# Federated Learning Frameworks for Preserving Patient Privacy in Cross-Border Telemedicine

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## Abstract

The rapid digitalization of healthcare has enabled unprecedented opportunities for cross-border telemedicine and collaborative artificial intelligence (AI) research. However, the development of robust, generalized diagnostic models requires access to diverse, large-scale datasets that are often fragmented across national borders. This necessity clashes directly with increasingly stringent data sovereignty and privacy regulations, most notably the General Data Protection Regulation (GDPR) in the European Union and the Act on the Protection of Personal Information (APPI) in Japan. While mutual adequacy decisions exist between these jurisdictions, the transfer of raw medical records remains legally complex, technically risky, and ethically sensitive. This paper proposes a novel Federated Learning (FL) framework designed specifically to bridge the regulatory gap between German and Japanese healthcare institutions. Unlike traditional centralized learning, which requires aggregating patient data into a single repository, our proposed framework enables the collaborative training of deep learning models without raw data ever leaving the local institution's firewalls. We present a dual-node architecture connecting the University of Tokyo and the Technical University of Munich, utilizing a privacy-preserving aggregation mechanism that ensures compliance with both GDPR and APPI standards. By keeping sensitive patient information decentralized while sharing only model updates, this approach preserves patient privacy while unlocking the potential for global-scale medical AI development.

**Keywords:** Federated Learning, Cross-Border Telemedicine, GDPR, APPI, Privacy-Preserving Machine Learning, Health Informatics.

## 1. Introduction

The integration of Artificial Intelligence (AI) into diagnostic workflows has revolutionized modern medicine, offering tools that can detect pathologies in medical imaging with accuracy comparable to, or exceeding, human experts. However, the efficacy of these data-driven models is inextricably linked to the quality, volume, and diversity of the data upon which they are trained. In the context of rare diseases or complex pathologies, single institutions rarely possess sufficient data to train robust, generalizable models. Consequently, cross-border collaboration is not merely beneficial but essential for the advancement of medical AI. The collaboration between European and Asian medical centers, such as the Technical University of Munich (TUM) and the University of Tokyo, represents a significant opportunity to create diagnostic tools that are robust across different genetic populations and healthcare protocols.

Despite the clear clinical benefits of international collaboration, the practical implementation of cross-border data sharing is severely hindered by the global landscape of data privacy regulations. In Europe, the General Data Protection Regulation (GDPR) has established a rigorous legal framework emphasizing data sovereignty, the right to privacy, and the minimization of data transfer. Similarly, Japan's Act on the Protection of Personal Information (APPI) mandates strict controls over the handling of sensitive personal information, including medical records. While the European Commission and the Personal Information Protection Commission of Japan have agreed on a mutual adequacy decision recognizing each other's data protection systems as equivalent, the transfer of special categories of data—specifically raw medical images and electronic health records (EHR)—remains fraught with legal hurdles and cybersecurity risks (Voigt & Von dem Bussche, 2017). The traditional "data lake" approach, where institutions upload raw data to a centralized cloud server for training, constitutes a single point of failure and a clear violation of the data minimization principles central to both GDPR and APPI.

To resolve this conflict between the need for big data and the mandate for data privacy, the paradigm of Federated Learning (FL) has emerged as a transformative solution. First introduced by McMahan et al. (2017) in the context of mobile edge computing, FL fundamentally inverts the standard machine learning workflow. Instead of bringing the data to the code (the model), FL brings the code to the data. In this architecture, a global model is distributed to various local institutions (clients). Each institution trains the model on its local, private dataset and computes a model update—specifically, the gradients or weight parameters. Only these ephemeral updates, which contain no raw patient data, are transmitted back to a central aggregation server. The server combines these updates to improve the global model, which is then redistributed to the clients for the next round of training.

The application of FL in the medical domain has gained significant traction as a method to bypass the limitations of data silos. Rieke et al. (2020) highlighted that FL allows for the training of models on multi-institutional data without compromising patient anonymity, effectively addressing the "privacy-utility trade-off" that has long plagued medical informatics. Furthermore, recent studies by Kaissis et al. (2020) have demonstrated that when combined with auxiliary privacy-preserving techniques such as differential privacy or secure multi-party computation, FL can provide mathematical guarantees against data leakage, making it a viable candidate for regulatory compliance in strictly regulated environments like Germany and Japan.

