

Why Federated, Privacy-Preserving Data Spaces are the Future of Digital Pathology

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Abstract—The clinical and research potential of histopathological data remains largely untapped due to its sensitive nature and the logistical barriers to multi-institutional sharing. Centralized data aggregation, the dominant paradigm for training robust AI models, conflicts directly with patient privacy regulations, hospital data governance policies, and the risks of exposing raw whole slide images. Federated data spaces are necessary for sharing and analyzing histopathological samples because they enable collaborative data use while ensuring that sensitive patient information remains protected behind local firewalls. This architecture overcomes current limitations such as strict regulatory and privacy constraints, challenges with data heterogeneity, and risks associated with transferring raw data, thereby supporting scalable, multi-institutional analysis through advanced privacy-preserving techniques.

This review examines why federated architectures, combined with privacy-preserving techniques such as differential privacy and secure aggregation, are essential for unlocking the full potential of histopathological data for rare disease research, unbiased AI development, and clinical discovery without compromising patient confidentiality.

Keywords: Federated Data Space, Privacy-Preserving Data Spaces, Digital Pathology, AI in Healthcare, Bio Image Processing.

I. INTRODUCTION

HISTOPATHOLOGICAL images are a cornerstone of modern medical diagnosis and research, containing rich morphological information critical for understanding disease progression, treatment response, and patient outcomes. The advent of digital pathology has transformed these samples into high-resolution whole slide images, creating unprecedented opportunities for computational analysis and artificial intelligence. However, the same factors that make this data valuable, its detail, its direct link to patient diagnoses, and its irreplaceable role in clinical decision-making, also make it among the most sensitive and tightly regulated forms of medical data. Institutions face strict legal and ethical obligations under frameworks such as GDPR and HIPAA, creating a fundamental tension between the desire to share data for scientific progress and the imperative to protect patient privacy.

Traditionally, this tension has been resolved by keeping data siloed within individual hospitals and research centers. While this approach ensures compliance and security, it comes at a steep cost. Models trained on single-institution data often

fail to generalize across diverse populations, staining protocols, and scanner types. Research on rare cancers stagnates because no single center possesses enough cases. Multi-center studies become mired in complex data transfer agreements and de-identification pipelines that are both time-consuming and imperfect [1]. The centralization paradigm, moving data to the analysis, has reached its practical and ethical limits for histopathology [2].

Federated data spaces offer a fundamental rethinking of this paradigm. Rather than moving sensitive whole slide images to a central repository, federated architectures bring the analysis to the data. As illustrated in Figure 1, this paradigm shift replaces centralized data aggregation with a distributed, privacy-preserving architecture in which algorithms travel across secure institutional nodes while data remain protected behind local firewalls.

This review examines why federated data spaces are not merely an alternative but a necessary evolution for histopathological research, enabling the diversity and scale required for robust AI without compromising the privacy that patients and regulations demand [3], [4], [5], [6]. This report also synthesizes the current state of federated data spaces for histopathological data sharing, focusing on the limitations of current data sharing and analysis methods, the technical and privacy-preserving features of federated data spaces, real-world implementations and case studies, and, research gaps and future directions [7], [8], [9].

II. LIMITATIONS OF CURRENT HISTOPATHOLOGICAL DATA SHARING METHODS

Current data sharing practices face fundamental privacy challenges that extend beyond simple de-identification. Even anonymized histopathological images remain vulnerable to reidentification attacks, particularly when combined with accessible metadata or external datasets [3], [5], [7], [10]. Simultaneously, strict regulatory frameworks such as GDPR and HIPAA impose tight controls on data movement, requiring explicit patient consent and often prohibiting cross-border data transfers unless stringent safeguards are in place. Compounding these issues, most existing systems adopt a compliance-focused rather than privacy-by-design approach,

