The Amalgamation of Federated Learning and Explainable Artificial Intelligence for the Internet of Medical Things: A Review

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***Abstract*—The Internet of Medical Things (IoMT) has emerged as a paradigm shift in healthcare, integrating the Internet of Things (IoT) with medical devices, sensors, and healthcare systems. From peripheral devices that monitor vital signs to remote patient monitoring systems and smart hospitals, IoMT provides a vast array of applications that empower healthcare professionals. However, the integration of IoMT presents numerous obstacles, such as data security, privacy concerns, interoperability, scalability, and ethical considerations. For the successful integration and deployment of IoMT, addressing these obstacles is essential. Federated Learning (FL) permits collaborative model training while maintaining data privacy in distributed environments, like IoMT. By incorporating Explainable Artificial Intelligence (XAI) techniques, the resulting models become more interpretable and transparent, enabling healthcare professionals to comprehend the underlying decision-making processes. This integration not only improves the credibility of Artificial Intelligence models but also facilitates the detection of biases, errors, and peculiar patterns in the data. The combination of FL and XAI contributes to the development of more privacy-preserving, trustworthy, and explainable AI systems, which are essential for the development of dependable and ethically sound IoMT applications. Hence, the aim of this paper is to conduct a literature review on the amalgamation of FL and XAI for IoMT.**

***Index Terms*—Wearable sensor devices, Federated Learning, Explainable AI, Trustworthiness, Data Privacy concerns**

I. Introduction

The Internet of Medical Things (IoMT) represents the integration of medical devices, sensors, software, and healthcare systems through network connectivity [1]. IoMT enables the collection, exchange, and analysis of healthcare data, revolutionising the healthcare industry [2], [3]. They empower healthcare providers with valuable insights for accurate diagnosis, personalised treatment planning, and proactive preventive patient care by leveraging real-time health data from devices like wearables, remote patient monitoring systems, and implantable sensors [4]. It facilitates remote patient monitoring, telemedicine, and personalised healthcare services, encouraging individuals to actively participate in managing their well-being [5]–[7].

IoMT analyses the diverse array of interconnected medical devices and sensors by collecting, transmitting, and evaluating the data [8]. These interconnected components work together seamlessly to revolutionise the way healthcare information is gathered, communicated, and processed [9], [10]. This enables healthcare providers to access real-time data, monitor patients remotely, and make informed decisions for improved patient care and outcomes. However, when using such highly sensitive patient data, it brings new challenges such as data privacy and security [11], [12].

To address such challenges, Federated Learning (FL) emerges as a potent solution to unleash the advancements of IoMT [13]. FL creates a collaborative training model without the need for centralised data transfer. By keeping data securely stored on local devices and performing model updates on the edge, FL ensures patient privacy, enhances data security, and preserves data ownership. FL, a decentralised learning approach, offers significant benefits to IoMT by transferring data to a central server [14], [15]. Hence, such models are trained directly on distributed devices while keeping the sensitive patient's data securely stored on those devices [16], [17]. This privacy-preserving characteristic of FL not only prioritises patient privacy but also ensures compliance with regulatory requirements governing healthcare data [18], [19].

Although FL has several benefits in IoMT, its implementation poses several significant challenges that must be tackled effectively [20], [21]. These challenges include the heterogeneity of devices and data, limited resources on edge devices, data imbalance and distribution, privacy and security concerns, network connectivity and latency issues, regulatory and ethical considerations, and federated model aggregation [22], [23]. Overcoming these challenges requires addressing compatibility issues, optimising resource-constrained devices, managing imbalanced data distribution, ensuring robust security measures, handling intermittent network connectivity, complying with regulations and ethical guidelines, and developing efficient aggregation techniques [24].

On the contrary, the informed decisions generated by the IoMT applications lack trustworthiness and interpretability. This can be resolved by utilising Explainable Artificial Intelligence (XAI) techniques. XAI refers to the advancement of AI models that are capable of delivering transparent and interpretable explanations for their decision-making processes. This is simply because it enables stakeholders to comprehend how and why these models arrive at their conclusions. XAI provides insights into the diverse IoMT data by generating human-interpretable explanations for the IoMT device's decisions, building trust among patients and healthcare practitioners. It also identifies which data points are influential in the model's predictions to highlight any potential data quality issues that help enhance the model's interpretability.

The IoMT device often handles sensitive patients' data, drawing high demand for advanced technologies like FL and XAI. There are a few surveys conducted on IoMT applications related to FL and XAI. The following are recent surveys of IoMT published in reputed journals. Prasad et al. [25] presented a detailed overview of the IoMT, which involves the integration of medical devices, wearable sensors, and healthcare systems to enable remote patient monitoring and personalised healthcare. They discussed various FL architectures and algorithms specifically designed for healthcare applications, along with their advantages and limitations, by studying some potential use cases. The authors concluded by highlighting future research directions.

Zikria et al. [26] present a comprehensive survey by detailing the importance of security and privacy in IoMT, its opportunities, challenges, and potential solutions. They discussed these opportunities by highlighting their potential applications in various domains such as smart cities, healthcare, entertainment, and surveillance. Thus, they summarised the paper with key challenges and the future scope of IoMT.

Razdan et al. [27] provide a detailed study of the convergence of healthcare and IoT technologies. They discussed the basic concepts of IoMT and enabling technologies in the field of IoMT by presenting several case studies. These cases include a range of healthcare domains, including remote patient monitoring, chronic disease management, telemedicine, and smart hospitals. Finally, they concluded by explaining the key challenges and future research.

Hence, the main aim of this paper is to foster the integration of FL and XAI technologies in the IoMT. This integration helps in enabling real-time monitoring, continuous learning, and adaptability for more efficient and patient-centric healthcare systems. The rest of the paper is structured as follows. Section 2 presents the literature review of the existing research works and explains the motivation of FL with XAI in IoMT that improves the efficiency of process analysis in tremendous healthcare scenarios. Section 3 discusses the key technical aspects related to the fusion of FL and XAI like data acquisition, data storage, data sharing, data interoperability, and privacy with practical challenges in IoMT context. Section 4 outlines the major applications of IoMT such as clinical decision support systems, disease diagnosis and prediction, personalised treatment recommendations, real-time monitoring and alerts, and drug discovery and development. Finally, we concluded by highlighting the benefits, extreme challenges, and future directions.

II. Background

The emergence of FL contributes to the resolution of numerous issues in the healthcare industry relating to resources, communication, and the preservation of patient privacy [28], [29]. As interfaces between AI systems and humans, XAI offers interoperability, explainability, and transparency. This section explores the role of FL and XAI techniques in IoMT. This section also discusses the motivation for integrating FL and XAI for IoMT.

FL improves the model by incorporating shared models from multiple sources while safeguarding the local data. XAI enables doctors to understand AI-generated diagnoses and recommendations. FL trains collaboratively using dispersed time series data which include health status data, electrocardiograms (ECGs), and continuous glucose monitoring (CGM) without centralising sensitive data. XAI can help identifying time-series prognostic factors and trends. XAI models can identify health trends or ECG abnormalities that indicate patient severity. Textual healthcare data includes electronic health records, medical records, and patient feedback. FL enables health care institutions to train Natural language processing (NLP) models in collaboration without sharing raw text data. XAI can highlight phrases and words in a document that contributed to a specific conclusion or classification. This facilitates better text analysis and decisions. Genomic information is safeguarded by privacy provided by FL. This permits scientists to train genomic analysis strategies without compromising the confidentiality of genetic data. Scientists

TABLE I
COMPARISON OF OUR SURVEY WITH EXISTING SURVEYS

Ref Paper	Highlights	Limitations
[25]	Outline FL architectures for IoMT, potential use cases benefits and limitations	Benefits of XAI in IoMT were not explored and integration challenges of FL in IoMT were missing
[26]	Presents the opportunities, challenges, and potential solutions in IoMT	The need for FL and XAI was not studied
[27]	Reviews enabling technologies and case studies of IoMT	Integration challenges for these enabling technologies are under-explored
Our Survey	Presents the key benefits of integrating FL and XAI in IoMT with technical aspects, important applications, practical challenges and future opportunities	

can comprehend disease inheritance patterns or modifications with the assistance of XAI. This assists in determining diagnostic and treatment goals. FL environments can use sensor data from real-time patient monitoring (RPM) or connected devices. This facilitates patient-privacy-protected sensor data analysis [30].

