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Research Article

Advancing Pandemic Preparedness in Healthcare 5.0: A Survey of Federated Learning Applications

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The intersection of Federated Learning (FL) and Healthcare 5.0 promises a transformative shift towards a more resilient future, particularly concerning pandemic preparedness. Within this context, Healthcare 5.0 signifies a holistic approach to healthcare delivery, where interconnected technologies enable data-driven decision-making, patient-centric care, and enhanced efficiency. This paper provides an in-depth exploration of FL's role within the framework of Healthcare 5.0 and its implications for the pandemic response. Specifically, FL offers the potential to revolutionize pandemic preparedness within Healthcare 5.0 in several vital ways: it enables collaborative learning from distributed data sources without compromising individual data privacy, facilitates decentralized decision-making by empowering local healthcare institutions to contribute to a collective knowledge pool, and enhances real-time surveillance, enabling early detection of outbreaks and informed responses. We start by laying out the concepts of FL and Healthcare 5.0, followed by an analysis of current pandemic preparedness and response mechanisms. We delve into FL's applications and case studies in healthcare, highlighting its potential benefits, including privacy protection, decentralized decision-making, and implementation challenges. By articulating how FL fits into Healthcare 5.0, we envisage future applications in a technologically integrated health system. By examining current applications and case studies of FL in healthcare, we highlight its potential benefits, including enhanced privacy protection and more effective decision support systems. Our findings demonstrate that FL can significantly improve pandemic response times and accuracy. Moreover, we speculate on the potential scenarios where FL could enhance pandemic preparedness and make healthcare more resilient. Finally, we recommend that policymakers, technologists, and educators address potential challenges and maximize the benefits of FL in Healthcare 5.0. This paper aims to contribute to the discourse on next-generation healthcare technologies, emphasizing FL's potential to shape a more resilient healthcare future.

1. Introduction

The world witnessed the unprecedented impact of the COVID-19 pandemic, highlighting the critical need for robust healthcare systems and effective pandemic preparedness strategies. As the healthcare landscape evolves to meet these challenges, the concept of Healthcare 5.0 has emerged, advocating for an integrated and technologically advanced health ecosystem [1]. The global experience of the COVID-19 pandemic has highlighted the importance of healthcare resilience in the face of such large-scale health crises. The World Health Organization defines resilience as "the capacity of a system, community, or individual to absorb disturbance, reorganize while changing, and retain

the same function, structure, identity, and feedbacks" [2]. In healthcare, resilience translates into the ability of health systems to prevent, respond to, recover from, and learn from acute shocks and chronic stresses, thereby ensuring the continuity of essential health services [3]. Healthcare resilience is significant for several reasons. Firstly, it safeguards the continued provision of essential health services, ensuring that populations can access the necessary healthcare even during a crisis [4].

Furthermore, healthcare resilience helps to limit the direct mortality and morbidity caused by the crisis, as seen in the COVID-19 pandemic, where healthcare systems' resilience heavily influenced the severity of the pandemic's impact across different regions [5–9]. Moreover, it mitigates the indirect health effects of the crisis, such as those resulting from interruptions in routine healthcare services like immunizations and chronic disease management [10]. Therefore, building resilient healthcare systems is critical for global health security. The ongoing global health crisis has underscored the urgent need for resilient healthcare systems capable of responding effectively to pandemics. As we work toward resilience, our strategies must integrate the most advanced technological tools available, harnessing the potential to revolutionize the future of healthcare. In the era of rapid technological advancements, healthcare systems are increasingly generating vast amounts of data from diverse sources, potentially improving patient outcomes and public health. However, the surge in data also raises concerns over data privacy and security, especially during pandemics, where data sharing becomes crucial for effective responses.

Advancements in technology have revolutionized healthcare for years, offering new opportunities for data-driven insights and care delivery. Among the emerging technologies, Federated Learning (FL) is a promising approach to machine learning, especially in healthcare care [11]. FL is a privacy-preserving technique that trains an algorithm across multiple devices or servers that hold local data samples without exchanging the data. The machine-learning model is trained on the edge devices or servers, and only the model updates are exchanged between the nodes [12]. The approach mitigates privacy and security concerns, making it highly suitable for healthcare, where sensitive data is prevalent. Parallel to the new technologies, the concept of Healthcare 5.0 is emerging as a new paradigm aimed at providing highly personalized and efficient care using digital technologies.

The rapid proliferation of IoT resources and applications has led to an increasing demand to process large volumes of data [13, 14]. The availability of big data analytics and computational methods, such as machine learning and deep learning, has facilitated effective data management. AI applications are successfully deployed to address issues related to optimized resource management and efficient antenna selection in wireless systems and other communication network areas. However, traditional AI models often require users to share their individual information with a master network for learning purposes, raising concerns about data privacy [15]. FL is highly effective when decision-making is based on large amounts of data scattered between various training nodes while simultaneously addressing privacy and security concerns [15]. In FL, machine-learning models are developed using data collected from multiple sources to enable predictions. However, transmitting raw data to a centralized location becomes impractical due to bandwidth limitations, security considerations, and storage facilities. FL operates as a distributed learning model to ensure optimal learning, efficient use of collected raw data, and transmission to a centralized location [15]. FL contributes significantly to the advancement of smart cities, as detailed in [16]. In smart urban cities, policymakers can employ FL to transmit sensitive information collected from IoT devices, enabling effective management of priority assets. The FL framework enables users to access data without compromising the personal information of other clients. The updated global model constructed by the server is then distributed to all clients, who download and utilize the new updated global model through cloud distribution to understand interference on their devices [17].

FL is an approach to machine learning that benefits privacy and efficiency [11]. FL offers a unique opportunity to take advantage of the vast amounts of data generated in healthcare settings while prioritizing patient privacy. FL has emerged as a promising solution to balance the need for data collaboration with privacy preservation. A decentralized machine-learning approach allows multiple institutions or devices to train a global model collaboratively while keeping raw data locally [18, 19]. By doing so, FL enables the aggregating of knowledge from distributed datasets without sharing sensitive information, offering an avenue for enhancing pandemic preparedness and response mechanisms. FL is a distributed model that allows training machine-learning models across multiple nodes, utilizing local data without direct exchange, thereby maintaining data privacy [12]. By minimizing the need to move data and instead focusing on learning from the data at its origin, FL paves the way for advanced, data-driven, and secure healthcare systems.

