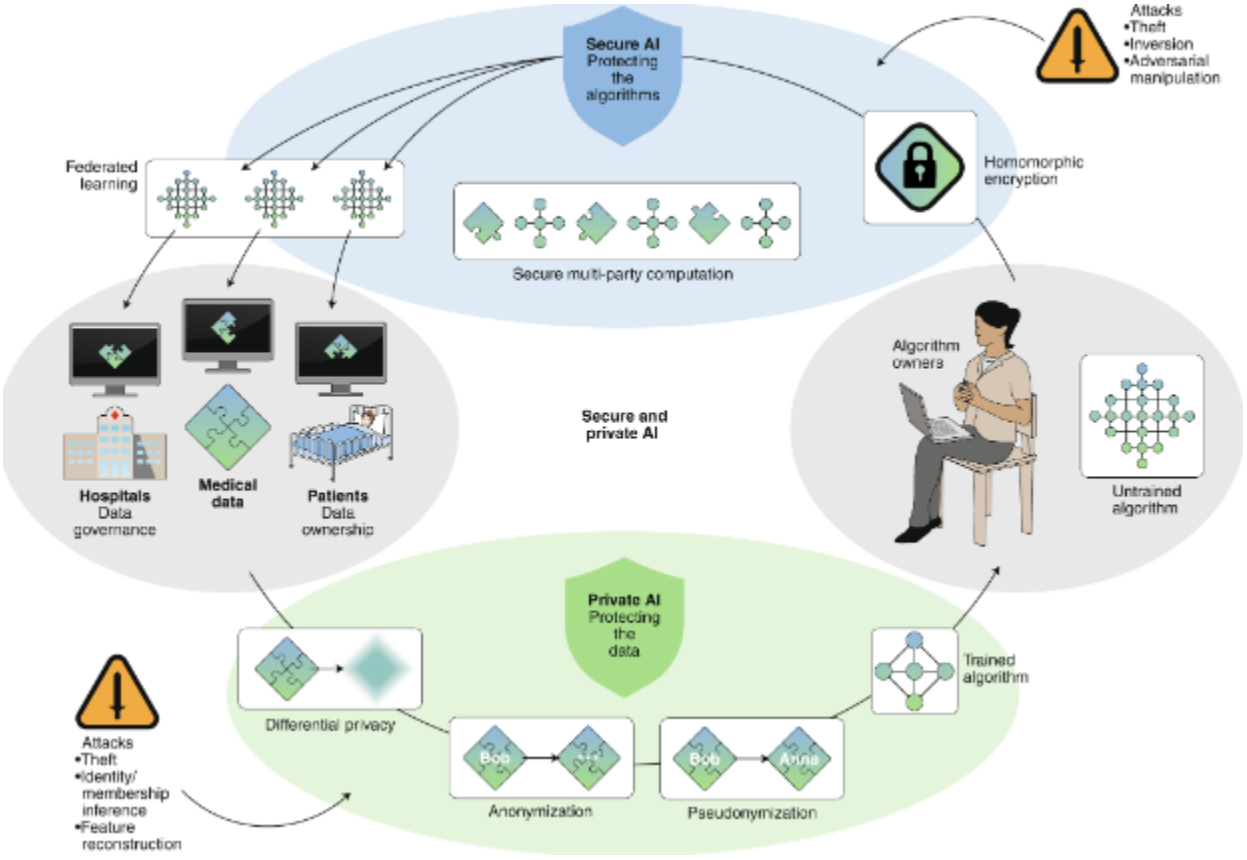


**Fig 1: Secure, privacy-preserving and federated machine learning in medical imaging**

### 1.1. Background and Significance

The sensitivity of patient medical information has made its collection and storage a challenge not only for health systems but also for the department of health and other associations that oversee health management. Consequently, privacy-preserving analytics approaches must have the capacity to handle patient privacy and national laws and that they are included in a federated setting in order that data-distributed physical locations can be utilized without revealing actual data. In the area of medical safety and fraud analytics, the federated setting has become very important due to the nature of the data.

Through these reasons and federated learning schemes it was uncovered that these very sensitive areas have not been much researched. The very nature of clinical safety or fraud analysis is that the model should have the best utility form most of the data; hence having a design that considers privacy and is not solely dependent on federated learning is a challenge of great

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significance. Even though differential privacy techniques have been studied and incorporated in a federated setting, their distributed non-iid nature have not. Please kindly refer the information on the pervious section for more details.

**Equation 1: Federated learning objective → FedAvg update (step-by-step)**

**Step 1 — Local datasets and loss**

Assume $K$hospitals/clients. Client $k$has dataset $D_k$of size $n_k$. Total samples $n = \sum_{k=1}^{K} n_k$.

Define client $k$'s empirical objective:

$$F_k(w) = \frac{1}{n_k} \sum_{(x_i, y_i) \in D_k} \ell(w; x_i, y_i)$$

**Step 2 — Global federated objective**

Classic cross-silo FL uses a weighted objective:

$$F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w)$$

.