Technologies like FL and XAI offer enormous possibilities for influencing many aspects of the healthcare industry, which include personalised treatment, remote health monitoring, and drug identification. Data privacy, system transparency, and safety are significant issues in the medical industry that FL and XAI address. Using these technologies, we can improve medical research, screening, and treatment while safeguarding patient privacy and promoting confidence in AI [31], [32].

A. Federated Learning

Recent advances in AI and the IoMT have increased the potential of medical technology. However, the large volumes of data used by AI models must be easily accessible to the centralised organisation that is responsible for constructing the model. FL approaches can be implemented in a decentralized fashion to analyze the produced data locally at the edge devices, protecting the confidentiality of the IoT device's data without having to upload and store the raw data on a central server. When it comes to sensitive industries like healthcare, keeping data locally has several privacy and security benefits. This is a significant distinction between FL methods and conventional ML approaches that are centralized [33]. Personal medical data is extremely difficult to access due to stringent privacy regulations protecting patient confidentiality. Researchers from health regulatory organisations have agreed that removing data is the only way to overcome the limitations of removing metadata like a patient's name or related information in order to safeguard and preserve user privacy. Therefore, FL has developed a revolutionary decentralized AI paradigm that aims to address issues of information security and privacy in the healthcare industry.

Data sharing raises concerns about privacy protection and legal issues [34]. FL enables the development of AI models using remote data for training purposes. Consequently, an important amount of IoMT data can be utilized without the necessity for data sharing [35], [36]. Rachakonda et al. [37] discussed, a machine learning technology called FL enables users to learn useful knowledge together across platforms or websites without relocating their data. In FL, where data is kept privately, the model is trained and shared between decentralized sites [38], [39]. Following local training, model changes are relayed back to a central server, enabling large-scale access to dispersed data while maintaining security, privacy, and data access rights. Whereas FL has been thoroughly investigated, the concepts that are now in use are still in development. They encounter problems with scalability, data security, aggregation methods, data provenance, and production readiness. Nair et al. [13] addressed, several AI-based technologies have been used in the present industrial environment to extract and analyse large amounts of data based on IoMT. In order to solve the problems of integrating AI into such lightweight distributed computing systems and also address privacy issues, the FL distributed machine learning paradigm has been widely used in IoMT-based systems.

B. Explainable Artificial Intelligence

The use of XAI in the context of medical IoT systems has highlighted the possibility that many types of data might each have an impact on a meaningful outcome. This necessitates an opportunity for medical IoT systems to better understand the reasoning behind a medical device's judgement. In addition, emerging AI systems might gain the confidence of medical IoT systems if their internal operations are made more clear. The development of medically applicable, XAI systems necessitates research into a wide variety of machine learning and human-computer interface approaches to provide a persistently high degree of learning performance.

While IoMT devices play an important role in healthcare, XAI technology is an integral part of the health data collected by IoMT devices, allowing greater transparency in the use of IoMT data to predict health information and the security of IoMT data. IoMT devices can be extensively used to assess patient's health parameters to drive XAI models used in the diagnosis and prediction of disease. In addition, XAI models are transparent in their core operational procedures, and they are widely used to detect and predict diseases using IoMT. They are also widely expected to offer informed decisions about patient's results and model's outcomes. The XAI approach also partially addresses the ethical and legal issues that arise during disease diagnosis [40].

The use of XAI can also assist organizations in meeting the requirements of rules concerning the accessibility and explainability of AI systems. The European Union's General Data Protection Regulation (GDPR) includes a requirement for transparency while handling personal information [41]. The complexity of AI algorithms makes it difficult to accurately maintain these standards in practise. Felzmann et al. [42]

proposed that GDPR requirements for transparency may not alone be sufficient to increase trust, which is one of the positive goals associated with transparency. In contrast, they propose a relational understanding of transparency, in which information provision is conceived as communication between technology providers and users and trustworthiness is measured by context, which mediates the value of transparent communications.

Furthermore, XAI raises security and privacy concerns because providing explanations for AI decisions may reveal sensitive information or reveal ways to manipulate the system, such as reverse engineering. Vigano et al.'s [43] concept of Explainable Security (XSec) is an application of XAI to the security field. The authors argue that XSec is special and difficult because of its many moving parts and wide range of stakeholders.

Explainability is ultimately a tool to increase trust in AI systems among end users. Although end users understand AI systems well, they may not necessarily trust them. Druce et al. [44] suggest that an AI system can gain user acceptance and trust by providing a three-fold explanation. This visual representation describes not only the system's generalization and performance in the current game state, but also the agent's performance in semantically equivalent environments. Healthcare is a complex field in which trust is a fundamental issue due to the possibility that important decisions will be made based on the output of AI algorithms. To ensure the trustworthiness of AI algorithms in healthcare, we must take all these measures. In Table II, we provide a summary of recent studies using XAI in healthcare.

FL and XAI have significant applications in the healthcare domain. FL allows collaborative disease prediction, clinical decision support systems, and privacy-preserving research by allowing healthcare organizations to train models using distributed patient data while preserving privacy. XAI improves diagnosis and treatment by providing transparency and interpretability in AI-driven systems. This improves trust and decision-making in the AI system developed and it also helps in patient monitoring and safety, offering explanations for alerts and predictions, enabling timely interventions. XAI also helps in addressing regulatory compliance and ethical considerations, ensuring transparency and accountability in AI systems used in healthcare. Together, FL and XAI have transformative potential in healthcare, driving improved patient outcomes, medical research, and ethical AI deployment.

C. Motivations of FL with XAI in IoMT

Integrating FL with healthcare data informatics, as seen in Fig.1, has greatly improved the effectiveness of analyzing highly sensitive data. Instead of moving data from one location to another to combine it or create a new dataset for analysis, the local client trains its model on its own data and then connects to other clients via the server, sharing only the results of its training. Hence, the data remains secure at the source, and the server's training results are made accessible to the network. As a result of this integration, both suppliers of the equipment and users of the application will benefit, like the organization that produces and supplies the required equipment to hospitals [28]. There are thousands of connected clients in this era, so identifying malicious users among the thousands of linked clients can be challenging, given the vast number of linking sectors and massive data production. Therefore, FL ensures that clients' data is preserved safely with their own model and that data leakage is prevented in order to overcome malicious data modification. Additionally, in Table III, we provide a summary of recent studies using FL in healthcare. FL integration will improve the efficiency of process analysis in a number of healthcare-related contexts:

- Integrating a data protection mechanism into FL's assessment and forecasting of healthcare data is a step towards more security and privacy [45], [46].
- Also, FL has made it possible for modeling predictions to draw from several datasets, giving doctors more insight into the risks and benefits of addressing them early in their patients' case [47].
- It is possible to predict patient similarities among different patients using FL-based healthcare models [48].
- Protected access to private information allows for in-depth studies of topics including drug resistance, illness therapy, mortality rates, and clarifications [49].
- For the effective administration of some emergency rooms in hospitals while maintaining patient confidentiality, FL-based models can be used to forecast patient death, length of stay, or admission rate [46], [50].

Increasing availability and quality of medical data, as well as a higher level of processing power, have made AI more important in clinical practice [56]. AI models are usually implemented using deep artificial neural networks, but they are sufficiently complex to be difficult to understand [57], [58]. Therefore, Deep Learning models are treated as black boxes [59]. Then, healthcare professionals don't trust prediction models because they are hard to understand [60]. Hence, XAI was developed to make AI models more accessible and easily comprehended [61]. Thus, XAI can supplement human interpretation of the raw data [62], [63] and will help increase the credibility of AI models used in healthcare.

