FEDERATED INTELLIGENT SYSTEM FOR HEALTHCARE

A Practical Guide

Edited By
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Preface

This book explores the integration of federated learning and intelligent systems within the healthcare domain, providing an in-depth understanding of how these systems enhance healthcare practices. It details their principles, technologies, challenges, and opportunities, with a particular focus on secure, privacy-preserving medical data sharing. Additionally, it examines the role of artificial intelligence and machine learning in healthcare, along with the ethical considerations surrounding these advanced technologies.

With an emphasis on practical implementation and real-world use cases, this book equips healthcare professionals, researchers, and technology experts with the knowledge needed to navigate the complexities of federated intelligent systems and harness their potential to transform patient care and drive medical advancements.

This volume serves as a platform for researchers to present their ideas on unlocking the future of healthcare with cutting-edge insights, transforming healthcare, embracing federated intelligence, and shaping the future. It features both novel technological advancements and conceptual, visionary scenarios.

The editors extend their deepest gratitude to the contributing authors for their invaluable expertise and dedication, which have significantly enriched this work. We also thank Martin Scrivener and the team at Scrivener Publishing for their continuous support throughout the book's preparation.

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Introduction to Federated Intelligent Systems in Healthcare

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Abstract

Federated learning is an extensive technique that helps organisations protect patients privacy. Training of deep learning model on federated healthcare data has been evaluated through this learning method. Evaluation and transfer of medical data have been justified potentially with the involvement of federated learning techniques. Decentralised training of the deep learning model has been ensured with the involvement of the federated learning technique. The acting of the hospital-to-client model has been ensured with the involvement of the FL technique. While conducting collaboration between different medical institutions secure preservation of patient information has been ensured with the implementation of this method. Enhancement of patient and institutional access to high-quality healthcare service has been ensured with better utilisation of federated learning techniques. Great promise for healthcare applications has been ensured due to the presence of the FL method. Improving the quality of data and reducing the risk of incorrect data annotation-related problems are solved successfully with the utilisation of federated learning technique. Data vulnerability and data breach-related problems are also solved successfully with better utilisation of this federated intelligent system. Instrumental and environmental noises are also solved potentially with better implications for federate intelligent systems. This study demonstrates the role of a federated intelligence system in ensuring the standardisation of medical datasets. Data partition-related aspects of the medical industry have been evaluated efficiently with the successful use of federated learning programs in healthcare. Conducting training on the collaborative machine learning model fl helps to create secure pool of information of multiple clients. The intelligence of the healthcare field has been emphasised with the successful implementation of federated learning. Security privacy, stability and reliability of the

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healthcare industry have been increased potentially with the involvement of federated learning techniques. The development of an entire healthcare management system has been confirmed successfully by evaluating different potential components of federated learning techniques. In addition, comprehensive changes in the operation of the medical field have been ensured with the involvement of federated learning and the internet of medical things that can. The growth and development of healthcare services have been ensured with the involvement of these technologies. Implementation of a federated intelligence system contributes to improving the ability to sense and transmit health updates successfully. Potential biomedical image analysis and security of information have been evaluated authentically due to the presence of IOMT or federated learning method. Distributed learning for the machine learning model of the medical industry has been highlighted due to the presence of federated learning in healthcare.

***Keywords*:** Federated learning, internet of medical things, medical data, machine learning, security privacy, healthcare services, medical dataset and deep learning