However, amidst this paradigm shift, specific challenges persist in preparing for pandemics within the Healthcare 5.0 framework. The challenges include the need for collaborative data-driven solutions while safeguarding individual data privacy, decentralized decision-making to respond rapidly to dynamic situations, and the requirement for real-time surveillance to detect and contain outbreaks effectively. In essence, this paper explores how FL can provide innovative solutions to these challenges, thereby enhancing pandemic preparedness within the context of Healthcare 5.0. This paper explores the role of FL in building the next generation of healthcare systems, Healthcare 5.0, to improve pandemic preparedness. Healthcare 5.0, a term describing a technologically advanced, highly integrated, and patient-centred healthcare model, is expected to use technologies such as FL to move healthcare. In this context, this paper seeks to explore the potential of FL in advancing healthcare resilience, particularly concerning pandemic preparedness in the evolving framework of Healthcare 5.0. We propose to examine the implications of FL for pandemic preparedness within the framework of Healthcare 5.0, ultimately seeking to understand how we can strengthen resilience in our future healthcare systems.

1.1. Motivation and Contributions. The motivation behind this paper comes from the pressing need to enhance healthcare resilience in the face of pandemics and the potential of FL in Healthcare 5.0. The global COVID-19 pandemic has highlighted the vulnerabilities of healthcare systems worldwide and the critical importance of effective pandemic preparedness and response mechanisms. Traditional approaches to healthcare care, which are heavily based on centralized data processing, need more privacy, scalability, and agility. FL, a distributed machine-learning approach that enables model training on decentralized data sources while preserving privacy, has emerged as a promising solution. Using the power of FL in the context of Healthcare 5.0, which emphasizes the integration of advanced technologies, there is an opportunity to revolutionize healthcare systems and strengthen pandemic preparedness.

This paper aims to bridge the gap between the potential of FL in healthcare and its practical application in the context of pandemic preparedness. Although FL has succeeded in various domains, its specific implications for healthcare care and pandemic response require further exploration. The paper fills the gap by providing a comprehensive analysis of the role of FL in Healthcare 5.0, focusing on its potential benefits, challenges, and future applications. By examining case studies and hypothetical scenarios, the article addresses the gap in understanding how FL can improve pandemic preparedness within the framework of Healthcare 5.0.

This paper makes several significant contributions to the understanding and practical implementation of FL in the context of Healthcare 5.0 for pandemic preparedness. The key contributions of this paper are as follows:

(1) The paper provides a comprehensive analysis of FL in healthcare, specifically focusing on its implications for pandemic preparedness. We explore the FL and Healthcare 5.0 concepts, providing a solid foundation for understanding their integration.

(2) The paper presents real-world case studies in which FL has been successfully implemented in healthcare environments. The case studies highlight FL's practical applications and benefits for pandemic preparation, highlighting its potential to improve predictive models, data privacy, and decision-making processes.

(3) Building on the concept of Healthcare 5.0, the paper explores future applications of FL in the context of a highly advanced and technologically integrated health system. The paper speculates potential scenarios and outlines how FL can contribute to a more resilient healthcare future.

2. Related Work

The progression of healthcare has been marked by a series of evolutions, each characterized by key technological and methodological breakthroughs. Today, we are on the precipice of Healthcare 5.0, a new era of healthcare that aims to provide highly personalized and efficient care using digital technologies [20]. Healthcare 3.0 with the introduction of the digital age and electronic health records [21]. Healthcare 4.0 brought us to the current era of digital healthcare, integrating the Internet of Things (IoT) devices, big data, and artificial intelligence into healthcare systems [22]. Healthcare 5.0 represents the next step in this progression, aiming to leverage technologies like AI, IoT, blockchain, and FL to create an intelligent, interconnected healthcare system. The emphasis is on understanding individual health characteristics and adapting healthcare care accordingly, leading to precision medicine [23]. Table 1 provides a concise comparison of the key aspects of healthcare paradigms, from Healthcare 3.0 to Healthcare 5.0. The key to this transformation is the integration of technologies. For example, AI can facilitate predictive analytics and intelligent decision-making. IoT can contribute through real-time patient monitoring and data collection. Lastly, FL can offer an efficient method for preserving privacy to develop robust AI models using diverse data sources, as mentioned earlier [24]. The progression to Healthcare 5.0 thus offers an opportunity to redefine and enhance healthcare delivery, addressing present and future health challenges more effectively.

The combination of AI, IoT, blockchain, and FL within Healthcare 5.0 revolutionizes healthcare delivery [25, 26]. The technologies empower healthcare systems to provide patient-centric, data-driven care, ensure data security and integrity, and foster collaboration among healthcare stakeholders. Together, they exemplify the transformative potential of Healthcare 5.0 in improving healthcare outcomes and pandemic preparedness. Imagine a patient with a chronic medical condition who uses a wearable IoT device to monitor vital signs continuously. The data from the IoT device is securely transmitted to a blockchain-protected electronic health record (EHR). AI algorithms analyze this data in real time, detecting subtle changes in the patient's health. The AI system alerts the patient's healthcare team if a concerning trend is identified. FL continuously improves the AI model's accuracy, leveraging insights from multiple healthcare institutions without exposing individual patient data. In this scenario, combining AI, IoT, blockchain, and FL enhances patient care, ensures data security, and enables healthcare professionals to provide timely interventions.

FL transforms how we handle and learn from data in numerous fields, with healthcare significantly benefiting. It is a distributed, privacy-preserving machine-learning approach that allows a model to be trained on multiple devices or servers that hold local data samples without exchanging actual data [24, 27]. FL allows each participating device, or node, or hospital to download the shared global model, improve upon it by learning from local data, and then upload the model updates back to the global model. The process is iterative until the model performance is optimized [28].

The FL approach has three significant implications. FL helps to resolve the traditional tension between data privacy and utility in machine learning. By keeping data local and sharing only model updates, FL avoids the need to centralize sensitive data, thus safeguarding privacy [29, 30]. This is especially relevant in healthcare, where data privacy is

Table 1: Comparison of Healthcare 3.0, Healthcare 4.0, and Healthcare 5.0.

Aspect	Healthcare 3.0	Healthcare 4.0	Healthcare 5.0
Focus	Digitization of patient records	Data-driven healthcare	Holistic integration of technology
Technological emphasis	Digital health information systems	Data analytics, IoT, EHRs	DAI, IoT, telemedicine, advanced tech
Key features	Automation of administrative processes	Data-driven decision-making	Patient-centric care, real-time data
Patient-centric care	Developing	T-Enhanced	Central focus
Integration of technology	Initial stages	Increasing integration	Seamless integration

paramount due to regulations like the US's Health Insurance Portability and Accountability Act (HIPAA) or the EU's General Data Protection Regulation (GDPR). Second, FL can improve the efficiency and scalability of machine-learning models. With traditional centralized learning approaches, large-scale data collection, transmission, and storage could present significant challenges. By learning from data at its origin, FL minimizes the need for data movement and allows for more scalable solutions [31, 32]. Finally, FL has the potential to yield more robust and generalizable models. Since it learns from diverse data sources without aggregation, it can capture broader data variations and thus yield models that are more resilient to overfitting and better at handling real-world heterogeneity [33]. FL has significant potential for data-driven fields, particularly healthcare, by enabling more secure, efficient, and robust machine-learning models. Table 2 provides a clear and structured overview of the importance of discussing FL in pandemic preparedness and its relevance to addressing challenges posed during the COVID-19 pandemic.

