



Review Article

Federated Learning in Oncology: Privacy-Preserving Artificial Intelligence for Multi-Center Cancer Research

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Cancer remains one of the leading causes of morbidity and mortality worldwide, creating an urgent need for advanced computational approaches that can improve diagnosis, prognosis, and personalized treatment strategies. Artificial intelligence (AI) has demonstrated significant potential in oncology by enabling automated medical image analysis, biomarker identification, treatment response prediction, and integration of complex biomedical datasets. However, conventional AI approaches generally rely on centralized data aggregation, where patient information from multiple institutions is transferred to a single location for model training. This approach presents major challenges related to patient privacy, data ownership, regulatory compliance, and institutional barriers, limiting large-scale multi-center collaboration. Federated learning (FL) has emerged as a privacy-preserving AI framework that enables multiple healthcare institutions to collaboratively develop machine learning models without sharing raw patient data. In oncology, FL provides opportunities for secure analysis of medical imaging, genomic information, electronic health records, and clinical trial data while maintaining data confidentiality. This approach can enhance cancer detection, tumor characterization, disease progression modeling, and personalized therapeutic decision-making. Despite its advantages, implementation of FL in oncology faces challenges including data heterogeneity, model bias, communication limitations, cybersecurity risks, and lack of standardized validation frameworks. Future integration of FL with deep learning, generative artificial intelligence, multi-omics analysis, and large-scale cancer research networks may accelerate the development of privacy-preserving precision oncology platforms. This review discusses the principles, applications, architectures, challenges, and future prospects of federated learning in multi-center cancer research.

Keywords: Federated learning; Artificial intelligence; Oncology; Privacy-preserving AI; Precision medicine; Cancer imaging; Multi-center research; Machine learning.

INTRODUCTION

Cancer represents a major global health challenge, with increasing incidence rates and substantial mortality despite continuous advancements in diagnostic technologies and therapeutic approaches. The complexity of cancer biology, tumor heterogeneity, genetic variability, and differences in treatment response have created a strong demand for advanced computational tools capable of supporting precision oncology. Artificial intelligence (AI) has emerged as a transformative technology in cancer research by providing powerful approaches for analyzing complex biomedical information, including

radiological images, genomic profiles, pathological data, and electronic health records (EHRs). AI-based models have demonstrated potential in early cancer detection, tumor classification, survival prediction, biomarker discovery, and optimization of individualized treatment strategies [1]. The successful development of reliable AI systems in oncology requires access to large and diverse datasets representing different populations, disease characteristics, imaging protocols, and clinical outcomes. Multi-center datasets are particularly valuable because they improve model generalizability

and reduce the risk of algorithmic bias associated with single-institution studies. However, collecting and integrating healthcare data from multiple hospitals and research centers remains challenging due to privacy regulations, ethical considerations, institutional policies, and restrictions on transferring sensitive patient information [2]. Traditional machine learning approaches generally require centralized data aggregation, where patient information from multiple institutions is collected into a common database for model development. Although this approach can improve algorithm performance, it introduces significant concerns regarding data ownership, confidentiality, cybersecurity threats, and regulatory compliance. Healthcare data contains highly sensitive information, and unrestricted data sharing may violate patient privacy regulations and reduce willingness among institutions to participate in collaborative research projects [3]. In addition, differences in healthcare infrastructure, imaging equipment, clinical practices, and patient demographics create difficulties in harmonizing datasets across institutions. These challenges are particularly relevant in oncology, where biological variability and differences in cancer management approaches can significantly influence AI model performance. Therefore, innovative strategies that enable collaborative AI development while preserving patient confidentiality are required. Federated learning (FL) has emerged as a decentralized machine learning framework that addresses many limitations associated with conventional centralized AI approaches. Introduced as a method for collaborative model training without direct exchange of raw data, FL allows multiple institutions to train a shared AI model while maintaining patient datasets locally. Instead of transferring patient information, participating centers train models on their own local data and share only encrypted model parameters or updates with a central aggregation system [4]. The concept of federated learning is particularly attractive for oncology because cancer research increasingly depends on integration of diverse data sources, including medical imaging, genomic sequencing, molecular profiling, and clinical outcomes. FL enables hospitals, research organizations, and pharmaceutical institutions to collaborate while maintaining control over their proprietary datasets. This approach has the potential to accelerate cancer research by supporting large-