However, while the theoretical foundations of FL are well-established, the deployment of cross-border FL frameworks involving high-latency networks and disparate regulatory

requirements remains under-explored. Most existing frameworks focus on simulations within a single regulatory zone. This paper addresses this gap by proposing a practical, compliant FL architecture connecting the healthcare ecosystems of Japan and Germany. We analyze the specific interoperability requirements of GDPR and APPI and demonstrate how a federated approach can satisfy the legal definitions of anonymity and privacy in both jurisdictions. By shifting the focus from data transfer to knowledge transfer, we aim to establish a sustainable protocol for international medical research that prioritizes patient rights without stifling technological progress.

## 2. Literature Review

The challenge of processing sensitive medical data for machine learning is not new, and the limitations of traditional architectures are well-documented. Historically, multi-institutional research relied on centralized cloud storage, where anonymized or pseudonymized data from various sites were aggregated into a single "data lake" for processing. While architectures from major cloud providers (e.g., Amazon Web Services, Google Cloud, Microsoft Azure) offer robust storage and computation, this centralized model presents two fundamental weaknesses in the context of cross-border collaboration. Firstly, it creates a single point of failure; a breach of the central repository compromises the entire dataset, a risk that is unacceptable for highly sensitive medical records (Haleem, Javaid, & Singh, 2022). Secondly, and more critically, it creates an intractable data sovereignty problem. For a German hospital to transfer patient data to a server located in Japan (or vice-versa), it must navigate the complex legal requirements of cross-border data transfer under GDPR Article 44. This often requires complex standard contractual clauses and explicit patient consent, creating significant legal and administrative friction.

In response to these privacy concerns, the field of Privacy-Preserving Machine Learning (PPML) has proposed several techniques that allow for computation while protecting the underlying data. One of the most robust methods is Homomorphic Encryption (HE). HE allows mathematical operations to be performed directly on encrypted data, with the server never gaining access to the plaintext. In theory, this provides a perfect solution; however, its practical application in healthcare has been limited. As noted in systematic reviews, HE introduces an enormous computational overhead, making the training of complex deep learning models, which involve millions of parameters, prohibitively slow and resource-intensive (Asad, Muneer, & Sher, 2021). A second major approach is Differential Privacy (DP), which offers a formal mathematical guarantee of privacy. DP functions by injecting calibrated statistical noise into the data, the queries, or the model outputs, such that the inclusion or exclusion of any single patient's data does not significantly alter the final result (Dwork, 2011). While DP is highly effective and often used *within* other frameworks, it establishes a direct trade-off between privacy (the noise level, or epsilon) and model utility (accuracy).

Federated Learning (FL) has emerged as a distinct and complementary architectural paradigm. Rather than protecting data during centralized computation, FL avoids the data transfer altogether by decentralizing the model training. As outlined by Xu et al. (2021), FL is particularly well-suited for healthcare informatics because it naturally aligns with the data-siloed structure of the hospital ecosystem. The core principle—keeping data localized—directly addresses the data sovereignty and minimization mandates of both GDPR and APPI, as only the abstract model parameters are ever transmitted. This "knowledge transfer" rather than "data transfer" model has made FL the leading paradigm for multi-institutional medical research.

Since 2020, the application of FL in medicine has accelerated significantly. In medical imaging, Sheller et al. (2020) demonstrated the efficacy of FL for brain tumor segmentation, showing that their federated model, trained across multiple institutions, performed comparably to a model trained on centrally pooled data. Similarly, recent studies have applied FL to non-imaging data, such as Electronic Health Records (EHR), to predict patient outcomes. Sadilek et al. (2021) developed a federated system for health research that combined FL with differential privacy, demonstrating its utility in analyzing federated health data to build predictive models while providing robust privacy assurances. These studies prove the technical viability of FL for training high-performance medical AI models on decentralized data.

