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SURVEY

A Survey of Federated Learning From Data Perspective in the Healthcare Domain: Challenges, Methods, and Future Directions

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ABSTRACT Recent advances in deep learning (DL) have shown that data-driven insights can be used in smart healthcare applications to improve the quality of life for patients. DL needs more data and diversity to build a more accurate system. To satisfy these requirements, more data need to be pooled at the centralized server to train the model deeply, but the process of pooling faces privacy and regulatory challenges. To settle them, the concept of sharing model learning rather than sharing data through federated learning (FL) is proposed. FL creates a more reliable system without transferring data to the server, resulting in the right system with stronger security and access rights to data that protect privacy. This research aims to (1) provide a literature review and an in-depth study on the roles of FL in the fields of healthcare; (2) highlight the effectiveness of current challenges facing standardized FL, including statistical data heterogeneity, privacy and security concerns, expensive communications, limited resources, and efficiency; and (3) present lists of open research challenges and recommendations for future FL for the academic and industrial sectors in telemedicine and remote healthcare applications. An extensive review of the literature on FL from a data-centric perspective was conducted. We searched the Science Direct, IEEE Xplore, and PubMed databases for publications published between January 2018 and January 2023. A new crossover matching between the approaches that solve or mitigate all types of skewed data has been proposed to open up opportunities to other researchers. In addition, a list of various applications was organized by learning application task types such as prediction, diagnosis, and classification. We think that this study can serve as a helpful manual for academics and industry professionals, giving them guidance and important directions for future studies.

INDEX TERMS Energy, federated learning, non-independent identical distribution, privacy and security.

I. INTRODUCTION

Artificial Intelligence (AI), the Internet of Things (IoT), and big data [1] are all rapidly developing technologies that have the potential to significantly alter the way that healthcare

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is provided. Owing to access and reliability restrictions, the requirements for analyzing and transmitting vast amounts of information produced by IoT devices with ensured good of service, and other factors, these new developments are not without their obstacles. The application of AI opened many opportunities to create a power system that works in real time. Effective deep learning (DL) techniques can be used to provide intelligent healthcare services like remote monitoring, care for seniors, and identifying patients who are at high risk of dying. However, to be improved, DL models must be trained on big datasets that come from IoT and medical devices. Given that medical equipment frequently captures sensitive information, this presents a significant barrier to ensuring data privacy. Therefore, sending these data to a centralized institution to undertake the training is typically not a realistic approach [2]. These challenges can be overcome by using mobile edge computing to harness the processing power of edge devices and enable training at the network edge without the need for data sharing [3]. The emerging model for facilitating training on the device is federated learning (FL), which is characterized by distributed centralized assemblies, which are organized by a single server (or group of servers). FL has also gained more and more scientific interest. In such systems, transmission between the server and users and learning from distributed information are two crucial and connected features, and their integration raises numerous recent research problems that are not present in conventional machine learning [4].

With the protection of data privacy, new technology is needed to allow each customer to train their own data locally and participate to build the main model. McMahan et al. introduced the idea of FL in terms of parallel data for the first time in 2016 and suggested the Federated Averaging (FedAvg) algorithm [5]. FedAvg is a collaborative method that lets multiple nodes train a model together while keeping the user input in each node; it eliminates the requirement for users to upload their private information to a centralized server and enables edge nodes to participate in training using their own data [5]. FedAvg satisfies the fundamental criteria for the protection of patient information by combining the updated user models [5]. Figure 1 displays a general diagram of the FL.

Learning in a federated setting faces several significant obstacles that are not present in traditional cloud-centric learning. An unbalanced data distribution caused by non-independent identical distributed data (non-IID) may be unfair and biased in the prediction and lead to deterioration of efficiency. This is one of the most significant issues. Other challenges include communication bottlenecks, which are the total number of iterations and the size of the model that is submitted at each iteration; heterogeneity of participating devices with respect to storage, computing power, and energy state; privacy and security considerations arising from the possibility of malicious user interference, etc [6].

The challenges faced in FL have an impact on the effectiveness of optimization and the precision of the learned model.

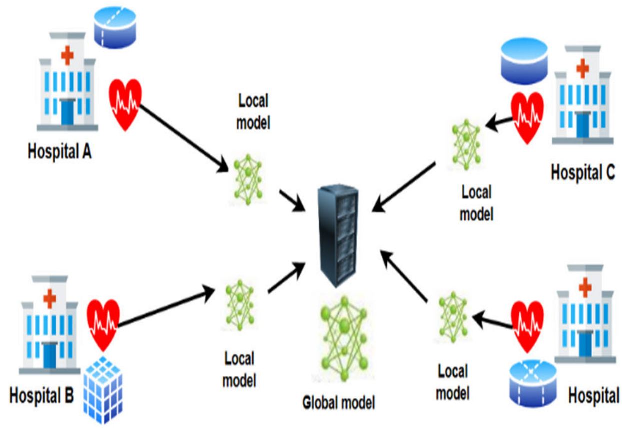

FIGURE 1. **The main concept of federated learning.**

Owing to their distributed nature, they also pose special design considerations like communication burden and privacy assurances. Additionally, the optimization problem may now include more hyperparameters as a result of FL. These include tuning aggregation model update rules, clients chosen in each epoch, iteration number, the configuration of update compression techniques, and other factors. These increase the number of hyperparameters already present in standard methods and, combined with the above problems, make the overall design and development of an FL framework difficult. Furthermore, giving a thorough review of benchmarking the FL in medical data is essential. This survey offers an overview of FL from an analytical point of view of data in FL, covering topics like statistical data heterogeneity, privacy and security, expensive communication, resource limitations, and efficiency. A number of challenges related to remote monitoring and e-health are highlighted. The conceptual structure of our study, which is depicted in Figure 2, provides an excellent illustration.

This article includes a survey of the current FL practices in the medical field. First, we show the definition, categorization, and type of FL. Then, the present FL methodologies are demonstrated to resolve the challenges with clinical information, along with the path of future FL study for healthcare systems. Furthermore, new research paths are offered to investigate to make FL more useful and powerful. Systems and infrastructure, in our opinion, are crucial to FL's success. Additional research is required to point out system problems with effectiveness, efficiency, and privacy.

The paper's contribution is to give a thorough review of FL's definition, characteristics, and types. Many studies have explored this topic, so what differentiates our study from previous ones is that the nature of the medical data requires special attention and adds extra challenges in the context of FL. This approach can help create a general framework for data scientists and other researchers to use when creating FL-based solutions to address future difficulties. Consequently, this work supports the following:

- The survey presents a more detailed review of the key FL features as well as strategies to help researchers quickly become familiar with FL without enduring a potentially difficult learning
  It gives the researcher good examples of FL applications and use cases to show how various FL designs may be applied in a variety of situations. This helps the researcher understand how FL can be used. Additionally, demonstrating FL's applications and using examples in specific medical situations would give healthcare practitioners more confidence to streamline their data for FL.
- It provides a summary of the most important FL problems that have been discussed recently in the literature. Additionally, it includes a detailed description of the relevant factors that influence the efficient implementation of FL.

The study is structured into eight sections, beginning with a brief introduction to Federated Learning (FL). Section II outlines the query approach, while Section III provides an overview of related works. Section IV delves into the different types of FL. In Section V, the challenges of FL, including data distribution, privacy and security concerns, expensive communication, limited resources, and efficiency are discussed. Section VI covers earlier studies in the medical and industrial domains. Section VII offers open directions based on the comprehensive survey, and finally, Section VIII provides concluding remarks.

II. QUERY APPROACH

The primary objective of this study is to create a broad and basic classification system, or taxonomy, for the selected research papers that satisfy the investigation's specific scope and criteria. This classification aims to provide an overview of the papers and their contents. To increase the likelihood of obtaining high-quality search results, three primary digital databases were chosen and queried. These included Science Direct (SD), which grants access to a wide range of scientific journals covering topics in medicine, science, and technology; IEEE Xplore digital library, which features publications pertaining to engineering and technology; and PubMed, which provides access to a diverse array of articles across various domains. The selection of these databases was based on their established academic credibility and their representation of diverse academic fields. The search terms utilized in the study are documented in Table 1.