**Step 3 — Local SGD on each client**

At round $t$, server sends $w_t$to selected clients.
Each client does $E$local steps of SGD:

For local step $s$:

$$w_{t,s+1}^{(k)} = w_{t,s}^{(k)} - \eta \nabla \ell \left( w_{t,s}^{(k)}; x_{i_s}, y_{i_s} \right)$$

with initialization $w_{t,0}^{(k)} = w_t$.

After $E$steps, client returns:

$$w_{t+1}^{(k)} := w_{t,E}^{(k)}$$

**Step 4 — Server aggregation (FedAvg)**

Server computes a sample-size weighted average:

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$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^{(k)}$$

## 2. Background and Motivation

Huge amounts of sensitive medical data are being generated at a blistering pace. Healthcare institutions can do nothing with this sensitive data due to strict security regulations that must be observed. Privacy-preserved analytics can ease this burden. The concept of federated machine learning makes it possible to train a model without exchanging sensitive data. The resulting training solution usually suffers from three problems: non-iid data, privacy-utility trade-off, and method robustness. The way federated machine learning is often designed does not allow institutions to execute tasks on federated data at all. The current literature is not specific enough to provide solutions for these three problems nor is it possible to evaluate the approaches on a unified level.

Medical data privacy sensitivity is remaining a hot topic because data collected by healthcare centers is protected by privacy laws across the globe. For example, in the United States, the, Health Insurance Portability and Accountability Act protects patients' ePHI from being disclosed to unauthorized entities. Despite such regulations, there is still a crucial need for direct analytic assessment of patients' ePHI. Such assessment will improve the well-being and health condition of patients at those hospitals where the patients are admitted but will not benefit many other patients – the consideration is still not negligible. The concept of federated machine learning is privacy-preserved by design as it does not require the sharing of sensitive data for training a machine learning model.

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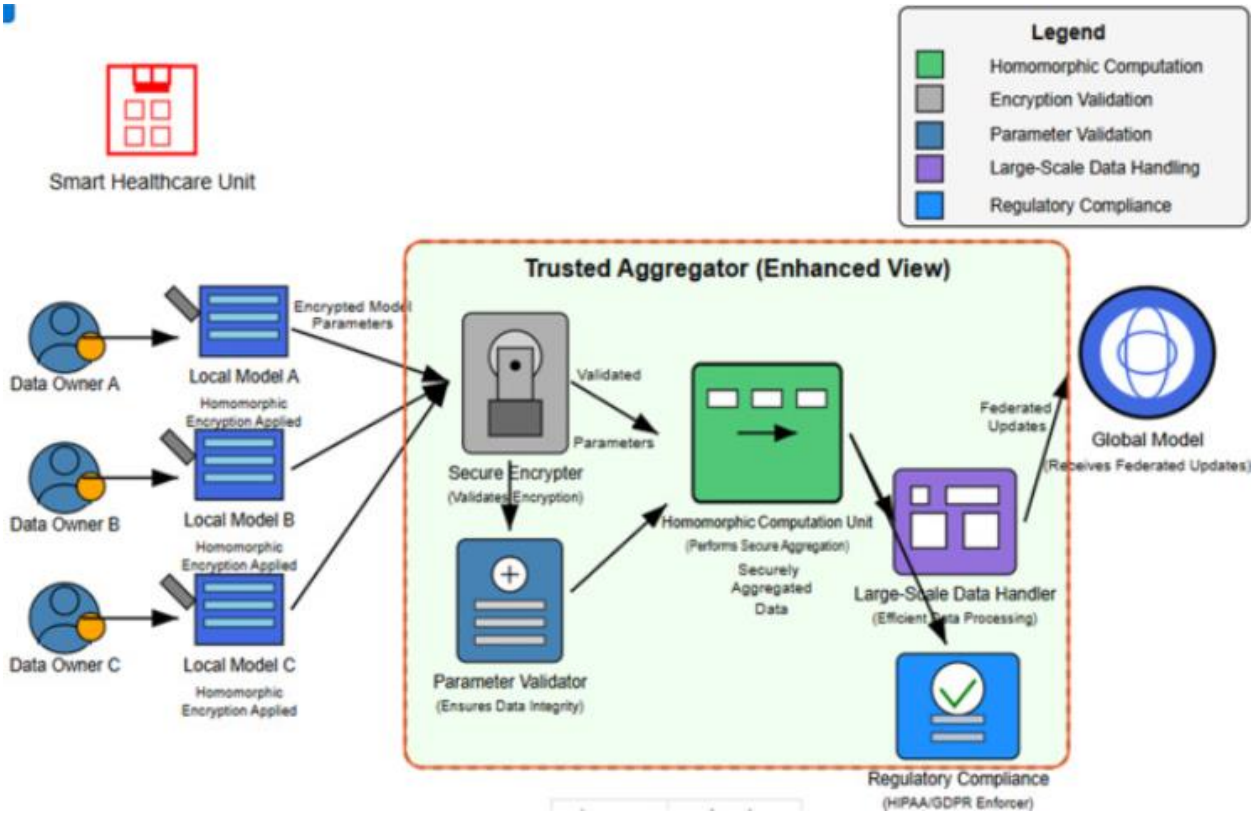