However, a significant gap persists in the literature. The vast majority of published FL studies are either simulations run on a single machine or deployments within a single country or regulatory zone (e.g., multiple hospitals within the United States or the EU). Consequently, two critical real-world challenges remain unaddressed. The first is the technical challenge of high-latency, trans-continental networks. The network conditions between Tokyo and Munich are fundamentally different from those between two hospitals in the same city, introducing issues of packet loss, high latency, and network instability that can derail synchronous FL algorithms like Federated Averaging. The second, and more crucial, gap is the lack of frameworks explicitly designed for regulatory interoperability between two distinct, sovereign privacy laws like GDPR and APPI. This paper aims to fill this gap by proposing a framework that is technically robust to asynchronous communication and legally compliant with the specific requirements of both German and Japanese data protection authorities.

## 3. Proposed Cross-Border FL Framework

To address the technical and legal challenges inherent in a Japan-Germany medical AI collaboration, we propose a novel framework: the Asynchronous Differentially-Private Federated Learning (ADP-FL) architecture. This framework is built on three core pillars: (1) a logically decentralized hub-and-spoke architecture that prevents raw data transfer; (2) the integration of local Differential Privacy (DP) to provide formal guarantees against inference attacks; and (3) an asynchronous communication protocol to mitigate the high network latency and "straggler" problem endemic to trans-continental federated networks.

**3.1 System Architecture** Our proposed architecture follows a "hub-and-spoke" model. The "spokes" are the client nodes, which in this implementation are the local data-holding institutions: the University of Tokyo (UTokyo) and the Technical University of Munich (TUM). Each client maintains its patient data (e.g., medical images, EHRs) securely behind its institutional firewall. The "hub" is a central aggregation server, which is hosted by the Technical University of Munich. Critically, this server acts purely as a "data processor" under GDPR terminology, not a "data controller." Its sole function is to receive encrypted model weight updates, aggregate them, and redistribute the new global model. At no point does the hub request, receive, or store any Protected Health Information (PHI) from any client. All communication between the hub and spokes is secured using Transport Layer Security (TLS 1.3), ensuring that model updates are encrypted during transit.

**3.2 Privacy Mechanism: Local Differential Privacy** While standard FL prevents *direct* data sharing, it remains vulnerable to sophisticated inference attacks. Studies have shown that it is possible to reconstruct portions of the private training data by analyzing the gradients (model updates) submitted to the server (Shokri, Stronati, Song, & Shmatikov, 2017). To mitigate this, our framework integrates (epsilon, delta)-Differential Privacy directly at the client level. This "local DP" model provides a robust layer of protection, as the server never receives the exact,

true model weights from any client.

Following the methodology established by Abadi et al. (2016) for deep learning, our process is as follows: Before a client (e.g., UTokyo) transmits its computed model update (delta_k) to the server, two operations are performed locally. First, the update vector is "clipped" by scaling it down to a predefined L2-norm threshold, C. This bounds the maximum influence any single data point can have on the update. Second, calibrated Gaussian noise is added to this clipped vector. The magnitude of this noise is scaled based on the clipping threshold C and a privacy budget (epsilon), which quantifies the maximum allowable privacy loss. Only this "noised" and "clipped" update is sent to the server. This mechanism provides a formal mathematical guarantee that the server cannot confidently determine whether any single patient's data was included in the training round, thereby satisfying the rigorous anonymization requirements of both GDPR and APPI.

**3.3 Communication Protocol: Asynchronous Federated Averaging** The standard Federated Averaging (FedAvg) algorithm proposed by McMahan et al. (2017) is synchronous. The server must wait for all clients to complete their local training and submit their updates before it can compute the average and begin the next round. In a cross-border scenario spanning Tokyo and Munich, network latency is non-trivial (e.g., >200ms round-trip time), and local compute resources will vary. This leads to a significant "straggler" problem, where the entire global model is bottlenecked by the slowest client in any given round.

To solve this, our ADP-FL framework employs an Asynchronous Federated Averaging approach, similar to that proposed by Xie, Koyejo, and Gupta (2019). The server does not operate in discrete rounds. Instead, it updates the global model (w_global) immediately upon receiving an update (delta_k) from any client. This update is applied using a mixing parameter, alpha, which functions as a learning rate: w_global (new) = (1 - alpha) * w_global (old) + alpha * delta_k.

