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Federated Learning and 5G/6G-Based Internet of Medical Things (IoMT): Applications, Key Enabling Technologies, Open Issues and Future Research Directions

Abdul Ahad[1,2] | Kazi Istiaque Ahmed[1] | Farhan Ullah[3] | Muhammad Aman Sheikh[4] | Mohammad Tahir[5,6] | Mohammad Hayajneh[7] | Ivan Miguel Pires[8]

[1]School of Software, Northwestern Polytechnical University, Xian, Shaanxi, People's Republic of China | [2]Department of Electronics and Communication Engineering, Istanbul Technical University, Istanbul, Turkey | [3]Cybersecurity Center, Prince Mohammad Bin Fahd University, Khobar, Saudi Arabia | [4]Cardiff School of Technologies, Cardiff Metropolitan University, Cardiff, UK | [5]Department of Computing, University of Turku, Turun, Finland | [6]Center for Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India | [7]Department of Computer and Network Engineering Department, College of IT, United Arab Emirates University, Al-Ain, UAE | [8]Instituto de Telecomunicações, Escola Superior de Tecnologia e Gestão de Águeda, Universidade de Aveiro, Águeda, Portugal

Correspondence: Muhammad Aman Sheikh (msheikh@cardiffmet.ac.uk) | Kazi Istique Ahmed (istiahmed@nwpu.edu.cn)

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ABSTRACT

The rapid expansion of smart healthcare technologies has created a growing need for systems that are not only intelligent and efficient, but also deeply respectful of patient privacy. As medical data becomes increasingly distributed across wearables, hospital networks, home-based sensors, and mobile applications, traditional centralized approaches struggle to keep pace with evolving security, latency, and interoperability demands. In this review, we explore federated learning (FL) as a promising pathway towards decentralized intelligence, one that allows healthcare institutions and Internet of Medical Things (IoMT) devices to collaborate without sharing sensitive patient data. Supported by emerging 5G and 6G communication technologies, FL has the potential to reshape modern healthcare by enabling real-time analytics, reliable remote monitoring, personalized treatment recommendations, and advanced medical diagnosis. High-bandwidth, low-latency networks provide the connectivity backbone required for FL to function smoothly across diverse medical environments. We examine FL's various forms, its integration into IoMT applications, and the role of enabling technologies such as edge computing, Device-to-device (D2D) communication, Massive Machine Type Communication (mMTC), Blockchain, Software Defined Networking (SDN), Network Function Virtualization (NFV), Digital twins, and Fog computing. At the same time, we acknowledge that this integration is far from straightforward. Challenges such as data heterogeneity, communication overhead, model drift, security risks, resource allocation, and clinical interoperability continue to shape the research landscape. By synthesizing current findings, identifying open issues, and outlining future research directions, this review provides clarity and drives forward research efforts within the integrated fields of AI, networking, and digital healthcare.

This article is categorized under:

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1 | Introduction

In the field of healthcare, the transition from traditional healthcare systems to smart healthcare has marked a paradigm shift in the way medical services are delivered and managed. Traditional healthcare primarily relied on in-person consultations, physical medical records, and limited access to real-time patient data (Perez et al. 2021). In contrast, smart healthcare leverages advanced technologies to provide more efficient, accessible, and patient-centric care. The introduction of technologies like telemedicine, wearable health monitoring devices, and electronic health records has significantly enhanced the quality and accessibility of healthcare services (Haleem et al. 2022).

However, the journey towards smart healthcare has not been without its challenges. Previous generations of mobile networks, such as 4G, although providing improved connectivity, were unable to meet the requirements of smart healthcare applications fully (Ahad et al. 2019). The need for low latency, high bandwidth, and reliable connections for tasks like remote patient monitoring, real-time diagnostics, and telemedicine posed significant limitations under 4G infrastructure (Zhang, Chen, et al. 2020).

The advent of 5G technology marked a significant milestone in addressing these shortcomings. With its promise of ultra-low latency, high data speeds, and network reliability, 5G has facilitated the growth of smart healthcare by enabling applications like remote surgery and augmented reality-assisted medical procedures. However, some requirements of the ever-evolving smart healthcare landscape, such as seamless virtual reality experiences and highly precise remote surgeries, remain unfulfilled under 5G (Ahad and Tahir 2023).

As the healthcare industry continues to push the boundaries of what technology can achieve, the anticipation now turns towards 6G. Expected to build upon the foundation laid by 5G, 6G is poised to bridge the remaining gaps in smart healthcare (Ahad, Tahir, Aman Sheikh, et al. 2020). With its predicted capabilities of near-instantaneous communication, enhanced network reliability, and extended support for immersive technologies, 6G promises to fulfill the most demanding requirements of healthcare applications. As we embark on this journey towards the sixth generation of wireless technology, the prospects for revolutionizing healthcare delivery and patient care remain on the horizon, offering unprecedented opportunities for the future of healthcare (Chengoden et al. 2023). Table 1 shows the comparison of 4G, 5G, and 6G for smart healthcare applications.

Furthermore, the shift from centralized to decentralized systems in smart healthcare applications represents a fundamental transformation in how healthcare data is collected, stored, and managed. In traditional centralized healthcare systems, data and control are concentrated in a central location or server, typically managed by healthcare institutions or organizations (Biswas et al. 2020). However, there are compelling reasons to transition towards decentralized systems in the context of smart healthcare.

1.1 | Challenges of Centralized Systems

Centralized healthcare systems, despite their efficiency in data management, come with inherent drawbacks that raise

TABLE 1 | Comparison of 4G, 5G, and 6G for smart healthcare applications.

Feature	4G	5G	6G (expected)
Latency	Moderate	Ultra-low	Near-zero
Data speed	High but not ultra-high	Very high	Extremely high
Network reliability	Good	Excellent	Exceptional
Bandwidth	Limited	High	Exceptionally high
Connection density	Limited	Very high	Extremely high
Device-to-device communication	Limited support	Enhanced support	Advanced support
Immersive technologies	Limited support for VR and AR	Better support for VR and AR	Seamless VR and AR experiences
Remote surgery	Challenging due to latency and reliability	Improved feasibility	Enhanced precision and safety
Telemedicine	Functional but may have latency issues	Low latency, better quality	Ultra-low latency, high quality
Real-time monitoring	Limited capabilities	Improved capabilities	Enhanced real-time monitoring
Data security	Standard security measures	Enhanced security protocols	Advanced encryption and security
Energy efficiency	Moderate	Improved	Highly efficient

concerns about security, scalability, and patient autonomy. One of the most pressing issues is data vulnerability. Since all information is stored in a single location, a breach in the system can lead to massive data leaks, exposing sensitive patient records and violating privacy regulations (Argaw et al. 2020). This single point of failure makes centralized systems attractive targets for cyberattacks, increasing security risks across the healthcare sector. Another major challenge is scalability. As the volume of healthcare data grows exponentially, centralized systems often struggle to expand efficiently. Increased data loads can lead to bottlenecks, slowing down system performance and reducing overall responsiveness (Aouedi et al. 2022). This issue becomes even more critical in large-scale healthcare networks that require seamless data processing to function effectively.

Latency is another significant concern. In centralized architectures, every data request must travel between the endpoints and the central server, introducing delays that can be particularly problematic in real-time healthcare applications. In scenarios where immediate access to patient data is crucial, such as emergency care or remote monitoring, any delay could have serious consequences (Rajagopal et al. 2023). Beyond technical constraints, centralized systems also limit patient autonomy over their health data. In many cases, patients have little to no control over how their information is stored, accessed, or shared. This lack of ownership not only discourages engagement but also creates barriers to data-sharing initiatives that could improve personalized healthcare (Piasecki and Cheah 2022).

These challenges emphasize the need for alternative solutions, such as decentralized or hybrid healthcare systems, which offer improved security, scalability, and greater patient control over personal health data. As the demand for more efficient and secure data management continues to grow, the limitations of centralized systems are becoming increasingly evident, paving the way for innovative approaches to healthcare technology.

1.2 | Why Transition to Decentralized Systems

Decentralized systems offer a transformative approach to healthcare data management, addressing many of the shortcomings of traditional centralized models. One of the most compelling benefits is improved security. By distributing data across multiple nodes instead of a single repository, decentralized architectures make it significantly harder for cybercriminals to compromise the entire network. Blockchain technology, in particular, introduces robust security measures that enhance data integrity and prevent unauthorized tampering (Kumar, Singh, et al. 2023). Beyond security, enhanced privacy is another key advantage. Decentralized systems grant patients greater control over their own health data, allowing them to determine who has access to their information. This not only strengthens consent management but also mitigates privacy concerns by reducing reliance on centralized databases that are prone to breaches (Saidi et al. 2022). The issue of latency is also addressed in decentralized architectures. Since data does not need to travel back and forth to a central server, response times are significantly reduced. This is particularly beneficial for real-time applications such as remote patient monitoring and telemedicine, where even a slight delay could impact clinical decisions and patient outcomes (Bashir et al. 2023).

Moreover, scalability is a natural strength of decentralized systems. Unlike centralized frameworks, which often struggle to handle increasing data loads, decentralized networks can expand dynamically by adding more nodes. This ensures the system can efficiently process and store vast amounts of healthcare data as demand grows (Kumar, Rana, and Jha 2023). Another critical advantage is interoperability. Decentralized systems facilitate seamless communication among different healthcare providers and platforms, enabling efficient data exchange and improved patient care coordination. By breaking down silos between institutions, healthcare providers can access more comprehensive patient histories, leading to better-informed treatment plans (Villarreal et al. 2023). Perhaps most importantly, decentralization fosters a patient-centric healthcare model. Patients regain control over their medical data, choosing how and when to share it with different providers, research institutions, or applications. This empowerment not only improves patient engagement but also encourages innovation in personalized healthcare solutions (Dulko et al. 2023).

The transition from centralized to decentralized systems in smart healthcare applications is driven by the need to address the vulnerabilities and limitations of centralized systems, including data security and privacy concerns, scalability challenges, and latency issues. Decentralized systems offer improved security, enhanced privacy, reduced latency, and greater scalability, making them better suited to meet the demands of modern healthcare, where data needs to be accessible, secure, and patient-centric.

1.3 | Artificial Intelligence and Machine Learning in Smart Healthcare

Artificial Intelligence (AI) and machine learning (ML) have emerged as pivotal components in transforming smart healthcare systems. Their integration into healthcare enhances the quality of care and facilitates the transition towards a secure and decentralized system (Xie et al. 2021). When combined with the power of 5G/6G, the Internet of Things (IoT), and federated learning (FL), remarkable results can be achieved regarding patient care, data security, and system efficiency (Nguyen et al. 2021). Figure 1 shows the general architecture of FL for 5G-based smart healthcare.

Artificial intelligence is revolutionizing healthcare by enhancing diagnostic accuracy, personalizing treatment plans, and improving overall efficiency. One of its most impactful applications is predictive analytics, where AI algorithms analyze vast amounts of patient data to forecast disease outbreaks, predict patient deterioration, and assess treatment outcomes. By enabling healthcare providers to anticipate trends and allocate resources proactively, AI helps create a more responsive and efficient healthcare system (Dogheim and Hussain 2023). In medical imaging, ML models have demonstrated remarkable accuracy in detecting abnormalities in x-rays, MRIs, and CT scans. These AI-powered diagnostic tools assist radiologists in identifying diseases such as cancer at an early stage, significantly improving patient prognosis through

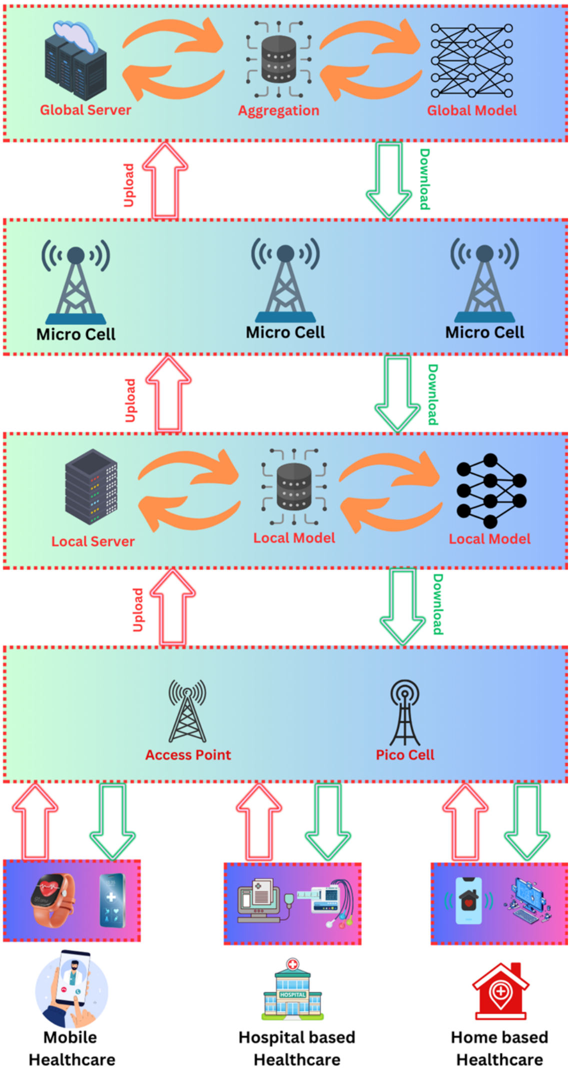

FIGURE 1 | Architecture of federated learning for 5G-based smart healthcare.

timely intervention (Koul et al. 2022). Beyond diagnostics, AI plays a critical role in personalized medicine. By integrating genomic and clinical data, AI-driven models tailor treatment plans to the unique characteristics of individual patients. This targeted approach not only enhances therapeutic effectiveness but also minimizes adverse effects, paving the way for a more patient-centric healthcare experience (Allami and Yousif 2023).

The power of natural language processing (NLP) further strengthens AI's influence in healthcare. By extracting valuable insights from unstructured clinical notes, NLP technologies improve the speed and accuracy of medical decision-making. Physicians can access relevant patient information more efficiently, reducing administrative burdens and allowing more time for direct patient care (Zhu et al. 2020). AI is also transforming patient care beyond hospital settings through remote patient monitoring. IoT devices equipped with AI-driven analytics continuously track vital signs and health metrics, providing real-time alerts for early intervention. This proactive monitoring reduces hospital readmissions and ensures that patients receive timely medical attention, particularly those with chronic conditions (Davis et al. 2022). Additionally, AI is revolutionizing drug discovery by accelerating the identification of promising drug candidates. By analyzing massive datasets, ML models can predict molecular interactions and optimize drug formulations, significantly reducing the time and cost associated with pharmaceutical research and development (Gupta et al. 2021).

1.3.1 | The Role of FL

FL is a privacy-preserving approach that allows AI models to be trained across multiple decentralized data sources without centralizing sensitive information. In healthcare, FL addresses data security and privacy concerns while still leveraging the collective intelligence of the healthcare ecosystem. It ensures that data remains on local servers, making it less vulnerable to breaches and unauthorized access (Li et al. 2023).