1.1 Introduction

Federated learning is used by healthcare federated intelligent systems to train models at the same time across different healthcare data sources, all the while keeping patient information safe. To find out what cooperative learning in medicine can do, where it came from, and what problems it has, we must examine it closely. It is called secondary study when we review and analyze books and research papers that have already been written. The results show that healthcare data can be used to learn useful things for shared smart systems without putting patients' privacy at risk. Still, there are many ways that data and privacy issues are still a problem. In conclusion, for federated learning to fully realize its promise of personalized patient care, it needs unity between different healthcare sectors, new technology, and strong data governance processes. Healthcare professionals can use Federated Intelligent Systems to make the most cutting-edge decisions based on data. These systems can maintain data privacy and accelerate joint model training across multiple separate data sources by using collaborative learning. Using this method, which keeps patient data safe and secure locally, helps to lower the privacy concerns that come with processing and storing data in one place. Wearable tech and digital health records have made the healthcare business generate more data. In response, more complex statistics and personalized care plans have been created. For example, in healthcare, shared intelligence systems can get useful information from patient data without revealing the patients' identities. Together, these technologies allow healthcare institutions to create more accurate diagnosis tools and prediction models. Treatment works better, and is of higher quality. Big data is used in healthcare to create shared intelligence systems that keep patient data safe. This piece examines group learning in healthcare by exploring its current state, problems, and potential future developments. Shared learning is a creative way to keep data private while using multiple data sources to train machine learning models. To get the most out of shared learning, our study aims to guide healthcare managers how to optimize data while ensuring and protecting patient privacy. To make shared learning more useful in healthcare, it's important to know how it can be used in real life. In studies and tests that have led to better patient tracking, sickness prediction, and individual treatment plans, federated learning has been useful. These cases show that strict privacy rules can be followed while shared learning is used to handle complicated and varied healthcare data.

Cancer study centers and hospitals use cooperative learning to make it easier to diagnose cancer. These companies could work together to make models that are more accurate and reliable by sharing changes to models instead of raw patient data. And this allows models to learn from the diverse types of patients and the knowledge of the participants. We can detect and treat cancer faster if we work together, ultimately for the benefit of the people. Scientists are also investigating how joint learning can be utilized to develop programs capable of predicting long-term illnesses [15].

Federated learning can better tell when a patient's state is about to get worse by mixing data from different healthcare sources, like smart tech and electronic health records. This allows doctors to assist the patient sooner, which could improve their health and lower costs. With the help of AI, shared learning, and the Internet of Things (IoT), the future of healthcare looks bright. By letting computers learn from multiple data sources at the same time, this combination could make medical care more accurate and efficient. Federated learning is a huge step forward in the healthcare business because it lets you use huge amounts of data safely without putting patients' privacy at risk. The healthcare industry can't work without strong teamwork, strict obedience to the law, and a steady flow of new ideas. If these problems are fixed, shared learning could make healthcare systems around the world better and personalized treatment even better.

1.2 Evolution and Principles of Federated Learning in Healthcare

Federated learning is a game-changing way to keep private patient data safe when healthcare needs to analyze data together. This new idea strikes a good balance between the strict privacy and data security rules in the healthcare industry and the advantages of big data analytics [16]. The idea behind collaborative learning is decentralized model training. Federated learning saves data close to home, while centralized machine learning uses data from many places to teach a model [1]. Healthcare devices, hospitals, and even clinics use their own data sets to help them learn. These small groups use their own data to train a shared model. They only send the changed model results to a central server, not the original data. There are many good things about this independent model teaching method. First, it makes sure that privacy rules like HIPAA in the US and GDPR in Europe are followed. This makes data breaches much less common. Sensitive patient data probably wouldn't get out while being stored or transported because raw data never leaves the local area. The only thing that is given to someone is the model choices, which are usually less private and nameless.