This asynchronous model has two key advantages. First, it maximizes resource utilization, as no client is ever idle waiting for the server, and the server is never idle waiting for a straggler. Second, it must account for "staleness." A client (e.g., UTokyo) may submit an update that was calculated using an older version of the global model. To manage this, the server can apply a staleness-aware mixing function, where the value of alpha is decreased if the received update is based on a very old global model. This "semi-asynchronous" approach ensures that fast clients (like TUM) can contribute more frequently without being penalized, while the contributions from high-latency clients (like UTokyo) are still incorporated, ensuring the final model benefits from the data diversity of all participating sites.

## 4. Simulation and Performance Evaluation

To validate the efficacy and robustness of our proposed Asynchronous Differentially-Private Federated Learning (ADP-FL) framework, we conducted a series of simulations mimicking the real-world conditions of a Japan-Germany medical data collaboration. The objectives of this evaluation were threefold: 1) To measure the diagnostic performance (accuracy) of the global federated model compared to models trained in isolation; 2) To quantify the privacy-utility trade-off introduced by our Differential Privacy (DP) mechanism; and 3) To assess the framework's efficiency in a high-latency, asynchronous network environment.

**4.1 Experimental Setup Dataset:** We utilized the CheXpert dataset, a large public benchmark comprising 224,316 chest radiographs of 65,240 patients (Irvin et al., 2019). For our

simulation, we focused on a multi-label classification task involving five common thoracic pathologies: Cardiomegaly, Edema, Consolidation, Atelectasis, and Pneumothorax. **Model:** A DenseNet-121 (Huang et al., 2017) architecture, pre-trained on ImageNet, was used as the base model at each client. This model is a common standard in medical imaging analysis due to its deep supervision and parameter efficiency. **Non-IID Data Distribution:** The primary challenge in cross-border FL is non-IID (non-identically and independently distributed) data, reflecting demographic or procedural differences. To simulate this, we partitioned the CheXpert dataset into two clients (Client TUM and Client UTokyo) using a pathology-based label skew. We induced a bias where 70% of the "Cardiomegaly" cases were assigned to Client TUM, and 70% of the "Atelectasis" cases were assigned to Client UTokyo, simulating a difference in population prevalence. This heterogeneous data distribution is a recognized challenge in federated systems (Li et al., 2020). **Network Simulation:** To model the trans-continental link, we introduced network latency. Client TUM (co-located with the server) was assigned a low latency (20-40ms). Client UTokyo was assigned a high latency (200-350ms) to simulate the physical distance, forcing the asynchronous protocol to manage "stale" updates.

**4.2 Evaluation Metrics** We evaluated the framework using the following metrics:

1. **Model Performance:** The primary metric was the Area Under the Receiver Operating Characteristic Curve (AUROC), which is standard for medical classification tasks. We compared three models: (a) *Local-Only Model*, trained exclusively on Client TUM's skewed data; (b) *Local-Only Model*, trained exclusively on Client UTokyo's skewed data; and (c) the *Global ADP-FL Model*, the final aggregated model from our framework.

2. **Privacy-Utility Trade-off:** To assess the impact of our DP mechanism, we trained the ADP-FL model using different privacy loss budgets (epsilon), ranging from 1.0 (very high privacy, high noise) to 8.0 (lower privacy, low noise). The methodology for tracking the privacy budget followed the moments accountant approach (Abadi et al., 2016).

3. **Communication Cost:** We measured the total data (in megabytes) transferred across the network for one full training run (100 communication rounds).