The novel operating idea of FL-XAI makes it feasible to provide a wide range of desirable benefits for the advancement of smart healthcare, some of which are described below:

- Advances in Data Privacy: In the FL-XAI-based smart healthcare system, the raw data is kept at medical facilities or equipment, and the central server just needs access to the locally updated information in order to train the XAI. This method ensures a higher standard of client security by reducing the chance that sensitive user information will be disclosed to an unauthorized party [64].
- An appropriate balance between accuracy and utility: FL-XAI has the potential to improve upon the drawbacks of centralized learning with concerns for accuracy, utility, and privacy. In addition, FL training maintains the potential for generalization of the model while compromising minimal accuracy. It is possible that the sustainability of the intelligent healthcare system will be enhanced as an outcome of the decentralized learning feature of FL.

TABLE II
A SUMMARY OF RECENT WORKS RELATING TO XAI IN HEALTHCARE

Ref. No	Technologies Used	Key Contributions	Limitations
[41]	AI and XAI	AI, and XAI in medical settings solve the present approach's technological issues.	Security, privacy, and confidentiality
[42]	AI	An integrated, interdisciplinary perspective is taken to analyze the topic of transparency in AI systems.	Transparency
[43]	AI and XAI	The purpose of this paper is to present a new paradigm in security research inspired by the XAI program: Explainable Security.	Security, privacy, and trust.
[44]	AI and XAI	The goal of this work is to boost user trust in autonomous agents based on deep reinforcement learning.	User trust and acceptance.

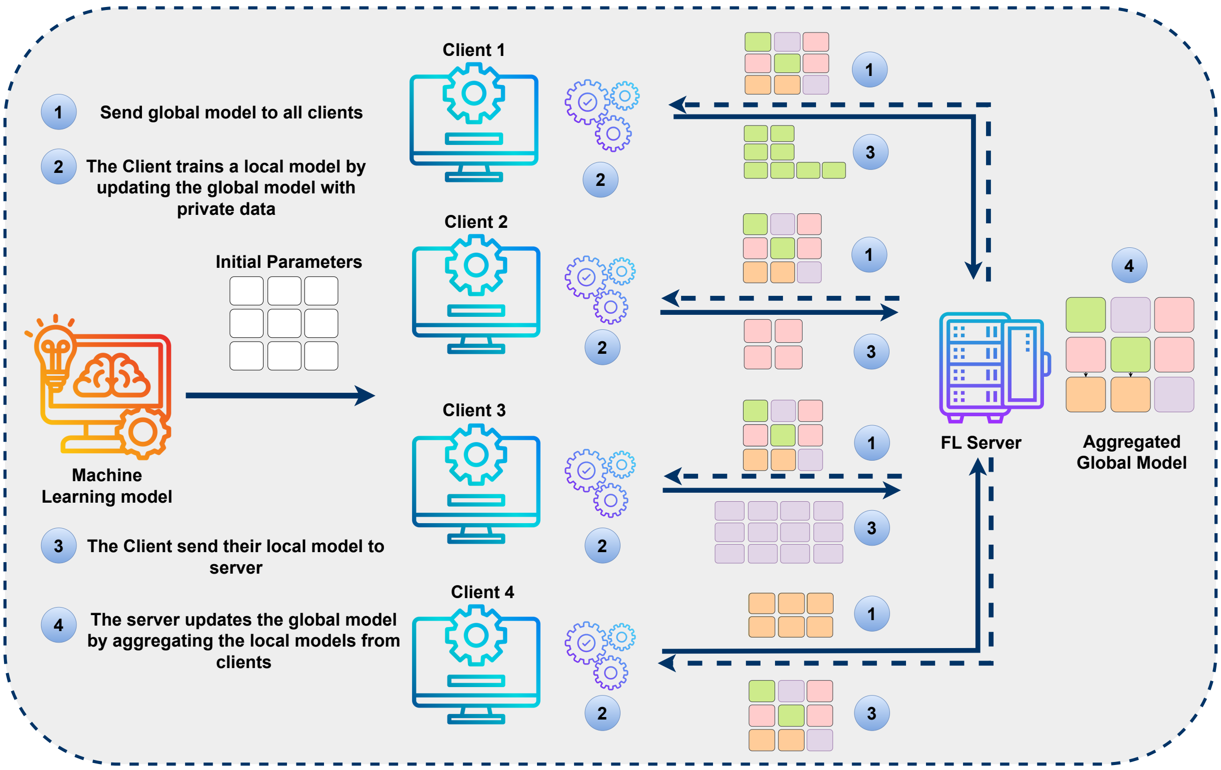

Fig. 1. Federated Learning with Healthcare

- An affordable training program for health data: FL-XAI could help lower expenses for communication, like delay and transmitting power, that come with transferring raw data by avoiding the loss of plenty of data to the central network. This is possible because model gradients frequently prove significantly smaller than their real datasets [65]. Thus, FL helps save a lot of bandwidth and decreases the chance of overload in large medical systems.

The purpose of this section is to identify and synthesize all the available information related to emerging topics-FL, XAI, and healthcare. Further, we discuss in detail how FL and XAI can be applied in healthcare applications to make them smarter. As a result, FL-XAI, FL-healthcare, and XAI-healthcare have been integrated comprehensively.

D. Systematic Literature Survey

In this review, we have conducted a thorough literature review using several reputable sources. Our research has primarily focused on peer-reviewed journals, and high-quality articles from reputed national and international conferences, seminars, books, symposiums, and journals. To ensure the credibility of our sources, we referred to well-known archives such as Google Scholar and arXiv, and publications from top databases like IEEE, Springer, Elsevier, Taylor & Francis, and Wiley. To identify appropriate references and publications, we used keywords such as FL, XAI, and IoMT. We then shortlisted all the fetched articles based on their titles, excluding any papers with irrelevance to IoMT or with poor quality. Next, we reviewed the abstracts of the remaining articles to determine their contributions. In the final step of our literature review, we extracted the necessary data for our analysis. By following these phases, we ensure that our study was based

TABLE III
A SUMMARY OF RECENT WORKS RELATING TO FL IN HEALTHCARE

Ref. No	Technologies Used	Key Contributions	Limitations
[28]	FL, AI, and XAI	FL, AI, and XAI in medical settings solve the present approach's technological issues.	security, privacy, reliability, scalability, and confidentiality
[51]	FL, homomorphic encryption	Innovative approach that integrates FL with smart wearable devices for the development of models through data transfer.	Potential applications to study particular conditions need to be assessed carefully.
[52]	FL, predictive model of in hospital mortality	FL problems and benefits in healthcare computational modelling and privacy and ownership uncertainties are addressed.	The research has to be analysed extensively with hyperparameters.
[53]	Federated machine learning	Decentralised FL Machine learning for clinical tasks utilising an EHR is more efficient.	The study might be expanded to anticipate additional clinical activities using dispersed data across institutions.
[54]	FL. ENIGMA shape tool	Efficient subcortical brain alteration research in multicentric samples	The suggested approach must be applied to massive genomic imaging datasets.
[55]	Federated NLP	To enable a learning medical system to collect important data for study and better diagnosis	It is necessary to compare the algorithm performance scores with the outcomes of other important datasets.

on high-quality and credible sources.

III. Technical Aspects

A. Data Acquisition

1) Introduction: The process of gathering raw data from multiple sources, such as sensors, equipment, or databases, is referred to as data acquisition [66]. It involves gathering and storing data for future analysis and use in a variety of industries, including research, business, and technology. One of the most important parts of modern healthcare systems is the data collection for IoMT systems [67]. It involves the systematic collection and monitoring of patient health data utilizing wearables, sensors, and connected devices. The IoMT system comprises various devices, including biosensors, smart implants, wearable medical devices, and remote monitoring systems [68]. These devices can measure a wide range of vital signs, including oxygen saturation, blood pressure, glucose levels, and temperature. Additionally, they can monitor things like physical activity, sleeping habits, compliance with medication, and other crucial health indicators. The placement of these devices on patients or in medical institutions, marks the beginning of the data-collecting process. These devices can wirelessly or locally take and save data to a centralized system or a cloud-based platform [69]. Depending on the exact monitoring requirements, the data can be gathered periodically or in real-time. After the acquisition, the data undergoes several processing and analysis phase, including data normalization, deletion of duplicate records, and integration with other patient records or medical data sources. IoMT data collection makes personalized healthcare possible. By continuously tracking and analyzing patient data, healthcare professionals can better understand patient's health patterns, detect risk factors, and modify treatment programs as necessary [70]. This individualized approach helps to maximize treatment effectiveness and raise the standard of patient care.