Pandemic preparedness and response mechanisms have been scrutinised in recent years, particularly during the COVID-19 pandemic. Current systems have demonstrated several gaps and shortcomings, emphasizing the need for a more resilient healthcare infrastructure [34]. A key challenge in pandemic preparedness is the need for real time, global data sharing and surveillance systems. Existing disease surveillance and information-sharing mechanisms must be more cohesive and provide timely and complete data, hampering the ability to identify and respond quickly to emerging threats [35]. In addition, varying standards and protocols for data sharing across countries and regions further complicate matters [36]. Another problem is that healthcare systems often need to be equipped to handle the demand for healthcare services during a pandemic. Many need more resources or flexibility to scale up operations in response to a sudden increase in patient volume [9]. There is also the issue of resource allocation. Determining the most effective use of limited resources—such as personnel, hospital beds, and medical supplies—remains challenging. These decisions must often be made quickly under conditions of extreme uncertainty [37]. Finally, current response mechanisms often need to consider a pandemic's socio-economic and psychological impacts adequately. The effects of a pandemic are not limited to direct health impacts but extend to economic disruption, mental health issues, and the exacerbation of social inequities [38].

3. Federated Learning

FL has increasingly found applications in the healthcare sector due to its ability to leverage dispersed datasets for learning while ensuring data privacy. Many healthcare applications already exist, with several more under exploration. One of the most promising applications is in medical imaging, where FL can facilitate the development of more accurate and generalizable diagnostic models. By leveraging data from different healthcare facilities, FL can help build robust AI models trained on diverse patient populations and imaging technologies, improving their applicability across different settings [39]. For instance, applying FL in brain tumour segmentation has shown significant promise [40].

Another application is predictive modelling for patient outcomes. In traditional settings, developing these models often involves centralizing data from different healthcare providers, which can be cumbersome and fraught with privacy concerns. FL provides an alternative where predictive models can be built using data from different sites without data ever leaving its original location [41]. FL is also being explored for use in wearable and IoT devices. The devices generate massive amounts of health data that can be used for personalized health monitoring and intervention. However, transmitting this data to a centralized location for processing can be inefficient and privacy invasive. FL provides a solution by allowing the data to be processed locally on the device, with only the learning outcomes transmitted to a central model [42]. Moreover, FL can facilitate the integration of multiomics data (genomic, proteomic, metabolomic, etc.) from diverse sources in a privacy-preserving manner, enabling the development of more comprehensive and precise disease risk prediction and treatment response models [43].

With the rapid advancements in computer software and hardware technologies, an ever-increasing amount of healthcare data is becoming available from various sources, including patients, healthcare organizations, pharmaceutical companies, and insurance firms [44]. The abundance of data presents an invaluable opportunity for data science technologies to extract insights and elevate the quality of healthcare services. However, due to strict privacy laws and data ownership considerations, acquiring massive, diverse, and centrally stored healthcare datasets faces significant challenges. Conversely, AI models demand a growing volume of healthcare data to make more informed decisions. In this context, FL emerges as a promising solution to address this issue.

3.1. Privacy. One of the remarkable features of FL is its ability to train models without compromising healthcare data privacy. FL holds tremendous potential for connecting diverse healthcare data sources while ensuring data privacy, using a central server to train a standard global model while keeping all sensitive data localized within the respective institutions [45]. Consequently, FL empowers healthcare organizations to engage in collaborative training without disclosing their data to external parties. The groundbreaking approach opens up new possibilities for industry and research, greatly enhancing healthcare worldwide. FL's positive impact extends to all stakeholders and the entire treatment cycle, providing clinicians with improved diagnostic tools, including enhanced medical image analysis. It fosters collaborative and expedited drug discovery, enables precision medicine by facilitating the identification of similar patients, and ultimately reduces costs and time-to-market for pharmaceutical companies [46].

Table 2: Importance of FL in pandemic preparedness and relevance to COVID-19.

Aspect	Explanation
Data privacy concerns	FL addresses data privacy concerns, crucial in healthcare where patient data are sensitive and must be protected
Decentralized decision-making	Pandemics require decentralized decision-making. FL's collaborative model training aligns with this need
Real-time surveillance	Timely data analysis and surveillance are vital. FL enables real-time model updates while protecting privacy
Relevance to COVID-19	Contact tracing: protects personal data while aiding in tracking potential exposure Drug discovery: accelerates drug discovery by analyzing patient data while preserving privacy Resource allocation: optimizes resource allocation in overwhelmed healthcare systems while ensuring data privacy

3.2. Reduced Computational Cost and Power Consumption. As the accuracy of AI models improves with increased data, training a model with all healthcare data centralized in one location becomes time-consuming and resource-intensive [47]. However, FL eliminates the need to store data in a specific location. Instead, a global model is trained based on parameters shared by local models. Unlike conventional models, FL does not require access to personal data from the local models, leading to decreased computational resource costs and lower power usage [48].

3.3. Personalization. One of the key advantages of FL is its ability to enable personalized model training. With FL, local models can be trained on the users' devices or local networks. At the same time, the cloud server aggregates the distributed datasets from various local nodes for training the global model [49]. However, relying solely on the shared model may not yield optimal results for a specific user, as it accounts only for the common traits shared by all health users. Each user incorporates the learned global model with unique health data to address this, facilitating personalized health monitoring. Local devices obtain the global model from the cloud and train their unique model to capture tailored services for each user. Moreover, using the global model from the cloud, a balanced dataset is created for every device, reducing the disparity between individualized and global models [50].

4. Federated Learning in Healthcare 5.0

FL models are implemented using PyTorch and pretrained on ImageNet and Scratch, with different GPU configurations [51, 52]. While the works highlight the trade-off between model accuracy and privacy preservation, they often overlook communication efficiency [51, 52]. The authors of [51] provided visual explanations and highlighted critical regions on patients' CXR images, generating maps for classification. In contrast, [52] explored integrating decentralized blockchain technology in DL models. The authors of [52] proposed a theoretical framework for differential privacy in COVID-19 CT imaging data using FL. Furthermore, the authors of [52] presented technical details of their DL model implementation, achieving enhanced sensitivity for COVID-19 detection from lung CT scans. On the other hand [53] proposed a novel dynamic fusion-based FL approach, focusing on communication efficiency and improved model performance while ensuring data privacy for COVID-19 identification. FL has been successfully implemented in various healthcare settings, showcasing its potential for transforming health service delivery and research.