TABLE 1. The digital databases and search terms employed in the study's search.

Database	Search keywords
Science direct	"Federated learning" AND (telemedicine OR "remote monitoring" OR e-health) AND ("data mining" OR "signal processing" OR "data analysis")
IEEE Xplore	("All Metadata":Federated learning) AND ("Full Text Only":telemedicine OR "Full Text Only":remote monitoring OR "Full Text Only": e-health) AND ("Full Text Only":data mining OR "Full Text Only":signal processing OR "Full Text Only":data analysis)
PubMed	((federated learning AND ((fft[Filter]) AND (english[Filter]) AND (2018:2022[pdat]))) AND (telemedicine OR "Remote monitoring" OR e-health AND ((fft[Filter]) AND (english[Filter]) AND (2018:2022[pdat])))) AND ("data mining" OR "data processing" AND ((fft[Filter]) AND (english[Filter]) AND (2018:2022[pdat]))) AND ((fft[Filter]) AND (english[Filter])) AND ((fft[Filter]) AND (english[Filter]))

III. RELATED WORK

Owing to FL's recent advancements, numerous research has been done to study its connected fields, including industry and healthcare. Table 2 provides a comparison of our paper with related reviews. In [7], the author reviewed a selection of typical FL strategies for the healthcare industry while summarizing the overall answer to the problems in FL scenarios. Another author pointed out all challenges related to the health domain using FL including data distributions, data protection techniques, and benchmark datasets; then, the important open direction was mentioned to find the proper solution [8]. Other researchers presented a comprehensive analysis of all types of non-IID and their impacts on the performance of FL, and the advantages and disadvantages of the most recent studies on how to deal with issues involving non-IID data in FL are also discussed [5]. Another paper [4] covered a wide range of current methodologies and offered various future work areas that are pertinent to many different research communities. Another author presented the current FL challenges from many perspectives, and all these difficulties are related to representations of data and security [9]. To help future landing applications, one paper [6] previewed existing applications that are used in industrial engineering, in which the author addressed six research areas that help improve the structure of FL for future optimization. In another paper, the systematic structure for FL was presented, and the key issues that are solved utilizing signal processing were pointed out [10]. One article [11] explored the distinctive characteristics and issues of FL, offered a thorough discussion of existing methodologies, and identified various future study topics that are pertinent to a variety of research communities. The survey highlighted the privacy-preservation method from a General Data Protection Regulation (GDPR) compliance standpoint while displaying the results of the previous studies; subsequently, a number of challenges with user privacy were highlighted, along with crucial strategies that address or lessen user privacy threats [12]. In another survey [13], the authors divided the FL approaches into three groups according to issues that were pointed out in the literature. Another researcher reviewed the implementation of FL in IoT networks after presenting the most recent advancements in FL and IoT and describing the visions guiding their merging [14]. The potential FL has contributed to several important IoT services was then

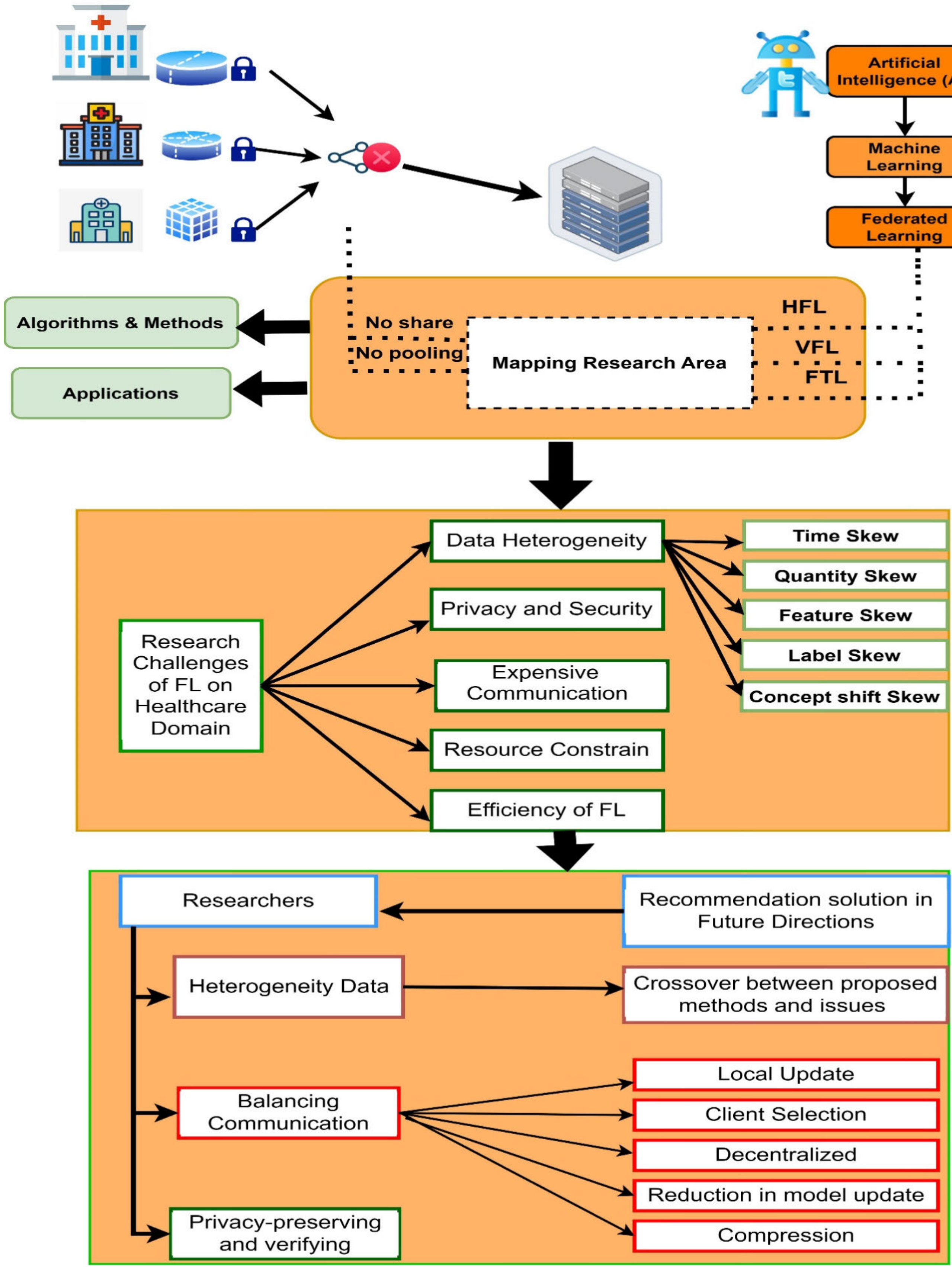

FIGURE 2. The intersection of federated learning and healthcare: A review of the literature.

TABLE 2. Lists different publications that address FL as well as other subjects with an emphasis on FL use cases.