The convergence of AI, ML, FL, 5G/6G, and the IoT is revolutionizing healthcare, offering unprecedented speed, connectivity, and intelligence. One of the most significant advantages of this integration is ultra-low latency, made possible by 5G and emerging 6G networks. This near-instantaneous data transmission is essential for real-time applications such as telemedicine consultations, remote robotic surgeries, and continuous patient monitoring, ensuring that critical decisions can be made without delays (Minopoulos and Psannis 2022). Beyond latency improvements, high bandwidth plays a crucial role in modern healthcare systems. With the ability to transfer massive medical datasets, including high-resolution imaging, real-time video feeds, and electronic health records, 5G/6G networks ensure seamless communication without compromising data quality. This is particularly beneficial for radiology, remote diagnostics, and AI-powered medical imaging, where rapid and accurate data exchange is vital (Ahad, Tahir, Sheikh, Ahmed, and Mughees 2021). At the core of this transformation is IoT connectivity, where wearable sensors and smart medical devices interact effortlessly with 5G/6G infrastructure. From continuous glucose monitoring for diabetics to smart implants that track cardiac activity, IoT-driven healthcare enables real-time data collection and proactive medical interventions. These connected devices not only improve patient outcomes but also help in managing chronic conditions more effectively (Manivannan et al. 2023).

To further enhance efficiency, edge computing is integrated with 5G/6G networks, allowing data to be processed closer to the source rather than relying on distant cloud servers. This reduces latency, minimizes network congestion, and enables real-time decision-making, which is especially critical in emergency care, remote monitoring, and AI-driven diagnostics (Mughees et al. 2020). Moreover, these advancements foster enhanced patient engagement by giving individuals secure access to their health data through IoT-connected devices. Patients can track their vital signs, receive real-time alerts, and actively participate in their treatment plans. This level of engagement promotes adherence to medical advice, improves self-care, and strengthens the doctor-patient relationship (Rayan et al. 2023). The integration of FL, 5G/6G, and IoT is more than just a technological upgrade; it marks a paradigm shift towards secure, decentralized, and patient-centric healthcare. These innovations enable real-time analytics, personalized treatment plans, enhanced data security, and optimized resource allocation. By harnessing the collective power of these technologies, healthcare providers can deliver superior, data-driven care while safeguarding patient privacy and ensuring system-wide efficiency. As digital healthcare continues to evolve, these advancements pave the way for a smarter, more connected, and more responsive healthcare ecosystem.

1.4 | Our Contribution

Table 2 compares literature related to FL for IoMT. To our knowledge, this is the first paper to present a review on this topic. Our contribution is to deliver a review of FL for 5G/6G-based IoMT considering several aspects.

We explore the significance of decentralized systems for the Internet of Medical Things (IoMT); it is paramount, and our exploration dives into why they are increasingly favored over centralized systems. Decentralized systems, in many ways, offer more flexibility, security, and scalability, making them better suited for the dynamic nature of IoMT.

Our study also encompasses an in-depth examination of FL, highlighting its various types and specific applications within IoMT. FL, with its ability to train on decentralized data, presents novel opportunities and advantages in the medical context, especially when considering patient privacy and localized insights.

A detailed breakdown of the 5G and 6G technologies that are crucial enablers for IoMT is presented. These next-generation communication technologies are set to revolutionize IoMT by offering increased speeds, reduced latency, and improved reliability. As a result, they will significantly enhance the functionalities, responsiveness, and overall efficiency of IoMT devices and systems.

An intricate part of this research is dedicated to shedding light on the challenges of integrating 5G/6G-based IoMT with FL. These challenges manifest differently across various domains, such as ML, Cyber Security, Telecommunication, and Medical Informatics. Each domain presents its unique intricacies that need meticulous attention and understanding.

Finally, we venture into potential solutions that can be employed to address the open issues related to the integration of 5G/6G IoMT and FL. Additionally, we provide insights into the possible future research directions that can be undertaken to resolve these challenges further, ensuring that the symbiosis of these technologies is seamless and advantageous.

1.5 | Organization of the Paper

This paper is organized as follows: Section 2 presents a brief overview of FL types. Section 3 presents the FL applications in the IoMT. Section 4 presents an overview of critical enabling technologies for 5G/6G-based IoMT. Section 5 presents open issues and future research directions for integrating FL with 5G/6G-based IoMT. Finally, the conclusion is presented in Section 6.

2 | Types of FL in Smart Healthcare Applications

FL can be instrumental in the healthcare sector by aiding the development of robust models while ensuring data privacy and compliance with regulatory frameworks. Here's how different types of FL can be employed for intelligent healthcare applications. Table 3 shows the summary of machine and deep learning algorithms with FL for smart healthcare applications.

2.1 | Horizontal Federated Learning

Horizontal federated learning (HFL) offers a decentralized approach to train ML models across multiple healthcare institutions while keeping patient data secure and local (Yang et al. 2019). The main advantage of HFL is that it allows institutions to collaboratively build accurate models without sharing sensitive patient data. Each institution has its local dataset, and the goal is to aggregate the results from all participating institutions to improve the model's performance (Yang, Wang, et al. 2022).

Let K denote the number of institutions, and each institution k has its own local dataset $D_k = \{(x_i, y_i)\}$, where x_i represents the input features and y_i denotes the corresponding labels. The objective of the FL process is to minimize a global loss function $\mathscr{L}(\theta)$, where θ represents the parameters of the model. The training process can be formalized as shown in Equation 1.

$$\min_{\theta} \mathscr{L}(\theta) = \frac{1}{N} \sum_{k=1}^{K} \mathscr{L}_k(\theta) \tag{1}$$

here $\mathscr{L}_k(\theta)$ is the local loss function for institution k, and N is the total number of data points across all institutions. The model parameters θ are updated iteratively using gradient descent or other optimization algorithms. Importantly, the data never leaves the institutions' local environments.

In each round of communication, institution k computes the gradient or update $\Delta\theta_k$ based on its local dataset, which can be expressed as shown in Equation (2).

$$\Delta\theta_k = \nabla_{\theta} \mathscr{L}_k(\theta) \tag{2}$$

The updates from all institutions are then aggregated (typically through a weighted average) to form a global update as shown in Equation (3).

$$\theta^{t+1} = \theta^t - \eta \sum_{k=1}^{K} \omega_k \Delta\theta_k \tag{3}$$

where ω_k is the weight corresponding to institution k, and η is the learning rate. The global model is then sent back to each institution, where the process is repeated.

TABLE 2 | Summary of existing surveys.

References	Description	Focus area	Enabling technologies	Main challenges discussed
Rauniyar et al. (2022)	Provides an in-depth exploration of Federated Learning (FL) for medical data analytics, integrating IoT, edge computing, and blockchain to ensure privacy-preserving distributed model training. Highlights applications in cancer detection, medical imaging, and COVID-19 diagnosis.	Healthcare (IoT, Edge, Blockchain-based FL)	IoT, Edge Computing, Blockchain	Privacy and confidentiality of medical data, scalability of multi-institutional FL, data sharing regulations (GDPR), and interoperability among healthcare systems.
AbdulRahman et al. (2020)	A foundational survey tracing the evolution of FL from centralized to distributed paradigms. Discusses how FL supports decentralized model training and improves data security in IoT and healthcare environments.	Cross-domain (IoT, Edge, Healthcare, General FL)	Cloud-Edge Architecture, Distributed Training Frameworks	Data heterogeneity (non-IID), communication cost in aggregation, resource constraints in edge nodes, and scalability of FL models.
Aledhari et al. (2020)	Offers a comprehensive taxonomy of FL architectures, technologies, and applications across healthcare, IoT, and mobile devices. Examines optimization strategies for communication and computation efficiency.	Generalized FL (Healthcare, IoT, Mobile Networks)	Edge Computing, IoT, Mobile Systems	Privacy leakage, data imbalance, energy efficiency, communication latency, and large-scale deployment issues.
Ji et al. (2021)	Investigates "Federated X Learning," combining FL with transfer, meta, multi-task, and reinforcement learning. Reviews adaptive aggregation and clustering approaches for dynamic learning environments.	Algorithmic Advances in FL	Adaptive Aggregation, Meta-learning, Bayesian Methods	Data heterogeneity, communication efficiency, model convergence, privacy trade-offs, and robustness in multi-task FL settings.

(Continues)

TABLE 2 | (Continued)

References	Description	Focus area	Enabling technologies	Main challenges discussed
Prasad et al. (2022)	Focuses on FL within Internet of Medical Things (IoMT) networks, highlighting secure collaboration using blockchain and encryption. Introduces a blockchain-based Cross-FL framework for hospital-level collaboration.	IoMT and Healthcare Analytics	Blockchain, Edge Devices, Homomorphic Encryption	Data privacy and ownership, communication overhead, trust and security in multi-party systems, and constrained resources in IoMT devices.
Nguyen et al. (2022)	Presents an overview of FL for smart healthcare, emphasizing collaborative learning across hospitals and IoMT devices without raw data exchange. Discusses privacy-enhanced and personalized FL.	Smart Healthcare (EHR, Remote Monitoring)	IoMT, Edge AI, Differential Privacy	Data heterogeneity, privacy preservation, communication bottlenecks, and scalability of FL in real-world medical systems.
Zhang, Kreuter, et al. (2024)	Analyzes 89 studies (2015–2023) covering horizontal, vertical, and transfer FL in healthcare. Reviews optimization methods to address non-standardized, missing, or imbalanced data.	Healthcare (Data-centric FL)	Communication Protocols, Local Optimization, Transfer Learning	Missing or incomplete data, reproducibility of models, high computational demand, and fairness across distributed datasets.
Antunes et al. (2022)	Reviews FL for electronic health records (EHR) focusing on secure aggregation and interoperability. Proposes a scalable architecture for inter-institutional collaboration and data sharing.	EHR and Clinical Data Analysis	Secure Aggregation, Differential Privacy, Data Encryption	Privacy and data leakage, heterogeneity of hospital databases, limited computation at local nodes, and interoperability challenges.
Teo et al. (2024)	A large-scale systematic review of 612 FL studies in healthcare. Evaluates technical architectures, clinical readiness, and radiology use cases, highlighting the gap between research and deployment.	Healthcare (Clinical FL, Medical Imaging)	Cloud FL Frameworks, Edge-Cloud Integration	Data privacy, heterogeneity in medical datasets, scalability for clinical deployment, and integration barriers across healthcare institutions.

(Continues)

TABLE 2 | (Continued)

References	Description	Focus area	Enabling technologies	Main challenges discussed
Our study	Focuses on Federated Learning in the context of 5G/6G-enabled IoMT networks. Examines how ultra-reliable low-latency communication (URLLC) and massive connectivity enhance real-time decentralized healthcare. Proposes a new taxonomy and identifies key research gaps in FL–IoMT integration.	FL and IoMT with 5G/6G Connectivity	5G, 6G, Edge Computing, Network Slicing, IoMT Devices, FL	Communication delay, resource allocation, energy efficiency, data heterogeneity, privacy-preserving model updates, and system scalability.

2.2 | Vertical Federated Learning

Vertical federated learning (VFL) is a decentralized learning framework that allows institutions to collaboratively train a ML model without sharing sensitive data. Unlike HFL, where data is split by samples, VFL splits data by features, meaning that different institutions hold different attributes (or features) of the same set of patients. Each institution might hold a different type of data, such as demographic data, medical records, or imaging data, but all institutions share the same patient pool (Liu et al. 2022; Huang et al. 2021).

Let K denote the number of institutions. Each institution k holds a subset of features $\mathbf{x}_k$ corresponding to the same set of patients. Let the combined feature set for all institutions be $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_K)$, where each $\mathbf{x}_k$ represents the features from institution k. The dataset at institution k is denoted as shown in Equation 4.

$$D_k = \left\{ \left(\mathbf{x}_{k,i}, y_i \right) \right\}_{i=1}^{N} \tag{4}$$

where $\mathbf{x}_{k,i}$ is the vector of features from institution k for patient i, and y_i is the target variable (e.g., disease outcome) corresponding to patient i.

The goal of VFL is to learn a global model $\mathcal{M}(\mathbf{x})$ that predicts the target variable y using the combined information from all institutions' features.

The training of the global model is performed by minimizing a global loss function $\mathcal{L}(\theta)$, where θ represents the parameters of the model. The global loss is expressed as shown in Equation (5).

$$\min_{\theta} \mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}\left(\hat{y}_i, y_i\right) \tag{5}$$

where $\hat{y}_i$ is the predicted value of y_i based on the model parameters θ, and $\mathcal{L}\left(\hat{y}_i, y_i\right)$ is the loss function that measures the difference between the predicted and actual outcomes for each patient.

The training procedure in VFL can be outlined as follows:

- **Initialization**: The global model θ_0 is initialized and the institutions establish a secure communication channel.
- **Local computation**: Each institution computes the local update based on its features $\mathbf{x}_k$ and the current global model θ^t. The local gradient $\Delta\theta_k$ is computed as shown in Equation (2).

  where $\mathcal{L}_k(\theta)$ is the local loss function at institution k.
- **Secure aggregation**: The local updates from all institutions are aggregated into a global update. This aggregation is typically done using secure multi-party computation (SMPC) or differential privacy techniques to ensure data security and privacy.
- **Global Model update**: The global model is updated based on the aggregated local updates as shown in Equation (3).

TABLE 3 | Summary of machine and deep learning algorithms with federated learning for smart healthcare applications.

ML/DL algorithm	Strengths	Limitations	References
Convolutional Neural Network (CNN)	Works well for medical image analysis, such as detecting COVID-19 from X-ray images. CNN is widely used for image-related tasks in healthcare.	Training CNN models with multiple layers can take a lot of time and require high computational power, which can be a challenge in federated learning (FL) environments with limited resources.	Qayyum et al. (2022), Pandianchery et al. (2023), Abd El-Mawla et al. (2024), Alhafiz and Basuhail (2025)
U-Net	Delivers high accuracy in medical image segmentation, such as identifying brain tumors from MRI scans.	Training U-Net is time-intensive since the model needs to process each image patch separately. There can also be redundant calculations due to overlapping patches, and a tradeoff exists between accuracy and contextual awareness.	Bechar et al. (2025), Asjad et al. (2024), Dang (2024), Zhang, Jin, et al. (2024)
Autoencoder (AE)	Helps reduce the complexity of medical data by removing unnecessary details and finding meaningful patterns through an unsupervised learning approach. This makes the data more compact and useful for analysis.	There is a risk that important medical details might get lost when compressing the data.	Kumar et al. (2024), Ard iç and Genç (2025)
Generative Adversarial Network (GAN)	Can generate artificial medical data to supplement small datasets, which helps in cases where real data is limited.	Training GANs is difficult because the learning process is unstable, there is no fixed way to measure their performance, and many trial-and-error attempts are needed to get good results.	Selvaraj et al. (2024), Liu et al. (2025), Rehman et al. (2024), Alalwan et al. (2024), Peketi et al. (2023)
Multilayer Perceptron (MLP)	Works for structured medical data, such as predicting mortality risk based on drug usage. It can generalize well across different datasets.	MLP struggles with complex problems and is sensitive to how features are scaled. It also requires tuning multiple settings, such as the number of layers and neurons.	Chowdhury et al. (2023), Bárcena et al. (2023)
Long Short-Term Memory (LSTM)	Suitable for analyzing sequential medical data, such as detecting human activity patterns over time.	Faces challenges like vanishing and exploding gradients, which make training LSTM models harder.	Kumar and Kim (2024), Qayyum et al. (2022)
Support Vector Machine (SVM)	Effective in handling complex decision boundaries and works well in high-dimensional data. It is also good at avoiding overfitting.	Requires a lot of memory and is difficult to adjust because choosing the right kernel is crucial. Additionally, it does not scale well for very large datasets.	Nair et al. (2022)

where ω_k is the weight assigned to the update from institution k, and η is the learning rate. The updated global model is then sent back to all institutions for the next iteration.