In the context of Healthcare 5.0's integration of wearable and IoT devices, FL emerges as a critical enabler of enhanced data analysis while preserving data privacy. FL seamlessly fits into this framework by allowing these devices to improve their machine-learning models collaboratively without compromising sensitive health data. Each device, such as a wearable health tracker or IoT sensor, locally trains its model using the data it collects. For example, a smartwatch can analyze heart rate data locally to predict irregular heartbeats. The locally trained models then send their updates to a central server, ensuring that only model updates, not raw data, are transmitted. The server aggregates these updates to create a global model, which is then shared with individual devices. The iterative process allows each device to improve its model based on insights from a broader dataset, enabling real-time health data analysis.

Real life examples illustrate the transformative potential of FL in healthcare 5.0 from different hospitals, as shown in Figure 1: (i) *Predictive Healthcare Models*: In a collaborative research effort, hospitals across regions utilize FL to train predictive models for diseases such as diabetes. The models are trained on diverse patient populations, resulting in more accurate predictions and personalized treatment plans. (ii) *Privacy-Preserving Medical Imaging*: FL is employed in medical imaging to develop AI algorithms for diagnosing conditions like cancer. Multiple healthcare institutions contribute to model training without sharing patient-specific data, ensuring privacy while advancing diagnostics. And (iii) *Global Health Data Research*: FL enables global health data research collaborations. Researchers can analyze data from various sources worldwide without data leaving individual institutions, leading to breakthroughs in understanding and addressing diseases.

Concrete scenarios exemplify how FL upholds data privacy while delivering substantial benefits. For instance, in remote patient monitoring, a wearable device can continuously analyze health data and detect anomalies, providing

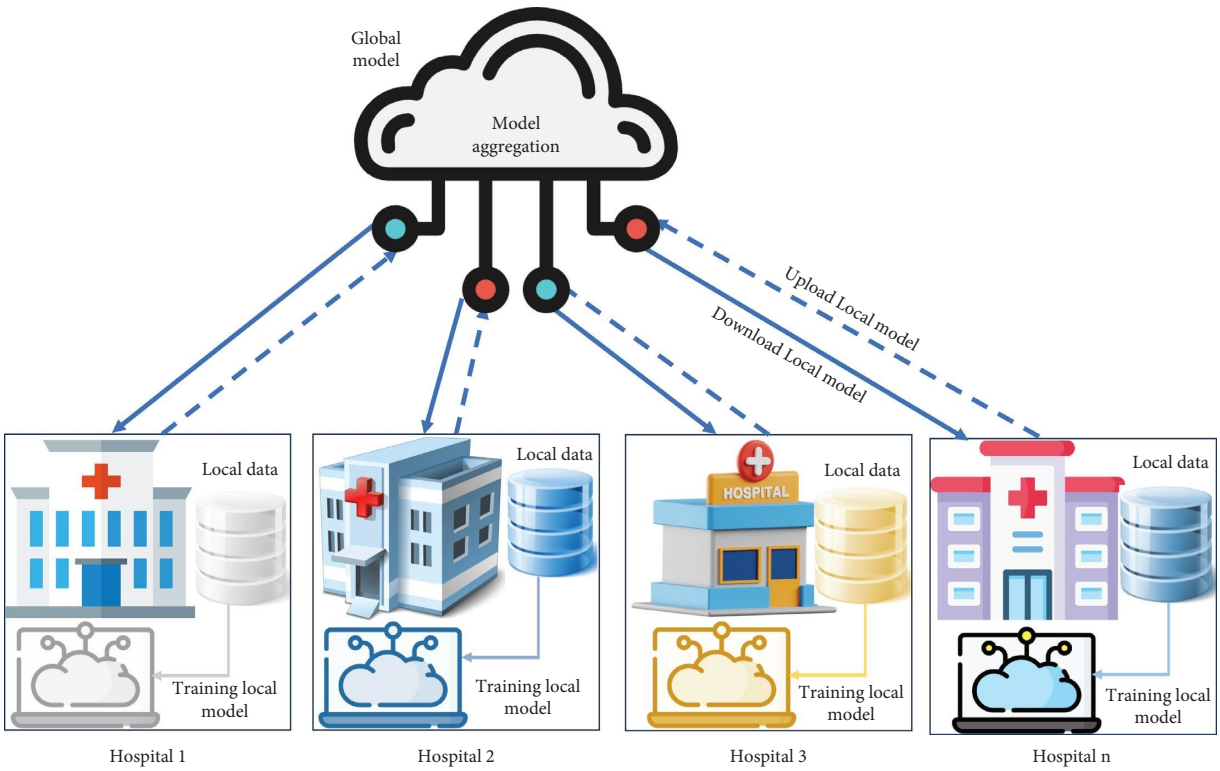

Figure 1: FL for Healthcare 5.0.

alerts to healthcare providers without disclosing the patient's detailed health information. In a broader context, IoT sensors in a city can collect environmental and population movement data. FL facilitates the collaborative analysis of this data to identify public health trends, such as early indications of disease outbreaks, without revealing individual identities or personal information. In addition, wearable fitness trackers employ FL in personalized fitness coaching to offer personalized recommendations based on individual health data, ensuring privacy while continuously enhancing the accuracy of fitness advice. Integrating FL with wearable and IoT devices, Healthcare 5.0 optimizes real-time health data analysis while maintaining rigorous data privacy standards, shaping a more resilient and patient-centric healthcare future.

Medical Imaging. The authors of [41] applied FL to create a multiinstitutional model for predicting cardiovascular events based on intravascular ultrasound (IVUS) images. Despite the geographical and institutional differences between the different datasets, FL enabled the creation of a robust predictive model without sharing raw patient data between institutions, ensuring data privacy. Case Study 2: *Predictive Modeling*. A collaborative study involving several hospitals in the U.S. utilized FL to develop models predicting patient mortality, readmission, and length of stay. The federated model performed comparably to traditional centralized models, with the added advantage of preserving data privacy [39].

Genomic Research. In a groundbreaking study, the Personal Genome Project used FL to develop models predicting disease susceptibility based on genomic data from several research institutions. The study demonstrated that FL could enable collaborative research while respecting the privacy and confidentiality of individual genomic datasets [24].

Wearable and IoT. Devices Google applied FL to improve the predictive text feature on their Android keyboard, Gboard. The same concept can be extended to healthcare wearables, where data privacy is crucial. Personal health data can be processed locally, with only the learning outcomes transmitted to a central model [54].

The case studies underline the potential of FL in facilitating multiinstitutional collaborations and patient-centric care while ensuring data privacy. The evolution towards Healthcare 5.0 stands to benefit immensely from these capabilities, particularly in enhancing pandemic preparedness and response.

Table 3 presents various healthcare domains, where FL has been successfully implemented and the benefits and challenges associated with each application. This table provides an overview of the diverse areas where FL is used to leverage collective knowledge from distributed datasets while addressing potential challenges.

4.1. The Role of FL in Pandemic Preparedness. FL is a decentralized machine-learning platform for the Internet of Things that allows several devices to cooperatively develop machine-learning models without transferring any actual

Table 3: Current applications of FL in healthcare.