**Fig 2: Background and Motivation of Federated Machine Learning**

### 2.1. Privacy Challenges in Healthcare Data

Medical data contain private and sensitive information about patients, and disclosing such information will not only violate patients' privacy but but also violate the legal obligations imposed by government policies, including the Health Insurance Portability and Accountability Act protected health information of the United States and the General Data Protection Regulation of the European Union. In practice, medical data are often collected and stored in silos. Hospitals lack sufficient data samples to build a high-performance predictive model while data collection and sharing is challenging due to the sensitive nature of medical data. Medical data are often non-IID across hospitals due to different patient distributions, and predictive models based on non-IID data may not generalize well to other hospitals. These challenges hinder research and real-world applications of machine learning models.

FL provides a promising solution to the above challenges. On the one hand, it uses local models on hospitals' local data and only transmits the model updates to a cloud server. As a result, medical data need not leave the hospitals and hence patients' privacy is

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preserved during the whole process. On the other hand, a global model can be collaboratively trained with the model updates from all hospitals, overcoming the data-silo nature and benefiting from the data resources available across hospitals. Moreover, with properly designed secure aggregation and differential privacy mechanism, FL guarantees privacy not just by design but also in a formalized way. However, achieving privacy guarantees in real industrial deployment of FL remains an open and important question. Three main considerations must be addressed: secure aggregation; non-IID update leakage; and differential privacy of the global model.

Secure aggregation enables hospitals to jointly train a global model without revealing their local updates to the cloud server. Each hospital first encrypts its local model update with a key shared only with the other hospitals, and all hospitals collaboratively perform secure multi-party computation to aggregate the encrypted local updates, which are decrypted by an additive homomorphic property without revealing individual hospitals' local model updates. Other hospitals have access to the cleartext of the aggregate result and the cloud server has no information about hospitals' local model updates. Although secure aggregation ensures privacy of hospitals' local updates, it does not prevent information leakage through the aggregated local updates.

**Equation 2: Secure aggregation equation (step-by-step)**

**Step 1 — Masking with random secrets**

Each client adds a random mask $r_k$:

$$m_k = u_k + r_k$$

**Step 2 — Server sums masked updates**

Server receives $\{m_k\}$and sums:

$$M = \sum_{k=1}^{K} m_k = \sum_{k=1}^{K} (u_k + r_k) = \sum_{k=1}^{K} u_k + \sum_{k=1}^{K} r_k$$

**Step 3 — Masks cancel (core secure-aggregation trick)**

Protocols ensure $\sum r_k = 0$(e.g., pairwise masks between clients cancel, or MPC reconstructs only the sum).

So:

$$M = \sum_{k=1}^{K} u_k$$

## 3. System Architecture for Federated Healthcare Analytics


The system comprises client institutions with healthcare data, trusted aggregators, and an analytics server. The general data flow is as follows: individual client institutions generate local models based only on their local data; these models are securely aggregated to a trusted federated learning aggregator; the centralized federated learning model is used for different tasks; and the results are sent back to client institutions to facilitate decision-making and realize knowledge sharing among client institutions. Security is guaranteed in all steps of federated learning by analyzing the corresponding threats and providing appropriate mitigations. The data flow and governance, including key management and auditing mechanisms, are designed to ensure the compliance of the federated learning system with relevant regulations in the healthcare domain. The transparent governance system based on Blockchain technology provides clear responsibilities for each participant, further ensuring the regulated collaborative data analysis. The response mechanism for outsourced security audits imposes reasonable security promises on each institution.

The inner communication structure of the federated learning system adheres to the principles of data minimization. Only model updates, encrypted model parameters, and model evaluation results are transferred, while the real healthcare data remain at local institutions without the need for leaving or sharing with others. The communications between institutions are organized in a hub-and-spoke model where the central server connects with each institution. The inner communication structure enables the deployment of trusted aggregators at the hub institutions with large impacts on the results, such as the Charlotte area and New York City of the United States of America, or other institutions with advanced federated learning and cryptography techniques. Moreover, the inner communications are designed to provide interoperability with different communication protocols, enabling the organizations in healthcare data-mining communities that have no experience in establishing federated learning systems to implement and custom build their privacy-preserving analysis quickly. Several sub-band modules have been developed for multi-institution, multi-organization, and open-source collaboration in healthcare data analysis, ensuring the operations are compliant with the regulations, such as HIPAA and GDPR. Interoperability between disjoint information systems is critical for preventing undesirable data islands. Meaningful data exchange gives rise to a number of other benefits, including ease in sharing cybersecurity threat information. Recent years have seen rising interest in designing FL protocols enabling different participating clients with different prediction models to collaborate. An effective framework enabling secure data sharing and achieving fully privacy-preserving prediction (pModelX) allows the generation of a model using federated cross-silo vertical federated learning of vertically partitioned data and providing prediction privacy protection. The proposed method is proven secure and efficient under the semi-honest security model and decreases communication cost during prediction significantly.