2) Challenges of Data Acquisition in the IoMT: IoMT data acquisition involves a number of challenges that must be overcome by healthcare systems to operate effectively and securely. IoMT devices produce enormous amounts of data from numerous sources, including sensors, wearable technology, and medical equipment. It can be difficult to manage and analyze huge heterogeneous data. Data security and privacy are important factors in IoMT data acquisition, since IoMT devices capture sensitive patient health information [71]. IoMT systems frequently include a variety of hardware and software from many suppliers. It can be difficult to guarantee these device's interoperability and the smooth transfer of data. For making knowledgeable healthcare decisions, the precision and dependability of data acquired by IoMT devices are essential. However, ensuring data quality can be difficult because of device issues, signal interference, and user error [72]. Some IoMT applications, such as remote patient monitoring or emergency response systems, demand real-time data transmission for quick analysis and decision-making. When dealing with enormous data volumes and constrained bandwidth, it might be difficult to achieve high-speed data transfer in simple IoMT networks [73], [74]. Another issue with IoMT data is its ethical use because it belongs to patient autonomy information and privacy rights.

3) How FL and XAI can help: In IoMT systems, XAI and FL are key data collection components. In IoMT systems, protecting patient privacy is essential since it frequently involves sensitive patient data. FL eliminates the requirement to share raw data with a central server and enables local model training on individual devices [75]. Instead, only model updates or gradients is sent, protecting the confidentiality of patient data. FL enable models to be trained directly on the data sources [76]. This makes it possible for models to be updated in real-time in response to dynamic changes in patient conditions. IoMT systems frequently use complex machine learning models, including deep neural networks, which might be challenging for beginners to understand [77], [78]. Understanding the predictions made by the models are easier by XAI techniques like feature importance analysis and model visualizations [79]. This interpretability helps to draw conclusions from the data and confirm the accuracy of the model's predictions. The use of AI technologies in healthcare environments requires a high level of trust and confidence. To increase openness and help physicians and patients understand the methodology behind a system's suggestions or forecasts, XAI methods help in offering explanations for the decisions made by the models [80]. XAI approaches can find inaccurate patterns, problems with the data quality, or biases in the training data by examining model outputs and explanations [81]. This boosts the data acquisition process and enhances decision-making choices for IoMT systems.

4) Summary: Data acquisition in IoMT systems involves gathering and using patient data via sensors and devices. It allows for continuous monitoring, real-time access, and integration of data from numerous sources. However, IoMT generates significant challenges with acquiring data that should be carefully considered. Scalable storage solutions, effective data processing abilities, and cutting-edge analytic tools are required to manage the huge amounts and varied types of data generated by IoMT devices. In order to make the proper decisions, it is also necessary to explain a broad spectrum of data types and sources. Data collection in IoMT systems is made easier by FL, which protects privacy, supports distributed learning, and supports real-time adaptability. XAI approaches improve data collecting by making AI models clear, understandable, and reliable, resulting in increased insights and error detection in the context of IoMT.

B. Data Storage

1) Introduction: Data storage is a vital part of information management because it allows us to store and maintain digital information for analysis, decision-making, archiving, and future referencing. In IoMT systems, data storage refers to the activity of safely storing and managing the enormous amount of data produced by medical devices, sensors, and other sources [82]. This involves utilizing cloud-based programmes, distributed file systems, or data centers designed to effectively handle the increasing storage needs. IoMT data contains a highly sensitive information about many different patients, making security and privacy crucial [83]. Therefore, appropriate storage systems are required to accommodate the patient data. Effective data storage systems assure data availability and integrity, enabling quick data retrieval and analysis for various applications, improving healthcare services and opening up new research opportunities.

2) Challenges of Data Storage in the IoMT: The specific characteristics and requirements of the healthcare industries provide a number of difficulties for data storage in IoMT systems. The numerous connected devices, sensors, and applications that are used by IoMT systems produce a large volume of data. There are issues with scalability, storage capacity, and effective data retrieval when managing and storing this enormous amount of data. Another issue for IoMT systems is to have real-time data storage and processing capabilities to allow prompt decision-making and responses [84]. For successful data storage in IoMT, difficulties with data integration and interoperability exist [85]. Policies governing data ownership, consent management, and data governance must be followed when storing data in IoMT systems. IoMT data storage faces significant difficulties with managing long-term data retention and maintaining data integrity. Data in IoMT systems have redundancy issues, and if the data is lost, there are no specified backup processes from the storage devices [86]. Healthcare organizations with limited resources must carefully monitor the cost of storage devices, cloud services, network bandwidth, and low computer resources. The long-term data storage in IoMT systems creates ethical concerns about data access, use, and permission [87].

3) How FL and XAI can help: FL and XAI offer various advantages for data storage in the context of IoMT, where sensitive and private health data is involved. With FL, the danger of unauthorized access or breaches during data storage is decreased because the data remains on the local devices or edge nodes rather than being centralized [88]. FL allows sharing of only model updates to a centralized server [89]. As a result, IoMT system's bandwidth and storage needs for storing data are reduced. Patients, professionals, healthcare providers, and regulatory authorities using IoMT systems are able to understand how their data is being used and what factors are affecting the decisions made by AI algorithms with the help of XAI. Regulatory norms and guidelines in the healthcare industry often ask for reasons to the choices made using AI. By offering comprehensible reasons for the choices made during data storage and analysis in IoMT systems, XAI approaches will assure compliance with regulations [90]. Healthcare workers can identify and fix possible problems by learning the reasoning behind decisions because of XAI, which also raises the general standard and dependability of data storage. With FL, IoMT systems' data storage will be more resource-efficient and scalable due to the distribution of processing and storage activity among several devices. By giving clear explanations, XAI helps in ensuring conformance to laws governing data privacy, informed authorization, and fair management of patient data during storage and processing [91]. AI models used for data storage benefit from continual learning and enhancement through XAI approaches.

4) Summary: In order to accommodate different data types and provide real-time processing and storage, IoMT systems require a scalable and secure infrastructure. Effective data storage systems enable effective data administration and analysis, which improve healthcare outcomes and research prospects. The amount of data created by the growing number of connected devices and sensors could surpass existing storage capacity. Due to the volume and rate at which data is produced, storing and processing data for effective real-time analysis is difficult. Healthcare information should be securely preserved since it must be kept for a long time for archival, research, or legal purposes. FL promotes collaboration in IoMT data storage, protects anonymity, and requires less bandwidth and storage. In AI-driven decision-making processes within IoMT systems, XAI improves transparency, trust, and error detection. FL and XAI can provide real-time updates and encourage patient participation with continuous learning. The combination of these methods results in data storage practices in the healthcare industry that are more effective, secure, and accountable.

C. Data Sharing

1) Introduction: The act of transmitting or exchanging information between people, systems, or organizations are known as data sharing. The process of transferring and exchanging health-related information among various devices, systems, or stakeholders within the healthcare ecosystem is referred to as data sharing in IoMT systems [84], [92]. IoMT devices like smartwatches, activity trackers, or medical sensors collect health-related information from users or patients [82]. These devices can locally process the data received due to their built-in computing power [93]. To minimize the amount of data that needs to be transferred or retained, this local processing may include fundamental data analysis, aggregation, or basic filtering. The processed data is then sent to centralized servers, cloud platforms, or other healthcare systems via secure communication methods [94]. To make sure that only authorized groups or individuals are able to access, modify, or share the data, strong access control measures are developed [95]. Once the data is shared and available, it can be used for various tasks by researchers, data scientists, and healthcare practitioners. This includes virtual consultations, personalized medicine, clinical research, real-time patient monitoring, predictive analytics, and public health initiatives [96], [97].