Central computers can help you keep track of changes to models. To create changes, it combines locally calculated modifications from several devices or institutions into the global model. The local groups receive this combined model back so they may retrain it using their own data. The world model may learn from many different data sources and improve over time if the data is kept hidden. The healthcare sector may gain greatly from federated learning as it allows models to be trained from a variety of data sources [10]. These differences happen because of the different types of patients, healthcare data sources, and patient groups. Federated learning allows teachers from various schools to work together on model lessons. The models are more useful now that they live longer and show a wider range of illnesses and patient results. With federated learning, it's also easier to look at other kinds of data. Smaller or less data-rich businesses may be able to get past data walls by using a global model built on a bigger dataset. This link could lead to better ways to predict the future, come up with treatments, and make diagnoses. When it comes to healthcare, learning to work together might be harder than usual. A number of technological challenges remain, such as making local devices faster, fixing issues with model convergence and bias, and keeping model update secrets safe while they're being sent [2]. People and groups with different goals and ideas about data governance find it hard to work together and trust each other. Even with these issues, it looks like collaborative learning will be very useful in the future. To make shared learning systems more reliable and safer, researchers are exploring how to use block chain technology, differential privacy, and secure multiparty computation. As shared learning spreads, it's likely that more healthcare businesses will use it. This will pave the way for further growth and progress. Federated learning changes how healthcare data is used for model training and forecast analytics [21]. It opens the promise of big data in healthcare by letting people work together to analyze data and protect privacy. This makes medical outcomes safer, more tailored to each person, and more accurate.

In healthcare, shared learning is becoming more and more common, so technical and real problems need to be fixed. Technology has trouble making conversation reliable and useful. Federated learning needs to be changed so that it can work with big setups without using more time or data. This is because both local hubs and central computers are always changing the way they share information. To make model training on spread-out networks better, researchers are looking into asynchronous updates and gradient compression. It is very important for shared learning to happen in healthcare that training data is correct and uniform. Healthcare data often comes from more than one place and isn't always of the same quality, style, or standard. This uncertainty could hurt learned models and show biases. To keep this from happening, federated learning systems need complicated ways to prepare and normalize data before they can join datasets for training. Models are stronger and can be used in more healthcare situations when they use federated average and meta-learning.

A lot more needs to be said about how to keep data safe and in control for shared learning. Strong privacy and data security rules must be followed by healthcare companies [14]. To meet these needs, federated learning needs to be carefully planned and put into action. Legal deals, rules on how to use data, and tracking tools are needed to keep an eye on joint learning. To safely share and handle data, businesses need the newest cryptography methods, such as homomorphic encryption and secure multiparty computing. Another problem is that shared learning doesn't work with all systems. Since different healthcare systems and gadgets use different methods and standards, it may be hard to combine and share data. Standardized data sharing forms and APIs are needed to make healthcare systems more open and help people talk to each other [22]. More standard and easy ways to share healthcare data are being made possible by FHIR. This is very important for group learning to work.

Even with these problems, cooperative learning could be good for healthcare. Predictive analytics can be used in healthcare in interesting ways. In joint learning, healthcare professionals can guess how patients will do, what problems they might have, and the best way to help them. These models might give doctors more accurate and complete data, which could help them treat patients better and make better decisions. A lot of different groups taught them about different things. Medical study might be helped by federated learning. Researchers can get more information without putting patients' privacy at risk. This allows them to do more study and come up with new ideas. Federated learning could help big genome projects that need genetic information from more than one source. By combining data from different study groups, federated learning could speed up personalized medical research. When AI and IoT are added to shared learning, it works better in healthcare. AI systems can look at any data and give useful information. IoT gadgets collect info about patients and give it in real time. Putting these two things together might make healthcare systems more adaptable and better able to meet the needs of patients and provide better care.

In the future, federated learning might be good for health. As healthcare companies work together and technology gets better, federated learning will become more common [17]. Federated learning systems are getting better and more reliable; thanks to research. They are also looking into new uses and ways to solve problems that already exist. Today's healthcare will be better, more accurate, and more tailored to each patient if shared learning programs grow. Federated learning is a new way to teach models use healthcare data. It improves healthcare by letting people work together to learn while keeping patient information safe. Federated learning should be used a lot; but first, problems with organization, law, and technology need to be fixed. The possible benefits make the work worth it. As long as healthcare companies use this technology, shared learning will shape personalized care that is based on data. Figure 1.1 shows evolution and principles of federated learning in healthcare.