2.3 | Federated Transfer Learning

Federated transfer learning (FTL) is an extension of FL that enables institutions with non-identical and non-iid (independent and identically distributed) data to collaboratively train a ML model without sharing their raw data. In the context of healthcare, this technique allows hospitals or healthcare institutions with different data distributions to transfer learned knowledge from one institution (the source) to another (the target) in order to improve model performance (Smith et al. 2017). FTL is particularly useful when the target institution has limited data or when the data distribution is significantly different between institutions.

Let there be K institutions, where each institution k holds its own dataset $D_k = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_k}$, with $\mathbf{x}_i$ being the input features and y_i representing the target variable. In FTL, we define two key domains:

Source domain: The data at the source institution S, which has sufficient labeled data $D_S = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_S}$. **Target domain**: The data at the target institution T, which may have limited data or a different feature distribution, represented as $D_T = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_T}$.

The goal of FTL is to transfer knowledge from the source domain to the target domain, so that a global model $\mathscr{M}(\mathbf{x})$ can be trained using data from both institutions.

Initially, the source institution trains a model $\mathscr{M}_S$ on its own data by minimizing the loss function as shown in Equation (6).

$$\min_{\theta} \mathscr{L}_S(\theta) = \frac{1}{N_S} \sum_{i=1}^{N_S} \mathscr{L}(\hat{y}_i, y_i) \tag{6}$$

where $\hat{y}_i$ is the predicted outcome and $\mathscr{L}(\hat{y}_i, y_i)$ is the loss function.

Once the model is trained on the source domain, it is transferred to the target institution. However, due to differences in data distribution between the source and target domains, the transferred model $\mathscr{M}_S$ may not perform well on the target domain data. To overcome this, the model is fine-tuned on the target institution's data D_T, adjusting the model parameters to minimize the loss on the target domain as shown in Equation (7).

$$\min_{\theta} \mathscr{L}_T(\theta) = \frac{1}{N_T} \sum_{i=1}^{N_T} \mathscr{L}(\hat{y}_i, y_i) \tag{7}$$

where $\mathscr{L}_T(\theta)$ is the loss function for the target domain, and $\hat{y}_i$ is the predicted outcome for the target institution's data.

FTL also benefits from FL techniques, allowing institutions to train a global model without sharing sensitive data. During the fine-tuning phase, each institution computes local updates to the model based on its own data and shares these updates (rather than raw data) with a central server for aggregation. The global model is then updated according to Equation (3). where ω_k is the weight for the institution k, and $\Delta\theta_k$ represents the local model update from each institution. The aggregation ensures that the global model benefits from the data of all institutions.

2.4 | Federated Reinforcement Learning

Federated reinforcement learning (FRL) is a decentralized ML approach that combines the principles of reinforcement learning (RL) with FL. It allows multiple institutions, such as hospitals or clinics, to collaboratively train a reinforcement learning agent while preserving the privacy of their data (Qi et al. 2021; Zhang, Yin, et al. 2020). In this setting, each institution trains its own local RL model using its local data and environment, and only model updates (not raw data) are shared with a central server for aggregation. This method ensures that sensitive patient data remains private while leveraging the collective knowledge of multiple institutions.

In the traditional RL setting, the agent interacts with an environment and learns an optimal policy π to maximize cumulative rewards. The agent's objective is to find a policy that maximizes expected rewards over time, formalized as shown in Equation (8).

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R_t\right] \tag{8}$$

where γ is the discount factor, R_t is the reward at time step t, and T is the total number of time steps. In a federated setting, each institution k has its own environment and local dataset, but shares model updates, not data.

Each institution updates its local action-value function $Q_k(\mathbf{s}, \mathbf{a})$, which represents the expected reward of taking action $\mathbf{a}$ in state $\mathbf{s}$. The update is based on the Bellman Equation (9).

$$Q_k(\mathbf{s}_t, \mathbf{a}_t) \leftarrow Q_k(\mathbf{s}_t, \mathbf{a}_t) + \alpha\Big(R_t + \gamma \max_{\mathbf{a}'} Q_k(\mathbf{s}_{t+1}, \mathbf{a}') - Q_k(\mathbf{s}_t, \mathbf{a}_t)\Big) \tag{9}$$

where α is the learning rate, $\mathbf{s}_t$ and $\mathbf{a}_t$ are the state and action at time t, and $\max_{\mathbf{a}'} Q_k(\mathbf{s}_{t+1}, \mathbf{a}')$ is the maximum expected reward from the next state $\mathbf{s}_{t+1}$. After updating the local model, each institution sends its model update θ_k (such as gradients or weights) to the central server.

The central server aggregates the updates from all institutions as shown in Equation (10). A common approach is to average the model updates from each institution k.

$$\theta_{t+1}^{\text{global}} = \frac{1}{K} \sum_{k=1}^{K} \theta_k \tag{10}$$

where K is the total number of institutions. This aggregated global model is then shared back with the institutions, allowing each to improve its local policy based on the collective knowledge. The institutions continue this iterative process of local training and global aggregation, improving the RL model over time.

In practice, the update to the global model can also be weighted based on the contribution of each institution's model update, as shown in Equation (11).

$$\theta_{t+1}^{\text{global}} = \theta_{t}^{\text{global}} - \eta \sum_{k=1}^{K} \omega_k \Delta\theta_k \tag{11}$$

where η is the learning rate for aggregation, ω_k is the weight assigned to institution k, and $\Delta\theta_k$ is the update from institution k.

This process of federated aggregation allows institutions to collaboratively train a global reinforcement learning model while keeping their local data private. It is particularly valuable in applications like smart healthcare, where each institution may have unique patient populations and environments, and collaboration can lead to a more robust and generalized decision-making model. However, challenges such as handling non-IID data, communication overhead, and delayed feedback must be addressed for efficient deployment.

3 | FL Applications in the IoMT

The interconnected infrastructure of medical devices, software applications, health systems, and services enables the collection, analysis, and exchange of health data. When FL is integrated with IoMT, it allows for on-device learning, which respects the privacy concerns that are paramount in healthcare. Table 4 shows the summary of AI-driven FL in IoMT.

3.1 | Remote Patient Monitoring

FL for remote patient monitoring involves deploying ML models on edge devices (such as smartphones or wearable devices) to collect and process patient data locally, without data transfer to a centralized server or cloud (Wu, Chen, et al. 2020). The primary objective of this FL approach for remote patient monitoring is to enable healthcare providers to make accurate and timely medical predictions or diagnoses for individual patients. By utilizing FL, healthcare providers can leverage the collective intelligence of multiple distributed sources to improve the quality of care provided (Ali, Al-Rimy, et al. 2023). Despite the potential benefits of FL for remote patient monitoring, several challenges must be addressed. One major challenge is the heterogeneity and variability of data collected from different edge devices. Each device may have different sensor capabilities, data formats, and data quality, making it difficult to combine and analyze the data effectively (Hu et al. 2022). Another challenge is establishing a secure and reliable communication framework between the edge devices and the centralized server (Ahad, Tahir, Sheikh, et al. 2020). This framework should ensure the confidentiality and integrity of data during transmission. Moreover, FL relies on the participation and cooperation of multiple stakeholders, including patients, healthcare providers, and technology companies. Despite its potential, FL for remote patient monitoring also has limitations. One limitation is edge devices' computational and resource constraints (Imteaj et al. 2021). Many edge devices, such as smartphones or wearable devices, have limited computing power and storage capacity (Ahad, Al Faisal, et al. 2017). This can impact the efficiency and scalability of model training and inference on these devices, especially when dealing with large and complex datasets.

3.2 | Personalized Treatment Recommendations

FL for personalized treatment recommendations is an approach that leverages the power of FL to provide individualized and privacy-preserving treatment recommendations in the healthcare field. One of the key objectives of implementing FL for personalized treatment recommendations is to overcome the limitations of individual data scarcity in healthcare settings (Wang et al. 2023). By leveraging the collective knowledge from multiple healthcare institutions, FL enables the training of robust and accurate treatment recommendation models that can consider diverse patient characteristics, medical histories, and treatment outcomes. This approach aims to address the challenges of limited individual data for training models in healthcare settings while also ensuring the privacy and security of sensitive patient information (Aouedi et al. 2022). Implementing FL for personalized treatment recommendations presents several challenges. Firstly, there is a need to establish robust communication protocols and infrastructure to facilitate the exchange of model updates securely and efficiently among participating healthcare institutions (Ahad, Tahir, Sheikh, Mughees, and Ahmed 2021). Secondly, the standardization of data formats and integrating different types of healthcare data from diverse sources poses a significant challenge (Aceto et al. 2018). Lastly, the heterogeneity and complexity of healthcare data require sophisticated ML algorithms and techniques to extract meaningful insights and make accurate treatment recommendations effectively (Ganie et al. 2022). Despite its potential benefits, FL for personalized treatment recommendations has some limitations. One limitation is the need for many participating healthcare institutions to ensure diversity and representativeness in the training data, which may be challenging to achieve in practice (Xu, Glicksberg, et al. 2021). Another limitation is the potential bias in the FL model due to variations in data quality and healthcare practices across different institutions (Rieke et al. 2020).

3.3 | Disease Prediction and Prevention

Disease prediction and prevention is an emerging approach in the field of healthcare that aims to utilize data from multiple sources to predict and prevent diseases. FL, a key technique in federated disease prediction and prevention, has been gaining increasing interest in recent years (Myrzashova et al. 2023). The use of FL techniques in healthcare enables the training of models that contain knowledge from multiple healthcare institutions while ensuring the security and privacy of personal data. FL has drawn increasing interest in recent years and has been applied in many on-device prediction tasks. In the paper

TABLE 4 | Summary of AI-driven federated learning in IoMT: Key application domains, challenges, and solutions.

References	Applications fields	Addressing challenges	Proposed solution
Xu, Glicksberg, et al. (2021)	Medical Records & Predicting Mortality	Various statistical concerns; System related challenges; Issues with Privacy	An analysis of current solutions that utilize Federated Learning.
Brisimi et al. (2018)	Relation to Heart Disease Mechanisms	Problems with Sparse SVM; Challenges with raw data sharing	Suggestion of a CPDS architecture that can discern the difference between patients who require hospitalization and those who don't.
Passerat-Palmbach et al. (2019)	Section for Preserving Privacy in Audits	Concerns about user privacy; Policy issues regarding data access; Security concerns	A combined approach using Blockchain and Federated Learning to ensure privacy in the system without revealing user identities.
Silva et al. (2020)	Method for Federated Learning in Brain Imaging	Absence of a production-ready FL system; Sourcing user data from various platforms is challenging	A dual module system that has a client for software purposes and a central module for managing data from the real world.
Chen et al. (2020)	Federated Learning for Parkinson's Disease Healthcare	Data integration from diverse sources is problematic	Offering a system that not only provides accurate medical guidance but also ensures data privacy and security. This system also distinguishes genuine Parkinson's disease through advanced detection methods.
Wu, Chen, et al. (2020)	Monitoring System for Home Usage	Personalized cloud systems might not be consistently reliable; Growing population of the elderly	A strategy using FL and CNN for continuously monitoring senior patients suffering from long-term illnesses, especially those unable to move frequently.
Choudhury et al. (2019)	Predicting Medication Reactions	The confidential nature of healthcare data; A gap in real-world research	A proposed model designed to forecast the human body's reactions to different medications.
Ma et al. (2020)	Information in Healthcare & Data Distribution	Data spread across numerous edge nodes	Suggest design modifications that bring in the versatility of hybrid electronics, which can enhance the electrical properties that contribute to high-quality performance.
Pershad et al. (2018)	Relationships Between Patients & Doctors, Technology & Public Health	Misinformation on Twitter, a major social media platform; Proliferation of misleading health information	Recommending the increased usage of Twitter for improving healthcare information quality and particularly for researching the potential of Twitter in sharing treatment data.

(Continues)

TABLE 4 | (Continued)

References	Applications fields	Addressing challenges	Proposed solution
Kim et al. (2019)	Federated Learning in Machines & Blockchain	Source verification is challenging; The architecture is intricate	Proposes a latency-based FL model that's dependent on blockchain, focusing on the optimal block generation time and reducing communication delays.
Miotto et al. (2018)	Deep Learning in Healthcare, Biomedical Informatics, and Genomic EHR	Data is multidimensional and diverse, complicating matters; Difficulty in extracting knowledge from intricate data	Offering a comprehensive yet simple system designed to bridge the disparity between intricate DL models and human comprehension.
Wiens and Shenoy (2018)	Focus on Healthcare Machine Learning	Concerns over privacy	Special considerations offered to healthcare specialists aiming to utilize/apply ML.
Kumar et al. (2021)	Enhanced Data Distribution using DL, FL, and Blockchain	Transformation of infectious disease data. Insufficient COVID-19 test kits	Architecture to obtain crucial data from diverse sources, culminating in a blockchain-based DL model.
Nguyen et al. (2022)	Integration of FL, Blockchain, Edge Computing, and IoT	Rapid virus transmission. Distinguishing between COVID-19 cases.	Augmentation of security and accessibility through Blockchain in FL without centralized networks.
Hölbl et al. (2018)	Blockchain in Distributed Healthcare Systems	Data confidentiality. Encryption techniques.	Harnessing blockchain's potential to navigate challenges and promote blockchain in healthcare.
Pokhrel and Choi (2020)	Vehicle Learning, Blockchain in Federated Learning	Challenges due to intricate frameworks	A FL strategy reliant on a blockchain algorithm ensuring efficient and secure updates.
McGhin et al. (2019)	Blockchain in Healthcare with IoT and Authentication	Data privacy concerns. Deficiencies in blockchain solutions.	Extensive detailing of various research methodologies in the study.
Lu et al. (2019)	Federated Learning in IoT with Secure Data Sharing on Blockchain	Data breaches	A blockchain solution for data sharing over multiple years, addressing ML issues with fortified safety.
Greenberg et al. (2020)	Machine Learning in Healthcare	Data security and privacy. Navigating uncharted scenarios.	Strategies to manage challenges encountered by healthcare workers during the COVID-19 crisis.
Kaye et al. (2021)	Medical Data Analysis in Healthcare	Pressure and Decision-Making in ICU settings	Evaluating the repercussions of the pandemic on ICU healthcare services and their delivery.
Xi et al. (2021)	Federated Learning in Healthcare	Mismatched Data Features	Comprehensive defense strategy against Backdoor Attacks, focusing on two ML goals for optimal results.