2) Challenges of Data Sharing in IoMT: In the healthcare industry, sharing patient data on centralized data exchange systems poses significant risks to the owners' private and sensitive data. Healthcare organizations, platforms, and devices use a variety of data formats, communication protocols, and standards involved in IoMT systems. So, it can be difficult to achieve smooth data sharing and exchange between various systems. It might be challenging to get informed patient consent for data sharing [98]. Patients must be fully informed about the risks and advantages connected with the use of their data, who will have access to it, and how it will be used [99]. IoMT systems must abide by a number of legal and regulatory frameworks when sharing data. Compliance with laws, which can vary between nations, will be problematic. It may also be difficult to share data across borders or between various healthcare organizations. Various issues, such as device failures, data transmission errors, or data entry mistakes, will negatively impact the reliability of the shared data [100]. In IoMT systems, sharing and managing massive amounts of data requires a strong infrastructure and advanced technological skills [101].

3) How FL and XAI can help: FL and XAI is essential to promote data sharing in IoMT systems while resolving privacy issues and guaranteeing transparency. FL makes it possible for local data to stay on edge devices, and only model updates are communicated with a centralized server. This safeguards data privacy and lowers the possibility of unapproved access [102]. FL can reduce the risk of data breaches or exposures connected with sending sensitive medical information to a central server by eliminating centralized data storage [103]. The XAI system improves transparency by offering reasons for its decisions, enabling healthcare professionals, patients, and regulatory agencies to better understand the thinking behind a given diagnostic or treatment recommendation [104]. Furthermore, XAI improves accountability by making it possible to recognize potential biases or mistakes in the system [81]. XAI can reveal details about the important features or patterns the model considers while making predictions. This knowledge extraction approach advances medical research and knowledge exchange by assisting healthcare professionals in better understanding diseases.

4) Summary: Data sharing in IoMT systems is transferring and exchanging health-related information among different devices and systems. In the healthcare industry, sharing patient data on centralized data exchange systems significantly increases the risk to the owners' private and sensitive data. FL supports collaborative model training in IoMT systems while assisting in the preservation of data security and privacy. By offering apparent reasons for AI-driven healthcare decisions, XAI facilitates data exchange and aids in the promotion of transparency, trust, and accountability. Together, these methods improve the efficiency and ethical use of AI in IoMT.

D. Data Interoperability and Privacy

1) Introduction: The seamless exchange and use of data between various platforms or systems is referred to as data interoperability [105]. Data interoperability is essential in IoMT systems for enabling the sharing and usage of healthcare data across a broad range of hardware, sensors, and software applications [106]. In order to collect, transmit, and analyze patient data to enhance healthcare outcomes, IoMT involves the integration of medical devices, wearables, sensors, and healthcare software. Data interoperability facilitates easy data sharing between devices, sensors, electronic health record (EHR) systems, health monitoring platforms, and other medical applications [107]. For example, a patient is wearing a smartwatch to track his heart rate, blood pressure, and level of exercise. The information collected by the smartwatch must be sent to a mobile app, which in turn must communicate the data to the patient's EHR system. Message Queuing Telemetry Transport (MQTT) protocol by [108] can be widely deployed in IoT based environments for seamless data interoperability.

The real-time transfer of data without any loss or misinterpretation is made possible through data interoperability, which guarantees that the smartwatch, mobile application, and EHR system can all function together without any issues [109]. Data privacy in IoMT systems means preserving the confidentiality and security of private health data collected, transmitted and stored by internet and connected medical devices.In IoMT systems, data standards and protocols are essential for ensuring data interoperability and privacy. A set of messaging patterns for service-oriented architecture with ZeroMQ open source framework and different messaging protocols helps in protection of data privacy in medical and different IoT systems [110]. IoMT systems' data interoperability paves the path for innovative applications including telehealth services, remote patient monitoring, and AI-driven healthcare analytics [111].

2) Challenges of Data Interoperability and Privacy in the IoMT: While data interoperability in IoMT systems has many advantages, it also presents several difficulties that must be resolved for efficient and seamless data sharing. It might be difficult and time-consuming to integrate and balance various data formats in IoMT systems [85]. The lack of standardization protocols makes it difficult for systems to comprehend and interpret data consistently, which limits interoperability [112]. The need for strong data encryption, authentication procedures, and access controls when working with patient's private health information makes it difficult to ensure secure data exchange while retaining interoperability and privacy. Data interoperability may be restricted by problems including inconsistent network coverage, reduced bandwidth, and infrastructural limitations, especially in faraway or resource-constrained areas. It can be difficult to integrate older systems with more advanced IoMT technologies and ensure data privacy, because it requires a lot of modification, data mapping, and interface development [29]. To fully utilize the capabilities of IoMT systems and provide better healthcare results, it is essential to overcome these obstacles.

3) How FL and XAI can help: Decentralised machine learning techniques assist in addressing data privacy issues while promoting efficient learning [113], [114]. In IoMT systems, this distributed learning strategy reduces the danger of data breaches and safeguards patient privacy. IoMT devices frequently save data from many hospitals, clinics, and patients and work in a variety of circumstances. FL enables the entities to continue to have ownership and control over the data while also participating in a collaborative learning process [45]. It encourages teamwork and collaboration without the direct exchange of data. Each device can customize its local model using FL based on its own data properties and use cases. Without compromising data privacy, this local adaptation raises the shared model's overall performance. XAI methods aid in the understanding of AI model conclusions by patients and healthcare providers. Transparent explanations from XAI promote collaboration amongst various IoMT system participants and increase trust in the decision-making process [115]. IoMT interoperability frequently involves a wide range of stakeholders, including doctors, researchers, and data scientists. By offering a standard language to discuss and assess the performance, biases, and limitations of AI models, XAI enables these stakeholders to interact effectively [116]. It encourages interdisciplinary cooperation and raises the standard of decision-making in general.

4) Summary: Optimising healthcare service in the digital age requires data interoperability. In IoMT systems, data interoperability is essential because it allows for the secure and smooth transmission of health data among platforms, systems, and devices ensuring data privacy. It improves patient care by giving a complete picture of their medical history, makes workflow and resource management more effective, guarantees continuity of care, aids population health management and medical research, fosters innovation and technological advancements, and addresses data security and privacy issues. Data interoperability and privacy between IoMT devices and institutions is promoted by FL, which enables collaborative training of AI models without disclosing private information. In addition, XAI approaches offer transparency and interpretability, boosting confidence and promoting efficient communication between various IoMT systems. Together, these strategies support data interoperability, privacy and seamless information exchange in IoMT systems, ultimately enhancing the healthcare outcomes and promoting medical research.

IV. Applications

A. Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) are simple computer-based tools that are designed to assist healthcare professionals in making clinical decisions. These systems provide evidence-based recommendations and related data at the place of care [117]. CDSS combines the data that is specific to a patient from a variety of sources like electronic health records (EHRs), clinical guidelines, and different databases, in order to generate related and actionable insights [118]. It makes use of different algorithms, rules, and knowledge repositories in order to analyze patient-related data and provide healthcare providers with decision support in real-time. The integration of FL and XAI has a considerable impact on CDSS, offering various benefits that improve their functionality and effectiveness. XAI techniques can be put into practice with FL-based CDSS models, which provide explanations for the recommendations given by the system. These explanations and the transparency can help the healthcare providers in understanding the outputs of CDSS and in building trust in making efficient decisions [119]. Clinicians can scrutinize the underlying factors, evidence, or rules that contribute to the CDSS recommendations, easing their acceptance and adoption of the system.