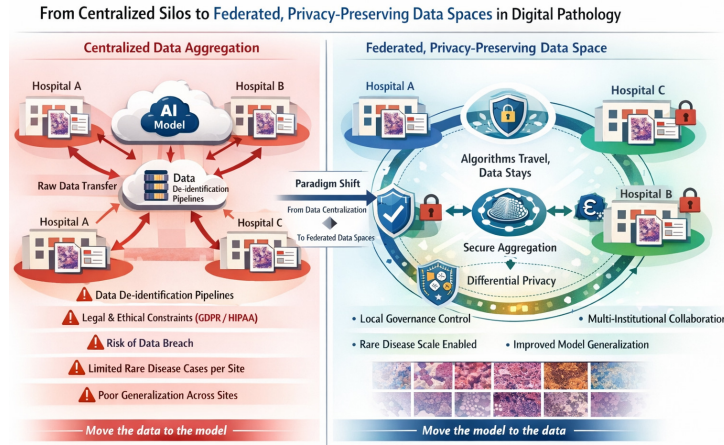


Fig. 1. Conceptual comparison between centralized AI training and federated, privacy-preserving data spaces in digital pathology. In the traditional centralized paradigm (left), raw whole slide images and associated patient data are transferred from multiple institutions to a central repository for model training, creating regulatory, ethical, and cybersecurity risks while limiting scalability for rare diseases. In contrast, federated data spaces (right) enable collaborative AI development by keeping sensitive histopathological data within institutional firewalls. Algorithms are deployed locally, and only privacy-preserving model updates are shared through secure aggregation mechanisms. This shift from “moving data to the model” to “moving the model to the data” enables multi-institutional collaboration, regulatory compliance, improved generalizability, and scalable rare disease research without compromising patient confidentiality.

leaving data exposed to cyberattacks and unauthorized access even when regulatory boxes are checked [7]. Beyond privacy concerns, significant technical barriers hinder large-scale data sharing. Histopathological datasets remain fragmented across institutions, characterized by varying image formats, inconsistent annotation standards, and incomplete metadata [11], [12], [13]. These annotation inconsistencies, differences in labeling protocols and class definitions, directly impede the development of robust, generalizable AI models [12], [13].

III. TECHNICAL AND PRIVACY FEATURES OF FEDERATED DATA SPACES

At the core of federated data spaces for digital pathology is federated learning (Figure. 2), which enables multiple institutions to collaboratively train AI models without sharing raw data. Instead of transferring whole slide images, only model updates, such as gradients or weights, are exchanged between participants, significantly reducing privacy risks. These updates are further protected through secure aggregation protocols, which ensure that individual contributions are combined in a way that prevents any single party from reconstructing another institution’s data [14], [15], [16]. Additional privacy layers can be applied through homomorphic encryption and additive secret sharing, which enable computation on encrypted data or distributed shares, providing strong privacy guarantees at the cost of increased computational overhead [17], [18], [19], [20]. Differential privacy complements these techniques by adding calibrated statistical noise to model updates, protecting against inference attacks while preserving model utility [21].

Dynamic consent management systems, sometimes leveraging blockchain technology, allow patients to grant, revoke, or modify data sharing permissions in real time, aligning with

the transparency requirements of frameworks like GDPR and HIPAA. Federated architectures are specifically designed to meet major privacy regulations by minimizing data movement and providing auditable access logs for all data usage [22], [23].

To lower the barrier to entry, accessible toolkits such as Fluke, HistoFL, and Histo-Cloud provide graphical interfaces and command-line tools that enable federated learning deployment without deep technical expertise [24], [25], [26], [27]. These platforms integrate cloud-based segmentation and annotation workflows, supporting collaborative model development and evaluation across institutions while keeping raw data local. Recent advances in cryptographic protocols continue to strengthen privacy guarantees. Additive secret sharing offers efficiency for secure multiparty computation but can incur high communication overhead. Homomorphic encryption, particularly with multi-key schemes, provides strong privacy but remains computationally demanding [28]. Multi-key encryption enhances privacy further but introduces complexity in key management and system scalability [29]. The choice of protocol involves trade-offs between privacy strength, computational cost, and practical scalability.

Federated frameworks have been specifically adapted to handle the unique challenges of gigapixel whole slide images. Platforms like MedShieldFL combine data augmentation, homomorphic encryption, and adaptive aggregation to enable privacy-preserving analysis at scale [30]. Weakly-supervised learning approaches reduce the annotation burden, supporting scalable model training across distributed datasets without requiring exhaustive manual labeling [31]. This is particularly valuable in federated settings, where pathologist expertise and labeling resources vary across participating sites. Weakly-supervised models can be trained on distributed datasets using