(Continues)

TABLE 4 | (Continued)

References	Applications fields	Addressing challenges	Proposed solution
Long et al. (2021)	Bioinformatics with Federated Learning	Inconsistent Data Features	Enhancing the Open Health System using FL and AI, discussing challenges and potential solutions.
Liu et al. (2019)	AI, Healthcare, Federate Learning	Concerns about data privacy. Issues with intricate models.	Highlights on recent AI advancements and their role in healthcare, pinpointing potential obstacles for AI's future in healthcare, and evaluating the influence of AI from financial, legal, and societal aspects.
Esteva et al. (2019)	AI, Healthcare, Federate Learning, Computer Vision, NLP	Concerns of data leakage. Ethical considerations. Challenge to train the NLP model.	In-depth exploration of computer vision in biomedical image analytics and a detailed explanation of NLP's role in areas like EHR data.
Xu, Peng, et al. (2021)	Federate Learning, AI, Medical Data	Concerns about data security. Data acquisition challenges. Issues of data leakage.	Detailed discussion on maintaining patient privacy, using FL to understand and treat depression.
Lu et al. (2020)	Healthcare, Federate Learning, Distributive learning	Ethical dilemmas in data sharing. Delays and costs in communication. Interruptions in the communication setup.	Comprehensive approach to enhance communication effectiveness using distributed FL over a network, highlighting how the algorithm performs multiple iterations for local updates, enabling communication between nodes.

(Lu et al. 2023), FL has been successfully utilized to extract personal information about patients from medical texts without sharing the actual data. In the paper (Ao and Fan 2023), the authors applied FL and a BERT-based NER model to extract personal information about patients from medical texts without compromising the privacy of the medical text data. Similarly, in the paper (Islam et al. 2022), the authors applied FL and deep learning neural networks to brain tumor image segmentation, effectively protecting patients' personal information. The use of FL in healthcare applications offers several advantages, particularly regarding privacy and security. With the increasing concern over privacy and security in healthcare, FL provides a promising solution. One of the main advantages of FL in healthcare is its ability to analyze various medical data (Joshi et al. 2022). This includes not only structured data, such as electronic health records but also unstructured data, such as free-text clinical reports and medical images. FL allows for the analysis of diverse types of medical data, enabling comprehensive disease discrimination and prediction (Subramanian et al. 2022).

3.4 | Drug Discovery

In recent years, the drug discovery and research field has witnessed significant advancements due to the application of ML techniques (Vatansever et al. 2021). ML approaches have shown promise in accelerating the drug discovery process and addressing some challenges. With the ability to leverage large datasets and complex algorithms, ML techniques have become valuable tools for analyzing and predicting compound activities, optimizing molecular properties, synthesis planning, protein folding, and hit discovery (Dara et al. 2022). However, one of the major challenges in drug discovery is the limited availability and sharing of data due to privacy concerns, intellectual property rights, and regulatory restrictions (Jones et al. 2017). FL approaches have emerged as a promising solution to address these challenges.

FL, a decentralized ML approach, allows multiple organizations or entities to collaboratively train models without sharing their raw data. This approach transforms the problem of discordant records in centralized ML into an intrinsic feature of FL. In centralized ML, discordant records pose a significant problem as the sharing of raw data becomes necessary and raises privacy concerns. However, FL overcomes this issue by allowing organizations to share only their local model updates, ensuring privacy and data security while constructing a better global model (Zhang et al. 2021). In drug discovery, FL offers a promising approach to address the need for protecting confidential and IP-sensitive data while extracting maximum knowledge from such data through ML techniques. FL has the potential to revolutionize the field of drug discovery by enabling collaborative training of models on decentralized private data (Oldenhof et al. 2023).

3.5 | Chronic Disease Management

Chronic diseases, such as diabetes, heart disease, and cancer, pose significant challenges for healthcare systems worldwide (Chimezie 2023). The effective management of chronic diseases requires continuous monitoring, personalized treatment plans, and timely interventions. The existing literature on FL approaches for chronic disease management showcases the potential benefits and challenges of implementing this innovative technique (Nair et al. 2023; Subashchandrabose et al. 2023; Berghout et al. 2022). In recent years, researchers have increasingly applied FL approaches to address the complexity and privacy concerns of chronic disease management (Patel et al. 2022). FL is a ML technique that allows multiple parties, such as patients, physicians, healthcare organizations, and industry partners, to collaborate and train a shared model without sharing sensitive data. Several studies have demonstrated the potential of FL in the context of chronic disease management (Nguyen et al. 2022). Additionally, previous research has explored the contemporary applications and technological challenges of FL in preserving sensitive biomedical data (Antunes et al. 2022). These studies highlight the potential of FL approaches in improving chronic disease management. FL approaches hold great promise in addressing the challenges associated with chronic disease management. The effective management of chronic diseases requires continuous monitoring, personalized treatment plans, and timely interventions. Implementing FL approaches in chronic disease management can greatly enhance these aspects of care delivery.

3.6 | Enhanced Imaging Diagnostics

The area of medical image processing and analysis has greatly contributed to significant advancements in clinical diagnosis by integrating various systems and techniques (Chen et al. 2022). These systems and techniques utilize images acquired from different imaging modalities such as endoscopy, x-ray, microscopy, computed tomography, optical coherence tomography, magnetic resonance imaging, functional magnetic resonance imaging (fMRI), magnetic resonance elastography, positron emission tomography, single photon emission computed tomography, and 3D ultrasound computer tomography. In enhanced imaging diagnostics, one emerging approach that has gained attention is FL. FL, a privacy-preserving ML technique, has recently garnered attention in the medical imaging field (Sohan and Basalamah 2023). It is being explored for its applicability and benefits in various medical imaging tasks, including whole-brain segmentation, brain tumor segmentation, and identification of disease-related biomarkers using fMRI. With FL, healthcare institutions can leverage the collective knowledge from diverse datasets while ensuring patient privacy and complying with data protection regulations (Dhiman et al. 2022). One of the key advantages of FL in the context of enhanced imaging diagnostics is its ability to train models using heterogeneous data sources. For instance, in the paper (Ao and Fan 2023), the authors used FL and a BERT-based NER model to extract personal information about patients from medical texts without sharing the actual text data. This approach allowed for identifying patterns and trends while ensuring data privacy. In addition to text data, FL can be applied to medical image data. In the field of enhanced imaging diagnostics, FL offers several advantages. Firstly, it allows for the collaborative training of models using diverse datasets from multiple healthcare institutions. This enables the creation of a more comprehensive and generalized model that can improve disease discrimination and prediction.

4 | Key Enabling Technologies for 5G/B5G-IOMT and Challenges With Federating Learning

The 5th generation (5G) and beyond 5G (B5G) communication networks are expected to greatly transform the IoT, particularly in critical areas like healthcare. The IoMT specifically refers to the medical and healthcare sectors' interconnected devices, applications, and health systems. Integrating 5G/B5G into IoMT will address issues prevalent in earlier-generation networks and provide seamless, low-latency, high-reliability connectivity and many more. Table 5 summarizes the key enabling technologies for 5G/B5G in the IoMT with FL, highlighting their improvements, integration challenges, and proposed solutions.

4.1 | Device-To-Device (D2D) Communication in the IoMT

In the rapidly evolving landscape of the IoMT, Device-to-Device (D2D) communication emerges as a pivotal mechanism. The primary allure of D2D in medical scenarios is its potential to dramatically reduce latency by bypassing the need to relay data through a central base station or core network (Ranjan et al. 2022). Especially in critical medical situations, this real-time data transfer can be the difference between life and death. Beyond latency, the reliability of medical systems is significantly enhanced with D2D. Unlike traditional setups, there isn't a singular point of failure, such as a centralized server. If the central infrastructure faces congestion or failure, medical devices can maintain their vital communication links directly. This inherent redundancy is especially crucial in healthcare, where consistent operation can be paramount.

Moreover, the efficiency of D2D cannot be overstated. Direct communication diminishes the central network's burden, leading to more optimal resource utilization. Hospitals and medical facilities, often dense with interconnected devices, stand to benefit immensely. For instance, a patient's real-time data might need swift sharing between a monitoring device and a nearby display screen—D2D excels in such local data transfers. Furthermore, this mechanism is potentially more energy-efficient, especially for nearby devices, which is a boon for battery-driven medical apparatus. Lastly, the aspect of privacy and security in D2D communication holds significance. Transmitting sensitive patient data directly between devices, instead of routing it through multiple points in a network, can reduce exposure and potential breaches (Alsubaei et al. 2019).

However, when we introduce FL, a decentralized ML approach, into this mix, several challenges arise. FL aims to train models on devices using local data without sending the actual data to a central server, ensuring data privacy. Yet, the amalgamation of FL with D2D in IoMT faces hurdles. The non-uniform data distribution across devices can lead to skewed or biased models (Chai et al. 2020). Moreover, the energy constraints of medical devices can hamper the iterative training process, potentially leading to incomplete or sub-optimal model training. The synchronization of model updates across devices, especially when they are directly communicating, becomes complex (Nassef et al. 2022). Additionally, while D2D offers enhanced privacy, ensuring secure model aggregation and preventing potential adversarial attacks in such a decentralized setup remains challenging (Beltrán et al. 2023).

4.2 | Massive Machine Type Communication in the IoMT

In the intricate ecosystem of the IoMT, Massive Machine Type Communication (mMTC) emerges as a vital component. mMTC is specifically crafted to support an immense density of devices, potentially catering to up to a million devices per square kilometer (Bhoi et al. 2022). This scalability is crucial in healthcare environments where myriad sensors, wearables, and other medical devices operate in tandem. Whether a smart hospital setting or a broader urban health infrastructure, mMTC ensures that vast arrays of devices can communicate seamlessly without congestion or service degradation (Ahmad et al. 2022). Connectivity is another salient aspect of mMTC's role in IoMT. Given the mission-critical nature of many medical applications, the consistent and ubiquitous connectivity that mMTC provides ensures that real-time patient monitoring, remote diagnostics, and other applications function without hitches. The inherently low-energy requirement of mMTC further ensures that battery-operated medical devices remain operational for extended periods without frequent recharges or battery replacements (Alves and Lopez 2021).

When FL enters the IoMT landscape with mMTC, it brings forth a set of challenges. FL, a decentralized approach to ML, thrives on using local data on devices to train models without centralizing this data. Given the high density of devices under mMTC, there is a pronounced risk of data heterogeneity. Different devices might possess vastly different data sets, leading to potential biases in model training. The communication overhead for synchronizing and aggregating model updates from so many devices is another hurdle (Boobalan et al. 2022). Ensuring that every device or node in the mMTC setup contributes effectively and uniformly to the FL process can be challenging (Wahab et al. 2021).

Moreover, while mMTC is designed for low-energy operations, the computational demands of FL might strain device batteries more than anticipated. Lastly, with data decentralization being a cornerstone of FL, securing this data from potential breaches or malicious attacks in a high-density mMTC environment remains a pressing concern.

4.3 | Edge Computing in the IoMT

In the evolving domain of IoMT, edge computing has carved out a pivotal role. By processing data closer to its source, be it a medical sensor, wearable, or any other connected device, edge computing significantly reduces the latency traditionally associated with centralized cloud infrastructures (Pan and McElhannon 2017). This becomes especially vital in medical scenarios where real-time data processing, such as remote patient monitoring or emergency interventions, can be paramount. By offloading computational tasks to the edge, hospitals and medical facilities can ensure faster response times, enhancing the quality and speed of patient care (Qiu et al. 2021). Additionally, local data processing also brings about a potential reduction in data transmission costs and network congestion.

However, integrating FL, which thrives on decentralized data processing and model training, into an edge computing-based IoMT presents its challenges. First and foremost, data heterogeneity becomes prominent. With numerous devices in a medical setup producing varying data, ensuring a comprehensive and unbiased model training across these edge devices is complex. The inherent diversity in computational capacities among edge devices further complicates the FL process (Wu, He, and Chen 2020). A high-end edge server might process data faster than a smaller edge device, leading to potential synchronization issues when aggregating model updates (Beutel et al. 2020). Security, while enhanced through localized data processing, remains a concern. The multitude of edge nodes amplifies the points of vulnerability, requiring stringent measures to thwart potential breaches or attacks (Pramanik et al. 2019). Furthermore, maintaining the consistency and quality of FL across a diversified edge infrastructure necessitates intricate orchestration, placing demands on computational and human resources (Ali, Li, and Yousafzai 2023).

4.4 | Network Function Virtualization in the IoMT

Network Function Virtualization (NFV) plays a transformative role in the IoMT landscape (Latif et al. 2017). Traditionally, network functions like routing, firewalling, and load balancing were tied to specific hardware appliances. With NFV, these functions become software-based, offering flexibility and scalability essential for the dynamic needs of IoMT (Vergütz et al. 2020). Healthcare environments benefit immensely from this decoupling of hardware and software. For instance, as patient loads fluctuate or new medical devices get integrated, the network can be reconfigured or scaled without requiring substantial hardware overhauls. This leads to cost savings and ensures that

TABLE 5 | Overview of key enabling technologies for 5G/B5G in IoMT with federated learning.

Key enabling technologies	Advantages	Challenges	Possible solutions
Device-to-Device (D2D) Communication	Enhances ultra-low latency (URLLC) communication by enabling direct communication between IoMT devices, reducing network bottlenecks and improving real-time decision-making.	Data heterogeneity and asynchronous updates due to variable device capabilities. Energy constraints of IoMT devices may limit their ability to participate in iterative federated learning.	Implement adaptive aggregation methods that can handle non-IID (non-independent and identically distributed) data. Optimize energy efficiency in D2D networks to ensure smooth federated learning updates across devices.
Massive Machine Type Communication (mMTC)	Facilitates high-density connectivity by enabling IoMT devices (such as wearables, sensors, and medical devices) to communicate seamlessly over the 5G/B5G network, ensuring reliable data transmission for federated learning.	Increased communication overhead due to high device density and varying data rates. The aggregation of updates from large numbers of devices may introduce network congestion, impacting the efficiency of federated learning.	Develop scalable aggregation techniques, like hierarchical federated learning, to manage high device density and reduce communication bottlenecks. Optimize machine learning-based resource allocation to balance bandwidth demands.
Edge Computing	Offloads computation tasks to edge nodes, closer to IoMT devices, enabling real-time data processing, reducing the dependence on cloud infrastructures, and improving response times for healthcare applications.	Variability in edge device computing capabilities leads to inconsistencies in model updates. Edge devices with limited computational power may face challenges in training complex models.	Develop federated learning algorithms that adapt to varying computational resources across edge devices. Investigate hybrid edge-cloud models to balance computation and data storage, enhancing overall performance.
Network Function Virtualization (NFV)	Provides flexible and scalable network resources on demand, enabling IoMT devices to dynamically adjust their network resource requirements. NFV supports efficient deployment and reconfiguration of healthcare applications.	Federated learning's decentralized model updates may conflict with the dynamic, virtualized infrastructure provided by NFV, resulting in synchronization issues and potential delays in model aggregation.	Create federated learning protocols that work seamlessly with NFV's dynamic reconfiguration. Use network slicing to prioritize federated learning tasks in real-time healthcare applications.
Software-Defined Networking (SDN)	Optimizes resource allocation for critical medical applications by providing centralized control over network traffic, enabling seamless integration of real-time data flows and federated learning updates.	Incompatibility between SDN's centralized control of network traffic and federated learning's decentralized model updates can lead to bottlenecks, especially during peak usage times.	Explore hybrid SDN frameworks that can dynamically support decentralized federated learning models while optimizing resource management. Use network slicing to allocate dedicated bandwidth for federated learning updates, ensuring minimal latency.