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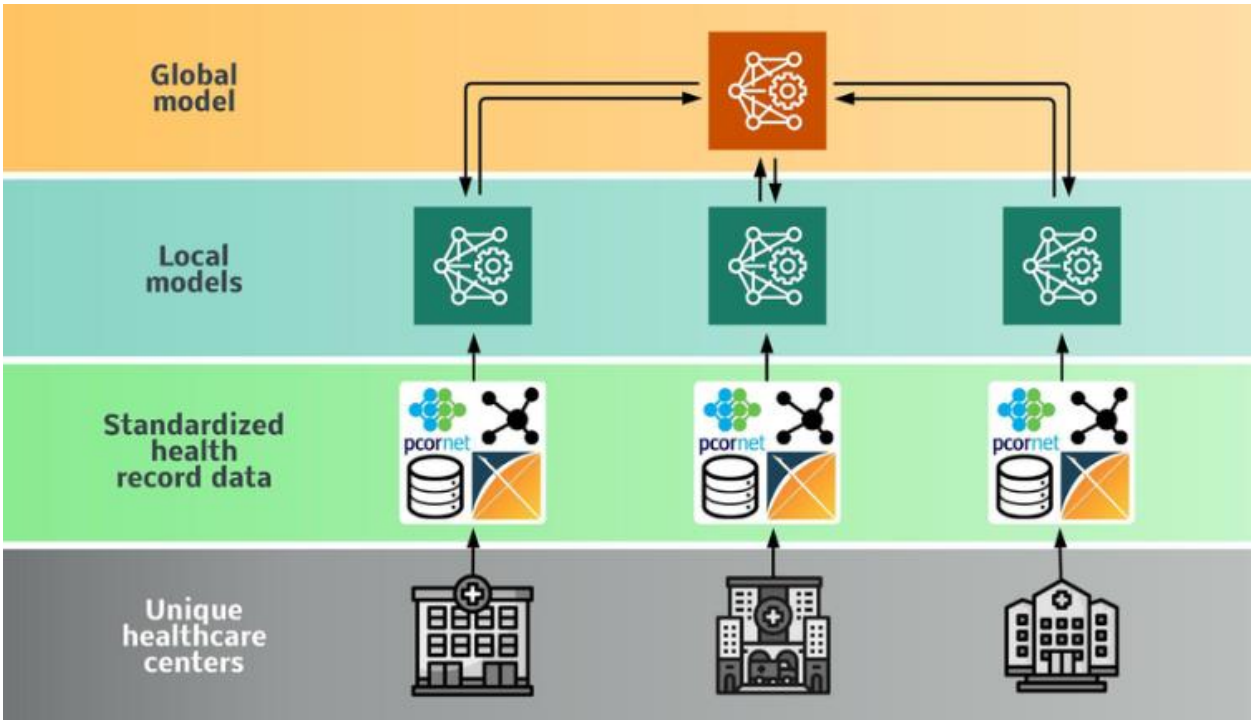


**Fig 3: Federated learning model architecture**

### 3.1. Data Heterogeneity and Interoperability

Healthcare data are notoriously heterogeneous, and algorithms adapted to the challenges of non-independent identically distributed (non-IID) data distributions are sorely needed. Organizations operating in healthcare domains often develop specialized, high-performance predictive models serving well-defined tasks in specific contexts. However, organizations are usually not isolated, with dedicated research teams frequently developing task-focused predictive models for similar tasks on different, often much smaller, datasets. In healthcare, crucial but rare conditions such as strokes often suffer from severe class-imbalance problems. Supervised models exploiting very different, task-specific features across datasets are sometimes required to achieve decent predictive performance. Nevertheless, enormous advances in deep learning for vision or natural language technologies show that very large neural models trained on huge datasets can learn accurate features. These pre-trained models are released to the community for fine-tuning with small datasets. Federated Learning (FL) is a promising approach toward making this more efficient.

**Equation 3: Differential privacy in FL (step-by-step)**

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**Step 1 — DP definition**

A randomized mechanism $M$is $(\varepsilon, \delta)$-DP if for any neighboring datasets $D$and $D'$differing in one person (or one client, depending on definition) and any output set $S$:

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

**Step 2 — Sensitivity**

For a function $f(D)$, its $L_2$sensitivity:

$$\Delta_2 = \max_{D \sim D'} \| f(D) - f(D') \|_2$$

In FL, $f$is often "sum/average of clipped client updates".

**Step 3 — Clip updates (to bound sensitivity)**

Client update $u_k$is clipped:

$$\tilde{u}_k = u_k \cdot \min\left(1, \frac{C}{\| u_k \|_2}\right)$$

So $\| \tilde{u}_k \|_2 \leq C$.