REFERENCES	SIMILARITIES	DIFFERENCES
[7]	Statistical, efficient communication, and personal data protection were all highlighted as problems in this study.	Our work is a detailed examination of the properties of the data distribution and how it affects model performance. Then, a roadmap for remaining problems and research paths are introduced in the FL application.
[8]	This work addressed some common challenges such as data distribution, privacy, and security.	Our study encompasses additional issues with federal learning that haven't been covered, like expensive communications, resource limitations, and FL effectiveness.
[5]	This work is devoted to a thorough survey of FL on non-IID data, given a detailed analysis of different data statistical, their effects on the performance of FL, and a discussion of the benefits and drawbacks of current techniques. Then, an outline of unresolved issues and research paths are presented in the inclusion of non-IID data.	Our work discusses additional, previously unmentioned issues with federal learning, including high communication costs, insufficient resources, and FL effectiveness.
[4]	This study covered some typical challenges like statistical difficulties, communication effectiveness, and privacy and security.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
[9]	In this study, typical issues including privacy concerns and system heterogeneity were pointed out.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
[6]	This study covers some typical challenges like statistical difficulties, communication effectiveness, and privacy and security.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
[10]	This survey covers some typical challenges like statistical difficulties, communication effectiveness, and privacy and security.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
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[12]	This study covers some typical challenges like statistical difficulties, communication effectiveness, and privacy and security.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL..
[13]	This study covers some typical challenges like statistical difficulties, communication effectiveness, and privacy and security	In contrast to our study, this one provides a thorough analysis of the usage of FL in numerous important IoT applications, including intelligent transportation, unmanned aerial vehicles (UAVs), and smart buildings. Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
[14]	Similar to our survey, this survey summarizes the existing FL problems.	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.
[15]	Statistical challenges, communication efficacy, and the need for privacy and security are all addressed	Our work is a thorough investigation into the relationship between data characteristics (specifically, non-IID data) and the accuracy of the system. Then, a roadmap for remaining problems and research paths are introduced in the FL.

discussed to include information exchange between IoT nodes, and intrusion [14]. One review summed up the most important problems with FL and how blockchain technology helps to solve those problems, and then, the unsolved problem of BFL was pointed out, along with a plan for how to solve it in the future [15].

IV. FEDERATED LEARNING

FL is a technique that enables many customers to train their information locally and decouples the capacity to perform machine learning (ML) from the necessity of storing the data on the server. FL covers methods from a variety of fields of study, including distributed systems, machine learning, and privacy. Without exchanging raw data, several parties can jointly train machine learning models in an FL system. Each party's machine learning model is the system's output (they may be similar or not similar) [16]. FL systems have problems with efficiency, scalability, and unrealistic system assumptions. Heterogeneity and autonomy should be considered during the building of the FL model [17].

Heterogeneity means diversity in features of study and means systems that use multiple types of processors or cores to get the best performance and energy efficiency. Heterogeneity in the context of machine learning and FL is concerned with data, task requirements, and privacy.

Autonomy is divided into a number of subcategories, including association autonomy and communication autonomy. Both of these subcategories emphasize the capacity to engage with FL, the capacity to participate in several FL systems, and the capacity to choose how much information should be shared with others [16]. Different types of FL exist, such as horizontal FL (HFL), vertical FL (VFL), and federated transfer learning (TFL), all of which are distinguished by the manner in which inputs are shared amongst various participants in the attribute and sample identity space. They are displayed in Figure 3 [18].

A. HORIZONTAL FEDERATED LEARNING

HFL can be used when the feature space of datasets from different sites overlaps but the sample space is different (Figure 3a). The nodes could be various healthcare organizations or suppliers of health data applications. By combining patient sample data from many organizations without compromising patient privacy, HFL intends to create a worldwide model.

B. VERTICAL FEDERATED LEARNING

VFL is illustrated in Figure 3b, which is used when two sets of data share the same sample space but have different feature spaces [18]. The profiles of the same people were shared by two nodes, but with distinct feature data. The nodes could be various healthcare organizations or suppliers of health data applications. By combining patient attributes from many institutions without directly transferring patient data, VFL seeks to create a global model. The sample data are the same for each node, but the labels and attributes of the patients vary [8].

C. FEDERATED TRANSFER LEARNING

TFL is applied when the two groups have different feature spaces and different sample populations [18]. One example is that one has two organizations: One institution is in China and the second is in the United States. Owing to geographic constraints, two institutions having overlapping user groups are highly unlikely. In this situation, a federation can use transfer learning techniques to deliver solutions for the full sample and feature space. This is described in Figure 3c [19].

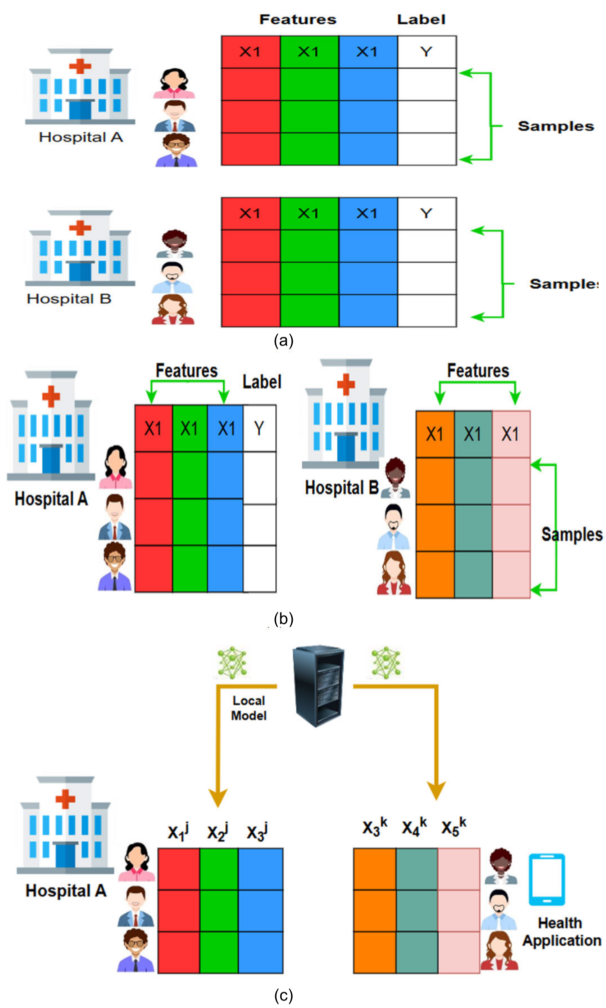

FIGURE 3. Types of federated learning.

V. CHALLENGES

Although FL has contributed in many areas, some challenges should be considered when designing a framework. Figure 4 shows the main challenges and most popular forms of data skew.

A. DATA DISTRIBUTION (STATISTICAL DATA HETEROGENEITY) CHALLENGE

Data distribution is typically categorized into independent identical distribution (IID) and non-IID. Imbalances in the amount of data, features, or labels can lead to non-IID. Non-IID occurs frequently in the medical field [8]. Some data are present on the server, but most challenges occur by integrating data from each client without explicitly exposing the private information of each client. FL can address the issue