(Continues)

TABLE 5 | (Continued)

Key enabling technologies	Advantages	Challenges	Possible solutions
Blockchain	Ensures data integrity and privacy by utilizing distributed ledger technology (DLT) to validate and secure model updates during federated learning, providing transparency and trust in IoMT data exchanges.	Blockchain's consensus mechanisms (e.g., proof of work, proof of stake) may introduce latency, conflicting with the low-latency demands of real-time federated learning applications in healthcare.	Focus on lightweight blockchain consensus algorithms, such as proof of authority, to reduce latency. Investigate hybrid models where blockchain secures federated learning updates while the data processing remains local to address efficiency concerns.
Fog Computing	Extends edge computing by providing an intermediary layer between edge devices and the cloud, enabling faster decision-making by processing data closer to the source, reducing latency.	Heterogeneity in fog node capacities and potential computational bottlenecks in distributed environments can hinder federated learning model synchronization and aggregation.	Propose multi-tier federated learning frameworks, where fog nodes handle initial model processing, and central servers aggregate updates. Adjust model training to the capacity of fog nodes to improve synchronization.
Digital Twin Technology	Enables the creation of virtual representations of physical medical devices and patients, providing a comprehensive view for personalized healthcare, predictive analytics, and optimized treatment plans.	Ensuring synchronization between digital twin models and federated learning models is challenging due to differences in data representations and varying update frequencies.	Develop federated learning protocols that can seamlessly integrate digital twin data without losing consistency. Implement cross-domain adaptation techniques to maintain federated learning model accuracy across diverse virtual environments.
Cellular IoT (CIoT)	Leverages low-power wide-area network (LPWAN) technologies to ensure scalable, long-range connectivity for IoMT devices, supporting large-scale data collection for federated learning without excessive energy consumption.	Heterogeneous device capabilities (e.g., sensors, wearables, medical equipment) in CIoT networks can cause data consistency issues, impacting the accuracy of federated learning models.	Handle device heterogeneity through advanced data pre-processing techniques. Optimize federated learning models to be energy-efficient while maintaining high accuracy in low-power devices.

medical applications receive the requisite network resources efficiently and on the fly. NFV also paves the way for the rapid deployment of new services, aiding in quicker response times, especially crucial in medical emergencies or outbreaks.

However, when one envisions the merger of NFV with FL within IoMT, a series of challenges come to the fore. FL's decentralized nature, which involves training on local datasets and aggregating model updates, can conflict with NFV's dynamic and virtualized environment (Yu and Li 2021). Ensuring consistency in model training across a virtualized infrastructure, which might be constantly adapting and reconfiguring based on network needs, becomes a herculean task. There is also the challenge of data integrity and security. As FL operates on local data, and given NFV's virtual nature, ensuring that data isn't compromised during virtual function migrations or adjustments is paramount.

Furthermore, the orchestration complexity rises exponentially. Coordinating FL processes across multiple virtualized network functions necessitates sophisticated orchestration tools and strategies. Lastly, the dynamic resource allocation characteristic of NFV could lead to computational discrepancies across nodes, making it challenging to achieve synchronized and consistent FL outcomes (Trindade et al. 2022).

4.5 | Software Defined Networking in the IoMT

Software Defined Networking (SDN) has emerged as a cornerstone in reshaping the connectivity landscape of the IoMT. At its core, SDN decouples the control plane from the data plane in networking, offering a centralized control mechanism to manage and adjust network resources dynamically (Mughees et al. 2021). In the medical domain, where the seamless data flow is imperative for patient care, SDN offers unprecedented agility. It enables healthcare facilities to adapt to changing network demands, from an influx of patient data, telemedicine consultations, or integrating new medical IoT devices (Padhi and Charrua-Santos 2021). By offering programmable, adaptable, and scalable network management, SDN ensures that critical medical applications receive prioritized bandwidth and that data flows are optimized for efficiency and speed (Baktir et al. 2018).

Yet, when intertwining the principles of FL with SDN in the IoMT context, challenges inevitably arise. FL, characterized by decentralized data processing and collaborative model training, requires a stable and predictable network environment. However, SDN's dynamic nature, while beneficial in many regards, can introduce inconsistencies in network resource allocation (Mendiola et al. 2019). These fluctuations can impact the FL process, especially when aggregating model updates from various nodes. Additionally, the centralized control inherent to SDN presents both an opportunity and a vulnerability. While it allows for efficient orchestration of FL tasks across the network, it also becomes a potential single point of failure or attack (Balasubramanian et al. 2021). Ensuring robust security for the SDN controller, especially when sensitive medical data is involved, is paramount. Another challenge lies in the potential disparity between the computational goals of SDN and FL. While SDN aims for optimal network utilization, FL seeks to maximize data processing efficiency. Balancing these objectives harmonized requires intricate network management strategies and can strain the capabilities of current SDN controllers.

4.6 | Blockchain in the IoMT

Blockchain's introduction to the IoMT promises to address some of the sector's long-standing concerns while opening avenues for novel applications. At its core, blockchain is a decentralized and distributed ledger technology, ensuring unparalleled data security and integrity (Moin et al. 2019). In the IoMT, where sensitive health information is continuously exchanged, the immutable nature of blockchain becomes a beacon of trust (Bhan et al. 2023). Each record, once inscribed, is cryptographically sealed. Altering this data would necessitate the modification of all subsequent blocks, an endeavor that is computationally rigorous and near impossible. Thus, medical records, patient histories, and treatment plans stored or referenced on the blockchain remain trustworthy and unchanged. Moreover, the decentralized architecture of blockchain mitigates the risks associated with centralized systems, like single points of failure or targeted attacks (Rathore et al. 2019). In IoMT settings, where device interoperability and data exchange are paramount, blockchain can be an unbiased intermediary, ensuring transparent and verifiable transactions (Nguyen et al. 2021). Imagine a scenario where patient consent for medical data sharing is needed. Blockchain can facilitate and record this consent, ensuring both transparency and non-repudiation.

However, the confluence of blockchain with FL in IoMT isn't without challenges. FL, by design, focuses on training ML models across devices while keeping data localized. When integrating with blockchain, the large size of models and the frequent data exchanges can bloat the blockchain, making it less efficient (Hylock and Zeng 2019). Moreover, the consensus mechanisms in blockchain, meant to validate transactions, can introduce latency, potentially at odds with the real-time needs of FL in medical scenarios (Yang, Shi, et al. 2022). Also, ensuring the smooth interplay between FL's iterative model updates and the blockchain's immutable records requires sophisticated integration techniques. Lastly, while blockchain's decentralization is its strength, it also introduces complexities in governance and standardization, which are especially crucial in the medical domain where compliance and regulations are stringent.

4.7 | Fog Computing in the IoMT

Within the IoMT sphere, fog computing is increasingly being recognized as a pivotal tool to bridge the gap between centralized cloud resources and edge devices (Alekseeva et al. 2022). By positioning computational power, storage, and networking capabilities closer to the data source, fog computing creates an intermediary layer that can process data more efficiently and responsively than relying solely on distant cloud servers. In medical scenarios, where real-time analytics and responses can be crucial, such as inpatient monitoring or emergency interventions, this immediacy is invaluable. Embedded within hospital infrastructure or medical equipment, fog nodes can swiftly analyze and react to data streams, ensuring timely medical insights and actions. Moreover, by reducing the need to relay data back to the central cloud constantly, fog computing can help conserve bandwidth and mitigate potential network congestion (Gasmi et al. 2022).

However, when the paradigm of FL is introduced into this fog-enhanced IoMT landscape, complexities arise. FL operates on training ML models at the data source, aggregating and centralizing only the model updates, thereby maintaining data privacy. In a fog environment, ensuring uniformity in this decentralized training process can be challenging due to fog nodes' diverse capacities and capabilities (Naeem et al. 2019). These discrepancies might introduce inconsistencies during model aggregation. Another hurdle is the dynamic nature of fog nodes, where resources might be reallocated based on demand, potentially disrupting the FL process. Ensuring efficient and secure model aggregation in this decentralized and intricate environment, especially with sensitive medical data at play, also becomes a concern (Mughees et al. 2023). The collaborative essence of FL, combined with the distributed nature of fog computing, requires sophisticated coordination and synchronization mechanisms to ensure smooth and effective learning outcomes.

4.8 | Digital Twin Technology in the IoMT

Digital twin technology has emerged as a transformative force in the landscape of the IoMT. A digital twin is a virtual representation of a physical entity or system, facilitating real-time monitoring, analysis, and even prediction (Liu et al. 2021). In the realm of IoMT, this translates to creating detailed virtual models of medical equipment, patient physiological systems, or even entire healthcare processes. The immediate advantage is the ability to simulate medical scenarios, predict equipment failures, or anticipate patient health deteriorations. For instance, a digital twin of a patient's cardiovascular system could predict potential risks or simulate responses to various treatments, paving the way for personalized healthcare strategies. Beyond individual patients, digital twins in IoMT can be extended to entire healthcare facilities. Hospitals can model patient flow and equipment utilization or even predict and manage resource shortages, all in a virtual environment before implementing changes in the real world. The continuous feedback loop between the physical and the digital realm ensures that these virtual models are perpetually updated, reflecting real-world changes and nuances (Haleem et al. 2023).

However, integrating FL, a decentralized approach to ML, with digital twin technology in IoMT presents distinct challenges. Firstly, ensuring data consistency across digital twins when FL is applied can be intricate (Sun et al. 2020). Given that FL operates by training on local datasets, there is a risk of developing siloed or slightly divergent models across different digital twins (Duan et al. 2021). Merging or aggregating these models while maintaining the accuracy and integrity of each twin can be complex. Moreover, the computational demands of continuously updating and refining digital twins can conflict with the iterative nature of FL, leading to potential resource allocation challenges (Zhao et al. 2023). Data privacy, a core tenet of FL, might also be tested. Creating a detailed digital twin requires in-depth data, potentially blurring the boundaries of what data remains local and what gets integrated into the twin. Lastly, ensuring that digital twins accurately reflect real-world scenarios while integrating insights from FL models necessitates advanced synchronization mechanisms and rigorous validation protocols.

4.9 | Cellular IoT Technology in the IoMT

Integrating Cellular Internet of Things (CIoT) technology into the IoMT offers a robust framework for seamless and efficient device connectivity. Unlike traditional cellular protocols tailored for high-bandwidth applications like video streaming or browsing, CIoT pivots towards accommodating many devices with varied data requirements (Bakar et al. 2023). Within the medical realm, where device ubiquity ranges from high-end medical imaging machinery to compact wearable sensors, CIoT's adaptability becomes invaluable. Its ability to provide consistent and expansive connectivity ensures that no medical device, be it in bustling urban hospitals or in remote clinics, gets left out of the communication loop. One of the standout features of CIoT, particularly technologies such as NarrowBand IoT (NB-IoT), is the emphasis on low power consumption (Ahad, Ullah, et al. 2017). This becomes particularly significant for wearables or implantable devices where battery longevity can directly impact patient health monitoring. Furthermore, modern healthcare facilities, often teeming with sensors, monitors, and IoT devices, benefit from CIoT's capacity to handle high device density without network congestion, ensuring smooth data flow and real-time analytics.

However, when we blend CIoT with FL within the IoMT, a few challenges emerge. FL's essence is decentralized learning, where devices train models locally and share only model updates, preserving data privacy. Given the massive scale and device heterogeneity in CIoT-based IoMT, coordinating these decentralized learning processes can be complex (Dian et al. 2020). Variability in device computational capacities might lead to asynchronous model updates, complicating the aggregation phase. While enhanced by FL, data privacy still faces challenges in CIoT environments due to the vast device landscape and varied communication protocols.

Ensuring uniform encryption standards and thwarting potential eavesdroppers or attackers in such a vast network can be daunting (Koutras et al. 2020). Moreover, CIoT's emphasis on low power consumption might sometimes be at odds with FL's computational demands, especially on smaller devices, leading to potential trade-offs between battery longevity and learning efficiency (Moges et al. 2023).

5 | Open Issues and Future Research Directions

FL, while promising in terms of data privacy and distributed learning, presents several challenges when integrated with a 5G/6G-based IoMT. Here are some open issues related to this integration. Figure 2 shows the open issues related to FL for 5G/6G-based IoMT with respect to ML, Telecommunications, Cyber Security, and Medical Informatics.

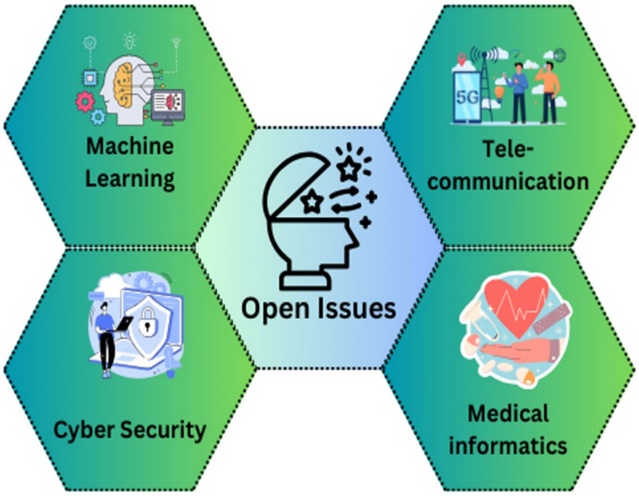

FIGURE 2 | Open issues related to federated learning for 5G/6G-based Internet of Medical Things (IoMT) with respect to Machine Learning, Telecommunications, Cyber Security, and Medical Informatics.

5.1 | Open Issues With Respect to ML

Integrating FL with a 5G/6G-based IoMT in the context of ML presents several open issues and challenges. Figure 3 shows the Open Issues related to FL for 5G/6G-based IoMT with respect to ML.

5.1.1 | Data Heterogeneity

Data heterogeneity is a pronounced challenge in the complex ecosystem of the 5G/6G-based IoMT, especially when FL is incorporated into diverse systems. The IoMT landscape has many devices, ranging from high-end hospital machinery to everyday wearables. Each device is not only different in its data collection capability but also in the nature and granularity of the data it captures. For instance, data procured from a sophisticated MRI scanner is vastly different from the readings of a simple fitness tracker.

All these sources of heterogeneity pose significant challenges for FL in IoMT. A model trained locally on one device might not generalize well when applied to data from another, leading to potential biases or inaccuracies (Tedeschini et al. 2022). Furthermore, the vast disparities in data could impede the iterative nature of FL, where devices frequently share model updates. Aggregating these updates to achieve a globally coherent model becomes a daunting task, requiring sophisticated techniques to address the nuances of data heterogeneity (Guendouzi et al. 2023). Without addressing these challenges, the promise of FL—privacy-preserving, decentralized ML—might remain unfulfilled in the ever-evolving 5G/6G-based IoMT realm.

5.1.2 | Quality of Local Updates

In the intricate network of the 5G/6G-based IoMT, the assimilation of FL brings a unique set of advantages and challenges. One of the standout challenges arises from the quality of local updates, an issue that holds significant implications for the overall effectiveness of the FL process (Yu et al. 2022).