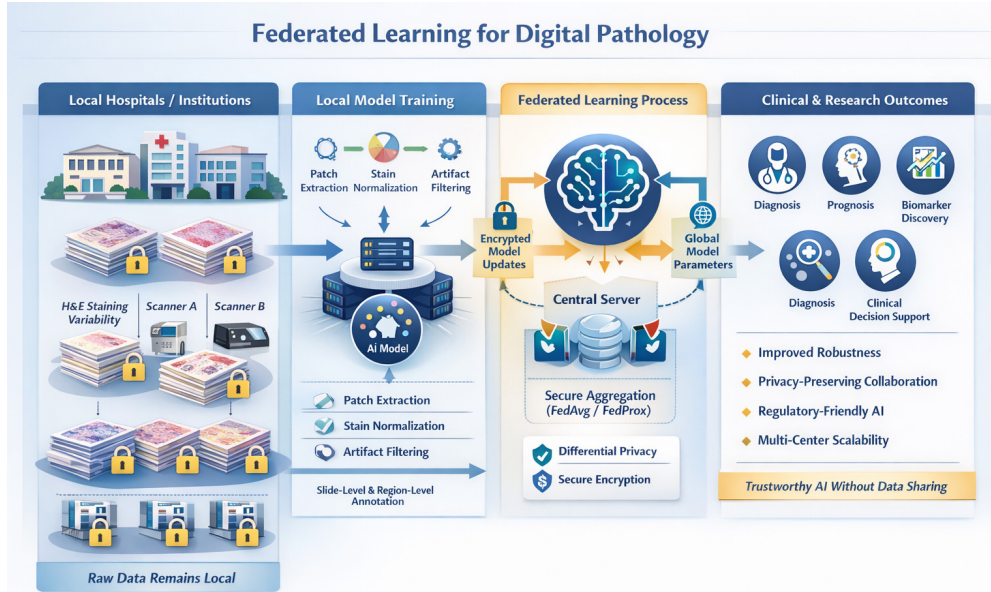


Fig. 2. At the core of federated data spaces for digital pathology is federated learning.

only the clinical reports or diagnostic codes already available in each institution's records, eliminating the need for exhaustive manual labeling of gigapixel whole slide images.

Multi-institutional studies have successfully applied federated learning to nuclei and tissue segmentation tasks, demonstrating improved generalization and robustness across diverse datasets [32], [33], [34], [35], [36], [37], [38]. Performance evaluations consistently show that federated models match or exceed the accuracy of centralized models, while preserving privacy and reducing regulatory barriers [39].

Data heterogeneity and sample imbalance across institutions have been addressed through dynamic aggregation strategies. Approaches such as FedSODA and adaptive weighting specifically account for sample imbalance and annotation variability, improving model performance across institutions with different data distributions [40], [41]. Synthetic data generation has also been employed to augment underrepresented classes and create more balanced training cohorts [42]. Comparative studies demonstrate that federated learning models achieve comparable or superior performance to centralized models, particularly in multi-institutional settings with heterogeneous data [43]. Importantly, federated-trained models generalize better to external datasets, supporting broader clinical applicability beyond the original training institutions [44], [45], [46]. Advanced aggregation methods such as FedSODA, FedProx, and adaptive weighting have been developed to address annotation variability and data heterogeneity across sites [47], [48]. These strategies improve both model robustness and interpretability, making federated approaches more reliable for clinical applications.

Real-world deployment of federated data spaces has re-

vealed significant variability in institutional IT infrastructure, a challenge that is being addressed through flexible architectural solutions. Cloud-based servers and modular platforms allow institutions with limited local computing capacity to participate without substantial upfront investment in hardware [49].

On the workflow side, adoption by non-technical staff is enabled through user-friendly graphical interfaces and standardized protocols that abstract away underlying complexity [50]. Pathologists and researchers can interact with familiar tools while federated processes run transparently in the background, ensuring that privacy-preserving collaboration integrates seamlessly into existing clinical and research workflows [51]. Real-world implementations of federated data spaces in histopathology demonstrate their ability to overcome traditional limitations, enabling privacy-preserving, scalable, and robust collaborative research. These case studies validate both the technical and organizational feasibility of federated approaches across diverse clinical environments.

IV. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite the significant promise demonstrated by federated data spaces for histopathological research, several critical gaps must be addressed before widespread clinical adoption becomes feasible. These challenges span computational efficiency, interoperability, privacy-utility trade-offs, ethical governance, and clinical integration. This section synthesizes current limitations and identifies priority directions for future research. Current federated learning frameworks remain resource-intensive, posing scalability challenges for large, multi-institutional deployments [52], [53], [54], [55]. Institutions with limited bandwidth or computational infrastruc-

ture may find participation impractical, potentially excluding precisely those smaller or resource-constrained centers whose diverse data would most benefit model generalizability. Furthermore, the computational demands of privacy-preserving techniques, particularly homomorphic encryption and secure multiparty computation, compound these overhead issues. Future research must prioritize communication-efficient protocols, model compression techniques, and adaptive aggregation strategies that reduce the frequency and size of data transfers without compromising model accuracy or privacy guarantees. The absence of standardized protocols and data formats remains a fundamental barrier to seamless integration across institutions and software platforms [56], [57], [58]. Histopathological data is captured using diverse scanner technologies, stored in varying file formats, and annotated according to institution-specific protocols. Even when institutions commit to participating in a federated data space, these heterogeneities complicate the development of universally applicable models. Federated learning frameworks must contend with non-independent and identically distributed data across nodes, where differences in tissue preparation, staining protocols, and scanning resolution create systematic variations that can mislead training if not properly addressed. Privacy-preserving techniques inherently introduce trade-offs between data protection and model utility. Differential privacy, for instance, adds statistical noise to model updates to prevent inference attacks, but excessive noise can degrade model performance to clinically unacceptable levels [59], [60], [61].