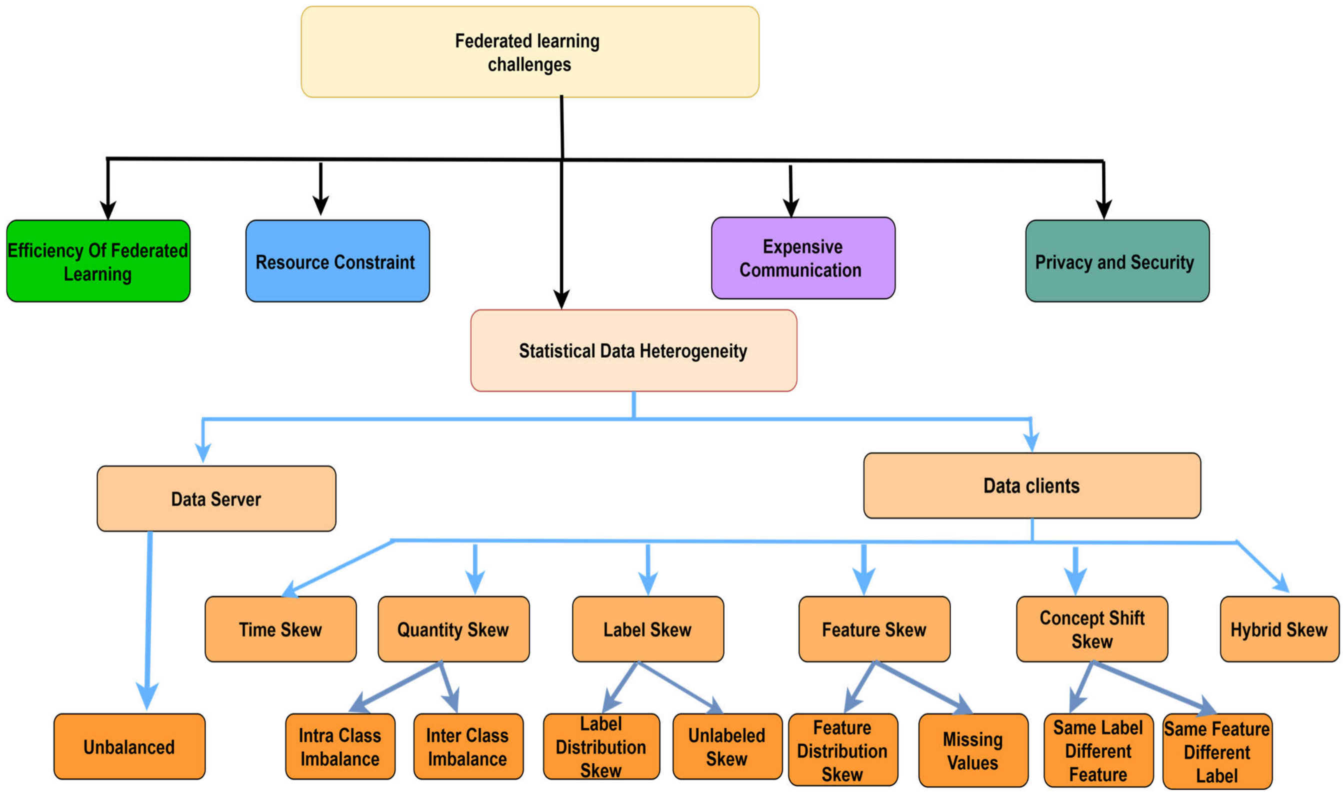

FIGURE 4. **The main challenges in federated learning.**

of restricted data quantity. However, due to data distribution at each client, FL also encounters issues with statistical data heterogeneity. Each client's data distributions are probably unique, which causes poor overall model performance [8]. In particular, non-IID data distributions have a significant effect on model learning performance. The weight divergence caused by different population distributions has the potential to significantly separate models [5]. Numerous types of non-IID exhibit data skew, or data that do not distribute uniformly. Figure 4 shows the main challenges and most popular forms of data skew.

1) DATA SERVER

Several researchers assumed that auxiliary data was included on federated servers to enhance the effectiveness of FL. In one study [20], extra IID data that served as auxiliary data were added to the federated server. Such supplementary data can be obtained from a small number of clients or from a publicly available dataset. These data were used by the server during training. The performance of the model was assessed using a test set with the same distribution as in most work, which presupposes that the global training data is balanced. This assumption is not true because, in real-world situations, the data frequently exhibits a long-tailed distribution [21]. Therefore, the imbalanced global data need to be further considered in the context of non-IID FL. For example, researchers [22] suggested stochastic-corrected loss from a statistical perspective and calibrated the output of various local models. The approach can simultaneously address the issue of unbalanced global data. The methodology suggested by the author reduces global imbalance through adaptive data augmentation and down-sampling, and it develops a mediator to reschedule client training based on the Kullback–Leibler divergence of their data distribution [23].

2) CLIENT DATA

Data distribution among clients are non-IID. Owing to the heterogeneity of the data for each client, each client generates a unique local model. As a result, the global model on the server will be different from the ideal model, causing slow convergence and poor performance [5]. Institutions can use a wide range of data-generating and gathering techniques; therefore, diverse fields of data are frequent. Differences could arise in the manufacturers, calibration, and acquisition techniques of the scanners utilized in various universities [24]. The following section describes many types of heterogeneity data:

a: TIME SKEW

The distribution of client data is time-dependent. The data collected by a device may vary by day, night, or season. For example, the infection characteristics of a new coronavirus infection may differ greatly between summer and winter [25]. To capture the FL's changing heterogeneity over time, the adaptable framework of continuous federated learning (CFL) has been suggested. CFL addressed complicated and realistic circumstances that are difficult to analyze in previous studies by collecting data from preceding local datasets and approximating the local objective functions [26].

b: QUANTITY SKEW (IMBALANCED DATA)

A skew in quantity denotes that various clients have different numbers of training information [5]. For example, if a model is trained to mix information from smartphones and hospitals, each phone gathers information from one client while the hospital can collect much information from many clients. The number of patients with particular disorders might vary significantly between hospitals just as well [27]. The ratio of normal to up-normal samples in the non-IID situation is wildly out of balance. For instance, normal instances are approximately 5%, while up-normal instances are 95%. Imbalanced data may be light or severe. A ratio of 1:4 indicates a light imbalance but a ratio of 1:1000 indicates a severe imbalance.

Inter- and intra-client class imbalance are two categories for quantity skew or imbalanced data. The first type refers to a client's class distribution, which differs from a uniform distribution in terms of how much data are distributed among classes. When a disparity occurs between the class distributions of various customers, this is known as intra-client class imbalance [28].

Some studies are presented here to solve the first type of quantity deviation. FedHome, which trains data locally for each user and then shares the global model in the cloud to achieve data privacy protection, has been suggested as an approach to monitor healthcare users at home [29]. A generative convolutional autoencoder is employed to deal with the imbalanced and non-IID distribution contained in the patient's information and achieve accurate health monitoring [29]. To identify security threats in IoT systems, like smart cities, smart medical care systems, and intelligent buildings, a robust federated DL framework employing a generative adversarial network has been proposed [30]. A dynamic sample selection optimization algorithm based on FL (FedSS) has been proposed to deal with heterogeneous data. FedSS flexibly chooses the training population during the gradient iteration dependent on a volume of local data to resolve the costly assessment of the local objective function with a wealth of information [31]. An FL system for confidential Functional magnetic resonance imaging (fMRI) analysis across multiple sites was presented in a previous paper [24]. Using MoE and adversarial domain alignment, the FL framework's throughput is enhanced and addressed domain shift issues. A 2DFL model was suggested that mixed the benefits of vertical and horizontal FL to exceed the drift client. The researcher used VFL to enhance performance by integrating patient features from different users, and then the server used HFL to average the received model from different clients [32].

Researchers tried to solve the issue of inter-client class imbalance. A previous researcher built a cooperative FL architecture that enables various medical institutions to test for coronavirus by scanning chest X-rays, and a number of significant elements and characteristics of the FL environment were investigated in the model, including the naturally occurring imbalanced and non-IID data [33]. In [34], FL was proposed to assess and diagnose depression to address the issue of patient privacy regarding their medical history. Hierarchical personalized federated learning is a new federated user modeling system that the author created [35]. The system enables the application of FL in user modeling with inconsistent clients. The framework is more flexible and can be used in real situations. Another paper [36] shows the viability of an FL system to detect coronavirus through a scanned image of a patient's chest. The patients are taken from seven different organizations: three data sets are from Hong Kong, and the rest of the datasets are from Mainland China and Germany to avoid the biasing of the system.

A few works have solved two kinds of data imbalance. A prior study introduced FLY-SMOTE, a fresh method that generates synthetic data for the minority class in supervised learning tasks using a modified SMOTE method, rebalancing the data in various non-IID contexts [37]. The last paper in this category suggested a way to improve FL by solving the heterogeneity of data, where the difference in size between classes can be solved by making the distribution of data in class close to the uniform distribution [28]. Clients are chosen only if their class distribution is close to uniform to participate in training and mitigate user imbalance issues [28].

c: LABEL SKEW

Label skew is a popular type in which the clients' label distributions Pk(y) vary. For instance, large institutions typically contain more records about diseases than small clinics in rare areas. The distribution of labels Y differs between each node in the non-IID setup. In particular, the FL environment only has one or more nodes that have the label yi [5], [38].