Many legal and ethical requirements in CDSS can be addressed with the combination of FL and XAI. FL ensures privacy protection and compliance with data privacy regulations, while XAI provides transparency and accountability by explaining the decision-making process. These points are very important to comply with legal frameworks, ethical guidelines, and regulations related to healthcare decision support [120]. FL and XAI help in continuous learning and the improvement of the model. The models can learn from the multiple institutions which is possible by the default distributed nature of FL [121], while XAI helps identify areas of improvement and refine decision-making processes [104]. Sometimes CDSS needs to handle enormous and different types of datasets and real-time decision-making situations. The greatest challenge is ensuring the scalability of FL and XAI techniques to accommodate the growing volumes of data and computational demands. Resource limitations, such as computing power and storage, may affect the feasibility and efficiency of FL and XAI implementation in CDSS.

Successful implementation of FL and XAI in CDSS depends on gaining acceptance and trust from healthcare professionals. Clinicians may be hesitant to adopt AI-driven systems if they lack transparency or if they do not understand the reasoning behind the recommendations. Educating and training clinicians on the benefits, limitations, and interpretability of FL-XAI-based CDSS models can help foster trust and improve adoption

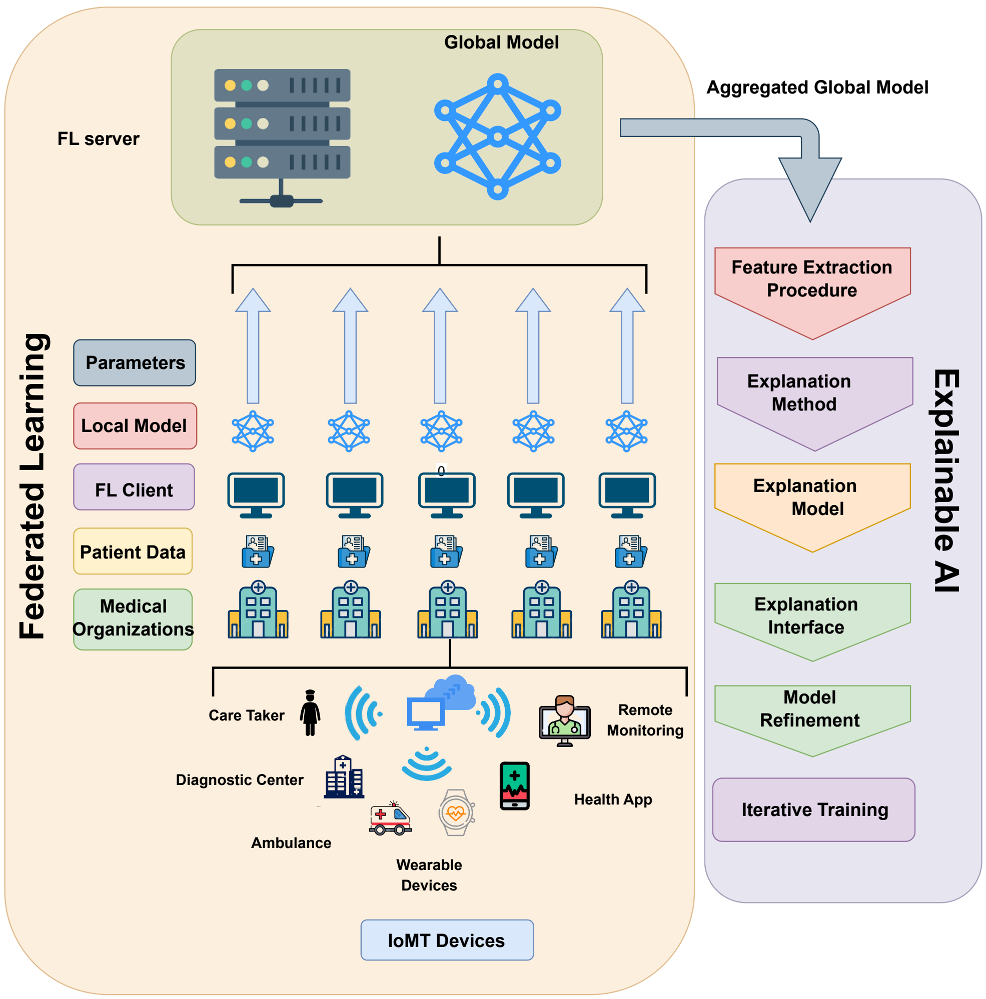

Fig. 2. FL and XAI Integration Opportunities

rates.
CDSS operates in a highly regulated healthcare environment. Compliance with regulations such as Health Insurance Portability and Accountability Act(HIPAA), General Data Protection Regulation(GDPR), and medical ethics guidelines is critical.

B. Disease Diagnosis and Prediction

Disease diagnosis is the process of determining the existence, nature, and causes of a disease or medical condition in an individual. It includes estimating several factors such as symptoms, medical history, physical examinations, laboratory tests, imaging studies, and sometimes genetic and molecular analyses [122]. The major goal of disease diagnosis is to identify the underlying disease or condition that is responsible for the abnormalities in the patient. It helps the healthcare providers to understand the type and the severity of the illness, decide the perfect treatment methods, and monitor the response to the therapy.
The combination of FL and XAI has a significant impact on disease diagnosis and provides numerous advantages that can improve the precision, confidentiality, interpretability, and reliability of diagnostic models. Healthcare workers can better grasp the underlying causes of diagnostic findings and pinpoint the major variables influencing forecasts with the integration of XAI and FL [28]. As a result, physicians can make defensible decisions based on interpretable insights while also promoting trust and the adoption of AI-based diagnostic suggestions. The combination of FL and XAI can help build trust between patients, healthcare providers, and AI systems [123]. Interpretable explanations provided by XAI enable patients to understand the reasoning behind diagnostic decisions, leading to increased confidence and acceptance of AI-based diagnoses [124]. Improved trust and acceptance can encourage patients to actively engage in their healthcare journey and follow recommended treatments.
The FL and XAI duo enables the disease diagnosis models to rapidly improve and refine their diagnostic capabilities [125]. The duo ensures that diagnostic models stay up-to-date with evolving disease patterns and can adapt to new information. FL uses data from different resources and patient groups, which makes the diagnostic models more robust. The integration of FL with XAI ensures that the models are not only accurate but also give transparent and interpretable results across different

settings and patient groups.

The integration of FL and XAI into clinical practice needs expertise in both the respective fields [126]. There is a need for healthcare professionals and data scientists to work together in order to design, implement and evaluate FL-XAI-based diagnostic models. FL and XAI implementation in disease diagnosis needs compliance with legal and ethical frameworks like data privacy regulations (e.g., HIPAA) and ethical guidelines for AI deployment in healthcare. Addressing these challenges requires a multidisciplinary approach, involving experts from healthcare, data science, privacy, and legal domains.

C. Personalized Treatment Recommendations

The term personalised treatment, also known as personalised medicine or personalised healthcare, refers to healthcare methods that take into account a patient's unique genetic profile, lifestyle, environment, and other aspects when making medical decisions and providing treatment. Enhancing the efficiency and security of medical procedures while reducing the risks of side effects is the aim of personalised treatment [127]. Medical professionals can determine a patient's risk of suffering a particular medical condition or disease by taking into consideration their genetic disposition, way of life, and environmental exposures. The focus of personalized treatment can also focus on early detection of patients at high risk of developing a particular disease Recommendations for lifestyle changes to improve physical and mental health can be incorporated into individualized treatments that consider the unique needs of the individual [128].