FL, inherently decentralized, empowers individual IoMT devices to process and learn from data locally without sharing raw data centrally. After local training, these devices transmit model updates to a central server, aggregating these updates to refine the global model. However, the quality and relevance of these local updates can vary significantly, given the diverse nature of IoMT devices and the data they handle.

This variability poses a considerable challenge when aggregating updates to enhance the global model. A simplistic aggregation might undervalue critical insights from some devices while overemphasizing potentially less relevant updates from others. The real-time demands of medical applications further amplify the challenge. Ensuring that the aggregated model remains timely and accurate, even in the face of varied local update quality, is crucial.

5.1.3 | Model Aggregation

The 5G/6G-based IoMT landscape is vast and intricate, teeming with devices that constantly gather and analyze data. FL is woven into this complex tapestry and promises privacy-centric, decentralized ML, where devices or nodes learn from their local data without directly sharing it. However, a pivotal challenge that emerges in this confluence is the issue of model aggregation.

At the heart of FL lies the principle that individual nodes process their data locally and send model updates, often in the form of gradients or weights, to a central server. This server then aggregates these diverse updates to refine or update a global model, which is subsequently sent back to the nodes for further rounds of local training. This iterative process of local training and central aggregation is the essence of FL.

However, in the context of IoMT, the challenge becomes profound. Medical devices in IoMT can range from advanced diagnostic tools in hospitals to wearable sensors monitoring vital statistics. Each of these devices might have different data distributions, quantities, and qualities. When these varied devices provide their local model updates, the central server aggregates potentially conflicting or vastly different updates into a coherent global model. A naive averaging of these updates might lead to a suboptimal or even detrimental model for certain devices.

5.1.4 | Model Drift and Adaptation

Integrating FL within the expansive realm of the 5G/6G-based IoMT offers an intriguing blend of decentralized data processing, learning, and real-time adaptation. However, as this symbiosis evolves, the challenges associated with model drift and the subsequent need for model adaptation become increasingly pronounced.

Model adaptation in the face of such drift is essential, especially given the critical nature of the medical domain. The stakes in IoMT are invariably high—misaligned models can lead to

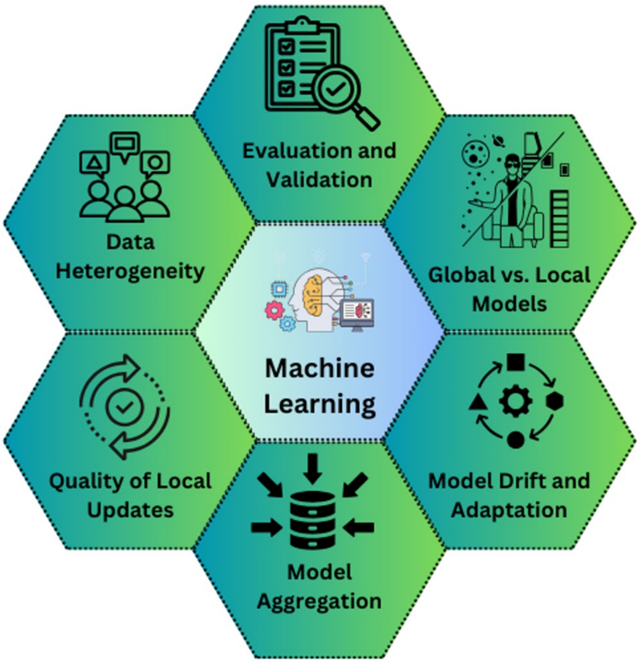

FIGURE 3 | Open issues related to federated learning for 5G/6G-based Internet of Medical Things (IoMT) with respect to Machine Learning.

incorrect insights, potentially affecting patient care or medical decision-making. However, continuous adaptation is not without challenges. Deciding when to adapt, understanding the significance of a drift, and determining the optimal way to integrate myriad local adaptations into a coherent global model are all pressing concerns.

Furthermore, the window for recognizing and adapting to model drift is often narrow in the real-time and dynamic IoMT environment powered by 5G and 6G. Ensuring that FL systems remain agile and responsive while maintaining data privacy and system integrity is daunting.

5.1.5 | Global vs. Local Models

FL is a beacon of decentralized learning and data privacy in the sophisticated landscape of the 5G/6G-based IoMT. But as this system unfolds, it grapples with the dichotomy of global versus local models, a challenge that has significant implications for the efficacy and relevance of the learning process.

However, the IoMT environment complicates this harmonious vision. The nature of medical data is inherently diverse and often deeply personal. A wearable device monitoring a patient with a cardiac condition in a temperate climate will generate data that are vastly different from a similar device worn by an athlete training in high-altitude conditions. In such scenarios, the relevance and applicability of a global model become questionable. While the global model provides a broad overview, it might miss out on the intricate, individual patterns a local model could capture. Conversely, relying solely on local models might lead to a fragmented learning ecosystem, where devices operate in silos, potentially missing out on broader insights or patterns that only emerge when larger datasets are considered.

5.1.6 | Evaluation and Validation

Within the vast expanse of IoMT, devices from hospital-grade diagnostic tools to personal health monitors continuously gather data. When FL is applied, these devices learn locally from their data subsets and periodically share model updates. The central premise is to collaboratively enhance a global model without compromising data privacy. However, assessing the accuracy, reliability, and generalizability of this globally aggregated model poses unique challenges.

Additionally, the dynamic and evolving nature of medical data within the IoMT amplifies the challenge. As patients' health conditions change, as devices get calibrated, or as new medical protocols emerge, the underlying data distributions can shift. Ensuring that the FL system continually validates and adjusts its models in the face of such dynamic changes is paramount.

5.2 | Open Issues With Respect to Telecommunication

Integrating FL with a 5G/6G-based IoMT in the context of telecommunication presents several open issues and challenges. Figure 4 shows the Open Issues related to FL for 5G/6G-based IoMT with respect to ML.

5.2.1 | Resource Allocation

The intertwining of FL within the vast infrastructure of the 5G/6G-based IoMT heralds a new era of decentralized computation and enhanced data privacy. However, as this integration deepens, the intricacies surrounding resource allocation emerge as a pivotal concern, particularly given the critical nature of medical applications and the complexities of 5G and 6G networks.

In essence, as the promise of FL in the 5G/6G-based IoMT materializes, resource allocation is a complex, multifaceted challenge. Addressing it demands a symphony of advanced network management techniques, intelligent scheduling, and an in-depth understanding of the medical domain and the intricacies of 5G and 6G telecommunications. The overarching aim is to ensure that, in the quest to harness the benefits of decentralized learning, the foundational medical services of the IoMT remain efficient, timely, and robust.

5.2.2 | Quality of Service

Quality of Service (QoS) represents the performance level and reliability of network services, ensuring that data transmission occurs seamlessly, with minimal delays and disruptions. In the context of IoMT, QoS isn't just a technical metric; it is intrinsically tied to patient outcomes, healthcare processes, and medical

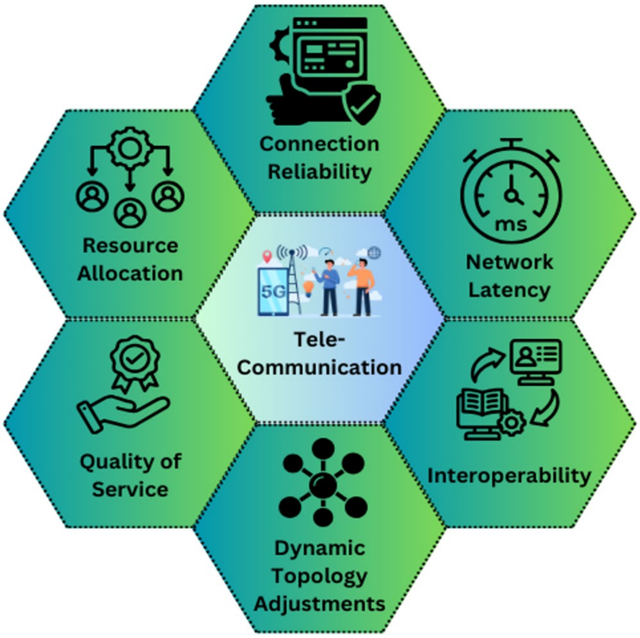

FIGURE 4 | Open issues related to federated learning for 5G/6G based Internet of Medical Things (IoMT) with respect to Telecommunications.

device reliability. A delay in transmitting a critical patient metric or an interruption in data flow from a medical device could have tangible, potentially life-altering implications.

The diverse nature of IoMT devices magnifies the challenge. From high-resolution imaging devices generating vast amounts of data to simple wearables capturing periodic health metrics, the range is vast. Ensuring consistent QoS across this spectrum, especially when these devices concurrently engage in FL tasks, becomes intricate. How does one prioritize network resources? Should a real-time heart monitor precede a device sending a FL model update? These are complex decisions with both technical and ethical dimensions.

5.2.3 | Dynamic Topology Adjustments

In the vast ecosystem of IoMT, devices are ceaselessly on the move, physically and in terms of network connectivity. From wearable health monitors that patients carry as they traverse different network zones to temporary medical sensors that are added or removed based on patient needs, the topology of the IoMT is in a constant state of flux. This dynamic nature isn't merely about the addition or removal of devices; it encompasses variations in device availability, connectivity quality, and even shifts in data generation rates.

The 5G and 6G frameworks, with their enhanced connectivity and reduced latencies, offer the bandwidth to handle this dynamic topology, but they also introduce their own challenges. The adaptive nature of 5G and 6G networks, with features like network slicing and dynamic resource allocation, can sometimes conflict with the needs of FL processes, especially during topology changes. Ensuring that devices, old and new, receive consistent network resources and maintain synchronized states with the ongoing FL process is paramount.

5.2.4 | Interoperability

Interoperability, in essence, refers to the seamless interaction and cooperation between diverse systems, devices, and applications. Within the IoMT, this takes on heightened importance due to the eclectic mix of devices involved—ranging from advanced hospital machinery to consumer-grade health wearables, each potentially designed by different manufacturers, operating on varied software platforms, and adhering to unique standards. This heterogeneity is further compounded by the different data formats, communication protocols, and network interfaces each device might employ.

However, achieving this seamless communication is fraught with challenges. Diverse devices might represent data differently, utilize varying model architectures, or even employ distinct optimization techniques. Ensuring that these disparate entities can effectively collaborate in a FL context requires standardization efforts, translation mechanisms, and adaptive algorithms capable of handling these differences.

5.2.5 | Network Latency

5G and 6G, often lauded for their promise of ultra-reliable low-latency communication (URLLC), are envisioned as a panacea for real-time applications and services. Within the IoMT, this promise translates to real-time patient monitoring, instant diagnostics, and even remote surgeries, where even a minor lag can have consequential outcomes. Yet, when FL integrates with this framework, the potential for latency and its implications grow in complexity.

Network demand is varied and often unpredictable in the diverse environment of IoMT, where devices range from sophisticated hospital machinery to personal wearables. A high-resolution medical scanner transmitting large volumes of data can momentarily clog the network, introducing latency that affects FL processes on other devices. Since many medical scenarios are time-sensitive, such delays could impact the timeliness and accuracy of insights derived from federated models.

5.2.6 | Connection Reliability

The 5G/6G-based IoMT represents a leap in the evolution of digital healthcare, promising unparalleled data rates, connectivity, and real-time processing. But as FL emerges as a cornerstone in this ecosystem, a pivotal concern becomes evident: connection reliability. Given the criticality of medical applications and the decentralized structure of FL, ensuring consistent and reliable connections is both a challenge and a necessity.

Addressing the connection reliability issue in the 5G/6G-based IoMT with FL requires a multi-pronged approach. Some technical solutions include advanced error-correction algorithms,

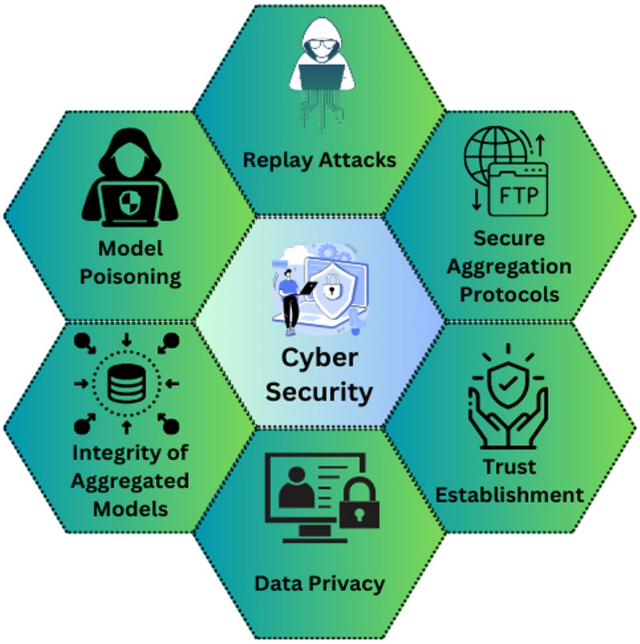

FIGURE 5 | Open issues related to federated learning for 5G/6G based Internet of Medical Things (IoMT) with respect to Cyber Security.

fallback protocols for data retransmission, and buffer mechanisms to handle temporary disconnections. On the operational front, leveraging 5G's network slicing capability, which allows for creating dedicated virtual networks, can ensure that critical IoMT devices and FL tasks receive priority connectivity, bolstering their reliability.

5.3 | Open Issues With Respect to Cyber Security

Integrating FL with a 5G/6G-based IoMT in the context of cyber security presents several open issues and challenges. Figure 5 shows the Open Issues related to FL for 5G/6G-based IoMT with respect to Cyber Security.

5.3.1 | Model Poisoning

Model poisoning, at its core, refers to a deliberate and malicious manipulation of the learning process. In a federated environment, numerous IoMT devices hospital equipment, wearable health monitors, or other medical sensors process their local data and subsequently share model updates with a central server or among peers. These updates are aggregated to refine a global model, which is then disseminated back to the devices for further iterations. This decentralized approach, while preserving data privacy, is susceptible to being exploited by adversaries. A rogue device, or one that's been compromised, can introduce skewed or malicious updates. When such tainted updates are integrated into the global model, the entire learning process can be derailed, leading to a model that might produce incorrect, biased, or even harmful predictions.

Addressing model poisoning in the 5G/6G-based IoMT with FL demands a multi-faceted strategy. Robust validation mechanisms to vet model updates, anomaly detection techniques to flag deviations, and secure authentication protocols to verify the legitimacy of devices are essential components. Additionally, leveraging cryptographic techniques to ensure the confidentiality and integrity of updates, as well as employing consensus algorithms to cross-verify updates with multiple devices, can further fortify the system.

5.3.2 | Integrity of Aggregated Models

At the heart of FL lies the principle of decentralized model training. IoMT devices, from hospital-based equipment to personal health monitors, train local models on their data. Periodically, they share model updates rather than raw data with a central server or among peer nodes. These updates are aggregated, forming the foundation of an updated global model that is then disseminated back to the devices. This iterative process, though privacy-preserving, introduces potential vulnerabilities during the aggregation phase. Ensuring the integrity of this aggregated model, that is, confirming that it accurately and faithfully represents the collective learning of all devices, becomes paramount.