Two situations occur in label skew: label distribution skew and unlabeled data. A novel FL technique is proposed to reduce accuracy degradation brought on by non-IID data at clients. As a result, weight divergence is used to identify the non-IID degrees of clients. Then, a powerful FL technique called CSFedAvg is suggested, where clients with less non-IID data will be selected to train models with a greater frequency [20]. Another study proposed a federated differentially private generative adversarial network framework, which enables multiple healthcare institutions to use the privacy-preserving data augmentation technique to create large and diverse datasets and solve the issue of missing COVID-19 training samples [39]. Federated learning on medical datasets using partial networks (FLOP) [40] demonstrates its usage specifically for medical applications by sharing just a partial model without sharing the health information of the client. FLOP is applied to help and early diagnose COVID-19 accurately. In the last paper in this category [41], an integrated generative adversarial network with FL was used to overcome the skewness label, showing that the proposed method

TABLE 3. A summary of all the details in the published FL that discussed issues of the distribution data.

FL study	Number of clients	Skew challenges	Algorithm	Case study	Dataset Description	Publicity
[29]	30	Quantity skew/ Intra-client class imbalance	generative convolutional autoencoder	human activity recognition dataset	MobiAct TRS=480/ user TES=160/ user	public
[30]	3	Quantity skew/ Intra-client class imbalance	Generative Adversarial Networks	KDD-CUP99 NSL-KDD UNSW-NB15	1st dataset= 24 attack classes and 41 features. 2nd dataset= 41 features and 4 attacks. 3rd dataset= 9 attack classes	Public + private
[31]	100	Quantity skew/ Intra-client class imbalance	Dynamic Sample Selection	MNIST	TRS=60000 images TES=10000 images	public
[33]	4	Quantity skew/ Inter-client class imbalance	Adaptive Hyperparameters Method	Covid-19	TRS= 55 patients 76 healthy TES= 21 patients 32 healthy	Public+ private
[24]	4	Quantity skew/ Intra-client class imbalance	The mixture of experts (MoE) and adversarial domain	Autism Brain	UM1: DS1=106 NYU: DS2=175 USM: DS3=72 UCLAI: DS3=71	Public
[20]	500	Label skew/ Label distribution skew	Client-Selected Federated Averaging	CIFAR-10 MINIST	CIFAR-10 (image) TRS=50000 TES=10000 MNIST (image) TRS=60000 TES=10000	Public
[39]	100	Label skew/ Label distribution skew	Generative Adversarial Networks	COVID-19	normal pneumonia =1250 COVID-19 pneumonia=350	Public
[34]	4	Quantity skew/ Inter-client class imbalance	Adaptive Hyperparameters Method	Mood Detection	DS= real data on BiAffect's free mobile app.	private
[35]	10	Quantity skew/ Inter-client class imbalance	Hierarchical Personalized Federated Learning	User modeling	ASSIST No. of Clients= 59 No. of records=327058 No. of users=3477 MovieLens No. of Clients= 10 No. of records=96538 No. of users=925	public
[40]	2	Label skew/ Label distribution skew	Partial network	COVID-19	Kvasir/ image TRS=13954 TES=1579 2nd dataset/ image TRS=8000 TES=2000	public
[36]	7	Quantity skew/ Inter-client class imbalance	-	COVID-19	DS1=10 patients DS2=35 patients DS3=10 patients DS4=2 patients	Public+privat e
[45]	350	Hybrid skew/ class distributions skew and uneven data sizes	gradient-based binary permutation algorithm	FEMNIST dataset	DS=805,263 optical digit and character images	Private

TABLE 3. *(Continued.)* **A summary of all the details in the published FL that discussed issues of the distribution data.**

[46]	10	Hybrid skew /feature and label skew	cluster algorithm	Pump condition classification, Material classification	DS1= acceleration data from five pumps. DS2= vibration data and material hardness labels	Public+private
[52]	9	Label skew	Generative Adversarial Networks	CWRU dataset Bogie dataset	CWRU= vibration acceleration signals collected from the drive end of the motor Bogie= test rig of a high-speed multi-unit train bogie-bearing system	Public+ private
[47]	20	Hybrid skew/ Inter-client class imbalance and class distributions	Adaptive clustering	CIFAR10 MNIST FMNIST	CIFAR-10 (image) TRS=50000 TES=10000 MNIST (image) TRS=60000 TES=10000 +DS=805,263 optical digit and character images	Public
[48]	-	Hybrid skew/label distribution skew and feature skew	Federated Clustering and Semi-Supervised learning.	WISDM MobiAct	DS1= 36 subjects/ 6 feutres DS2== 60 subjects/ 9 feutres	Public
[37]	-	Quantity skew/ Intra and inter client class imbalance	FLY-SMOTE	Hotels Dataset Bank Dataset Adult census income Dataset Compass Dataset	Ds1= 17 feutres Ds2= 46 feutres Ds3= 14 feutres Ds4= 28 feutres	private
[28]	-	Quantity skew/ Intra and inter client class imbalance	data sampling	CIFAR-10 MNIST	CIFAR-10 (image) TRS=50000 TES=10000 MNIST (image) TRS=60000	Public
					TES=10000	
[49]	4	Hybrid skew/ Inter-client class imbalance and label distribution skew	Client clustering affinity-propagation	CIFAR-10 MNIST	CIFAR-10 (image) TRS=50000 TES=10000 MNIST (image) TRS=60000 TES=10000	Public
[41]	5 10	label distribution skew	Generative adversial network	EMNIST FashionMNIST SVHN CIFAR10	DS1=26 handwritten letters DS2= 10 different kinds of clothing images Ds3=different house numbers in street DS4=10 classes of color images from the real world	Public
[50]	-	Hybrid skew/ label distribution skew/model heterogeneity	Model Distillation Update	HHAR	six daily activities	Public
[51]	100	Hybrid skew/ free riders (clients with very less data samples), severe class imbalance and highly skewed distribution of samples	Irrelevance Sampling	MNIST KMNIST EMNIST-47 HAR Cardiotocography	DS1= MNIST (image) DS2= hand-written Japanese characters of Hiragana DS3= containing both characters and digits DS3= A network of 23 different sensors (including seismic, acoustic and passive infrared sensors) are placed around a road segment in order to classify vehicles driving past them DS4= 30 subjects performing daily activities DS5= fetal heart rate (FHR) and uterine contraction	Public

TABLE 3. *(Continued.)* **A summary of all the details in the published FL that discussed issues of the distribution data.**

[22]	50	Hybrid skew/ label distribution skew and inter client class imbalance	probability-corrected loss	Fashion-MNIST EMNIST CIFAR-10	DS1= 10-class dataset for fashion product image Ds2=26-class dataset for character image DS3= 10-class image	Public
[32]	-	Quantity skew/ Intra client class imbalance	VFL HFL	HAR	11771 activities/ 30 subjects	private
[43]	20	Feature distribution skew	disentangled federated learning	colored-MNIST 3dshapes dSprites Office-Caltech1 DomainNet	-	Public
[26]	7	Time skew	Continual Federated Learning	split-CIFAR10 split-CIFAR100 datasets, split-Fashion-MNIST	-	Public

TRS=Training Set, TES=Test set, DS=Dataset and No.=number

enhanced the performance and increased the accuracy of the system.

d: FEATURE SKEW

In this type of skew, different clients have different feature P(xi) distributions. For IID, the distribution of feature X is the same for all clients, but in non-IID scenarios, the distribution of feature X is different for each client [8]. The FL training process may encounter issues if certain features are missing from one or more nodes in the feature distribution skew [42]. Most forms of this skew are feature distribution skew and missing values. Disentangled federated learning, which aims to improve the framework's stability, interpretability, and speed of convergence by overcoming the problem of feature skew, was proposed in another study [43].

e: CONCEPT SHIFT SKEW

Concept shift skew can take one of two forms: the same label with different features or the same features with a different label [8], [44]. There is no work of this type.

f: HYBRID SKEW

Client data have two or more of the types of skew detailed above [25]. A previous paper [45] introduced a hierarchical FL system with a cloud edge to improve system accuracy in including heterogeneity information. The framework applied a gradient-based binary flipping algorithm to select some users and create homogeneous nodes. The researcher introduced the application of industrial FL to give customers services on end devices [45]. This strategy addresses skewed information users by grouping customers into cohorts with similar representation to improve the throughput of the system [46]. The work demonstrated the need to eliminate variation in user samples as well as solve the drift client by introducing an FL-based clustering algorithm. The proposed framework achieved low-cost communication and more accuracy compared to Fed-Avg [47]. Personalized human activity recognition (HAR) integrates federated clustering with semi-supervised learning to capture the heterogeneity of data. The suggestion method dealt with the issue of unlabeled data by creating pseudo-labels [48]. In [49], dynamic clusters based on the cosine transform and affinity index were used to address the unbalanced data volume of clients and skewed data, and the authors were able to enhance the accuracy of the model by 20%. The model distillation update based on FL was built to handle the heterogeneity of the model and data, showing that the framework provided greater stability and efficiency [50]. Another paper suggested using a method called ''irrelevance sampling'' to choose clients based on the amount and quality of data; in severely skewed data, this technique achieved 50%-80% faster convergence [51].