This integration allows healthcare organisations, research institutes, and other devices to retain their data resources on the client side. This enables comprehensive and diverse dataset creation on the client side. An increase in the dataset can help in obtaining more accuracy in prediction. This retention of data on the client side can help provide more robust and accurate personalised treatment based on prediction [129]. By integrating federated learning and XAI, healthcare providers can offer highly personalised treatment plans for individual patients. This integration also allows the analysis of large-scale data to recognise patterns specific to certain patient groups or conditions. With the help of XAI, healthcare providers can interpret and understand the factors that contribute to the model's decision-making process [130]. This enables them to customise the treatment plans to individual patient needs effectively. This integration also helps healthcare providers make decisions. Federated Learning enables continuous updating of models on the client side using data from various sources. This continuous updation of the client model with aggregated knowledge from the FL server can help adapt to changes in patient conditions, treatment enhancement, or emerging medical research in real-time. This greatly helps healthcare providers to have up-to-date and relevant information to make critical decisions about patient care. The integration also fosters a collaborative environment for healthcare research [131], [132]. Researchers from multiple institutions can team up for data analysis and model development without sharing their own data. This accelerated collaboration can help to achieve faster discoveries, advancements in medical research, and the rapid development of personalised treatments.

In any case, it is particularly difficult to apply FL and XAI for personalized treatment of IoMT. Few difficulties are:

Some medical conditions may affect only a limited portion of the population. This results in the patient group may be small and imbalanced with respect to representation. This makes it challenging to create representative models that cater to these specific cases. It also demands longitudinal data to track a patient's progress over time. However, acquiring continuous and comprehensive data from various sources can be difficult. This delays the development of accurate and personalized treatment models [133]. Personalized treatment models heavily depend on high-quality and consistent data. But, data collected from different clients in the IoMT may vary in quality. This may lead to potential challenges in ensuring data integrity and reliability [25]. Personalized treatment must adhere to ethical guidelines and regulatory requirements to avoid potential biases. Addressing ethical considerations with respect to personalized treatment decision-making and sharing of data becomes critical.

D. Real-Time Monitoring and Alerts

Real-time alert reporting in healthcare is a crucial procedure that involves constant data collection and analysis in order to identify any problems or fluctuations and take timely action. By taking steps to address possible issues, the objective is to optimise the health of patients, improve the quality of service, and ensure their health [134]. Healthcare professionals are able to identify any unexpected changes or abnormalities by monitoring patient's health conditions in real-time, including heart rate, blood pressure, oxygen saturation, and other pertinent factors. This is particularly important since patient's health may change quickly in intensive care units (ICUs) [135]. Alerting systems for emergencies are frequently used in hospitals and healthcare institutions to analyse patient data and provide warnings when certain thresholds are exceeded. For example, if a patient's temperature increases to a potentially dangerous level, an alarm is set, causing medical professionals to look into the situation and take necessary action [136].

Real-time monitoring and alerts in lots of places can be significantly impacted by FL and XAI. FL enables numerous devices or systems to simultaneously train a model while maintaining decentralised and private data. Every device or node trains its model independently and only shares model updates with the centralised server instead of transmitting raw data to the server. This technique provides several benefits for real-time monitoring and alerts. FL enables the spreading of monitoring and alarm systems among several devices, or edge nodes. In situations where real-time monitoring is required at the edge of the network or in remote locations where access to central servers is unstable, this distributed solution is very beneficial. Real-time monitoring frequently involves the analysis of a great deal of data from several sources. FL makes monitoring systems more scalable and cost-effective by distributing the processing load over numerous devices [25].

XAI is the ability of AI models to offer clear and comprehensible explanations for their decisions and forecasts. The following advantages are available from XAI when it comes to real-time monitoring and alerts. In the medical field, trust is crucial. XAI contributes to the development of confidence and trust in the technology by offering plausible reasons for AI-driven decisions. When medical professionals understand how AI solutions arrive at specific diagnoses or treatment suggestions, they are more motivated to adopt them. XAI can supplement the knowledge of medical professionals by offering additional clarifications and ideas. All of these reasons are commonly used by clinicians to validate AI recommendations, resulting in more accurate and certain confident decision-making [137].

In real-time monitoring, low latency is vital to providing timely insights and responses. FL involves the transfer of information between the edge devices and the central server during the model update. This can increase communication overhead and affect the responsiveness of the system. Effective compression techniques and optimized communication protocols are required to minimize latency while preserving model accuracy [11]. IoMT devices have limited computation ability and memory. Executing complex FL and XAI algorithms on resource-constrained edge devices will be a challenge for real-time monitoring. Many XAI algorithms were not designed to be implemented for real-time applications. Developing and adapting XAI methods that can provide explanations for real-time decisions without significant delay is a challenge. Additionally, explaining complex XAI insights to healthcare providers and patients in real-time monitoring cases demands effective human-computer interaction design for effective understanding and decision-making [138].

E. Drug Discovery and Development

Drug discovery is the process of finding and developing new medicines to treat diseases through targeting specific genetic molecules or pathways related with the disease. Drug discovery traditional methods such as target-based screening, random screening and leaf optimization have been highly time consuming and resource intensive. Technology adoption can show a significant improvement in drug discovery process [139]. Recent advancements in methods such as high throughput screening, omics technologies, structure determination, and computational drug design are technological methods have significantly contributed to drug discovery. Potential drugs such as pembrolizumab, ivacaftor, and venetoclax are the outcome of technology adoption in drug discovery [140]. Pembrolizumab, developed through advanced genomic profiling has shown higher efficacy in treating various types of cancer. Based on the method of structure-based drug design and genomics, the drug Ivacaftor has transformed the way cystic fibrosis patients are treated with specific genetic mutations. Venetoclax, developed using rational drug design has shown effectiveness in making cancer cell death. These drugs have shown promising results in treating patients that highlights the positive outcomes of technology inclusion in the field of drug discovery.

In IoMT, drug discovery is one of the key applications driving significant advances in medicine and patient outcomes [141]. It includes network-connected medical devices and wearable sensors to gather and send the data for various purposes. This huge amount of patient data generated by the IoMT devices, which includes physiological measurements, clinical records, and genetic information, is instrumental for new drug discovery. This data is useful for new drug discovery and therapeutic repurposing of existing drugs. However, competitive concerns, risks of sharing patient data, and privacy regulations often pose challenges to IoMT.

To handle these challenges, FL can be a solution. FL technology allows collaborative training of ML models on decentralised, distributed data. By training the models on decentralised data, data sharing can be neglected. This data sharing is the primary challenge for applications like healthcare and finance. In drug discovery of IoMT, multiple medical organisations can train models using their respective datasets while patient data privacy is retained [142]. This approach aids in enhancing the accuracy through inputs from multiple models and aggregating the inputs to get the global model, which can be accurate and robust. FL enables the integration of input from multiple local models trained on multiple different organisations, leading to improved insights and discoveries in drug development. The drug development process in IoMT may make use of the combined strength of several organisations by utilising FL, without sacrificing data security and privacy [143]. It encourages creativity, accelerates scientific advancement, and aids in the creation of patient-specific therapies that are efficient and individualised.

XAI's integration with FL can yield various benefits. XAI methods can justify predictions made by the aggregated model in drug discovery and provide insights about the decisions by defining them with molecular descriptors, genetic markers, or patient characteristics that contributed to the predictions [144].It can also define the relationship between the drugs and their target interactions. This can reveal how specific compounds or molecular features react to the new combination in new drug discovery initiatives. Additionally, it helps identify the most relevant traits in the drug development process, revealing which molecular or genetic traits had the most impact on model predictions. In addition, explaining the factors that influence model decisions helps in assessing safety and efficacy. It aids in evaluating the potential risks associated with specific drugs. Lastly, XAI explanations can also guide iterative design and optimisation efforts.

The adoption of FL and XAI in the drug discovery of IoMT presents its own unique challenges.

With respect to FL adoption, the key challenge is to train the models across multiple distributed devices while keeping the data in distributed and decentralised form. Another challenge is ensuring the privacy and security of patient data during the process, which is so critical. In addition, data gathered from various sources may vary in forms, formats, quality, and standards. It is so complex to integrate and normalise the data to ensure compatibility and consistency. For resource-constrained IoMT devices, communication overhead is another challenge. Data bias is another common challenge applicable to all learning technologies, which is also applicable to FL. Data distribution across devices can be vulnerable to producing biassed output.