1.3 Applications of Federated Learning in Healthcare

Finding the best treatment plan for each patient has become much easier; thanks to federated learning. It has also made it easier to identify diseases and rate their seriousness. This new technology gives clinicians safe access to a huge number of various kinds of information. This solves one of the most important problems in healthcare right now. Most of the time,

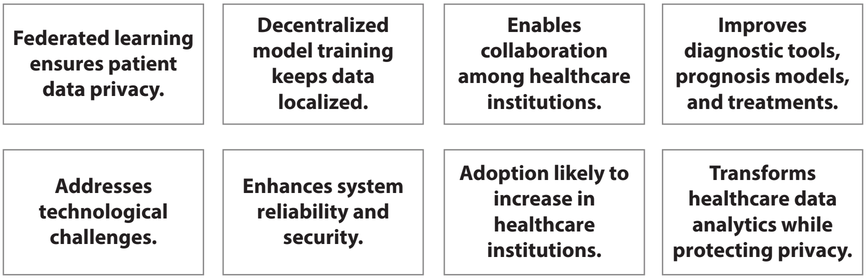

Figure 1.1 Evolution and principles of federated learning in healthcare. *(Source: Self Developed).*

cooperative learning is used in medicine to find and evaluate illnesses. A lot of different data sources are used by federated learning algorithms to find trends and make accurate predictions about the future state of health [7]. A system that puts together EHRs from different sources might be able to figure out how likely it is that a patient will get diabetes or heart disease. This is why it's so important to stop chronic diseases before they begin and to act swiftly to mitigate their effects if they do arise. Also, shared learning makes it simple to create AI-powered systems that help doctors make decisions. These tools can help professionals better evaluate cases, make care plans, and make suggestions based on proof. Using picture data from multiple modes, a learning model made by a group of doctors might help find cancer and other problems more quickly. When genome data from several study groups is put together, it might be possible to find genetic markers that are linked to certain illnesses. It is possible to do a more exact and focused study because of this [4]. Table 1.1 shows the applications of federated learning in healthcare.

Doctors may use joint learning to make sure they meet the specific needs of each patient. Federated models bring together data from different sources to make sure that every patient gets the best care possible. If a person has a certain type of cancer, a multisite oncology model might decide not to give them chemotherapy based on their genetic make-up, medical background, and how they responded to earlier treatments. A custom plan like this could lead to better outcomes with fewer side effects and more patient agreement. Federated learning enables professors from different universities to collaborate on projects without putting patients' privacy at risk. Privacy laws like GDPR and HIPAA make it possible for scientists to work together to train models on private data without sharing the real data [12]. The medical sector would gain from this partnership's potential to expedite medicinal breakthroughs. Operations performance

Table 1.1 Applications of federated learning in healthcare.

Aspect	Description
Improved Treatment Planning	Federated learning facilitates personalized treatment plans by analyzing diverse patient data sources.
Disease Prediction	Algorithms can predict the likelihood of diseases like diabetes or heart disease by analyzing electronic health records (EHRs).
AI-Based Decision Support	AI-based tools assist doctors in evaluating and planning treatments based on available data.
Faster Disease Detection	Radiologists use learning models to detect tumors and other abnormalities faster using image data.
Personalized Study Possibility	Combining genomic data from different study groups enables the discovery of genetic markers for illnesses.
Personalized Care Plans	Federated models ensure that all patients receive optimal care by considering data from various patient groups.
Privacy-Preserving Collaboration	Allows collaboration among researchers without compromising patient privacy, in compliance with privacy laws.
Operational Efficiency Improvement	Helps hospitals predict patient admissions and optimize resource utilization based on data from multiple hospitals.
Technological Challenges	Issues include maintaining model update secrecy, reducing computing load on local devices, and addressing model biases.
Potential Healthcare Transformation	Federated learning could revolutionize healthcare by enabling data-driven decision-making while safeguarding patient privacy.
Enhanced Medical Research	Predicts diseases, suggests personalized treatments, and improves diagnostic accuracy and operational efficiency.