Addressing the scalability challenge requires fundamental innovations in federated architecture. Hierarchical federated learning, which introduces intermediate aggregation nodes between local institutions and the global server, offers one pathway to reducing communication bottlenecks [62]. Adaptive federated learning approaches dynamically adjust participation frequency and aggregation strategies based on node characteristics and data distributions, optimizing resource utilization. Model compression and knowledge distillation techniques further reduce communication overhead by transmitting compact representations rather than full model updates [63]. These efficiency gains are not merely technical conveniences, they determine whether federated approaches can scale from proof-of-concept studies involving a handful of academic centers to national or regional networks encompassing dozens or hundreds of clinical sites.

Technical standards must be complemented by user-facing tools that lower the barrier to participation for clinicians and researchers without specialized machine learning expertise. Platforms such as Fluke, HistoFL, and Histo-Cloud represent important steps toward accessibility, but broader adoption requires continued investment in intuitive interfaces, standardized libraries, and interoperable protocols [64], [65]. The development of common evaluation benchmarks and reference implementations would accelerate progress by enabling fair comparison of competing approaches and reducing duplication of effort across research groups. For federated pathology to move from research niche to clinical standard, participation

must become as straightforward as running a local analysis—the complexity of distributed, privacy-preserving computation should be handled invisibly by the underlying platform. Addressing these research gaps will determine whether federated approaches remain academic proofs-of-concept or become foundational infrastructure for the next generation of precision medicine.

V. CONCLUSION

The evidence reviewed here confirms that federated data spaces are not merely a theoretical alternative but a practical solution for contemporary challenges in histopathological research. For researchers, the path forward requires intentional adoption of federated learning frameworks that prioritize privacy, interoperability, and scalability. For clinicians, advocacy for user-friendly, integrated platforms is critical. The success of federated data spaces depends on their seamless incorporation into existing clinical workflows, where pathologists can contribute to and benefit from collaborative research without added administrative burden or disruption to patient care. Clinicians' domain expertise is also invaluable for guiding research priorities, ensuring that federated models address real diagnostic needs and produce outputs interpretable in clinical contexts. For policymakers, the imperative is twofold: harmonization and investment. Cross-border research collaboration, such as that envisioned by the Baltic Assembly, requires aligned legal and ethical frameworks that enable data sharing while protecting patient rights. Policymakers must support the harmonization of privacy regulations, consent requirements, and governance standards across jurisdictions. Simultaneously, investment in infrastructure—including secure networks, computational resources, and training programs—will be necessary to build the capacity for federated data spaces to operate at regional or national scale.

Table 1 summarizes the key themes emerging from the literature on federated data spaces for histopathology, highlighting how each theme addresses specific limitations of traditional data sharing models. Enhanced privacy and regulatory compliance is achieved by keeping data local, thereby overcoming regulatory barriers, privacy risks, and reidentification threats. Federated architectures further address data heterogeneity and interoperability through adaptive aggregation and standardization, mitigating the data silos, lack of standardization, and annotation inconsistencies that plague multi-institutional studies. Together, these themes illustrate the multidimensional nature of federated data spaces, where technical innovation must proceed in parallel with governance and standardization efforts.

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TABLE I
KEY THEMES IN FEDERATED DATA SPACES FOR HISTOPATHOLOGY

Theme	Key Insight	Overcomes Limitation(s)
Enhanced Privacy and Regulatory Compliance	Federated data spaces keep sensitive data local, enabling collaborative analysis without raw data transfer	Regulatory barriers, privacy risks, reidentification
Data Heterogeneity and Interoperability	Adaptive aggregation and standardization in federated spaces address data fragmentation and heterogeneity	Data silos, lack of standardization, annotation inconsistency
Efficient Privacy-Preserving Technologies, Scalability and Standardization	Use of homomorphic encryption, secret sharing, and secure multiparty computation. Need for standardized protocols and optimized aggregation to support clinical adoption	Scalability, computational cost, privacy leakage, communication overhead, lack of interoperability
Ethical Governance and Fairness	Integration of ethics-by-design and accountability frameworks	Lack of trust, fairness, and transparency