Addressing the issue of aggregated model integrity necessitates a combination of strategies. Implementing rigorous validation mechanisms to assess the quality and authenticity of model updates is crucial. Advanced cryptographic techniques can be employed to ensure that updates are genuine and haven't been tampered with during transmission. Furthermore, consensus algorithms might be adopted to ensure that most devices concur on the updates, offering a layer of verification.

5.3.3 | Data Privacy

FL, at its essence, is rooted in the promise of data privacy. Rather than centralizing data for training ML models—a process fraught with privacy concerns and potential breaches—FL enables IoMT devices to compute model updates locally. These devices, which could range from advanced medical imaging machinery to personal health wearables, share only these model updates, not the raw data, with a central server or among peers. At first glance, this paradigm offers an optimal solution to the data privacy conundrum.

With its advanced communication capabilities, the introduction of 5G and 6G technology further complicates the landscape. While 5G and 6G enhance the speed and reliability of data transmission, facilitating real-time FL, they also open up potential vulnerabilities. The vast web of interconnected devices in the IoMT, all communicating over 5G and 6G networks, increases the attack surface for adversaries aiming to intercept and analyze model updates or inject malicious updates.

A multifaceted approach is necessary to ensure data privacy in this dynamic setting. Advanced encryption techniques need to be employed to secure model updates during transmission, ensuring that even if intercepted, the data remains unintelligible. Differential privacy, a method that introduces controlled noise into the data or computations, can be incorporated to ensure that shared updates don't reveal specifics about individual data points. Moreover, robust authentication and authorization protocols are crucial to ensure that only legitimate devices participate in the FL process, mitigating the risk of malicious actors in the network.

5.3.4 | Trust Establishment

Trust establishment in the context of FL within IoMT concerns the ability to verify and have confidence in the legitimacy and reliability of participating devices, their computations, and the data they produce. In a federated environment, myriad IoMT devices—ranging from sophisticated medical equipment in hospitals to wearables and home-based health monitors—contribute to the learning process. Given this vast and diverse network, how does one ascertain that a device is genuine? How can one be confident that the model updates or data it provides haven't been tampered with or are not the result of faulty computations?

The intricacy of trust establishment is further amplified by the dynamic nature of 5G/6G networks and the IoMT ecosystem. Devices may join or leave the network frequently, and their operational states could change based on software updates, physical conditions, or even potential cyber-attacks. In such a fluid environment, maintaining a consistent trust framework becomes challenging.

5G and 6G, with their enhanced connectivity and features like network slicing, provide the infrastructure to support vast numbers of connected devices. However, it also necessitates robust mechanisms to authenticate these devices and validate their contributions. Simple password-based authentications or static certificates might not suffice in this context. Dynamic, multi-factor authentication methods, possibly leveraging biometrics or behavioral patterns, might be required to ensure the legitimacy of devices.

5.3.5 | Secure Aggregation Protocols

As the 5G/6G-based IoMT integrates with FL, it becomes a beacon of promise for next-generation healthcare, merging vast connectivity with decentralized and collaborative data processing. But amidst this transformative union, a sophisticated challenge takes shape: ensuring the secure aggregation of model updates. In the sensitive realm of medical data, where patient privacy and accurate model training intertwine, the adoption of secure aggregation protocols is not just a technical requirement but a paramount ethical obligation.

To address this, secure aggregation protocols must encompass multiple dimensions. First, robust encryption techniques must be used to ensure that model updates remain confidential during transmission. But beyond mere encryption, differential privacy measures can be integrated, adding controlled noise to updates to ensure that individual data points aren't discernible, even if updates are intercepted.

5.3.6 | Replay Attacks

Replay attacks, as the name suggests, involve an adversary capturing legitimate data or signals and retransmitting them later to deceive the system. This could manifest in various ways in the context of FL within the IoMT. An attacker might capture legitimate model updates from a device and then continuously retransmit these updates, causing the central server or other devices to believe that the same data is being repeatedly generated in real time. Such a scenario not only compromises the integrity of the aggregated model but can also delay or disrupt the FL process, as the system becomes inundated with redundant or outdated information.

Addressing replay attacks in the 5G/6G-based IoMT with FL necessitates a multi-layered strategy. Timestamping model updates and employing sequence numbers can ensure that data is chronologically ordered and any repeated or out-of-sequence data can be flagged. Implementing robust authentication and encryption protocols can ensure that captured data, even if replayed, remains undecipherable and is thus rendered useless. Additionally, adopting behavioral analytics, where the system learns and recognizes typical data patterns from devices, can help in identifying anomalies or repeated patterns indicative of replay attacks.

5.4 | Open Issues With Respect to Medical Informatics

Integrating FL with a 5G/6G-based IoMT in medical informatics presents several open issues and challenges. Figure 6 shows the open issues related to FL for 5G/6G-based IoMT with respect to Medical Informatics.

5.5 | Data Quality and Consistency

The convergence of the 5G/6G-based IoMT and FL holds the promise of reshaping healthcare, enabling a landscape where vast arrays of devices collaboratively process data in real time while preserving privacy. Yet, as we navigate this promising frontier, a foundational concern emerges: ensuring data quality and consistency. In healthcare, where decisions grounded in data can have life-altering implications, addressing this issue is not merely a technical endeavor but an ethical imperative.

Addressing data quality and consistency in the 5G/6G-based IoMT with FL necessitates a multi-pronged approach. Comprehensive data validation frameworks, which can automatically flag outliers or improbable data points, are essential. Standardization protocols, ensuring data across devices adheres to common formats, units, and terminologies, can enhance consistency. ML techniques, like anomaly detection, can be employed to identify and rectify inconsistencies in real time. Additionally, establishing feedback loops where inconsistencies or quality issues in the aggregated model are traced back to their source can help iteratively refine data capture and processing mechanisms.

5.5.1 | Semantic Interpretation

The IoMT ecosystem is vast and varied. Devices from different manufacturers, designed for distinct purposes and situated

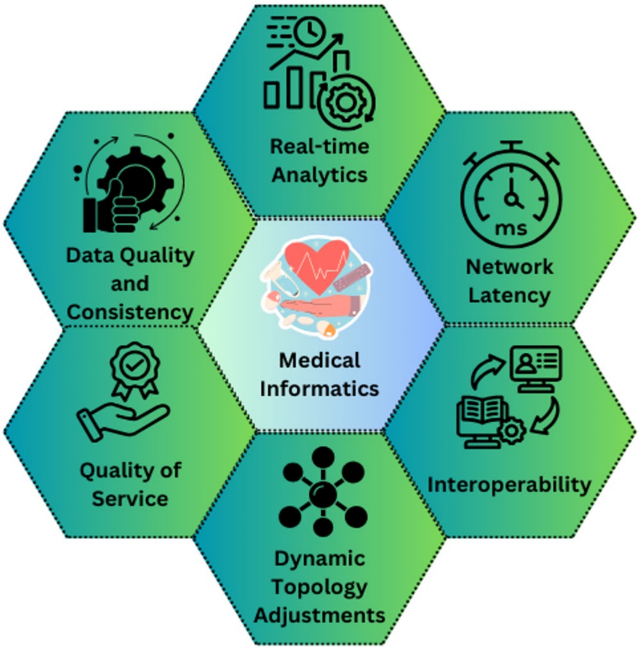

FIGURE 6 | Open issues related to federated learning for 5G/6G based Internet of Medical Things (IoMT) with respect to Medical Informatics.

in diverse environments, populate this network. Each device, while collecting and transmitting health-related data, might have its terminologies, encodings, and representations. For instance, one device might record blood oxygen levels as "O2 saturation," while another uses "SpO2." Such semantic discrepancies can pose significant challenges in a FL context, where insights from these myriad devices are aggregated to refine a global model. If not addressed, the learning process can become muddled, leading to models that are, at best, ineffective and, at worst, misleading.

5G and 6G promise enhanced connectivity and real-time data exchange while facilitating rapid FL cycles. However, they also add layers of complexity to the semantic challenge. Data's increased volume and speed demand advanced, real-time semantic interpretation mechanisms, ensuring that data from every device is immediately understood in its correct context.

Addressing semantic interpretation requires a holistic approach. Implementing standardized ontologies and vocabularies across the IoMT can provide a common ground for data interpretation. Advanced ML and natural language processing techniques can be employed to automatically detect and reconcile semantic discrepancies in real time. Feedback mechanisms, where potential semantic issues identified during model aggregation are flagged and communicated back to the respective devices or manufacturers, can ensure iterative improvements in data representation.

5.5.2 | Model Validity and Generalizability

Within the intricate fabric of the 5G/6G-based IoMT interwoven with FL, a central challenge emerges, rooted in the core principles of data science: ensuring model validity and generalizability. In the high-stakes realm of healthcare, where models inform clinical decisions with profound implications on patient outcomes, addressing this issue isn't just about achieving academic precision but upholding the ethos of medical practice.

To address these issues, a multi-faceted approach is crucial. Rigorous validation mechanisms using separate test datasets can ensure model validity. Techniques like bootstrapping or cross-validation, applied in a federated context, can offer insights into model robustness across diverse datasets. Regularly assessing the demographic and clinical distribution of data contributing to the FL process can help identify and rectify potential biases, ensuring generalizability. Feedback loops, where the performance of the global model on local data is continuously monitored and reported back, can provide real-time insights into areas of improvement.

5.5.3 | Clinical Integration

FL in the IoMT ecosystem emphasizes decentralized, collaborative learning across many devices, from sophisticated hospital equipment to personal health monitors. While this approach offers the allure of harnessing diverse, real-time data without compromising patient privacy, it also introduces complexities in integrating the derived insights into clinical decision-making processes. For instance, the predictive model from a FL system might flag potential health anomalies based on data from a patient's wearable device. However, if this alert doesn't integrate seamlessly with the hospital's Electronic Health Record (EHR) system or fails to reach the treating physician in a user-friendly, actionable format, its clinical value diminishes.

A multifaceted approach is vital to addressing clinical integration challenges. Interoperability standards, ensuring that FL outputs can seamlessly integrate with various EHR systems, are foundational. User-centric design, focusing on how clinicians interact with technology, can ensure that insights are presented in an intuitive, actionable manner. Continuous feedback loops, where clinicians provide input on the utility, relevance, and accuracy of FL insights, can foster iterative improvements, ensuring that the technology remains aligned with the dynamic nuances of patient care.

5.5.4 | Patient Privacy and Consent Management

The capabilities of 5G and 6G, with their promise of high-speed, real-time data exchange, further complicate this privacy matrix. While they facilitate rapid FL cycles, the sheer volume and granularity of processed data could increase the risk of potential privacy breaches. Moreover, with 5G and 6G enabling more devices to join the IoMT network, managing these devices' diversity and potential vulnerabilities becomes crucial to prevent inadvertent data leaks or exposure.

Addressing these concerns necessitates a comprehensive, multi-tiered strategy. Advanced cryptographic techniques, such as differential privacy and secure multi-party computation, can ensure that FL insights remain privacy-preserving. Transparent logging mechanisms, potentially leveraging technologies like blockchain, can provide immutable data usage records, aiding in consent verification. Dynamic consent management systems, where patients can continuously update their preferences in real time and where these preferences are instantly propagated across the FL network, can ensure that consent is always current and honored.

5.5.5 | Real Time Analytics

The fundamental premise of the IoMT, supercharged by 5G's capabilities, is the continuous, high-speed transmission of medical data from a plethora of devices, ranging from high-resolution imaging machinery in hospitals to wearables monitoring vital statistics. This wealth of data, flowing in real-time, provides an unprecedented opportunity for immediate analysis and action. However, the challenge becomes multifaceted when FL enters the equation with its principle of decentralized data processing. How can insights be derived collaboratively from multiple devices, each processing its own data subset and then aggregated and acted upon—all in real-time?

Addressing the real-time analytics challenge in this context requires innovative solutions. Edge computing can play a pivotal role, allowing data processing to occur closer to the source, thereby reducing the need for extensive data transmission and expediting analysis. Advanced algorithms tailored for federated environments can optimize model training and aggregation based on device capabilities and data criticality, and enhance real-time responsiveness. Furthermore, prioritization mechanisms, which identify and process clinically urgent data first, can ensure that real-time analytics align with medical imperatives.

5.5.6 | Regulatory and Ethical Challenges

From a regulatory standpoint, the IoMT, bolstered by 5G and 6G capabilities, amplifies the complexity of ensuring patient data security and privacy. FL, though designed to keep raw data localized, introduces new dimensions to the data protection narrative. While patient data might not be centrally stored or directly shared, the model updates and aggregated insights must be scrutinized to ensure they don't inadvertently leak sensitive information. Regulatory bodies, which have traditionally focused on direct data handling and storage practices, are now faced with overseeing this nuanced, indirect data exchange.

Addressing these regulatory and ethical challenges demands a multidisciplinary, collaborative approach. Engaging ethicists, regulators, technologists, and clinicians in continuous dialogue can pave the way for robust frameworks safeguarding patient interests while fostering innovation. Transparent and educative initiatives to demystify the workings of FL in the IoMT for patients can empower individuals to make informed decisions about their data. Continuous monitoring and feedback loops, ensuring that regulatory and ethical considerations are embedded in the iterative evolution of technologies, can further enhance trust and compliance.

5.6 | Future Research Directions

The amalgamation of 5G/6G and FL in smart healthcare paints a picture of vast potential intertwined with complex challenges. Based on the aforementioned open issues, the following avenues emerge as promising directions for future research: Figure 7 shows the Future Research Directions in the FL for 5G/6G based IoMT. Table 6 summarizes the key future research directions in FL for 5G/6G-enabled IoMT, highlighting their application areas, associated challenges, and potential solutions.

5.6.1 | Advanced Privacy-Preserving Techniques

Integrating 5G and 6G technology with FL in smart healthcare is revolutionary, offering unprecedented possibilities in medical service delivery. However, the sensitive nature of healthcare data mandates rigorous privacy safeguards. Consequently, advanced privacy techniques have emerged as a vital research frontier. Homomorphic Encryption, which enables computations on encrypted data without decryption, offers a route to secure real-time medical data processing within 5G and 6G networks. Meanwhile, Differential Privacy, by introducing controlled noise to data, can preserve data anonymity in FL, though the challenge lies in balancing obfuscation with model accuracy. Secure Multi-Party Computation (SMPC) presents a potential methodology for collaborative yet private model training, though enhancing its efficiency for expansive 5G/6G networks remains an area of focus. Additionally, Decentralized Identity Verification could redefine healthcare data privacy by placing patients at the helm of their data access.

5.6.2 | Optimized Resource Allocation Algorithms

The proliferation of 5G/6G-based smart healthcare systems integrated with FL poses unique challenges, especially in efficiently managing computational and network resources. Optimized resource allocation has emerged as an essential avenue for future research to address these challenges. Given the sheer volume of devices, sensors, and medical equipment in the IoMT ecosystem, there is a pressing need to develop algorithms that can dynamically allocate bandwidth, computational power, and storage in real time, ensuring that critical medical applications receive priority. Additionally, as FL involves distributed training across numerous devices, efficient allocation ensures that devices with limited resources can participate without being overwhelmed or becoming bottlenecks. Traditional resource allocation approaches might falter in such intricate environments, necessitating the exploration of ML and AI-driven techniques. Leveraging deep reinforcement learning or neural networks can aid in predicting resource demands and making adaptive allocation decisions. As the healthcare landscape becomes increasingly connected and decentralized, advanced algorithms that can optimize resource distribution, reduce latency, and ensure seamless operations will be crucial to the success and reliability of 5G/6G-integrated federated healthcare systems.