Healthcare domain	Application of federated learning	Benefits	Challenges
Medical imaging	Collaborative analysis of radiological images across multiple institutions	Improved accuracy in diagnosis	Data heterogeneity, privacy concerns
Clinical research	Collaborative analysis of patient data for clinical trials	Enhanced generalizability of results	Data standardization, trust among institutions
Disease prediction	Aggregated analysis of patient health data for disease prediction	Improved early detection of diseases	Data privacy, bias in distributed data
Precision medicine	Analysis of genomic and patient data for personalized treatment	Tailored treatment options	Data interoperability, ethical considerations
Drug discovery	Collaborative analysis of molecular data for drug discovery	Accelerated identification of potential drug candidates	Data security, intellectual property concerns

data. FL's architecture is seen in Figure 2, including data collection, FL, evaluation and monitoring of healthcare layers. Data collection is from heterogeneous devices, while FL processes data locally and sends updated models to evaluate patients' healthcare. The doctor, nurse and patient or patient's family can monitor the patient's health based on collected data form different devices. Preventing the leak of patient information improves the intelligent healthcare system. In the healthcare system depicted in Figure 2, which is based on FL, embedded sensors collect medical data from healthcare providers, multiple edge devices work together to develop FL algorithms, and machine-learning techniques evaluate the patient's well-being and, if necessary, seek out immediate help in the cloud. Due to the extraordinary guarantee it offers for analyzing fragmented sensitive material, FL is a paradigm that has lately gained popularity. It allows training a common global model on a centralized server while keeping data in the appropriate organizations instead of integrating data from many sources or depending on the conventional find-then-replicate technique. Below, we discuss the advantages of adopting FL over conventional methods in the healthcare domain. FL can significantly influence pandemic preparedness and response due to its data-centric and privacy-preserving attributes.

4.1.1. Enhanced Surveillance and Early Detection. FL can help develop robust and generalizable models for disease surveillance, facilitating early detection of emerging threats across different geographical regions and patient demographics. In practice, this could mean creating algorithms that analyze medical images, electronic health records, or genomic data from disparate locations to predict the emergence of disease hotspots [41].

4.1.2. Real-Time Decision-Making. During pandemics, healthcare systems need to make quick and informed decisions on resource allocation. FL can enable the development of predictive models that forecast the demand for healthcare resources such as hospital beds, ventilators, and medical personnel in real-time, helping healthcare systems better prepare for and manage surges in patient volume [39].

4.1.3. Advancing Therapeutic Research. FL can help accelerate the development of treatments and vaccines during a pandemic. It can do so by allowing researchers to leverage diverse datasets from multiple institutions for drug discovery and clinical trials without sharing raw patient data, thus overcoming privacy-related and regulatory constraints [55].

4.1.4. Improving Public Health Interventions. FL can support the creation of models that predict the spread of diseases and the impact of various public health interventions, informing strategies for social distancing, lockdowns, and reopening [43].

4.1.5. Patient Monitoring and Care. With the rise of telemedicine and remote patient monitoring during pandemics, FL can enable the development of personalized care models that consider individual patient data from wearables and IoT devices without compromising privacy [54]. In essence, FL provides a flexible and privacy-preserving framework for harnessing the power of collective data in healthcare, as shown in Figure 2. Its use in pandemic preparedness and response could be a game-changer in managing future health crises.

Table 4 illustrates the strengths and limitations of traditional pandemic preparedness mechanisms are presented. Each mechanism is listed along with its respective strengths and potential drawbacks. The comparison can help readers understand the existing methods used for pandemic preparedness and the challenges that need to be addressed for more effective preparedness strategies.

Table 5 provides a clear and structured comparison between FL and traditional pandemic preparedness methods, highlighting the advantages of FL in various scenarios and specifying the situations of FL excels.

4.2. Benefits of FL in Pandemic Preparedness. In the context of pandemic preparedness, FL can provide numerous benefits that address the key challenges of data privacy, decentralized decision-making, and overall efficiency.

4.2.1. Privacy Protection. Traditional methods of data consolidation for healthcare research often pose significant privacy risks. However, by design, FL allows models to be trained on data across various locations without moving or sharing raw data, thereby ensuring privacy. This can facilitate broader and more cooperative research efforts during pandemics while complying with data protection regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) [56, 57].

4.2.2. Decentralized Decision-Making. FL enables decentralized decision-making by allowing local model training and insights. This can be invaluable in pandemic situations, where regional disease progression and resource availability disparities require tailored responses. By providing locally relevant insights, FL supports decision-making at the point of care, which can lead to more effective resource allocation and patient management [44, 58].

4.2.3. Scalability and Efficiency. FL leverages distributed data sources, allowing for scalable and efficient model training. This is especially important in a pandemic, where time is of the essence and rapid insights are needed to inform public health interventions. In addition, FL reduces the computational load on any system by distributing the learning process across multiple nodes, making it a sustainable and scalable approach for large-scale health data analysis [59, 60].