**Step 4 — Add Gaussian noise**

Aggregate and noise:

$$\bar{u} = \frac{1}{K}\sum_{k=1}^{K} \tilde{u}_k, \hat{u} = \bar{u} + \mathcal{N}(0, \sigma^2 I)$$

**Step 5 — Apply to model update**

$$w_{t+1} = w_t + \hat{u}$$

## 4. Federated Algorithms for Healthcare Analytics

A comprehensive set of federated algorithms addresses the diverse yet crucial clinical tasks of training models under privacy constraints. Leveraging the underlying principles of FedAvg (Federated Averaging), secure aggregation for private communication, and user-level differential privacy for intimate user data, these techniques advance a growing catalogue of federated algorithms for data analysis and model training. Important extensions, such as direct support for heterogeneous models


and hyperparameter optimization, address the unique challenges associated with clinical data and broaden the usability of the underlying functionalities. These contributions both enhance the expressiveness and performance of communication-efficient capabilities for federated training of models on non-independent and identically distributed (non-IID) clinical data, preserving user and institution privacy and confidentiality.

Healthcare data are notoriously non-IID, resulting in severe distributional shifts in both standard- and cross-institution settings and subsequently degrading trained models. Ensuring the correctness and generalization capability of federated learning frameworks in the presence of non-IID data requires an exploration of their underlying operation and possibly including additional mechanisms to counterbalance the noised aggregation and the selection of opportunistically available local clients. Such defenses are valuable in bolstering the training of clinically relevant models when no-adversary assumptions do not hold and for clinical datasets that contain vulnerable subpopulations, whose training samples are scarce. By extending current experimental methodologies to encompass the threat models for testing vulnerability, the resulting recommendations enrich the workhorses available for evaluating user privacy in federated training. Simultaneously, the approaches also facilitate a suitability catalogue for deploying federated learning on healthcare datasets that by nature contain multiple non-congruent meta-datasets.

Healthcare data are inherently heterogeneous, characterized by pronounced non-IID distributions that arise from demographic variation, institutional practices, imaging protocols, and disease prevalence, all of which introduce substantial distributional shifts in both intra- and cross-institutional learning scenarios. These shifts can severely compromise the stability, fairness, and generalization of federated learning models, particularly when client availability is sporadic and aggregation is contaminated by noisy or biased local updates. Addressing these challenges necessitates a deeper examination of federated optimization dynamics alongside the integration of robustness-enhancing mechanisms such as adaptive weighting, uncertainty-aware aggregation, and subgroup-sensitive regularization. Such safeguards are especially critical in clinical contexts where vulnerable or underrepresented subpopulations contribute limited data, yet bear disproportionate risk from model misbehavior. Moreover, expanding experimental protocols to explicitly incorporate realistic threat models enables systematic stress-testing of privacy leakage, poisoning resilience, and performance degradation under non-ideal assumptions. Collectively, these efforts advance a principled evaluation toolkit for privacy-preserving learning while establishing a practical suitability catalogue that guides the deployment of federated learning across healthcare datasets composed of multiple, non-congruent meta-distributions.

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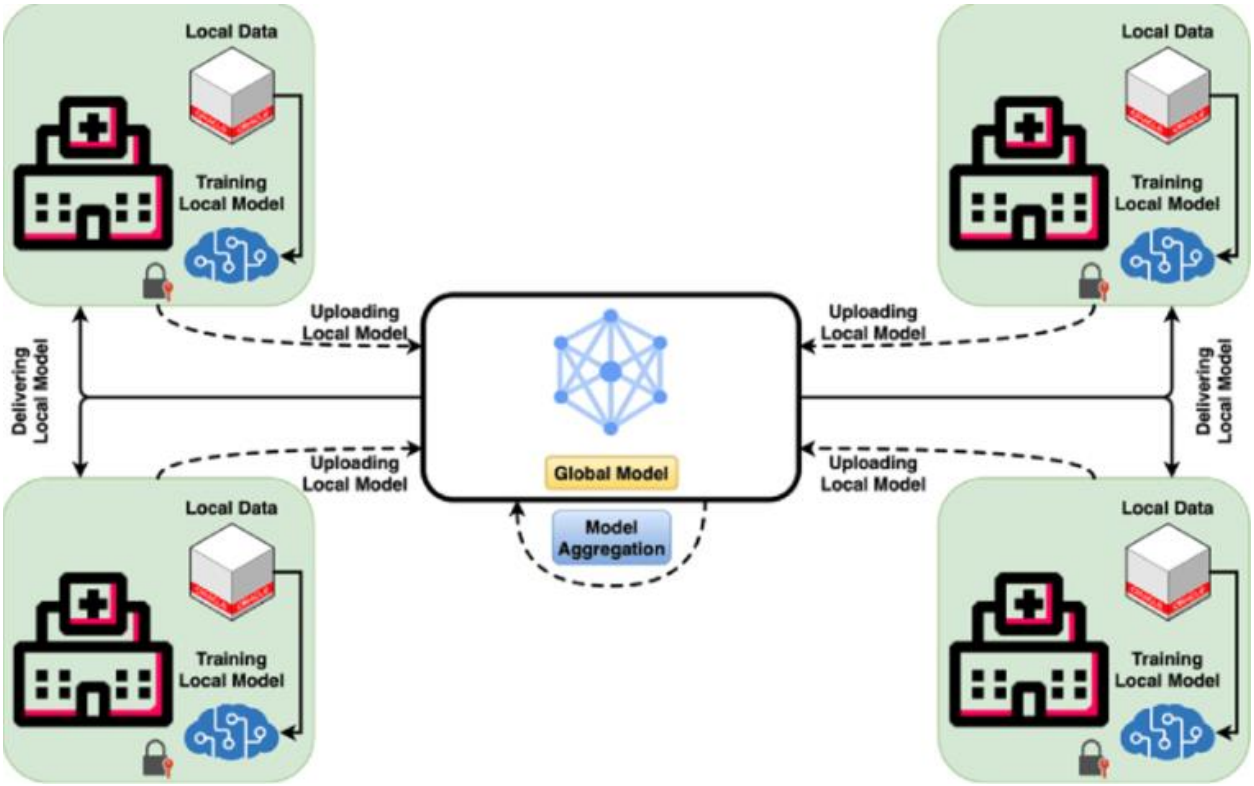