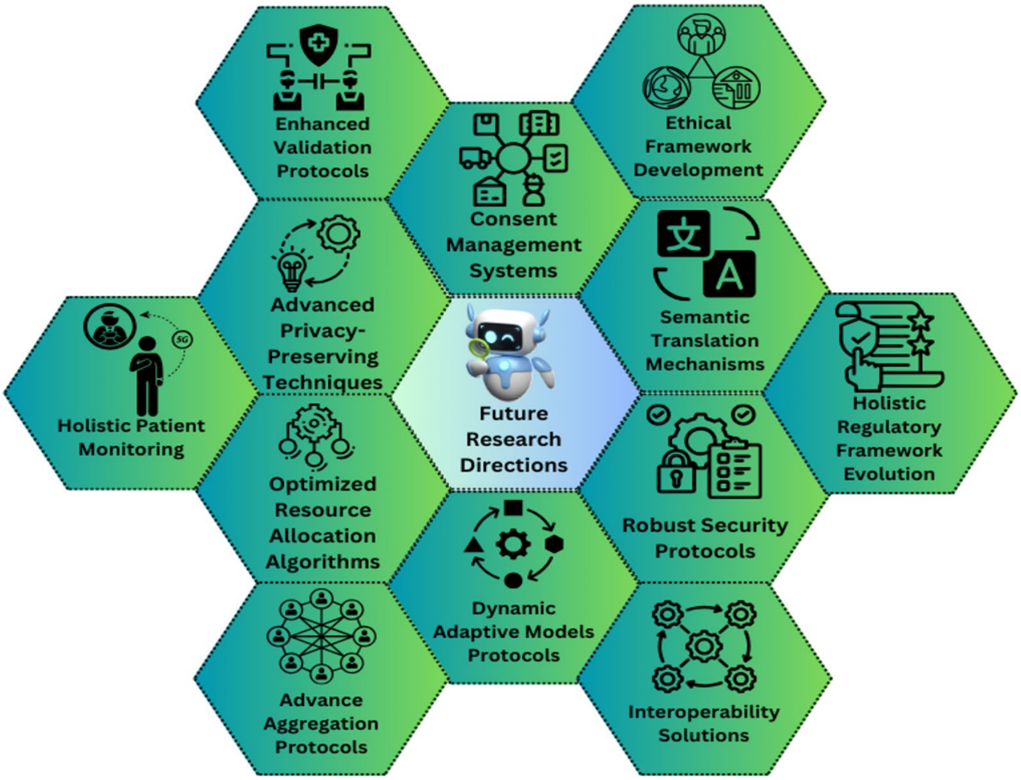

FIGURE 7 | Future research directions in the federated learning for 5G/6G based Internet of Medical Things (IoMT).

5.6.3 | Advance Aggregation Protocols

In the intricate ecosystem of 5G/6G-based smart healthcare integrated with FL, one of the pivotal components dictating efficiency and reliability is the aggregation protocol. As FL decentralizes model training across numerous devices, it becomes imperative to have robust and efficient protocols to aggregate locally trained models into a comprehensive global model. This ensures that insights derived from diverse data sources are harmoniously integrated, enhancing the overall accuracy and reliability of the model. The need for improved aggregation protocols is a crucial research direction for several reasons. Firstly, heterogeneity in data distribution and device capabilities can lead to skewed or biased model updates. Advanced protocols can weigh these updates differently, ensuring the aggregated model remains unbiased and representative. Secondly, the inherent latency and bandwidth limitations of the 5G and 6G networks, coupled with the voluminous nature of medical data, call for protocols optimized for swift and minimal data transfers. Techniques such as model sparsification or quantization can reduce the data payload during aggregation while preserving model fidelity.

5.6.4 | Dynamic Adaptive Models Protocols

The ever-evolving realm of 5G/6G-based smart healthcare, when combined with FL, underscores the significance of employing dynamic adaptive models. As the healthcare environment experiences continuous changes in terms of patient demographics, disease patterns, technology integration, and treatment methods, models that can adapt in real time are no longer a luxury but a necessity. Integrating dynamic adaptive model protocols is an essential research direction in this context. Such protocols address several challenges endemic to the healthcare sector. Given the diverse nature of data from various devices in the IoMT ecosystem, static models can quickly become obsolete or unrepresentative. Dynamic adaptive models, on the other hand, are designed to evolve, learning from new data streams without entirely forgetting previous learnings. This ensures the models remain relevant and accurate, catering to long-standing and emerging healthcare trends.

5.6.5 | Interoperability Solutions

As the convergence of 5G/6G and FL promises to revolutionize smart healthcare, interoperability emerges as a pivotal area warranting rigorous research and development. The essence of modern healthcare lies in its interconnectedness—with a plethora of devices, platforms, systems, and applications working in tandem. The potential of 5G/6G-based smart healthcare can only be unlocked when these disparate systems can seamlessly communicate, exchange, and interpret data across a unified framework. Interoperability solutions, therefore, are fundamental to ensuring that health data, irrespective of its source, can be effectively integrated and utilized. With FL in the mix, the challenge amplifies. Unlike traditional centralized models, FL operates across multiple nodes, each with its potentially unique data structure and format. Solutions that can harmonize this diverse data are needed, enabling coherent, cross-device, cross-platform learning and insights.

TABLE 6 | Summary of future research directions in federated learning for 5G/6G-based IoMT: Applications, challenges, and possible solutions.

Future research direction	Application areas	Challenges	Possible solutions
Advanced privacy-preserving techniques	• Sensitive medical data sharing across hospitals • Remote patient monitoring (RPM) • Genomic data analysis • AI-based diagnostics	• Maintaining privacy while enabling model training • High computational cost of encryption methods • Balancing privacy with accuracy	• Homomorphic encryption • Differential privacy • Secure Multi-Party Computation (SMPC) • Lightweight cryptographic algorithms
Optimized resource allocation algorithms	• Edge computing for medical devices • Distributed hospital systems • Real-time IoMT analytics	• Limited device resources (battery, CPU, RAM) • Network congestion in 5G/6G systems • Uneven device participation in FL	• AI-driven resource prediction • Deep reinforcement learning for dynamic allocation • Priority scheduling for critical devices (ICU, emergency)
Advanced aggregation protocols	• Federated learning with heterogeneous devices • Medical imaging FL (CT, MRI) • Multihospital collaborative training	• Non-IID medical data problems • Unbalanced dataset contributions • High communication cost	• Weighted aggregation based on data quality • Model sparsification/quantization • Compression of model updates
Dynamic adaptive model protocols	• Models for chronic disease progression • Personalized treatment recommendations • Elderly health monitoring	• Continuous updates causing model drift • Rapid changes in patient data patterns • High computational overhead	• Lifelong learning models • Online learning with drift detection • Hybrid global–local adaptation frameworks
Interoperability solutions	• Integration of different IoMT devices • Cross-platform EHR sharing • Multi-vendor medical equipment	• Inconsistent data formats • Incompatible communication protocols • Device manufacturer differences	• Standardized medical ontologies (FHIR, HL7) • API-based interoperability frameworks • Automatic data harmonization layers
Robust security protocols	• Secure hospital communication networks • IoMT device authentication • FL model transmission	• Attacks (poisoning, backdoor, replay attacks) • Many vulnerable devices on the network • Network delays affecting security checks	• Blockchain-based verification • Multi-factor authentication for IoMT devices • Real-time anomaly detection in model updates
Semantic translation mechanisms	• Multi-language hospital systems • AI-based EHR data extraction • Cross-country medical collaborations	• Different terminologies between systems • Misinterpretation of medical parameters • Lack of unified standards	• Semantic mapping engines • NLP-driven terminology translation • Global medical vocabulary databases
Consent management systems	• Managing patient consent for AI training • Multi-institution research projects • Wearable/implantable medical devices	• Different legal requirements (GDPR, HIPAA) • Changing patient preferences • Synchronizing consent across distributed systems	• Blockchain for immutable consent logs • Real-time dynamic consent dashboards • Smart contracts for consent enforcement

(Continues)

TABLE 6 | (Continued)

Future research direction	Application areas	Challenges	Possible solutions
Enhanced validation protocols	• Clinical model deployment • Multi-center diagnostic models • Image analysis across hospitals	• Ensuring global model accuracy • Diverse and unbalanced datasets • Validation complexity across IoMT nodes	• Federated cross-validation • Bootstrapping techniques • Aggregated evaluation metrics
Ethical framework development	• AI in diagnosis and treatment • Predictive healthcare analytics • High-risk medical decision support systems	• Lack of transparency in AI decisions • Bias in model outputs • Patient distrust in automated systems	• Explainable AI (XAI) methods • Ethical review protocols • Transparent model reporting standards
Holistic patient monitoring	• Continuous health tracking • Mental–physical health integration • Smart home healthcare	• Combining diverse sensor data • Ensuring continuous real-time analytics • Battery and power constraints	• Multi-modal sensor fusion • Prioritization of critical signals • Energy-efficient monitoring algorithms

5.6.6 | Robust Security Protocols

Healthcare data is among the most sensitive and private information about an individual. Any breach or misuse can lead to dire consequences regarding individual privacy and broader societal trust in digital healthcare solutions. Therefore, as FL decentralizes the data processing model, it becomes crucial to ensure that each node or device in this vast network adheres to the highest security standards. This involves securing local computations, the integrity of model updates, and the aggregation process. Additionally, with 5G and 6G technology promising high-speed, low-latency communication, ensuring real-time security checks without compromising on the promised speed is an inherent challenge. This necessitates research into lightweight yet robust security algorithms that can operate efficiently within the bandwidth and latency constraints of 5G and 6G networks.

5.6.7 | Semantic Translation Mechanisms

In the evolving landscape of 5G/6G-based smart healthcare integrated with FL, the significance of semantic translation mechanisms cannot be overstated. As healthcare systems worldwide become more interconnected and reliant on diverse sources of data, the challenge of ensuring seamless communication and interpretation of information across these systems becomes central to their efficacy. Semantic translation mechanisms aim to bridge this gap by providing tools and protocols that can automatically, or with minimal human intervention, translate data and model representations across systems. This is especially crucial for FL in healthcare, where the accuracy and consistency of information can directly impact patient outcomes. For instance, a heart rate monitored by one device and termed differently in another system should be cohesively integrated into a federated model without losing meaning or context.

5.6.8 | Consent Management Systems

As healthcare becomes increasingly digitized and data-centric, the protection of patient rights, particularly in terms of data privacy and autonomy, becomes paramount. FL, with its distributed nature, promises improved privacy by allowing data to remain localized. However, it also introduces complexities in managing patient consent across multiple data sources and jurisdictions. Consent management systems serve as intermediaries, ensuring that every piece of patient data used in a FL process adheres to the permissions granted by the patient. As the landscape of healthcare data evolves, including electronic health records, wearable device data, genomic information, and more, these systems must handle multifaceted consent parameters. For instance, patients might consent to share their wearable device data but not their genomic data. Managing these nuances in a distributed learning environment poses technical and ethical challenges.

5.6.9 | Enhanced Validation Protocols

Integrating 5G/6G technologies and FL in smart healthcare has ushered in a new paradigm of distributed ML over diverse datasets. However, the robustness and validity of the models produced within this framework become imperative, especially given the critical nature of healthcare decisions. Thus, enhanced validation protocols emerge as a crucial research direction for 5G/6G-based smart healthcare. In traditional centralized ML, validation protocols are designed to ascertain the effectiveness and reliability of models using reserved data sets, ensuring that the model can generalize well to unseen data. Within FL, this becomes inherently complex due to the decentralized nature of data sources. Models must be validated across diverse, fragmented, and potentially unbalanced datasets sourced from various devices or institutions. The challenge here is twofold: ensuring that individual model contributions are accurate and that the aggregated global model performs consistently across all participating nodes.

5.6.10 | Ethical Framework Development

As the convergence of 5G/6G technology with FL propels the domain of smart healthcare into uncharted territories, the ethical implications of these innovations become increasingly profound. Consequently, establishing comprehensive ethical frameworks is a pivotal research direction for 5G/6G-based innovative healthcare with FL. Future research should emphasize the creation of ethical frameworks that prioritize transparency and consent. Given that healthcare data is among the most intimate and personal, there must be precise mechanisms for patients to understand how their data is used, even if it remains on their devices. Moreover, the federated models' decisions, particularly in critical areas like diagnosis or treatment recommendations, must be explainable, ensuring that healthcare professionals can understand and trust AI-driven suggestions.

5.6.11 | Holistic Patient Monitoring

Holistic Patient Monitoring goes beyond conventional health metrics, striving to provide a comprehensive view of a patient's well-being, considering physical, psychological, environmental, and social factors. This perspective recognizes health as an interplay of various elements and aims to capture the nuances influencing a person's condition. With 5G's high-speed, reliable, and low-latency communication, real-time data from many sensors, wearables, and medical devices can be seamlessly collected, ensuring timely insights and interventions. Future research in HPM can explore creating more sophisticated models that understand the intricate relationships between diverse health metrics. For instance, correlating sleep patterns with dietary habits, mental health status, and daily activities could provide more profound insights into individual health dynamics. This could lead to predictive healthcare, where potential health issues are identified even before they manifest prominently.

5.7 | Holistic Regulatory Framework Evolution

Integrating 5G and 6G into healthcare promises high-speed data transmission, real-time remote monitoring, and advanced telemedicine applications. On the other hand, FL introduces decentralized ML models that enable data analysis without centralizing sensitive patient data, thus maintaining privacy. While separate regulations govern each of these advancements, their convergence presents unique challenges that demand an integrated regulatory perspective. Future research in this arena should focus on understanding the combined implications of these technologies. For instance, while FL may secure patient data at source, the high-speed transmission capabilities of 5G and 6G networks could introduce vulnerabilities during data transit. How do we ensure end-to-end security and privacy in such an ecosystem? A holistic regulatory framework would need to address these issues.

6 | Conclusion

This review paper examined the integration of FLFL with 5G/6G-enabled IoMT, highlighting its potential to enhance healthcare systems by enabling decentralized, privacy-preserving model training across diverse medical devices. The combination of FL with 5G/6G technologies offers real-time data processing, ultra-low latency, and improved connectivity, which are crucial for applications such as remote patient monitoring and real-time diagnostics. However, several challenges remain in the integration process, including data heterogeneity, ensuring the quality and consistency of local updates, and addressing the computational limitations of IoMT devices. The aggregation of decentralized model updates, along with maintaining data privacy and security in a highly connected environment, presents critical hurdles. Moreover, the need for dynamic, adaptive models to accommodate rapidly evolving medical data and patient needs underscores the complexity of this integration. Future research should focus on developing robust aggregation protocols, improving resource allocation algorithms for device heterogeneity, and advancing privacy-preserving techniques, such as homomorphic encryption and differential privacy. Addressing these challenges will be essential for realizing the full potential of FL and 5G/6G IoMT in transforming healthcare delivery into a more secure, efficient, and personalized system.

Author Contributions

All authors contributed equally to the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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