REFERENCES

- [1] M. Hammad and S. Ahmad, "Future Directions for AI in Medical Image Analysis," in *AI for Medical Image Analysis: Reconciling Innovation and Ethical Considerations*. Cham, Switzerland: Springer Nature Switzerland, 2026, pp. 233–264, doi: https://doi.org/10.1007/978-3-032-02963-8_9.
- [2] M. Soliman *et al.*, "Secondary use of health data: Applications, models, algorithms, and ethical considerations," *AI and Ethics*, vol. 6, no. 2, article 165, 2026, doi: <https://doi.org/10.1007/s43681-026-01017-2>.
- [3] E. Witt, "The digital looking glass: Ethical aspects of large data collections," *Bundesgesundheitsblatt-Gesundheitsforschung-Gesundheitsschutz*, vol. 58, no. 8, pp. 853–858, 2015, doi: <https://doi.org/10.1007/s00103-015-2187-5>.
- [4] J. Casaletto *et al.*, "Federated analysis for privacy-preserving data sharing: A technical and legal primer," *Annual Review of Genomics and Human Genetics*, vol. 24, no. 1, pp. 347–368, 2023, doi: <https://doi.org/10.1146/annurev-genom-110122-084756>.
- [5] E. S. Dove, G. T. Laurie, and B. M. Knoppers, "Data sharing and privacy," in *Genomic and Precision Medicine*. Academic Press, 2017, pp. 143–160, doi: <https://doi.org/10.1016/b978-0-12-800681-8.00010-4>.
- [6] B. Malin, D. Karp, and R. H. Scheuermann, "Technical and policy approaches to balancing patient privacy and data sharing in clinical and translational research," *Journal of Investigative Medicine*, vol. 58, no. 1, pp. 11–18, 2010, doi: <https://doi.org/10.2310/jim.0b013e3181c9b2ea>.
- [7] S. Yazijy, R. Schölly, and P. Kellmeyer, "Towards a toolbox for privacy-preserving computation on health data," *Studies in Health Technology and Informatics*, vol. 290, pp. 234–237, 2022, doi: <https://doi.org/10.3233/shti220069>.
- [8] P. R. Silva, J. Vinagre, and J. Gama, "Towards federated learning: An overview of methods and applications," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 13, no. 2, article e1486, 2023, doi: <https://doi.org/10.1002/widm.1486>.
- [9] Y. Zhang *et al.*, "FedSODA: Federated cross-assessment and dynamic aggregation for histopathology segmentation," in *Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP)*, Seoul, Republic of Korea, 2024, pp. 1606–1610, doi: <https://doi.org/10.1109/ICASSP48485.2024.10447367>.
- [10] A. K. Conduah, S. Ofoe, and D. Siaw-Marfo, "Data privacy in healthcare: Global challenges and solutions," *Digital health*, vol. 11, 2025, doi: <https://doi.org/10.1177/20552076251343959>.
- [11] A. Jimenez-Pastor *et al.*, "Data harmonization and challenges toward the generation of repositories: Sharing practices and approaches," in *Trustworthy AI in Cancer Imaging Research*. Cham, Switzerland: Springer Nature Switzerland, 2025, pp. 121–142, doi: https://doi.org/10.1007/978-3-031-89963-8_6.
- [12] P. N. Schofield, J. M. Ward, and J. P. Sundberg, "Show and tell: Disclosure and data sharing in experimental pathology," *Disease Models & Mechanisms*, vol. 9, no. 6, pp. 601–605, 2016, doi: <https://doi.org/10.1242/dmm.026054>.
- [13] S. C. Koganti *et al.*, "Task-ready PanNuke and NuCLS datasets: Reorganization, synthetic data generation, and experimental evaluation," *IEEE Access*, vol. 13, pp. 137986–138005, 2025, doi: <https://doi.org/10.1109/access.2025.3589477>.
- [14] S. S. Sandhu *et al.*, "Medical imaging applications of federated learning," *Diagnostics*, vol. 13, no. 19, article 3140, 2023, doi: <https://doi.org/10.3390/diagnostics13193140>.