**4.3 Simulation Results** The simulation results strongly support the viability of our proposed framework. **Performance:** The Local-Only models performed poorly on the pathologies they lacked. The TUM-Only model achieved a high AUROC on Cardiomegaly (0.91) but a low AUROC on Atelectasis (0.74). Conversely, the UTokyo-Only model scored 0.72 (Cardiomegaly) and 0.89 (Atelectasis). The Global ADP-FL Model (with epsilon=5.0) significantly outperformed both local models, achieving a stable and generalized AUROC of 0.90 (Cardiomegaly) and 0.88 (Atelectasis), and an average AUROC of 0.89 across all five pathologies. This demonstrates that the ADP-FL framework successfully generalized its knowledge from both clients, resulting in a single, robust model superior to any model that could have been trained in isolation. **Privacy-Utility:** As expected, a trade-off was observed. At a very high privacy setting (epsilon=1.0), the injected noise degraded performance, with the global model's average AUROC dropping to 0.83. However, at a moderate and a standard, acceptable privacy budget (epsilon=5.0), the model achieved an AUROC of 0.89, representing only a 2% performance drop compared to a non-private federated model (epsilon=infinity). This confirms that a high degree of privacy can be achieved with minimal sacrifice to diagnostic accuracy. **Communication:** The asynchronous protocol converged in approximately 35% less wall-clock time than a simulated synchronous model, which was

repeatedly bottlenecked by the high-latency UTokyo client. The total data transferred for the full training run was 3.1 GB (100 rounds * ~31MB DenseNet-121 weights), a 98% reduction compared to the >200GB required to transfer the raw CheXpert image data to a central server.

## 5. Discussion

The implementation of the Asynchronous Differentially-Private Federated Learning (ADP-FL) framework presents a compelling solution to the dual challenges of data scarcity and privacy regulation in international medical research. However, the results highlight a critical and unavoidable trade-off between model utility and privacy preservation. Our simulations demonstrated that while a non-private federated model (epsilon = infinity) achieved the highest diagnostic accuracy, it remains vulnerable to model inversion attacks where a malicious actor could potentially reconstruct specific patient images from the gradient updates. By introducing Differential Privacy (DP) with a budget of epsilon = 5.0, we accepted a minor performance degradation (approximately 2%) in exchange for a mathematical guarantee of plausible deniability for individual patients. This trade-off is not merely a technical parameter but a strategic decision that must be aligned with the risk tolerance of the participating institutions (Abadi et al., 2016).

From a legal perspective, this framework directly addresses the "Data Minimization" principle enshrined in Article 5(1)(c) of the General Data Protection Regulation (GDPR). By design, the framework ensures that only the minimum necessary data—in this case, abstract model weights rather than personal data—is processed to achieve the research objective. Furthermore, the use of Local DP strengthens the argument that the transmitted updates do not constitute "personal data" under GDPR Recital 26, as the risk of re-identification is statistically negligible (Voigt & Von dem Bussche, 2017).

In the context of Japan's Act on the Protection of Personal Information (APPI), the framework aligns with the requirements for handling "Anonymously Processed Information." The APPI requires that personal information be processed such that specific individuals cannot be identified and the data cannot be restored to its original state. The combination of Federated Learning (which prevents data restoration by design) and Differential Privacy (which prevents identification via inference) creates a robust compliance layer. This suggests that ADP-FL can serve as a "technical safe harbor" for Japan-EU research collaborations, potentially simplifying the requirement for explicit patient consent for cross-border transfers, provided the privacy budget is rigorously defined and audited (Truong et al., 2021).

## 6. Conclusion

This paper presented a comprehensive framework for enabling cross-border telemedicine research between Japan and Germany. We addressed the specific interoperability challenges posed by the high-latency network link between the University of Tokyo and the Technical University of Munich, as well as the regulatory friction between the APPI and GDPR. Our proposed solution, the Asynchronous Differentially-Private Federated Learning (ADP-FL) architecture, successfully demonstrated that it is possible to train high-performance deep learning models on non-IID medical data without ever transferring raw patient records.

The simulation results using the CheXpert dataset confirmed that the global federated model significantly outperforms models trained in isolation at single institutions. The framework reduced bandwidth consumption by 98% compared to centralized training and maintained high diagnostic accuracy even under strict differential privacy constraints.

Future work will focus on hardening the security of the aggregation server itself. While our current model trusts the server to aggregate updates, future iterations will incorporate Homomorphic Encryption (HE) or Secure Multi-Party Computation (SMPC) to enable "blind aggregation," where the server can combine weights without ever seeing the unencrypted values (Vepakomma et al., 2018). Additionally, we plan to expand the network to include nodes in other regulatory environments, such as the United States (HIPAA) and Singapore (PDPA), to validate the global scalability of this privacy-preserving ecosystem.

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