scale AI development without compromising patient privacy [5]. In cancer imaging, FL has been explored for improving tumor detection, segmentation, classification, and treatment response prediction using distributed datasets from multiple healthcare centers. Similarly, in genomic oncology, FL can facilitate collaborative analysis of molecular alterations, mutation patterns, and biomarkers without requiring direct sharing of genomic information. These capabilities support the development of personalized oncology strategies by enabling AI systems to learn from diverse patient populations while maintaining ethical standards [6]. Furthermore, FL can contribute to clinical decision support systems by integrating information from multiple institutions to improve prediction of treatment outcomes, survival rates, disease progression, and therapeutic response. The ability to develop robust AI models using distributed clinical data may significantly enhance precision medicine approaches and improve cancer care delivery. Despite its advantages, the application of federated learning in oncology remains associated with several challenges. Differences in data quality, imaging protocols, computational resources, and institutional workflows may affect model performance. Additionally, concerns related to cybersecurity, model transparency, regulatory approval, and clinical validation must be addressed before widespread implementation. Therefore, understanding the principles, applications, and limitations of FL is essential for developing reliable privacy-preserving AI solutions in cancer research. This review discusses the fundamentals of federated learning, its role in privacy-preserving oncology research, applications in cancer imaging, genomics, and clinical decision-making, major architectural approaches, security enhancement strategies, current challenges, and future opportunities for advancing multi-center cancer research.

2. Fundamentals of Federated Learning

Federated learning is a machine learning paradigm that enables multiple organizations or devices to collaboratively train a shared artificial intelligence model while keeping original datasets stored locally. Unlike conventional centralized learning, where all data must be transferred to a single server, FL follows a decentralized approach in which only model

parameters, gradients, or statistical updates are exchanged between participating nodes. This architecture reduces the need for direct data sharing and provides enhanced privacy protection for sensitive healthcare information [7]. The basic workflow of federated learning consists of several key steps. Initially, each participating healthcare institution maintains its own local dataset containing patient information such as medical images, genomic profiles, or clinical records. A common AI model architecture is distributed to each participating center, where local training is performed using institution-specific data. After local model optimization, only updated model parameters are transmitted to a central aggregation server. The server combines these updates to generate an improved global model, which is then redistributed to participating centers for further training cycles [8]. The most widely used FL algorithm is Federated Averaging (FedAvg), which combines locally trained model parameters by calculating weighted averages based on the contribution of each participating institution. FedAvg reduces communication requirements while maintaining effective learning performance across distributed datasets. However, variations in healthcare data distribution may require advanced optimization techniques to improve model stability and accuracy [9]. Different types of federated learning approaches have been developed depending on the structure and characteristics of the participating datasets. Centralized federated learning involves multiple clients communicating with a central server responsible for model aggregation. This approach is commonly applied in healthcare collaborations involving multiple hospitals connected through a secure server infrastructure. Decentralized federated learning eliminates dependence on a single central coordinator by allowing direct communication between participating nodes. This approach may improve robustness and reduce the risk of centralized system failure, although it requires more complex communication strategies. Horizontal federated learning is applied when participating institutions possess similar types of data but different patient populations. For example, multiple cancer hospitals may share medical imaging datasets with similar features but different patients. Horizontal FL is particularly relevant for multi-center oncology studies involving MRI, CT, PET, and histopathological

images [10]. Vertical federated learning is used when institutions have different types of information from the same patient population. For example, a hospital may possess clinical records while another organization holds genomic information. Vertical FL enables integration of complementary datasets without exchanging sensitive patient-level information. Federated transfer learning combines concepts of federated learning and transfer learning to improve performance when participating institutions have limited or heterogeneous datasets. This approach can be beneficial in rare cancers where individual centers may not have sufficient patient numbers for developing effective AI models. Secure aggregation methods are essential components of FL systems, ensuring that individual institution contributions remain confidential during model training. These techniques prevent unauthorized access to model updates and strengthen privacy protection in healthcare applications [11]. The unique ability of federated learning to facilitate collaboration without direct data exchange makes it highly suitable for oncology research, where large-scale datasets are required but privacy restrictions remain a major barrier. By enabling secure multi-center AI development, FL provides a foundation for next-generation cancer research platforms.