- [15] N. Appavu, "Examining federated learning architecture's capability to protect data privacy during the training of collaborative healthcare models," in *Proc. 9th Int. Conf. Inventive Systems and Control (ICISC)*, 2025, pp. 1–6, doi: <https://doi.org/10.1109/icisc65841.2025.11187468>.
- [16] M. Singh *et al.*, "Advancing AI integration in healthcare using federated learning: Trends and challenges in federated learning for AI-enabled healthcare," in *Enabling Collaborative Health Intelligence With Federated Learning*. Boca Raton, FL, USA: CRC Press, 2026, pp. 29–56, doi: <https://doi.org/10.4018/979-8-3373-3306-9.ch002>.
- [17] S. M. Hosseini *et al.*, "Cluster-based secure multi-party computation in federated learning for histopathology images," in *Distributed, Collaborative, and Federated Learning*, Lecture Notes in Computer Science. Cham, Switzerland: Springer Nature Switzerland, 2022, pp. 150–161, doi: https://doi.org/10.1007/978-3-031-18523-6_11.
- [18] A. V. Sri *et al.*, "Privacy-preserving federated learning for retinal disease diagnosis using Paillier homomorphic encryption with multiple encryption keys," *IEEE Access*, early access, 2026, doi: <https://doi.org/10.1109/access.2026.3664444>.
- [19] H. Wang *et al.*, "MVFL: Verifiable privacy-preserving federated learning using multi-key homomorphic encryption," *The Journal of Supercomputing*, vol. 81, no. 8, article 915, 2025, doi: <https://doi.org/10.1007/s11227-025-07419-z>.
- [20] I. Walskaar, M. C. Tran, and F. O. Catak, "A practical implementation of medical privacy-preserving federated learning using multi-key homomorphic encryption and Flower framework," *Cryptography*, vol. 7, no. 4, article 48, 2023, doi: <https://doi.org/10.3390/cryptography7040048>.
- [21] S. Shukla *et al.*, "Federated learning with differential privacy for breast cancer diagnosis enabling secure data sharing and model integrity," *Scientific Reports*, vol. 15, no. 1, article 13061, 2025, doi: <https://doi.org/10.1038/s41598-025-95858-2>.
- [22] A. Najdi *et al.*, "Technical framework to ensure data subject's rights in GDPR: A conceptual design," in *Proc. Australasian Computer Science Week (ACSW)*, 2025, pp. 40–47, doi: <https://doi.org/10.1145/3727166.3727190>.
- [23] I. Mitrovskaa *et al.*, "Federated learning governance using Eclipse Dataspace Components connectors," in *Proc. IEEE Int. Conf. Big Data*, 2024, pp. 6860–6867, doi: <https://doi.org/10.1109/bigdata62323.2024.10826122>.
- [24] M. Polato, "FLuke: Federated Learning Utility framework for experimentation and research," *Future Generation Computer Systems*, vol. 167, article 108241, 2025, doi: <https://doi.org/10.1016/j.future.2025.108241>.
- [25] B. Lutnick *et al.*, "A cloud-based tool for federated segmentation of whole-slide images," in *Medical Imaging 2022: Digital and Computational Pathology*, vol. 12039, SPIE, 2022, article 120390B, doi: <https://doi.org/10.1117/12.2613502>.
- [26] M. Y. Lu *et al.*, "Federated learning for computational pathology on gigapixel whole-slide images," *Medical Image Analysis*, vol. 76, article 102298, 2022, doi: <https://doi.org/10.1016/j.media.2021.102298>.
- [27] B. Lutnick *et al.*, "A tool for federated training of segmentation models on whole-slide images," *Journal of Pathology Informatics*, vol. 13, article 100101, 2022, doi: <https://doi.org/10.1016/j.jpi.2022.100101>.