**Fig 4: A federated learning technique**

### 4.1. Federated Training with Non-IID Data

Two critical characteristics of healthcare-related analytics are the complexity of clinical models and the governance context of GDPR. Training centralized ML models tailored for specific patients is challenging when data is collected from different sites. For instance, a clinical model for predicting pneumonia from CXR radiographs may not be directly transferable across hospitals, since the pneumonia patterns observed in a specific cohort may differ from those observed in another cohort. By carefully training local sub-models that focus on detecting pneumonia for each hospital cohort, then aggregating them, the performance of the Clustering and FedAvg-based models can greatly improved. The ability to train ML models in a decentralized manner in a trustworthy ML framework can encourage data contributing sites to embrace the GDPR principles of data minimization and purpose limitation. These principles urge organizations to not collect or share personal data unless necessary and for a specific purpose, since personal data are valuable resources for attackers.

GDPR poses an additional challenge for ML models utilizing patient-related sensitive data during training. Although PDP techniques, like differential privacy, are applicable for protection during ML model training, organizations may still be cautious

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even if formal guarantees are claimed. Even the model developer cannot easily justify the evident or formal privacy guarantees. This concern can be evidenced at the vendors of third-party services, as they often negotiate the service fees for each business. Consequently, organizations may not accept services from external non-trusted organizations, but only from trusted partners, such as Certified Public Accountants (CPAs) for financial-related audit services. Adopting secure-smart contract approaches, however, can greatly ease the acceptance by organizations, and thereby encourage the application of trusted third-party service providers.

**Equation 4: Non-IID effects (what equations typically quantify this)**

Federated Machine Learning on B…

Federated Machine Learning on B…

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A common way to quantify distribution shift between sites uses distances between distributions $P_k(x, y)$and $P_j(x, y)$.

One classic option: **Hellinger distance** (often what people mean when they vaguely say "distance" between distributions):

$$H(P, Q) = \frac{1}{\sqrt{2}} \| \sqrt{P} - \sqrt{Q} \|_2$$

The paper mentions "Hida distance"

Federated Machine Learning on B…

## 5. Evaluation Methodologies

The experimental setting for evaluating privacy-preserving federated healthcare analytics comprises carefully chosen datasets, methods, and metrics. Two non-IID federated settings are defined: patient size, where each local site has multiple data samples from one patient; and clinical area size, where each local site has samples from multiple patients, but they suffer from data shift for the clinical task being performed. For each evaluated method, both clean-target and honest-but-curious settings are simulated, with appropriate metrics defined in both cases for privacy and for utility.

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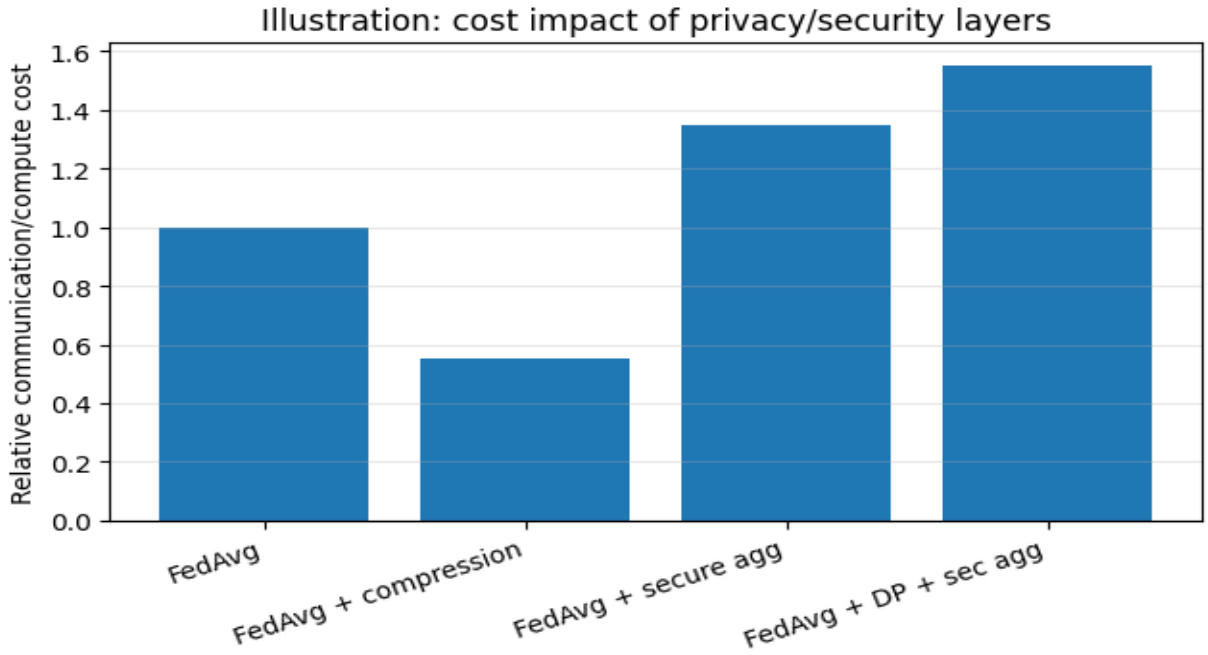