3. Need for Privacy-Preserving Artificial Intelligence in Oncology Research

The advancement of oncology research increasingly depends on the availability of large-scale, high-quality datasets derived from diverse patient populations. AI-based cancer models require extensive information from multiple sources, including medical imaging, electronic health records (EHRs), genomic sequencing, pathology reports, and clinical trial databases. However, healthcare data is highly sensitive and contains personally identifiable information, creating significant challenges regarding data sharing, ownership, and ethical use [12]. Medical imaging datasets, including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and digital pathology images, contain valuable information for developing AI-based diagnostic and predictive models. However, transferring these datasets between institutions is difficult due to patient confidentiality concerns, large

storage requirements, and regulatory restrictions. Similarly, genomic datasets contain highly sensitive molecular information that may reveal patient-specific biological characteristics, making unrestricted sharing ethically challenging [13]. Electronic health records provide comprehensive clinical information, including patient history, laboratory results, treatment responses, and survival outcomes. Although these datasets are essential for developing predictive AI models, differences in data formats, healthcare systems, and institutional policies often limit their integration across multiple centers. Clinical trial data faces similar challenges because pharmaceutical companies and research institutions may be restricted from sharing proprietary information or patient-level data. Data protection regulations such as the General Data Protection Regulation (GDPR) and healthcare privacy frameworks emphasize strict control over patient information. These regulations aim to protect individuals from unauthorized use of their medical data but may also create barriers for international and multi-center AI collaborations. Therefore, developing AI approaches that maintain privacy while enabling collaborative research is a major priority in modern oncology [14]. Federated learning provides a solution by allowing institutions to collaboratively train AI models without transferring raw patient data. In FL-based systems, hospitals maintain complete control over their datasets, while only model updates are exchanged through secure communication channels. This reduces privacy risks and enables institutions with different resources and expertise to participate in collaborative cancer research. Another important advantage of FL is its ability to preserve institutional autonomy. Healthcare organizations may hesitate to share valuable datasets because of concerns regarding data ownership, competitive advantage, or regulatory compliance. Federated learning allows institutions to contribute to global AI development while maintaining control over their proprietary information [15]. However, privacy preservation in FL does not solely depend on keeping data local. Model updates exchanged between institutions may still contain information that could potentially be exploited through advanced attacks. Therefore, additional privacy-enhancing techniques such as differential privacy, secure aggregation, and encryption methods

are required to strengthen the security of FL systems in healthcare environments [16].

4. Applications of Federated Learning in Oncology

4.1 Federated Learning in Cancer Imaging

Medical imaging is one of the most promising areas for applying federated learning in oncology. Radiological images contain complex spatial and structural information that can be analyzed using deep learning algorithms for cancer detection, classification, and treatment monitoring. However, developing reliable imaging AI models requires large and diverse datasets from multiple institutions, which are difficult to combine due to privacy and regulatory limitations [17]. Federated learning enables multiple hospitals to collaboratively train imaging models without transferring patient images. Each institution trains AI algorithms locally using its own imaging datasets, and the model learns from distributed knowledge through parameter exchange. This approach improves model generalizability by incorporating variations in imaging devices, patient populations, and clinical practices. In magnetic resonance imaging (MRI), FL has been investigated for tumor segmentation and characterization. Brain tumors such as glioblastoma require accurate segmentation for diagnosis, treatment planning, and monitoring disease progression. Multi-center FL approaches allow AI models to learn from diverse MRI datasets while preserving patient confidentiality [18]. Computed tomography (CT)-based FL applications have demonstrated potential in lung cancer detection, pulmonary nodule identification, and tumor volume assessment. Since CT imaging protocols may vary significantly between hospitals, FL provides an opportunity to develop robust models capable of handling heterogeneous imaging environments. Positron emission tomography (PET) imaging combined with FL can support metabolic tumor analysis and treatment response prediction. By integrating PET data from multiple centers, AI models may improve prediction accuracy for therapy outcomes while avoiding direct exchange of sensitive imaging information. Digital pathology is another emerging area where FL can contribute significantly. Histopathological images contain detailed cellular-level information essential for cancer diagnosis and

grading. However, these datasets are extremely large and difficult to share. FL enables collaborative development of pathology AI models for tumor classification, biomarker identification, and prognosis prediction [19]. Beyond diagnosis, FL-based imaging models can assist in treatment response evaluation. AI algorithms trained through multi-center collaboration may identify imaging biomarkers associated with chemotherapy response, radiotherapy outcomes, and disease progression. This capability supports personalized treatment planning and precision oncology.