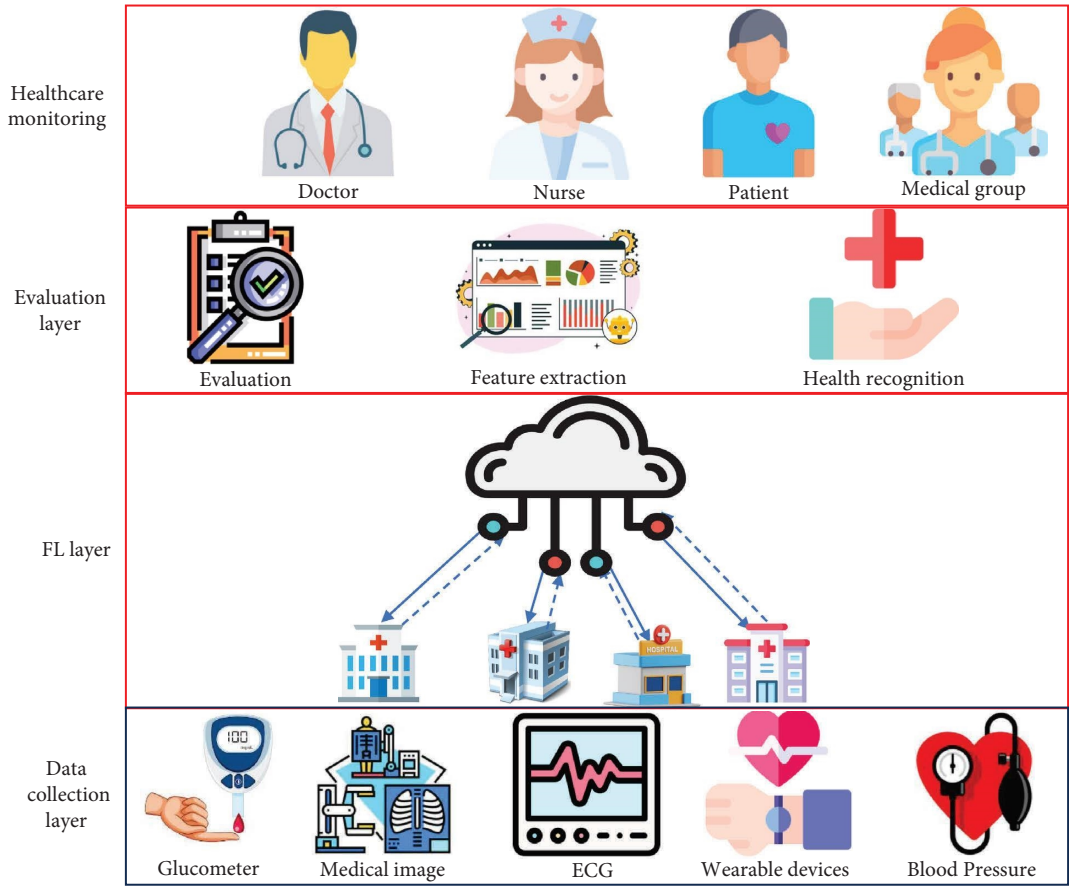

Figure 2: FL-based healthcare monitoring for Healthcare 5.0.

Table 4: Existing pandemic preparedness mechanisms.

Mechanism	Strengths	Limitations
Surveillance systems	Early detection of outbreaks	Limited coverage and timeliness
Vaccination programs	Effective in reducing disease spread	Limited availability and production capacity
Healthcare infrastructure	Adequate treatment facilities	Overwhelmed during large-scale pandemics
Quarantine measures	Containment of infected individuals	Compliance challenges and economic impact
Contact tracing	Identification of exposed individuals	Relies on accurate and timely reporting
Stockpiling medical supplies	Quick response to outbreaks	Limited shelf life and availability of specific items

4.2.4. Enhanced Generalizability. FL's ability to incorporate diverse and decentralized data can lead to models with greater generalizability. During a pandemic, predictive models and decision-making tools can better account for disease presentation and progression variability, treatment responses, and patient outcomes across different populations and geographical regions [61].

4.2.5. Facilitating Collaborative Research. Pandemic responses require collaborative efforts. FL can facilitate multiinstitutional, interdisciplinary research without data sharing, enabling a collective approach to problem-solving, which is critical in pandemic preparedness and response [62].

Table 6 presents an overview of the potential benefits FL can offer in the context of pandemic preparedness. Each benefit is described concisely, showcasing how FL addresses key challenges and effectively provides advantages in responding to pandemics.

Table 7 provides a structured overview of the regulatory and ethical considerations in FL and suggests corresponding remedies and best practices for addressing each concern when implementing FL systems in healthcare and other domains.

4.3. Challenges and Limitations FL in Pandemic Preparedness. Despite the potential benefits of FL in pandemic preparedness, there are several challenges and limitations.

4.3.1. Data Heterogeneity. FL assumes that data across different locations are identically and independently distributed, which may not be accurate in healthcare settings [63]. Hospitals, for example, may have different patient

Table 5: Comparison between FL and traditional pandemic preparedness methods.

Advantages	Strengths	Limitations
Data privacy protection	FL ensures privacy by not sharing raw patient data Only aggregated model updates are exchanged among institutions	Conventional methods often require sharing sensitive healthcare data Patient data privacy concerns can pose ethical and legal challenges
Decentralized	FL empowers local decision-making, adapting to localized outbreaks	Traditional centralized systems may lead to slow and less adaptive decisions
Decision-making	Institutions or regions can make data-driven decisions based on local insights	Delays in data processing can hinder critical decision-making during a pandemic
Real-time surveillance	FL allows real-time insights as models are updated collaboratively Institutions can continuously update models, providing up-to-the-minute data	Data aggregation and analysis in traditional methods can be time-consuming Delays in data processing can hinder critical decision-making during a pandemic
Resource-constrained environments	FL accommodates resource-constrained environments Enables collaboration among institutions with varying resources	Traditional methods may require substantial infrastructure and data centres Institutions with limited resources may face barriers to participation
Research collaboration	FL fosters global research collaboration by allowing data analysis without data sharing Researchers worldwide can collaborate on diverse datasets without compromising privacy	Traditional research often involves data silos and barriers to data sharing Data sharing limitations can hinder international research efforts

Table 6: Summaries the potential benefits of FL in pandemic preparedness.

Benefits	Description
Privacy preservation	Local model training preserve data privacy by keeping raw data at individual institutions
Enhanced data security	Encrypted communication and decentralized model training reduce data security risks
Improved data utilization	Aggregating knowledge from multiple sources enhances insights for more effective responses
Decentralized decision-making	Collaborative model training enable local decision-making with the benefit of shared knowledge
Real-time surveillance	Aggregated data from various sources enable early detection and monitoring of outbreaks
Improved predictive models	Larger and diverse datasets result in more accurate and robust predictive models
Resource optimization	Efficient allocation of resources based on aggregated insights and predictions
Rapid response and adaptability	Quick model updates enable adaptive responses to changing pandemic conditions

populations, treatment protocols, and health record systems, leading to significant heterogeneity in the data. This can impact the performance and generalizability of FL models, requiring careful design and validation of models [64].

4.3.2. Computational and Communication Overheads. FL involves iterative communication between the central server and local nodes, which can incur considerable computational and communication overheads. This can be challenging, particularly in resource-constrained settings or during a pandemic when systems are strained [65].

4.3.3. Data Security and Trust. Although FL does not involve sharing raw data, transmitting model parameters could potentially expose sensitive information if intercepted. This necessitates robust cybersecurity measures, which may require significant investment [66]. Trust among institutions participating in FL is also crucial, as any breach can undermine the system [67].

4.3.4. Regulatory and Ethical Issues. While FL can somewhat mitigate privacy concerns, there are still unresolved regulatory and ethical issues. These include ensuring patient consent for data use, determining liability in case of inaccurate predictions, and ensuring fair benefit sharing among participating institutions [68].

4.3.5. Interoperability and Standardization. The need for more standardization in healthcare data and systems can complicate the implementation of FL. Interoperability issues need to be addressed for effective data integration and model deployment across different systems [69].

5. FL in Healthcare 5.0: A Resilient Future

Healthcare 5.0, a vision of the future healthcare system, seeks to create an environment that is personalized, preventive, predictive, participatory, and purpose-driven [70]. FL can potentially significantly enhance healthcare in practical ways. For instance, in busy urban hospitals, FL can optimize resource allocation and reduce patient wait times through predictive models. Collaborative data analysis with FL can improve disease detection and diagnosis, helping doctors detect diseases earlier and initiate timely treatments. In addition, FL facilitates the creation of highly personalized treatment plans based on genetic markers, improving patient outcomes. In remote areas, FL-enabled telemedicine ensures access to specialized care, while in pharmaceutical research, FL accelerates drug discovery, potentially lowering medication costs. These examples demonstrate how FL can make healthcare more efficient, effective, and patient-centric, benefiting providers and patients. In this context, FL can play a pivotal role in materializing this vision.