(*Continued*)

Table 1.1 Applications of federated learning in healthcare. (*Continued*)

Aspect	Description
Expected Growth in Healthcare	As technology advances, federated learning is expected to gain traction and expand its applications in healthcare.

(Source: Self Developed)

is impacted by federated learning. Hospitals may operate more efficiently, anticipate which patients will require admission, and make better use of their resources by using federation models. A pooling learning system might be able to forecast the number of patients admitted based on information from many hospitals. This aids managers in scheduling the usage of their workforce and assets.

Even though it has benefits, setting up group learning in healthcare is hard. Technology problems include keeping model update secrets confidential while they are being sent, making sure that local devices don't have to do too much work, and fixing issues with model bias and convergence. However, improvements in edge computing, differential privacy, and secure multiparty computation are making these problems better [13]. Federated learning has the potential to transform the delivery of healthcare by enabling data-driven decision-making while safeguarding patient confidentiality. Federated learning improves several aspects of medical research and patient results, including operating efficiency and diagnostic accuracy, as well as illness prediction and individualized therapy ideas. Federated learning in healthcare is likely to grow as technology advances and fosters new ideas.

Federated learning is causing a huge change in the healthcare industry because it allows people to work together to analyze data quickly and securely, while also meeting strict privacy standards. The goal of this new method is to protect patient privacy while giving researchers access to the huge amounts of data that current medical processes create. Federated learning could change healthcare in many ways in the future. It could speed up processes, help find and predict diseases, and create personalized treatment plans, among other things. One great thing about shared learning is that it could help the medical field get better at making predictions. FEMI may be able to find trends and patterns that would be hard to see in a single file by combining data from different schools [18]. Many electronic health records (EHRs) may be used together with pooled learning algorithms to help better predict when long-term diseases like diabetes and heart disease will start. If doctors can find diseases early on, they might be able to stop them from happening, which could lower the number of cases and the seriousness of these issues. One more benefit of shared learning is that it might help improve the formulas that are used to group threats. By drawing attention to people who are more likely to have problems, this could help healthcare workers in optimizing the use their time and resources. This method of learning could be useful for advanced diagnosis tools and analytical tools that make predictions. In many areas, like imaging, cooperative learning has shown promise. By using a range of picture data sources to teach models, radiologists could make systems that can correctly find cancer and broken bones. Testing tools that are run by AI could help patients get better care by making assessments faster and more accurately. Another possible benefit of federated learning is that it may make it easier to find DNA traits that are linked to diseases. By putting together DNA data from many study centers, scientists may be able to find trends that help make personalized care better [23].

Individualized health plans are another area where joint learning is making big changes. Many times, common sense says that all people should be handled the same, no matter what makes each one special. In pooled learning, data from many sources about a patient is put together to make personalized treatment plans. A merged model with information from several cancer centers may look at a patient's genes, medical history, and response to previous treatments, among other things, before prescribing chemotherapy [19]. This personalized way makes it easier for patients to take their medications as prescribed, which is good for their health and behavior. Because shared learning fosters collaboration, medical researchers can also benefit from shared insights and ideas. Privacy laws like HIPAA and the General Data Protection Regulation (GDPR) are met by federated learning, which allows experts to collaborate on shared models without sharing raw data. This joint tool speeds up the process of medical finding by putting together data and information from many different sources. Federation-based learning could be useful for large-scale clinical studies with many subject groups. As a result, experts can arrive at more comprehensive and valuable findings.

Federated learning could help healthcare groups work better. A big problem for healthcare centers is how to effectively manage the flow of patients while getting the most of the resources they have. When pooled learning models are used to predict how many patients will be accepted, it's easier for the management to plan how to share staff and resources. With these methods, it may be possible to find trends and patterns in data from a number of hospitals. This makes the hospital run more smoothly, care for patients better, and make better decisions. Federated learning can be helpful in healthcare, but it's not always easy to put it into practice. Technical problems that need to be fixed include fixing model bias and convergence, making local devices' computers less busy, and making sure that changes to models are kept secret while they are being sent. Some of these issues are starting to be solved; thanks to progress in edge computing, safe multi-party processing, and differential privacy. Edge computing cuts down on delay and boosts efficiency by handling data closer to where it comes from. Secure multi-party computing allows more than one person to work on a calculation at the same time without sharing any personal data. In addition to hiding information that could be used to identify a person, this adds noise to the dataset.