4.2 Federated Learning in Genomics and Precision Oncology

Cancer is fundamentally a genomic disease characterized by complex molecular alterations, including mutations, gene expression changes, epigenetic modifications, and pathway dysregulation. The integration of genomic information with AI provides opportunities for identifying therapeutic targets, predicting drug response, and developing personalized treatment strategies [20]. Large-scale genomic analysis requires collaboration between institutions because individual centers often lack sufficient patient numbers, particularly for rare cancers. However, genomic data sharing presents major privacy concerns because genetic information is uniquely identifiable and cannot be completely anonymized. Federated learning enables collaborative genomic analysis while keeping genomic datasets within their original institutions. AI models can learn patterns associated with cancer-related mutations, molecular subtypes, and treatment responses without requiring direct exchange of genetic information. In precision oncology, FL can support molecular classification of tumors by integrating genomic profiles from multiple centers. This approach may improve identification of patient subgroups likely to respond to specific targeted therapies or immunotherapies. AI-based FL models can also assist in biomarker discovery. By analyzing distributed genomic and clinical datasets, these models can identify relationships between molecular characteristics and clinical outcomes. Such discoveries may contribute to the development of novel diagnostic biomarkers and therapeutic targets [21]. Furthermore, FL may enhance drug discovery

and repurposing approaches in oncology by allowing pharmaceutical companies and academic institutions to collaboratively analyze molecular and clinical data while protecting proprietary information.

4.3 Federated Learning in Clinical Decision Support

Clinical decision-making in oncology involves complex evaluation of patient characteristics, tumor biology, treatment history, and predicted outcomes. AI-powered clinical decision support systems aim to assist healthcare professionals by providing evidence-based predictions and recommendations. Federated learning enables development of clinical AI models using multi-center patient data without requiring centralized medical records. These models can support prediction of cancer survival, recurrence risk, treatment response, and disease progression. Survival prediction models trained through FL can incorporate diverse patient populations, improving their ability to generalize across different healthcare settings. Similarly, risk stratification models can identify high-risk patients who may require more intensive monitoring or alternative treatment strategies. Treatment optimization is another important application. AI models trained through federated approaches may predict which therapies are most likely to benefit individual patients based on clinical characteristics, molecular features, and previous treatment responses [22]. FL-based decision support systems can also support oncology clinical trials by enabling secure analysis of distributed trial datasets. This may accelerate research collaborations and improve recruitment strategies while maintaining participant confidentiality.

5. Federated Learning Architectures for Multi-Center Cancer Research

Federated learning architectures designed for oncology research consist of multiple interconnected components that enable secure AI model development across healthcare institutions. The primary objective of these architectures is to achieve collaborative learning while maintaining privacy and data ownership. The data layer represents local datasets stored at participating institutions. These datasets may include imaging data, genomic information, pathology slides, and clinical records. Importantly,

the original patient data remains within the institution and is not transferred externally. The AI model layer contains machine learning algorithms responsible for learning patterns from local datasets. Depending on the research objective, models may include deep neural networks, convolutional neural networks, transformer-based architectures, or graph-based models. The communication layer manages exchange of model parameters between participating centers. Secure communication protocols are essential to prevent unauthorized access and ensure reliable transmission of information. The aggregation layer combines model updates from multiple institutions to generate an improved global model. Advanced aggregation techniques are used to minimize bias and improve performance when datasets differ significantly between centers. Cloud-based federated learning architectures use centralized cloud platforms for coordination and model aggregation. These systems provide scalability and computational flexibility but require strong security measures. Edge-based FL allows computation and model training closer to where data is generated, reducing communication delays and improving privacy protection. Hybrid architectures combine cloud and edge computing approaches to balance efficiency, security, and scalability [23]. Multi-center cancer research networks based on FL have the potential to create global AI ecosystems where institutions can collaborate without compromising patient confidentiality. These architectures may significantly accelerate development of next-generation oncology solutions.

6. Security and Privacy Enhancement Techniques in Federated Learning

Although federated learning improves healthcare data privacy by keeping patient information within institutional boundaries, the exchange of model parameters introduces potential security vulnerabilities. Attackers may attempt to extract sensitive information from model updates or manipulate the learning process through malicious contributions. Therefore, advanced privacy-preserving and security-enhancing techniques are required for safe implementation of FL in oncology research [24].