The implementation of XAI is evolving with various challenges. Modern ML models, such as deep neural networks, create difficulties even for XAI methods to interpret their decisions. Personalised XAI methods are needed to handle such complex models. There is often a trade-off between explainability and model performance, as advanced models may attain high accuracy but lack interpretability, and vice versa can also happen. Moreover, balancing the transparency requirement of the model with accurate prediction is a challenge in the drug discovery process. Another significant challenge is the need for domain-specific knowledge for decision-making. Integration of domain expertise into XAI methods to generate explanations aligned with specific requirements can be challenging.

F. Practical implication of disease prediction model using FL and XAI in IoMT

FL and XAI are involved in developing predictive models for disease detection and personalized treatment as part of IoMT. In this context, consider a network of hospitals and healthcare institutions that work together to develop and improve disease prediction models while preserving patient privacy. Each organization has access to patient data collected from various IoMT devices such as wearable sensors, EHRs, and imaging systems. The goal is to develop accurate predictive models for diseases such as cardiovascular conditions or cancer while ensuring data security and privacy. To achieve this, FL can be deployed, allowing each institution to train a local model using its own patient data without sharing the raw patient data with other organizations or a central server. Instead, only model parameters can be shared among the organizations. The central FL server aggregates these updates to create a global model without accessing individual patient data, ensuring privacy. Once the global aggregated FL model is trained, XAI techniques are applied to provide interpretability and transparency in the model's decisions. XAI Methods, such as rule-based explanations, feature importance analysis, or visualizations, help healthcare professionals understand why the model made derived these specific predictions or treatment recommendations. This helps build trust and allows clinicians to validate and refine the model's outputs. The benefits of implementing FL and XAI in this IoMT application are numerous. FL allows collaborative learning while preserving data privacy and security, permitting for the development of robust disease prediction models. While XAI provides interpretability, helping healthcare professionals understand the reasoning behind the model's predictions, facilitating personalized treatment suggestions, and confirming compliance with regulatory requirements.

V. Challenges

A. Challenges in adopting FL and XAI in healthcare

The utilization of FL and XAI in healthcare faces potential barriers, including data privacy and security concerns, challenges in accessing and combining distributed healthcare data, regulatory and ethical considerations, interpretability-performance trade-offs between these technologies, technical infrastructure requirements, and cultural and organizational upgradation challenges. These challenges require addressing privacy and security protocols, confirming data access and availability, traversing regulatory frameworks, balancing interpretability and performance, establishing robust technical infrastructure, and adopting cultural acceptance. Overcoming these challenges is crucial to yield the potential benefits of FL and XAI in healthcare, promoting privacy-preserving collaboration, transparent decision-making, and improved patient outcomes.

B. Open Issues

Data privacy and security: Although FL's distributed capabilities protect data, IoMT data can still be vulnerable to attacks. IoMT data includes patient information that is often sensitive and personal, such as medical records or location data. This criterion makes it a valuable target for attackers. Since the devices of IoMT often have limited resources such as processing power and memory, it can be hard to implement strong security methods to secure the information. FL offers a privacy-preserving approach by training models locally on distributed devices without sharing raw data. Although, the FL models are trained locally, there exist security issues which can impact the privacy of medical data. Data security and Integrity, for instance, allows IoMT devices to generate and transmit sensitive medical data. These data are protected against cyber-attacks, unauthorized access or secured data transmission channels.

Heterogeneity of IoMT devices: IoMT devices such as wearable sensors and fitness trackers are heterogeneous with respect to software, hardware, and communication abilities [145]. This heterogeneity of devices makes it difficult to develop and implement FL and XAI techniques that can work with all the devices in IoMT.

Data Bias: Like any learning technology, FL can also introduce data bias. Since IoMT data are sensitive in nature. If the data distribution is not even, this may lead to biassed output. This may be accidental because of the data collected from various sources. But applications such as healthcare are highly sensitive. So, intentional data bias may also be possible by making an adversarial attack on the system.

Access to data: In the FL context, data is distributed across various devices, making it challenging to access and aggregate the data for training a centralized model. Privacy concerns and data security regulations may restrict the sharing of patient data, hindering the collaborative model training process. On the other hand, in XAI, accessing and interpreting the data required to provide transparent and interpretable explanations for AI models can be complex due to the distributed nature of IoMT data and the need to maintain patient privacy. Managing a balance between accessing relevant data, protecting patient privacy, and complying with regulations is crucial for the successful application of FL and XAI in the IoMT.

Thus, the IoMT devices and technologies have become more and more prevalent because of which ethics and regulation plays a vital role in the healthcare. Patient safety, medical data privacy, equity, and algorithmic accountability are addressed by them. The ethical guidelines and regulations are framed by group of healthcare providers, technology developers, policy-makers, and regulatory bodies to leverage the technological advancements in the medical IoT field.

C. Integration Challenges

Problem of data distribution: Healthcare data is sourced from multiple systems like electronic health records (EHRs), imaging systems, and laboratory information systems. The data formats used in every formats are widely varying considering the data integration and interoperability highly complex. This process cease the utilization of powerful technology applied over healthcare data as it lacks, standardization and data sharing protocols. Hence, merging FL and XAI can be challenging because the data is spread across different institutions in FL. Due to this, it is difficult to fully understand how the data is distributed, which is important for XAI methods that depend on analysing data distribution to provide explanations. It is necessary to carefully figure out how to bring together and analyse explanations from the scattered data sources to successful integration of FL with XAI.

The problem of model aggregation and explanations: Model aggregation becomes more and more complex when FL is integrated with XAI. In FL, the local models of different participants in FL may use different architectures, algorithms, or feature representations, which have to be aggregated at the server. As the local model may be trained on different subsets of data, maintaining model accuracy and ensuring fairness is expensive, causing variations in data distributions and biases across devices, which leads to disparities in model performance.This model diversity can make it difficult to make stable and coherent explanations across distributed models. Therefore, this integration demands devising methods to aggregate explanations from multiple models or methods to provide individualised explanations from each participating model.

The problem of privacy-preserving explanations: The primary intention of technology like FL is to protect data privacy, and XAI aims to provide explanations that disclose the inner workings of a model. Balancing the objectives of these technologies can be challenging. Because generating detailed explanations may accidentally reveal sensitive information from the distributed data sources, So, this integration demands developing privacy-preserving explanation techniques that provide understanding without violating privacy constraints. Thus, ensuring secure storage , encrypted data transmission and data sharing between the healthcare providers, and adhering to strict privacy policies and implementing robust access control mechanisms are vital steps in addressing privacy concerns.

The problem of communication overhead: FL depends on communication between the central server and participating devices to exchange model updates. XAI adoption may increase communication overhead due to the requirement to transmit explanation-related information. This can affect the efficiency and latency of the FL system. Effective customised communication protocols and compressed representation of explanations are needed to minimise the impact on FL performance. Thus, the IoMT connects various medical devices, sensors, and systems to collect and exchange data for analysis and effective decision-making. When FL and XAI are integrated, it can amplify the communication overhead, leading to several problems like energy consumption and bandwidth constraints as well.

VI. Conclusion

This paper presents an extensive review of the amalgamation of FL and XAI for the IoMT. The integration of FL and XAI for IoMT holds immense potential for revolutionizing the healthcare domain. FL enables collaborative and privacy-preserving model training across distributed devices, allowing healthcare organizations to harness the collective knowledge of diverse data sources while safeguarding sensitive patient information. By incorporating XAI techniques, such as generating interpretable and transparent explanations for the predictions made by FL models, healthcare practitioners, and patients can gain insights into the reasoning behind those decisions. This integration enhances trust, accountability, and comprehension of AI-driven healthcare systems, empowering stakeholders to make informed decisions and fostering the adoption of these technologies in the complex and critical field of medicine using IoMT technology. In conclusion, the integration of FL and XAI within the context of the IoMT remains a relatively unexplored area, thereby presenting opportunities for future research.

Acknowledgement

The authors would like to gratefully acknowledge the grant GUJCOST/STI/2021-2022/3922 from the Government of Gujarat, India, and support from Pandit Deendayal Energy University (PDEU) to perform this work.

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