Table 3 presents information extracted from previous research such as the number of clients, type of skew, suggested algorithm, case studies, dataset descriptions, and publicity. This information might be quite helpful, especially when choosing one of the case studies in this table and creating new approaches. The majority of FL algorithms in these studies were tested based on MNIST, and CIFAR datasets, and fewer studies were tested on medical datasets. However, none of the reviewed studies mention methods to explain the analysis of skew data or built heterogeneity datasets that represent most of the types of heterogeneity data. Some research used Dirichlet distribution that only covers label skew. Most of the reviewed studies expected results with high accuracy and performance, although the results obtained from these techniques varied from one study to another. The question is how to select an appropriate algorithm that deals with more skew and doesn't affect other challenges like privacy or communication. How to make a partitioning strategy that covers all types of heterogeneity data.

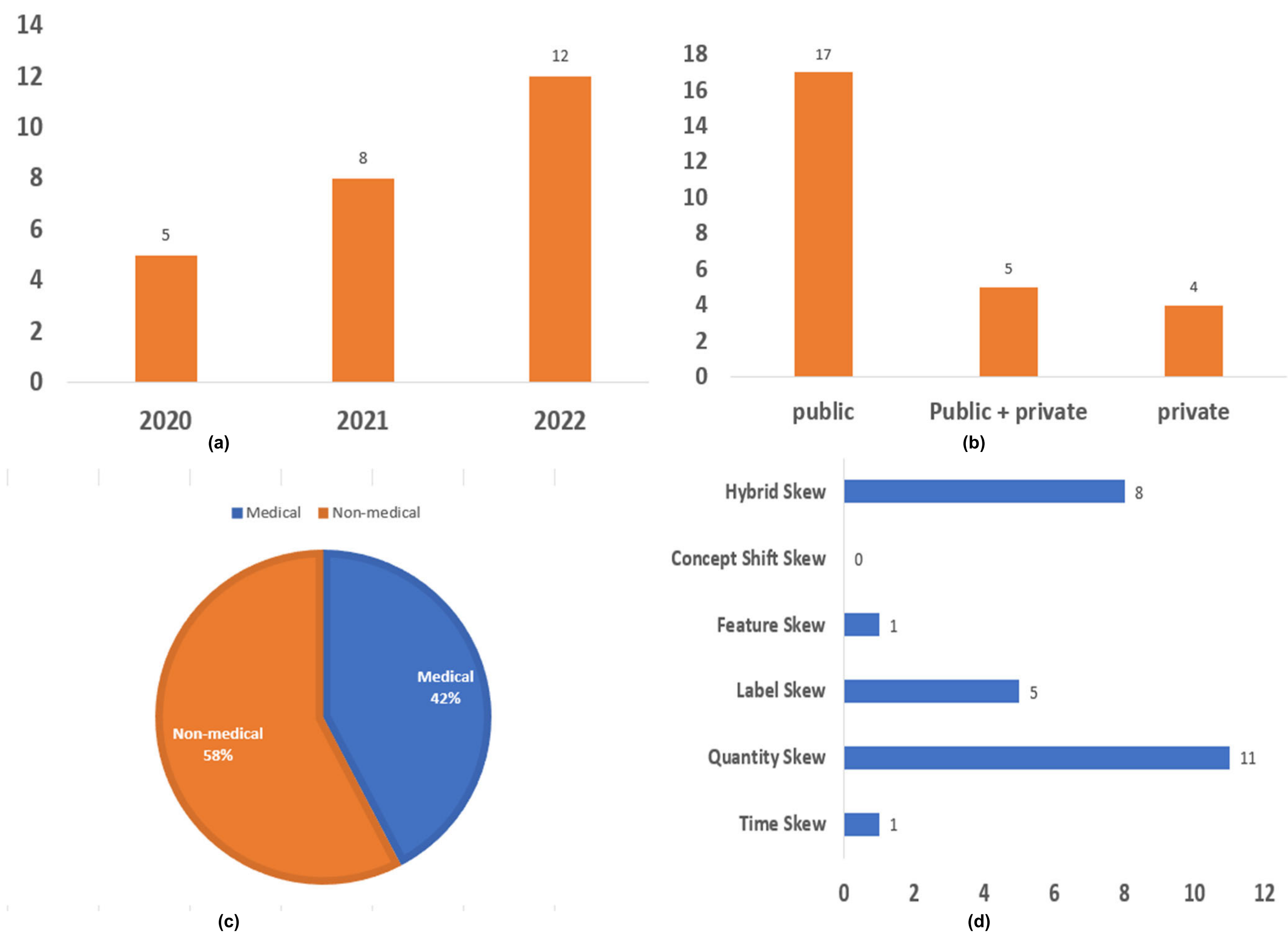

FIGURE 5. Numerical description of published articles in federated learning.

Based on the results of the numerical study, the following conclusions were drawn. To start, Figure 5a shows the heterogeneous distribution of the number of FL studies published by year of publication. In 2022, there should be an ongoing linear growth in the number of publications published. The amount of data points that are accessible for the researchers to test their framework is also shown in Figure 5b. Figure 5c shows the percentage of FL used in the medical field. This percentage must increase to reduce the human losses that occur due to diseases or disasters such as COVID-19, smallpox, etc. Based on Figure 5d, quantity skew is the most frequent, while there are challenges like time skew, feature skew, and concept shift skew that were not taken into account. To bridge this gap, researchers must think more comprehensively to cover most of the challenges.

B. PRIVACY AND PRESERVING CHALLENGES

A key component of FL is privacy. Security models and analytics are required to provide certain privacy guarantees. Differential privacy and homomorphic encryption-based approaches are common options for data privacy protection [18]. Table 4 provides a detailed overview of the approach, benefits, and limitations of numerous previous studies that have been conducted in this field. The purpose of this discussion is to raise awareness among researchers that several studies in the literature may be misleading due to unrealistic assumptions made by the authors, such as presuming that all clients have the same attributes or that the server is trustworthy. Additionally, some studies might have had excellent accuracy but required more time, which could impede their usefulness in real-world situations.