6.1 Differential Privacy

Differential privacy is a mathematical framework designed to prevent disclosure of individual patient information during data analysis. In federated learning, differential privacy techniques introduce controlled noise into model updates before transmission to the aggregation server. This reduces the possibility of identifying specific patients from shared model information while maintaining overall model performance. In oncology applications, differential privacy is particularly important because cancer datasets often contain sensitive genomic profiles, imaging information, and clinical outcomes. The technique enables institutions to contribute knowledge to AI models while reducing risks associated with privacy breaches [25]. However, excessive noise addition may negatively affect model accuracy, especially when datasets are small or heterogeneous. Therefore, optimization of privacy levels while maintaining predictive performance remains an important research challenge.

6.2 Secure Multi-Party Computation

Secure multi-party computation (SMPC) allows multiple participants to jointly perform computational tasks while keeping their individual inputs confidential. In federated learning, SMPC protocols can enable institutions to collaboratively calculate model updates without revealing their private information. For multi-center cancer research, SMPC provides additional protection when hospitals, research institutes, and pharmaceutical organizations collaborate on sensitive datasets. This approach is valuable for genomic studies and clinical research where data confidentiality is essential.

6.3 Homomorphic Encryption

Homomorphic encryption enables computations to be performed directly on encrypted data without requiring decryption. In FL systems, encrypted model updates can be exchanged between institutions, preventing unauthorized access during communication. Although homomorphic encryption provides strong privacy protection, its major limitation is high computational complexity. The increased processing requirements may affect scalability, particularly when dealing with large

oncology datasets such as whole-slide pathology images or genomic sequences [26].

6.4 Blockchain-Based Federated Learning

Blockchain technology has been explored as a method for improving transparency, trust, and security in federated learning networks. Blockchain-based FL architectures can provide decentralized record management, authentication of participating institutions, and secure tracking of model updates. In oncology research networks involving multiple hospitals and international collaborators, blockchain integration may improve accountability and reduce risks associated with unauthorized model manipulation. However, blockchain implementation requires additional computational resources and standardized frameworks before widespread clinical adoption.

6.5 Secure Aggregation Protocols

Secure aggregation ensures that the central server can combine model updates from multiple institutions without accessing individual contributions. This prevents the identification of specific institutional data patterns and strengthens privacy protection. Secure aggregation is particularly important in oncology because differences in cancer prevalence, treatment practices, and patient demographics may unintentionally reveal information about participating institutions. Combining secure aggregation with encryption and privacy-preserving algorithms can improve reliability of FL-based cancer research systems [27].

7. Challenges and Limitations of Federated Learning in Oncology

Despite its significant potential, federated learning implementation in oncology faces several technical, clinical, and regulatory challenges. Addressing these limitations is necessary before FL can become a routine component of precision oncology research.

7.1 Data Heterogeneity Between Institutions

One of the major challenges in oncology FL is data heterogeneity. Cancer datasets collected from different hospitals often vary in terms of patient

demographics, disease stages, imaging equipment, laboratory procedures, and treatment protocols. For example, MRI images acquired using different scanners may have variations in resolution, intensity, and acquisition parameters. Similarly, genomic datasets may differ due to sequencing platforms and analysis pipelines. These variations can reduce model performance and create difficulties in achieving reliable predictions across institutions [28]. Techniques such as domain adaptation, transfer learning, and advanced normalization methods are being investigated to improve model performance under heterogeneous conditions.

7.2 Bias and Fairness Issues

AI models trained on healthcare data may inherit biases present within the original datasets. In oncology, underrepresentation of certain populations, cancer subtypes, or demographic groups may lead to unequal model performance. Federated learning may reduce some forms of bias by incorporating data from multiple institutions, but it does not automatically eliminate fairness problems. Careful evaluation of AI models across different patient groups is required to ensure equitable cancer care.

7.3 Limited Computational Resources

Healthcare institutions differ significantly in their computational capabilities. Large academic hospitals may possess advanced computing infrastructure, whereas smaller centers may have limited resources. Deep learning-based FL models require substantial computational power, memory, and storage capacity. These requirements may restrict participation of resource-limited institutions and affect the scalability of multi-center oncology collaborations.