As technology improves, it looks like shared learning will become more important in healthcare. Recent progress in artificial intelligence, blockchain technology, and private computers will make shared learning systems much safer and more effective [24]. As AI systems get better, they will be able to diagnose and predict things better. Blockchain technology might be able to keep a lasting record of all data transfers. This makes collaborative learning methods more transparent and trustworthy. Patient info will be kept safe; thanks to improvements in private computer technology. Federated learning could change healthcare by letting decisions be based on data while still protecting patient privacy. Its application in areas like organizational performance, personalized care planning, diagnosis accuracy, and prediction analytics demonstrates its wide-ranging impact. As new joint models and tools come out, federated learning will greatly improve both medical study and patient results. This new method could make treatment of patients more accurate, individualized, and efficient all over the world. This would be very good for the healthcare business.

1.4 Challenges and Limitations of Federated Learning in Healthcare

Federated learning has a lot of potential to change the world, but it has a lot of problems in healthcare. There are some problems that need to be fixed before shared learning processes and their health benefits can be fully realized. Data that are not all the same is a big problem. EHRs, medical images, smart tech, and DNA data are some of the places where healthcare data comes from. Formats, layouts, and quality vary across different sources.

It might be harder to train collaborative learning models when there is heterogeneity because the models have to be able to handle a lot of different, possibly inconsistent data [6]. Institutional differences as to how data is labeled and pre-processed make this problem worse, and they need complicated strategies to be harmonized and standardized. Communication waste is still a big problem. Federated learning sends changes to models from local devices or institutions to a central computer on a regular basis. The primary server puts together updates to make the world model better. This can take a lot of time and energy when working with large models or many partners. To keep federated learning working in healthcare settings, one needs effective communication channels and optimization methods that cut down on delay and data use.

Another problem is the difficulty of combining models. Putting together information from different sources could lead to model divergence and chaos. Differences in how the data is distributed locally can lead to poor model performance or prevent it converging altogether. Researchers are looking into adaptive aggregation algorithms, customized federated learning, and weighted average as ways to fix these problems [9]. However, getting many healthcare systems to work consistently and reliably is still a problem. Because of GDPR in Europe and HIPAA in the US, data safety and security are very important in shared learning. Federated learning stores data locally, which makes it less likely that data will be stolen; nonetheless, model changes are still a security risk. Advanced encryption, safe multi-party computing, and differential privacy methods are needed to keep data private and secure while it is being sent and gathered.

To solve these problems, people from different fields need to work together. To build and use federated learning systems, engineers, data scientists, healthcare workers, and lawyers must all work together. This partnership could lead to the creation of data formats that are special to healthcare data, privacy-protecting processes, and useful communication methods. Edge computing, which does computations closer to the data source, and blockchain technology, which handles data in a public and safe way, look like they could help improve collaborative learning [8]. To keep up with the changing needs of shared learning in healthcare, new ideas and better ways of doing things need to be explored and researched all the time. Federated learning could change how healthcare decisions are made based on data, but it needs to get past some problems first. Federated learning methods may work best in healthcare if people from different fields work together and think creatively. This will make sure that they are used safely and effectively to improve patient outcomes and medical study. Figure 1.2 shows the challenges and limitations of federated learning in healthcare.