5.1. Personalized Care. FL enables the creation of sophisticated machine-learning models that can utilize patient data across different locations to provide highly personalized care. By keeping data localized, FL allows for developing personalized models that account for individual variations without breaching privacy, a critical component of Healthcare 5.0 [71]. FL is reshaping personalized care within the Healthcare 5.0 framework, offering tailored treatments and healthcare services while safeguarding patient privacy. By collaboratively analyzing diverse datasets without sharing individual patient data, FL opens the door to highly customized care. For example, a patient diagnosed with diabetes benefits from a treatment plan refined through FL, incorporating insights from similar cases to optimize their care. In addition, FL empowers predictive health monitoring through wearable devices, issuing early warnings for potential health issues based on real-time data analysis while preserving user privacy. Medication personalization becomes more precise, considering genetic markers and the responses of similar patients to adjust dosages effectively. Lastly, mobile health apps leverage FL to offer tailored wellness advice, ensuring users receive recommendations aligned with their unique attributes and preferences. The examples showcase how FL blends customization and data privacy, exemplifying the future of patient-centric Healthcare 5.0.

5.2. Preventive and Predictive Health. FL can help build robust prediction models for disease onset and progression, aiding preventive care. This can help anticipate health issues

Table 7: Regulatory and ethical considerations in FL and remedies.

Considerations	Concerns	Remedies and best practices
Data privacy and compliance	Legal consequences of mishandling data	Implement strict access controls, encrypt data, data anonymization, audit trails
Security threats	Vulnerability to security breaches (e.g., model inversion, poisoning attacks)	Robust encryption, secure aggregation, regular threat assessments
Bias and fairness	Propagation of biases leading to unfair outcomes	Diverse data sources, fairness assessments, bias-awareness training
Informed consent	Ensuring informed consent from FL participants	Clear consent agreements., transparent communication
Transparency and accountability	Challenges in establishing accountability and transparency	Consortium governance, auditing mechanisms, transparency reports
Data quality and heterogeneity	Varied data quality and format from multiple sources	Data preprocessing, quality control
Education and training	Adequate training in data ethics and FL principles for project participants	Education programs, ethical guidelines

before they manifest clinically, enabling early interventions. Moreover, FL's ability to learn from diverse, real-world datasets can enhance the accuracy and generalizability of these predictive models, a central pillar of Healthcare 5.0 [72].

5.3. Participatory Health. Healthcare 5.0 envisions a system where patients actively participate in their health management. FL, given its decentralized nature, aligns well with this vision. It can allow patients to contribute their data to improve healthcare models while maintaining control over their data, fostering patient trust and participation [73].

5.4. Purpose-Driven Care. The ultimate goal of Healthcare 5.0 is to improve patient outcomes and healthcare delivery. FL can facilitate this by improving the quality and efficiency of care, whether it is through optimizing hospital operations, enhancing disease detection and diagnosis, or personalizing treatment strategies [74].

By integrating FL into Healthcare 5.0, we can ensure that the next generation of healthcare is technologically advanced and resilient to health crises such as pandemics. This approach can set the foundation for a health system that respects patient privacy, harnesses the power of collective data, and responds effectively to emerging health threats.

FL has made significant strides in real-world healthcare applications within the Healthcare 5.0 framework. Google's FL of Cohorts (FLoC) showcases the potential of FL for cohort-based patient data analysis, preserving privacy while facilitating research. Secure Multiinstitutional FL for Brain Tumor Segmentation exemplifies how FL can be employed for collaborative medical imaging tasks across institutions. The Stanford COVID-19 Chest X-ray Dataset demonstrates FL's role in pandemic response by enabling collaborative disease detection across healthcare providers. Apple's use of differential privacy in health research underscores FL's contribution to population health insights. These projects illustrate FL's power to advance healthcare while maintaining stringent data privacy, underscoring its transformative potential in Healthcare 5.0.

6. Case Studies

The following case studies will glimpse how FL within the framework of Healthcare 5.0 could significantly enhance pandemic preparedness.

6.1. Predictive Modeling for Pandemic Preparedness. A predictive modelling study to forecast flu trends across different regions can serve as a model case. Healthcare systems can train local prediction models using FL without sharing raw data, preserving patient privacy. The results from individual local models can then be aggregated to create a global model that predicts flu trends more accurately. This federated predictive model could be integral to pandemic preparedness, enabling proactive responses to potential flu outbreaks [75].

6.2. International Collaboration on Vaccine Development. Another case worth mentioning is the global effort to develop vaccines during a pandemic. Historically, such efforts have been hampered by barriers to data sharing due to privacy concerns. FL could transform this process by allowing for collective learning without sharing individual patient data. This would facilitate faster vaccine development and deployment, significantly boosting global pandemic preparedness [76].

6.3. Diagnostic Imaging for Pandemic Response. During the COVID-19 pandemic, diagnostic imaging was crucial in disease diagnosis and management. FL could facilitate the development of AI models that can interpret diagnostic images from diverse populations without sharing the actual images, ensuring privacy. These models can enhance pandemic responses by speeding up diagnoses and improving treatment outcomes [77, 78].

6.4. Global Infectious Disease Surveillance System. Given the increasing interconnectedness of our world, a global infectious disease surveillance system could be critical for future pandemic preparedness. In this scenario, FL could enable the creation of a global model that learns from diverse, geographically distributed data from health systems worldwide without compromising patient privacy. It could help track infectious disease patterns and trigger early warning signals, potentially preventing the spread of future pandemics [79].

6.5. Personalized Vaccine Development. As we move towards more personalized healthcare, developing personalized vaccines could become a reality. FL could play a crucial role by facilitating the learning of models from diverse genetic, environmental, and lifestyle data, enabling the development of personalized vaccines without sharing sensitive individual data. This advancement could drastically enhance the speed and effectiveness of vaccination campaigns during a pandemic [80].

6.6. AI-Assisted Remote Patient Monitoring. The recent pandemic has significantly increased remote patient monitoring systems. In a future scenario, FL could enable the creation of AI models that learn from vast amounts of data generated by these systems across the globe. These models could predict disease progression and trigger alerts, enabling timely interventions and reducing the burden on healthcare systems during pandemics [81].

6.7. Privacy-Preserving Contact Tracing. As seen in the COVID-19 pandemic, contact tracing is a crucial strategy in controlling the spread of infectious diseases. A FL-based contact tracing app could be developed to learn from mobile data without sharing raw data. This would ensure privacy-preserving contact tracing and could contribute to more efficient control of future pandemics [82].