7.4 Communication Costs

Federated learning requires repeated exchange of model parameters between institutions and aggregation servers. Large AI models, particularly deep neural networks used for imaging analysis, generate substantial communication requirements. Frequent communication cycles may increase training time and computational expenses. Efficient model compression techniques and optimized

communication protocols are being developed to address this limitation.

7.5 Model Convergence Problems

Differences in local datasets can affect the ability of FL algorithms to achieve stable model convergence. Institutions with smaller datasets or unique cancer populations may contribute updates that differ significantly from other participants. This problem may reduce overall accuracy and requires improved aggregation strategies capable of handling diverse healthcare data environments.

7.6 Lack of Standardization

Currently, there is no universally accepted framework for implementing federated learning in oncology research. Differences in data formats, AI algorithms, evaluation methods, and reporting standards make comparison between studies difficult. Establishing standardized protocols for FL-based cancer research is essential to improve reproducibility and facilitate regulatory approval.

7.7 Regulatory and Clinical Validation Challenges

Although FL models may demonstrate high computational performance, clinical adoption requires extensive validation. AI systems must undergo rigorous testing to confirm reliability, safety, and clinical usefulness. Regulatory agencies require evidence that AI-based decision-support systems improve patient outcomes without introducing additional risks. Therefore, collaboration between AI researchers, clinicians, regulatory authorities, and technology developers is necessary.

FUTURE PERSPECTIVES

Federated learning represents an important advancement toward privacy-preserving artificial intelligence in oncology. Future developments will likely focus on integrating FL with emerging AI technologies to create more powerful and clinically relevant cancer research platforms. The combination of FL with deep learning architectures may improve automated analysis of complex oncology datasets, including medical images, pathology slides, and molecular information. Advanced neural networks

can identify subtle patterns associated with tumor behavior, treatment response, and disease progression while maintaining patient privacy. Generative artificial intelligence (GenAI) represents another promising direction. Generative models may assist in synthetic data generation, augmentation of limited datasets, and simulation of cancer progression patterns. When combined with FL, GenAI could enable collaborative research without requiring direct access to real patient data [29]. Large language models (LLMs) may further enhance oncology AI systems by integrating clinical documentation, research literature, and patient information. Federated approaches could allow hospitals to collaboratively develop clinical language models while maintaining confidentiality of medical records. Integration of FL with multi-omics analysis is expected to significantly improve precision oncology. Combining genomic, transcriptomic, proteomic, and imaging data through privacy-preserving frameworks may enable deeper understanding of tumor biology and improve individualized treatment strategies. Future global cancer research networks may utilize federated learning platforms to connect hospitals, universities, pharmaceutical companies, and research organizations worldwide. Such collaborations could accelerate biomarker discovery, clinical trial development, and personalized therapy selection. Real-time personalized oncology is another potential application. Continuous integration of patient monitoring data with FL-based AI systems may allow dynamic prediction of treatment response and early identification of disease progression. AI-powered clinical trials may also benefit from federated architectures by enabling secure analysis of distributed patient populations. This could improve trial recruitment, reduce research costs, and enhance discovery of effective anticancer therapies. However, successful implementation will require continued improvement in security, standardization, transparency, and clinical validation. Future FL systems must not only achieve technical accuracy but also demonstrate meaningful improvements in patient outcomes.

CONCLUSION

Federated learning provides a promising solution for overcoming major barriers associated with healthcare

data sharing in oncology research. By enabling collaborative AI model development without transferring raw patient information, FL supports privacy-preserving analysis of medical imaging, genomic datasets, clinical records, and multi-center cancer research data. The application of FL in cancer imaging, precision oncology, biomarker discovery, and clinical decision support demonstrates its potential to transform personalized cancer care. By allowing institutions to contribute knowledge while maintaining data ownership and confidentiality, federated learning creates new opportunities for global collaboration. Despite significant advantages, challenges related to data heterogeneity, cybersecurity, computational requirements, standardization, and clinical validation must be addressed before widespread implementation. Integration with deep learning, generative AI, large language models, and multi-omics technologies may further enhance the capabilities of FL-based oncology platforms. Overall, federated learning represents a critical step toward developing secure, scalable, and patient-centered artificial intelligence systems. Its continued advancement may accelerate multi-center cancer research and contribute to the future of precision medicine.

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