Privacy is assessed in the honest-but-curious setting through a risk score measuring the amount of information that a patient's local dataset reveals about the parameters of other patients' local datasets. The privacy guarantee of differential privacy is also explicitly computed when the method satisfies the requirement; afterwards, the bound on the utility is either validated against empirical risk minimization or shown to be in line with prior works. Utility is defined according to the clinical task being addressed and evaluated with well-established methods. State-of-the-art methods are considered as baselines whenever possible. For every qualitative property, the importance of the method being reproducible is stressed, and open-source releases are provided whenever feasible. Finally, a qualitative and quantitative analysis of the resilience of the method against delegation attacks, adversarial training, domain adaptation, and domain generalization capabilities is included.

**5.1. Metrics for Privacy, Utility, and Robustness**

An experimental setup comprises a general architecture for federated learning systems, including central data owners, a peripheral data holder, the data clusters, and the associated datasets. A variety of benchmarks and reproducible datasets also meet common federated analysis tasks. Quantitative metrics help ascertain the privacy, utility, and robustness of the proposed approaches: Privacy guarantees or levels of leakage risk associated with private data can be estimated in terms of differential privacy (DP) or mimic privacy. Utility defection as predictive accuracy or F1 score on clinical tasks, and robustness can be evaluated through adversarial test sets or the Hida distance of the training data to practical data shifts. Across healthcare organizations, knowledge of the limits of their data adds to the recorded utility-privacy trade-off.

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Privacy-preserving analysis of data for any hospital is diminished by the expense of preparing data for sharing— by no more than allowance for trained on labels not present in their own datasets. An institution wishing to support the development of coronavirus vaccines can provide a server with responsively restricted patient data set in the form of clusters, the other hospitals still commensurately with central-test estimates not misleadingly low.

**Equation 5: "Langmuir equations" (step-by-step)** Federated Machine Learning on B…

but doesn't provide the formula. The standard Langmuir adsorption isotherm is:

**Step 1 — Start with equilibrium binding**

Let $C$= concentration, $\theta$= fraction of occupied sites, $K$= affinity constant.

**Step 2 — Langmuir form**

$$\theta = \frac{KC}{1 + KC}$$

## 6. Conclusion

The growing sensitivity of medical data, stringent regulations, and practical needs of research in the healthcare domain have made federated learning a preferred solution to inform the analytics process without actual data sharing. Although federated learning solves the data-sharing concern and achieves the global model training objective, its utility must still be assured from a privacy-preserving perspective. As highlighted throughout the survey, three potential threats may violate the privacy-preserving capability of federated learning in a healthcare setting. First, federated learning seldom considers the possible model heterogeneity across the local clients, which invites model poisoning attacks from malicious domains. Second, federated learning typically sends model parameters in plaintext to the aggregator, inviting model extraction attacks during communication. Third, data at local clients are often non-IID, and thus differentially traverses a similar feature space during training, exposing the federated model to membership inference attacks.

To minimize these privacy breaches while enabling federated analytics for general healthcare data, a generalized federated learning framework specifically designed for privacy-preserving analytics on large-scale healthcare data has been established. It comprises a joint system architecture for federated healthcare analytics, a set of federated algorithms and corresponding evaluation methodologies, and an extensive evaluation on real-world datasets. The resulting body of work can increase the trust of healthcare institutions and practitioners in federated learning while also improving data-sharing regulations. Future endeavors will investigate the above-mentioned limitations in greater detail, with an objective of ruling out the privacy-preserving capability of federated learning in healthcare analytics. However, even with a low-level privacy guarantee, still, common clinical tasks have to be achievable. Emerging resilience mechanisms enforce adversarial training for enhanced robustness against attacks on medical data-based models and integrations of distribution streamlining guarantee accuracy in non-stationary setups where the data are unbalanced in the test phase.