It is also significant to highlight that few researchers have taken into account fundamental elements like scalability, time, accelerating algorithms, and evaluation on huge datasets, which are essential for guaranteeing the efficacy and viability of privacy-preserving federated learning. Here displayed some studies that help researchers to develop new algorithms that balance these factors more effectively. An FL-based blockchain support system was suggested to support the privacy of users in smart cities or healthcare systems, in which a user receives a well-trained model without providing the server with any of his data [53]. Human Activity recognition (HAR) was designed based on a wearable sensor using FL called HARFLS. It shares model weights using the federated averaging approach, and it extracts features using a perceptive extraction network (PEN). Additionally, the use of homomorphic encryption reduces the possibility of information leakage during upload and weight distribution [54]. The mutual information can be integrated with FL to build a system against malicious nodes by determining the gradient correlation between the local training model and aggregate models. The proposed method can speed up communication and guarantee the privacy of the client [55]. A private recommender system was designed to learn local and global models without requiring the sharing of users' statistics or personal information of users; the suggested strategy is reliable and ensures low communication costs [56]. A federated semi-supervised learning architecture was suggested for 3D chest CT segmentation of COVID-19-affected regions; the approach can obtain important data from clients who did not have labeled data [57]. Federated machine learning with anonymous random hybridization (FeARH) uses a hybrid method and adds randomization to parameter sets that are shared among many parties to address the issue of inconsistent parties in federated machine learning [58]. Another study recommended using a neural network model based on studies into video surveillance systems at the computing edge to disseminate video analysis on the edge development board [59]. Distributed federated non-intrusive load monitoring is proposed that can achieve the highest levels of user privacy while maintaining high performance [60]. A previous study introduced a distributed autonomous self-learning system for spotting hacked IoT devices without requiring human intervention or labeled data. The proposed system is utilized to detect anomalous variations in device communication behavior, which may be brought on by nefarious opponents [61]. Another study suggested leveraging IoT to monitor and analyze healthcare data using a deep federated learning (DFL) architecture, where DFL was applied to detect skin diseases to provide many benefits by mainly preserving information, caring for patients remotely, and obtaining high accuracy in patient classification [62]. A previous author described an IoT-based Alzheimer's disease (AD) detection system that protects privacy and can identify early-stage AD by listening to audio recorded in an IoT environment; this system, called ADDETECTOR, has the advantages of being simple to deploy, highly effective, and privacy-protective [63]. Another author presented a backdoor-tolerant FL framework via Shapley value by modeling it as a coalitional game. The proposed technology could succeed in the face of an individual or mass attack scenario in the healthcare environment [64]. An efficient and privacy-preserving FL with irrelevant updates framework was suggested, where a non-interactive key generation algorithm was used to reduce the negative impact of irrelevant updates, speed up model convergence, and improve prediction accuracy [65]. To ensure user privacy in dispersed healthcare systems, a paper [66] suggested a DFL framework. To solve the issue of the restricted availability of healthcare data for developing DL models, the paper describes an experiment for applying DFL to identify skin disorders [66]. Another paper proposed a unique FDFF-based algorithm called double deep Q-network (DDQN) that is made possible by an integrated system called SMEC, which offers a reliable method for determining real-time treatment policy from a large number of dispersed observational EMRs and ensures the confidentiality of EMRs via additively homomorphic encryption [67]. Ideas on how improvements in edge computing and machine learning might be combined to provide a practical, privacy-aware clustered FL approach for COVID-19 diagnosis (CFL) were presented [68], and the author offered an alternate strategy that makes use of differential privacy and secure multiparty computation. Another method allows us to decrease the rise of noise injection as the number of participants increases without surrendering privacy and while preserving a predefined rate of confidentiality [69]. Another author offered the privacy-preserving mobility prediction framework (PMF) [70] through FL as a solution to this issue without considerably compromising prediction accuracy, where the clients did not upload any sensitive data but uploaded the local model to the main server to update the global model. To detect the severity of arrhythmias, a previous researcher proposed explainable artificial and deep convolutional neural networks, in which a model assisted doctors in interpreting results and making the correct decision to save the patients' lives [71]. The last paper in this category [72] employed the accelerated federated soft-impute algorithm with a differentially private tensor completion method to build a strong framework against different attacks and provide high protection to the users.

C. RESOURCE CONSTRAINT CHALLENGE

One paper provided a method built on FL principles to make sure the locally developed ML models are capable of generalization [73]. In addition, FL was expanded to include optimal model selection decision-making using optimal stopping theory and adaptive weighting over a customized and generalized framework [73]. In another article, various FL approaches were analyzed, and the framework is designed using the message queuing telemetry transport protocol. Parameter server-based FL and fully decentralized FL tools were proposed to implement systems that support smart healthcare networks and medical diagnosis. The system aided a physician to identify areas of interest that capture the tumor and minimize the time for treatment [74]. The distributed gradient descent analyzed the convergence bound and then offered a control method that chooses the optimal balance between local update and global parameter aggregation to minimize the loss function within a predetermined resource budget [75]. Convolutional neural network architectures based on FL were introduced to detect seizures solely using the EPILEPSIAE database's electrocardiogram (ECG) signal; the results show improved performance metrics and saved energy for clients [76]. Another study suggested an asynchronously updated FL architecture [77] for classifying ECG arrhythmias in a safe environment; the proposed

TABLE 4. Comparison between existing studies.

References	Approach	Advantage	Limitation
[53]	Blockchain-based IoT	Improved scalability	The proposed model is limited to a theoretical model but can be applied to a live blockchain and federated learning-based distributed network, which will impact the performance because of the additional delays
[54]	perceptive extraction Network (PEN) homomorphic encryption technique	Four widely used datasets. F1/ Ntotal 97.29% /10 97.06% / 20 96.65% /30 92.38% /40 90.39% /50	As more clients utilize the system, more clients take part in the training, which increases the level of uncertainty in the system.
[55]	Mutual information	minimize the danger caused by malicious nodes accuracy is 98%	The author assumes that malevolent nodes upload false training variables in the framework, causing a significant error rate for the modeling framework.
[56]	differentially private	Merely two rounds are required. Lower the cost of communication. Limit the loss of privacy.	The assumption that each silo holds data from numerous users is a shortcoming of the current research. The framework is particularly unsuitable for environments where each entity represents a single user. The presented solution has only been evaluated in situations when silos share the same properties, which is a second drawback.
[57]	Federated semi-supervised learning	reduces the load of annotating more efficient when using traditional data sharing	There are potential domain gaps between supervised and unsupervised clients. It is an unsolved problem of how to better model this domain gap and mitigate it during federated learning. Another example is how to adaptively aggregate contributions from different clients based on the quality and not just the quantity of a client's database. Because there are a lot of variables in the semi-supervised framework, and complexity is even higher compared to regular FL
[58]	hybridization algorithm	AUCROC is 0.8312 AUCPR is 0.6778	not enough experiments
[59]	Neural network	• Reduces equipment expenses • Reduce operating energy use • Suitable for genuine project configurations	Acceleration algorithms are necessary for the model to satisfy real-time demands.
[60]	Distributed Federated Non-Intrusive Load Monitoring (DFNILM)	• Accomplish acceptable efficiency • high level of privacy preservation	• The model is gathered using a single variable server • At least one computing device in every residence is capable of performing the training of the local energy disaggregation model. • All households' computational units have the same amount of processing power.
[61]	anomaly detection approach	• detection rate =95.6%) • fast (time≈ 257ms)	There are several suppositions • No dishonest producers • The Security Gateway is secure. • IoT device selection that is automatic
[62]	Deep federated learning	• 97% is the area under the curve. • Cut back on operating expenses.	The reliability of IoT devices and their capabilities to handle heavy operations.
[63]	Federated learning and differential privacy	• Accuracy of 81.9% • a low time overhead of 0.7 s	a small number of clients (N=3)
[64]	Shapley Value	• high accuracy • flexible in multi-attacker environments	One potential drawback is that some hackers may carry out a more cunning and well-planned backdoor attack using brand-new triggers that have not yet been identified; in this case, BatFL might have trouble quickly and efficiently detecting the backdoor attack.
[65]	non-interactive secret polynomial generation protocol	• Improve accuracy and convergence • Enhance efficiency	The limitation is that SPs are honest and non-colluding. Both of them are trusted by all entities involved in our scheme. The server and EHR owners are considered to be honest-but- curious, which means that they will perform our scheme as designed, but they are likely to exploit other EHR owners
[66]	Deep federated learning	• Area Under the Curve is 0.97 • better system outcomes in terms of accuracy, precision, recall, and F1-score	The limitation is Evaluating the experiment on a larger dataset: We got initial results for this due to the finite availability of the skin diseases dataset, but we need to build and evaluate the model using a much larger dataset and We believe this will open new research

TABLE 4. *(Continued.)* **Comparison between existing studies.**

			avenues for both IoT device dropout and data transmission aspects.
[67]	federated reinforcement learning	The findings provide encouraging results for DDQN's clinical policy.	DDQN encounters certain challenges in adopting a strict policy when patients are critically infected. Therefore, with low and medium SOFA values, DDQN is advised used.
[68]	clustered federated learning (CFL)	The F1-Scores have increased on the X-ray and ultrasound datasets, respectively, by 16% and 11%.	Certain difficulties and restrictions exist such as inefficiency, security concerns, and the difficulty of optimizing CFL variables.
[70]	fine-tuned personal adaptor	• protects personal privacy • Reduced number of variables are needed to update • Low communication expense	The framework needs to accommodate a wider variety of machine learning models and use cases.
[71]	1-Dimensional Convolution Neural Network-based autoencoder	• Lower communication expenses • Protect user data privacy • It can be expanded to a wide range of other medical uses.	• Since distributed environments raise the risk of data poisoning attacks, techniques for data integrity and authentication should be developed. • Distributed edges' data and devices are thought to be homogeneous. • Device-specific traits may restrict the local models' capacity to be used across different devices and may lower the accuracy of the aggregated model.
[72]	differentially private tensor completion method	considerable time and space reductions privacy protection of user data	Client information may be updated regularly, but the model requires the utilization of the first noticed information of every client to finish tensor completion. For the completeness of dynamical tensors, this approach is inadequate.

framework is efficient in terms of light operation (for example, low execution time and memory usage) and achieves great accuracy in detecting arrhythmias.