- [28] P. Yao *et al.*, “HEGD-FL: A privacy-preserving decentralized federated learning framework based on homomorphic encryption,” in *Proc. IEEE Int. Symp. Parallel and Distributed Processing with Applications (ISPA)*, 2024, pp. 1305–1312, doi: <https://doi.org/10.1109/ispa63168.2024.00012>.
- [29] H. Park and J. Lee, “LMSA: A lightweight multi-key secure aggregation framework for privacy-preserving healthcare AIoT,” *Computer Modeling in Engineering & Sciences*, vol. 143, no. 1, article 827, 2025, doi: <https://doi.org/10.32604/cmes.2025.061178>.
- [30] D. K. Murala *et al.*, “MedShieldFL: A privacy-preserving hybrid federated learning framework for intelligent healthcare systems,” *Scientific Reports*, vol. 15, no. 1, article 43144, 2025, doi: <https://doi.org/10.1038/s41598-025-27303-3>.
- [31] Y. Lin *et al.*, “Federated learning with hyper-network: A case study on whole-slide image analysis,” *Scientific Reports*, vol. 13, no. 1, article 1724, 2023, doi: <https://doi.org/10.1038/s41598-023-28974-6>.
- [32] Y. Feng *et al.*, “Dual-dimensional optimization framework: Feature fusion for cross-modal medical image segmentation,” in *Proc. Int. Conf. Computer Engineering and Networks*, Singapore: Springer Nature Singapore, 2025, pp. 405–416, doi: https://doi.org/10.1007/978-981-95-3320-6_25.
- [33] J. Wicaksana *et al.*, “FedMix: Mixed supervised federated learning for medical image segmentation,” *IEEE Transactions on Medical Imaging*, vol. 42, no. 7, pp. 1955–1968, 2023, doi: <https://doi.org/10.1109/tmi.2022.3233405>.
- [34] F. Zhu *et al.*, “Model-level attention and batch-instance style normalization for federated learning on medical image segmentation,” *Information Fusion*, vol. 107, article 102348, 2024, doi: <https://doi.org/10.1016/j.inffus.2024.102348>.
- [35] L. Wang *et al.*, “Discovering maximum frequency consensus: Lightweight federated learning for medical image segmentation,” in *Proc. 33rd ACM Int. Conf. Multimedia (MM)*, 2025, pp. 5117–5126, doi: <https://doi.org/10.1145/3746027.3755528>.
- [36] T. Deng *et al.*, “FedDBL: Communication- and data-efficient federated deep-broad learning for histopathological tissue classification,” *IEEE Transactions on Cybernetics*, vol. 54, no. 12, pp. 7851–7864, 2024, doi: <https://doi.org/10.1109/tyb.2024.3403927>.
- [37] S. Shukla *et al.*, “Federated learning in computational pathology: Classification of tall cell patterns in papillary thyroid carcinoma,” in *Medical Imaging 2024: Digital and Computational Pathology*, vol. 12933, SPIE, 2024, article 129330Q, doi: <https://doi.org/10.1117/12.3006890>.
- [38] Y. Shen *et al.*, “A federated learning system for histopathology image analysis with an orchestral stain-normalization GAN,” *IEEE Transactions on Medical Imaging*, vol. 42, no. 7, pp. 1969–1981, 2023, doi: <https://doi.org/10.1109/tmi.2022.3221724>.
- [39] Y. Wang *et al.*, “Federated deep multiple instance learning for histopathological whole-slide image classification,” *Biomedical Signal Processing and Control*, vol. 113, article 109059, 2026, doi: <https://doi.org/10.1016/j.bspc.2025.109059>.
- [40] P. Sahoo *et al.*, “FedMRL: Data heterogeneity-aware federated multi-agent deep reinforcement learning for medical imaging,” in *Medical Image Computing and Computer-Assisted Intervention (MICCAI 2024)*, Lecture Notes in Computer Science. Cham, Switzerland: Springer Nature Switzerland, 2024, pp. 438–448, doi: https://doi.org/10.1007/978-3-031-72384-1_60.
- [41] A. Hassani and I. Rekik, “UniFed: A universal federation of a mixture of highly heterogeneous medical image classification tasks,” in *Machine Learning in Medical Imaging*, Lecture Notes in Computer Science. Cham, Switzerland: Springer Nature Switzerland, 2024, pp. 32–42, doi: https://doi.org/10.1007/978-3-031-73290-4_4.
- [42] S. Arya *et al.*, “Federated impression for learning with distributed heterogeneous data,” in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, Cham, Switzerland: Springer Nature Switzerland, 2024, pp. 215–225, doi: https://doi.org/10.1007/978-3-031-77610-6_20.
- [43] S. Bakas *et al.*, “Federated learning in healthcare: From research to real-world deployment,” *Annual Review of Biomedical Engineering*, vol. 28, 2026, doi: <https://doi.org/10.1146/annurev-bioeng-080125-041414>.
- [44] S. Haggrenmüller *et al.*, “Federated learning for decentralized artificial intelligence in melanoma diagnostics,” *JAMA Dermatology*, vol. 160, no. 3, pp. 303–311, 2024, doi: [doi:10.1001/jamadermatol.2023.5550](https://doi.org/10.1001/jamadermatol.2023.5550).
- [45] U. Baid *et al.*, “Pan-cancer tumor infiltrating lymphocyte detection based on federated learning,” in *Proc. IEEE Int. Conf. Big Data*, 2024, pp. xx–xx, doi: <https://doi.org/10.1109/bigdata62323.2024.10825083>.