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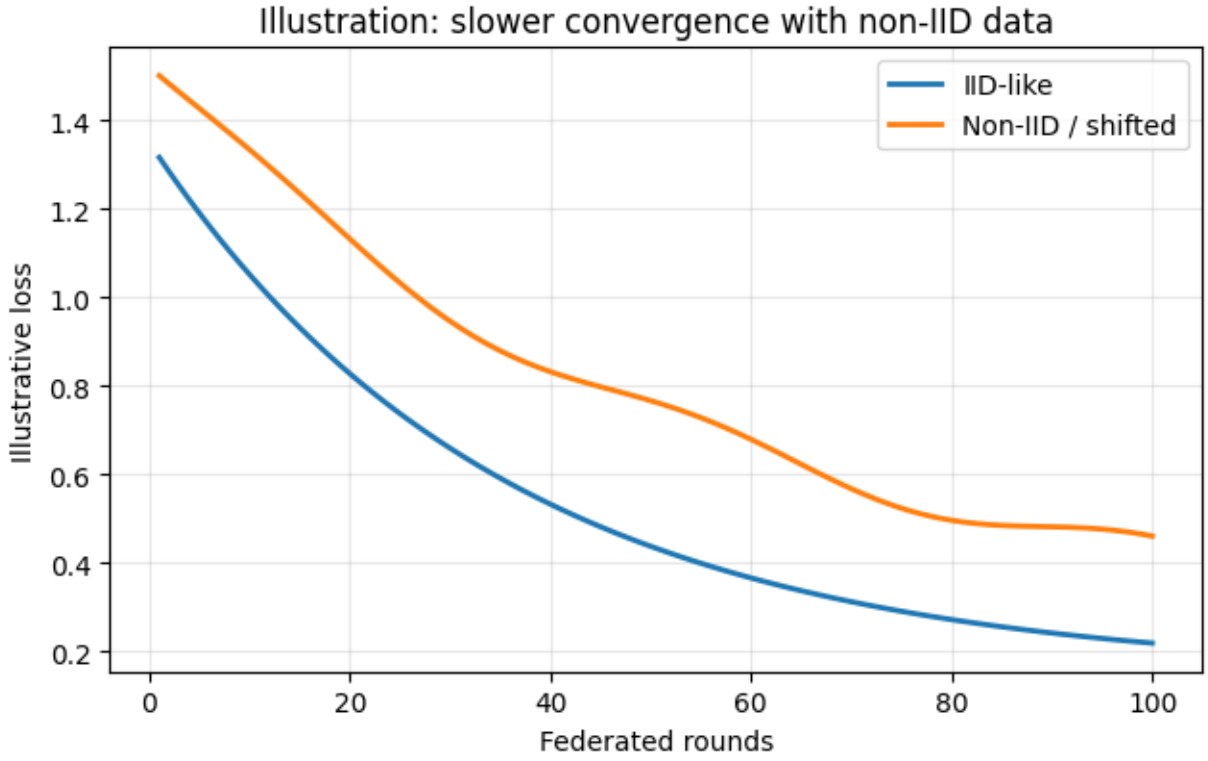


**6.1. Emerging Trends**

Medical data possess sensitive attributes that can expose the patients' privacy if exposed unintentionally. The international regulations enforce data protection and privacy preservation in the processing of medical data. Even with regulations in place for the use of data, it is necessary to satisfy the needs of an analysis of medical data with privacy preservation and optimizing the accuracy of the analysis model. Federated learning is the most promising principle solving the above issues, as it utilizes distributed devices to collaboratively generate a shared model without requiring access to the training set of the different medical institutions. Privacy is guaranteed through a hybrid deep learning technique where the deep learning part of the model is on a mobile device with private data while a shallow model is located on remote cloud.Emerging data evaluation algorithms leverage Langmuir equations from physical chemistry for survival analysis, neural networks are fused with area under the curve to optimal prediction of disease risks. GDPR enforces a minimum scope for data processing accomplishing a non-IID training schema in real-world applications and secure aggregation minimizes the introduced privacy risk. Differentially private federated learning has the potential to fulfill a higher level of privacy.

| Paper topic | Key equation (typical) | What it captures |
|---|---|---|


| | | |
|---|---|---|
| FedAvg aggregation | w_{t+1} = Î£_k (n_k/n) w_{t+1}^k | Data-weighted averaging of client models |
| Local SGD update | w â†□ w âˆ’ Î· âˆ‡â„“(w; x,y) | Client-side learning on private data |
| Secure aggregation | Î£_k (u_k + r_k) âˆ’ Î£_k r_k = Î£_k u_k | Server learns only the sum, not individual updates |
| Differential privacy (DP) | M(D)=f(D)+N(0,Ïƒ^2I), Ïƒâˆ□Î”/Îµ | Formal privacy via noise calibrated to sensitivity |
| Data-shift robustness metric | H(P,Q)= (1/â√2)‖â√Pâˆ’â√Q‖_2 | Distance between distributions (Hellinger-type) |
| Risk / leakage score | R = E[ attack_success ] or MI(D; updates) | How much updates reveal about private data |
| Langmuir equation mention | Î¸ = KC/(1+KC) | Saturating response vs concentration |

**Table: Equations/metrics commonly paired with paper themes**

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