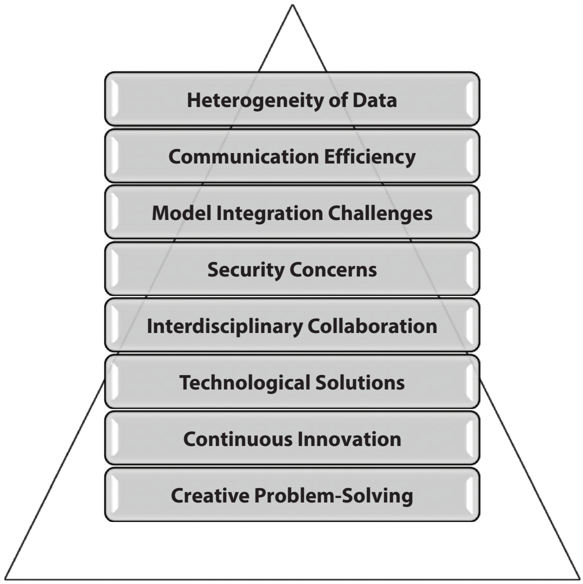

Figure 1.2 Challenges and limitations of federated learning in healthcare. (*Source: Self Developed*).

To use healthcare's full potential for shared learning, we need to keep coming up with new ideas and working together across different fields to solve important problems. It is hard to send model changes quickly between central computers and local nodes, so it's important to use communication methods that are both long-lasting and scalable. Because healthcare data is so big and different, it is very important to make these communication methods better, so that delay and bandwidth use go down. Researchers are looking into ways to speed up communication, like gradient compression and efficient update timing, because shared learning is becoming more useful in real-life healthcare settings. Getting different data sources to work together and balance is another big problem. Healthcare data can come in a lot of different ways, such as genetic patterns, random medical pictures, and organized electronic health records. To keep connection in a shared learning system, each type of input needs its own set of preparation and standardization methods [20]. To solve the problems and make it easier for different datasets to work together, we need more advanced ways to harmonize data, like ontological mapping and global information standards. Effective data enrichment methods may possibly make model training better by getting more full and accurate data from more sources. It is not possible for federated learning to happen if patient information is not kept private and secret. Even though keeping data locally in collaborative learning makes it less likely that data will be stolen, there may still be problems with how model changes are sent. To keep model changes safe, more advanced encryption methods like homomorphic encryption can be used. This keeps private data safe even while it's being sent. Differential privacy methods make security better by making it harder to figure out who someone is when the models are changed. Adding noise to the data makes this possible. Due to technological constraints, shared learning models cannot be combined. Divergence happens when regional data trends are different from the world model. This may cause the model to either fail to converge or to perform poorly. Researchers are looking into different ways to do adaptable aggregation. These methods change the update weights when the amount and quality of nearby data change. Strategies for personalized shared learning are also being developed to further enhance performance and accelerate the merging of models [25]. These approaches allow the global model to be fine-tuned to better suit the local situation.

Besides technical problems, organizational and legal difficulties make shared learning even harder to use. For getting around in the regulatory world, which has strict data security rules like GDPR and HIPAA, one needs detailed legal systems and compliance processes. All healthcare organizations should have a clear strategy for keeping data safe. These need to include ways to share data, keep track of changes, and get permission. Following all the rules and creating an environment where people trust each other and work together are important for joint learning to work. We can't say enough about how important it is for experts from different areas to work together to solve these issues. Shared learning in healthcare has caused a lot of complicated problems that need to be solved by data scientists, engineers, doctors, and judges working together. Working together with people from different fields is more likely to lead to new healthcare data forms, better ways to communicate, and software that protects users' privacy. Shared learning is more likely to work for healthcare companies if they work together to make rules and guidelines. It's hard to say 'no' when you think about the cool new ways that cutting-edge tech like blockchain and edge computing can be used for group learning. Edge computing makes model changes more efficient and cuts down on delay by examining data closer to where it comes from. Using edge devices, healthcare companies might be able to speed up and improve learning processes while also reducing the working load on core systems. Blockchain technology could be a safe and open way to control the flow of data. It is separate and can't be undone, so it could be useful for shared learning. Federated learning