7. Challenges, Opportunities, and Future Directions

7.1. Overcoming Data Shortage. One of the inherent advantages of FL is its ability to analyze multisite data without pooling, which offers a partial solution to the data shortage problem. However, achieving better model training still relies on addressing the challenges related to data quality, bias, and scalability [83]. Within the healthcare system, various general problems, such as the scarcity of quality data, data cluttering, and inefficiency, can hinder the generalization of sample results. Moreover, specific data-related challenges arise in the context of the COVID-19 situation. For example, only lab-confirmed COVID-19 infections are confirmed, which poses limitations in countries with limited diagnostic capacity and a shortage of testing kits, especially in low-income nations. Researchers face the challenge of obtaining access to biased data with similar demographics, device brands, and environmental factors to produce generalizable results. Addressing the data-related complexities becomes a crucial aspect of conducting effective healthcare research.

7.2. Challenges of Data Heterogeneity. Collaborating across multiple institutions in the context of COVID-19 data poses data standardization problems. The heterogeneous nature of the data requires preprocessing steps such as data scaling, resizing of images, and model augmentation to ensure compatibility for FL analysis [24, 26]. Traditional FL frameworks are designed for balanced data, where each institution contributes an equal amount of data, which may not be feasible in the COVID-19 scenario. This inherent data imbalance can lead to issues with the FL algorithm, FedAvg, particularly under extremely skewed data distributions [84]. Studies have shown that the FL model experiences accuracy degradation due to data imbalance [85, 86]. While some novel FL frameworks have been developed to address imbalanced data [87], there is a need for further exploration and research in the field to tackle data heterogeneity effectively.

7.3. Communication Overhead. The FL model training process involves synchronization of distributed data, requiring uplink (user to server) and downlink (server to user) communication [88]. The number of users participating in training and the overhead associated with computation and communication directly impact model performance [86]. Surprisingly, communication efficiency has received limited attention in COVID-19 research studies, and most studies do not consider it [51, 52]. However, in other research areas, significant communication overhead has been reported [86, 89], prompting efforts to reduce communication overhead while maintaining data privacy [90].

7.4. Privacy Concerns in FL. Although FL offers promising secure collaboration, it does not guarantee privacy. In healthcare data collection, there is an inherent risk of privacy leakage. The FL training process is based on shared information and is vulnerable to potential data leakage through model gradients, reverse engineering of model updates, and model manipulation [91, 92]. Multiple studies have reported data leakage issues, with patient information potentially being back-traced from shared gradients [93]. Efforts to address this problem have been made, as evidenced in [52], but more secure FL frameworks are encouraged for sensitive research areas like COVID-19. Further study and untapped countermeasures are needed to ensure robust data privacy in FL, making it an active and critical research area [84].

7.5. Collaboration Trust Concerns. FL systems collaborate with decentralized parties, which can be based on trusted or untrusted relationships. Trusted collaborations involve enforceable agreements and set principles, providing a standard collaboration approach. On the contrary, untrusted collaborations offer a broader spectrum of information but have inherent risks, including privacy concerns, integrity execution, model encryption, and susceptibility to malicious attacks [94]. Solid and trusted collaborations are crucial in healthcare, especially during COVID-19. Each party involved prioritizes their patients' privacy and seeks to safeguard information from business rivals or the general public to prevent panic. Implementing the FL collaborative mechanism requires either a trustworthy third party as the overall controller or stricter mutually agreed protocols, which may involve additional costs and efforts [84]. Addressing these trust concerns becomes essential to ensuring the success and security of FL collaborations in sensitive research areas like healthcare.

7.6. Considerations of Reliability. The reliability of a user in FL is contingent on their availability to participate in a round of computation for model training. Distributed learning in the data center and FL across silos typically exhibit more excellent reliability with minimal dropouts. However, in cross-device FL, the output may be less reliable, with dropout rates potentially exceeding 5% in a computation round [84]. Healthcare collaborators with robust computational resources and advanced systems for improved model training are generally considered more reliable [95, 96].

7.7. Traceability and Accountability in FL. Ensured traceability of resources is a crucial requirement in FL systems, encompassing data access history, training structure, selection of hyperparameters, and modifications [94]. Once an optimal model is achieved, traceability and accountability are vital in determining participants' contribution levels, enabling relevant compensation, and establishing a revenue model [97]. These aspects also aid researchers in explaining and interpreting a global model by investigating the data sources from which the models are trained. Each user can access its raw data within intranode security measures. Although issues related to the traceability of FL training data

Table 8: Challenges and mitigation strategies for implementing FL in pandemic preparedness.

Challenges	Mitigation strategies
Data privacy	Employ encryption and secure communication protocols for data transmission Utilize differential privacy techniques to add noise to individual data
Data heterogeneity	Standardize data formats and feature representations across institutions Use transfer learning and data augmentation to handle variations in data quality
Data interoperability	Adopt standardized data schemas and APIs for seamless data exchange Implement data mapping and transformation techniques for interoperability
Trust and collaboration	Establish data sharing agreements and governance frameworks Utilize FL consortiums to build trust and promote collaboration
Model performance degradation	Employ advanced model aggregation methods to mitigate performance degradation Implement robustness checks to ensure model quality and consistency
Communication overhead	Use efficient communication protocols to reduce overhead Implement asynchronous communication for distributed model updates
Scalability and resource allocation	Optimize computation and memory resources for efficient model training Employ edge computing to reduce the burden on central servers
Regulatory and ethical compliance	Ensure compliance with data protection and ethical guidelines Obtain necessary approvals and permissions for cross-institutional data sharing

records have been addressed in some research studies [98], more attention is needed to improve transparency and accountability in FL systems.

Table 8 presents the key challenges of implementing FL in pandemic preparedness and provides potential mitigation strategies to address each challenge effectively.

8. Conclusion

We have embarked on a journey to explore the transformative potential of FL in the context of Healthcare 5.0, emphasizing its critical role in enhancing healthcare resilience, especially in the face of pandemics. By harnessing the power of FL, we can predict, prepare for, and respond to pandemics in ways that were once unimaginable. This is not just about technological innovation; it is about safeguarding lives, ensuring timely healthcare delivery, and, ultimately, making our healthcare systems more robust, adaptable, and better equipped to address global health challenges. The future brims with potential as we stand at the intersection of cutting-edge research and real-world applications. Ongoing research endeavours and implementing FL in real-life healthcare projects will continue to shape how we utilize this groundbreaking technology. With each project, breakthrough, and innovation, we have moved closer to a healthcare landscape that is resilient, highly responsive, and capable of ensuring the well-being of individuals and populations alike. The profound impact that FL can have on healthcare includes more than just a technology; it is a catalyst for change, a powerful force that can revolutionize healthcare and empower us to face pandemics and health crises with unwavering strength. The potential is limitless, and as we embrace FL in Healthcare 5.0, we take a bold step toward a future where healthcare is not just a system but a lifeline, ready and resilient in the face of adversity.

Data Availability

The data supporting the findings of this study are available within this article.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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