- [46] R. H. Junejo *et al.*, “Federated ViT: A distributed deep learning framework for skin cancer classification,” *IEEE Access*, vol. 13, 2025, doi: <https://doi.org/10.1109/access.2025.3612477>.
- [47] M. Delehousse *et al.*, “Performance analysis of aggregation algorithms in cross-silo federated learning for non-IID data,” in *Proc. 4th Int. Conf. Embedded and Distributed Systems (EDiS)*, 2024, pp. 74–79, doi: <https://doi.org/10.1109/EDiS63605.2024.10783224>.
- [48] H. Pan *et al.*, “Adaptive aggregation weights for federated segmentation of pancreas MRI,” in *Proc. IEEE Int. Symp. Biomedical Imaging (ISBI)*, 2025, pp. 1–5, doi: <https://doi.org/10.1109/ISBI60581.2025.10981148>.
- [49] L. A. Schoenpflug *et al.*, “Navigating real-world challenges: A case study on federated learning in computational pathology,” *Journal of Pathology Informatics*, vol. 16, article 100464, 2025, doi: <https://doi.org/10.1016/j.jpi.2025.100464>.
- [50] M. Lablans, S. Bartholomäus, and F. Uckert, “Providing trust and interoperability to federate distributed biobanks,” in *User Centred Networked Health Care*. Amsterdam, The Netherlands: IOS Press, 2011, pp. 644–648, doi: <https://doi.org/10.3233/978-1-60750-806-9-644>.
- [51] B. Clarke *et al.*, “Large-scale implementation of digital pathology for clinical diagnoses: Experience, challenges, and lessons learned,” *Critical Reviews in Clinical Laboratory Sciences*, early access, 2025, doi: <https://doi.org/10.1080/10408363.2025.2549309>.
- [52] M. Touhami *et al.*, “Federated learning for histopathology image classification: A systematic review,” *Diagnostics*, vol. 16, no. 1, article 137, 2026, doi: <https://doi.org/10.3390/diagnostics16010137>.
- [53] S. Fonio, “Benchmarking federated learning frameworks for medical imaging tasks,” in *Image Analysis and Processing*, Lecture Notes in Computer Science. Cham, Switzerland: Springer Nature Switzerland, 2023, doi: https://doi.org/10.1007/978-3-031-51026-7_20.
- [54] M. Chavero-Diez *et al.*, “Federated learning frameworks: Quality and interoperability for biomedical research,” *NAR Genomics and Bioinformatics*, vol. 8, no. 1, article lqag010, 2026, doi: <https://doi.org/10.1093/nargab/lqag010>.
- [55] M. Romanchikova *et al.*, “The need for measurement science in digital pathology,” *Journal of Pathology Informatics*, vol. 13, article 100157, 2022, doi: <https://doi.org/10.1016/j.jpi.2022.100157>.
- [56] E. Alozie *et al.*, “Technical considerations of federated learning in digital healthcare systems,” in *Federated Learning for Digital Healthcare Systems*. Academic Press, 2024, pp. 237–282, doi: <https://doi.org/10.1016/b978-0-443-13897-3.00009-6>.
- [57] S. Shukla and S. Doyle, “Federated learning in computational pathology: A literature review,” *Journal of Medical Imaging*, vol. 12, no. 6, article 061412, 2025, doi: <https://doi.org/10.1117/1.jmi.12.6.061412>.
- [58] R. Haripriya *et al.*, “Federated adaptive aggregation: Improving privacy and scalability in healthcare AI,” *Cluster Computing*, vol. 28, article 617, 2025, doi: <https://doi.org/10.1007/s10586-025-05290-4>.
- [59] J. Yang *et al.*, “Matrix Gaussian mechanisms for differentially private learning,” *IEEE Transactions on Mobile Computing*, vol. 22, no. 2, pp. 1036–1048, 2023, doi: <https://doi.org/10.1109/tmc.2021.3093316>.
- [60] Y. Li *et al.*, “An optimized scheme of federated learning based on differential privacy,” in *Blockchain and Trustworthy Systems*. Singapore: Springer Nature Singapore, 2023, doi: https://doi.org/10.1007/978-981-99-8101-4_20.
- [61] D. Cui and C. Wang, “PD-ADPVFL: Performance-driven adaptive differential privacy vertical federated learning,” in *Intelligent Computing*. Singapore: Springer Nature Singapore, 2025, doi: https://doi.org/10.1007/978-981-96-9958-2_23.
- [62] M. H. Alhazmi, “Adaptive federated clustering for uncertainty-aware learning on decentralized big data platforms,” *PLOS ONE*, vol. 20, no. 12, article e0337069, 2025, doi: <https://doi.org/10.1371/journal.pone.0337069>.
- [63] A. N. Onaizah *et al.*, “Deep learning-based brain tumour architecture for weight sharing optimization in federated learning,” *Expert Systems*, vol. 42, no. 2, article e13643, 2025, doi: <https://doi.org/10.1111/exsy.13643>.
- [64] L. A. Schoenpflug *et al.*, “A review on federated learning in computational pathology,” *Computational and Structural Biotechnology Journal*, vol. 23, pp. 3938–3945, 2024, doi: <https://doi.org/10.1016/j.csbj.2024.103037>.
- [65] S. Suwer *et al.*, “Privacy-by-design with federated learning will drive future rare disease research,” *Journal of Neuromuscular Diseases*, vol. 13, no. 1, pp. 6–19, 2026, doi: <https://doi.org/10.1177/22143602241296276>.