D. EXPENSIVE COMMUNICATION

Communication is a significant bottleneck in federated networks. Communication is related to the privacy of clients and the need to keep data generated locally on each device without sharing them with anyone. Federated networks can potentially consist of a huge number of devices (such as millions of smartphones), and communication within the network is limited by resources such as bandwidth, energy, and power [78]. For IoT heterogeneous systems, a previous author provided an optimal approach for client distribution and available resources across hierarchical FL design [79]. This study concentrated on general classical methods that are trained using gradient-based techniques while taking into account the practical issues of unevenly dispersed data among users, and the suggested method provided a 75%–85% reduction in contact tours and lower connection expenses [79]. In another paper [80], a unique FL strategy was presented that avoids sending private information over a network and outperforms traditional FL models by requiring less communication. The suggested method provides good results in terms of accuracy rate with an enhancement varying from 3.01% to 11.09% and a nearly 34% drop in transmission costs [80]. The researcher developed a communication-efficient and privacy-preserving framework for FL in IoT to safeguard the privacy of each client and drastically cut down on communication costs [81]. A new compression method, named sparse ternary compression, was proposed to decrease the amount of communication per client, the workload of aggregation from the client, and the consumption of energy [2].

E. EFFICIENCY OF FEDERATED LEARNING

Using blockchain technology and smart contracts, a unique collaborative early warning framework for COVID-19 [82] was developed to crowdsource early warning duties to various dispersed channels, such as healthcare facilities, nonprofits, and even private persons. The platform enables two types of surveillance: social collaboration surveillance based on the learning markets method and medical federation surveillance based on FL, and it combines the monitoring data on new cases to notify [82]. The researcher presented a way to mix FL with an asynchronous aggregation model to enhance efficiency. The results demonstrate high accuracy when utilizing ML/DL elements, showing that asynchronous FL could greatly enhance the prediction accuracy of local edge models, reduce communication costs, speed up the simulation, and consume real-time streaming data [83]. The huge cluster split into numerous smaller clusters, according to another paper [84]. This resulted in smaller aggregated update sizes, lower communication overhead, and much higher system efficiency. Federal learning was combined with basic DL techniques to implement a framework that treats patients suffering from depression while preserving patient privacy [85]. Figure 6 shows that statistical data heterogeneity and privacy and security were the most important challenges in this survey. Given many different types of data heterogeneity, there are more problems to solve, such as long communication times, individual models that do not converge to the real global model, higher communication costs, and low

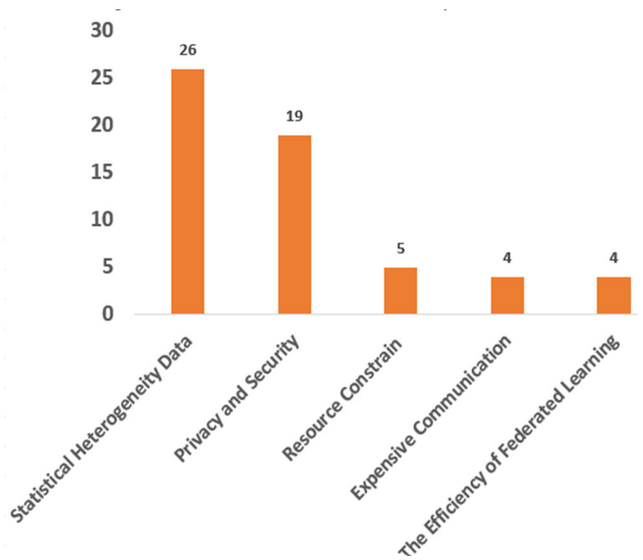

FIGURE 6. A numerical description of the most important challenges in federated learning.

efficiency. Therefore, addressing the problem and finding a suitable solution is necessary.

VI. FEDERATED LEARNING IN DIFFERENT APPLICATIONS

This section discusses some applications related to industrial engineering and medical applications to demonstrate the important role of federal learning in real life, as indicated in figure 7.

A. APPLICATION IN HEALTHCARE

The amount of patient data possessed by each medical institute can be substantial, yet it may not be sufficient to train their prediction models [86]. FL is one of the most efficient strategies to remove analysis barriers between various hospitals and avoid biasing of the model. Many studies in the healthcare field are presented in this section.

1) COVID-19

An FL model was proposed to create an accurate framework that can be able to detect COVID-19. The dataset is collected from different clients using ambient sensors and wearable devices [87]. Another author [57] developed a federated semi-supervised learning architecture for 3D chest CT segmentation of COVID-19-affected regions. The suggested approach can extract useful data from clients who only have unlabeled data. Other researchers [82], [88], suggested FL based on blockchain and smart contracts for early warning of coronavirus. Another study recommended diagnosing COVID-19 utilizing FL on medical datasets using partial networks; without sharing local patient data, the algorithm can enable many institutions to successfully and cooperatively train a partially shared model [40].

2) HUMAN ACTIVITY RECOGNITION

FL was created for wearable sensor-based human activity recognition; it shares model weights using the federated averaging technique and extracts features using a perceptive extraction network [54]. Another paper [89] introduced the first federated transfer learning system for real Parkinson's disease auxiliary and wearable healthcare activity identification experiments. One author designed a framework for classifying human activity such as walking, sitting, standing, and stretching; the system can mitigate data heterogeneity and unlabeled data [48]. In the same way, another author developed [32] a secure framework for personal HAR reinforcement in CPSS and fixed the problem of patients not having enough activity data. Portable activity monitoring with a Raspberry Pi is designed to capture heterogeneity in activity among patients and improve patient monitoring accuracy [50].

3) ELECTRODIAGRAM

One study suggested an approach called asynchronous FL that can improve classification accuracy while also protecting privacy, adapting to changing individuals, and using the least amount of network traffic possible [77]. Another researcher [71] put forth a model to diagnose the unprocessed time series of patient-provided ECG signal data. The suggested architecture will promote greater participation from healthcare data owners in the creation of effective machine learning models, more precise diagnostic support in regions with limited access to cardiologists or healthcare facilities, and more comprehensible categorization findings.

4) ELLIPTIC SEIZURE

A previous study developed and applied a novel FL architecture for epileptic seizure identification [76] across a variety of mobile devices, and the results demonstrate an improvement in all performance parameters, with a geometric mean of 90.90%, a sensitivity of 90.24%, and a specificity of 91.58%.

5) BRAIN TUMOR

To assist intelligent healthcare networks and medical diagnosis, a researcher suggested [74] federated and decentralized learning tools. Brain tumor segmentation was used as an example of implementation. A real-time testbed was used to quantify the trade-offs between training accuracy and latency and to highlight the crucial operational factors that influence performance in actual deployments.

6) ALZHEIMER'S DISEASE

A smart healthcare system in [63] was suggested that protects patient privacy and enables low-cost AD detection; the experimental findings demonstrate that, when all privacy-preserving techniques are used, the proposed method produced an accuracy of 81.9% and a minimal time of 0.7 s.

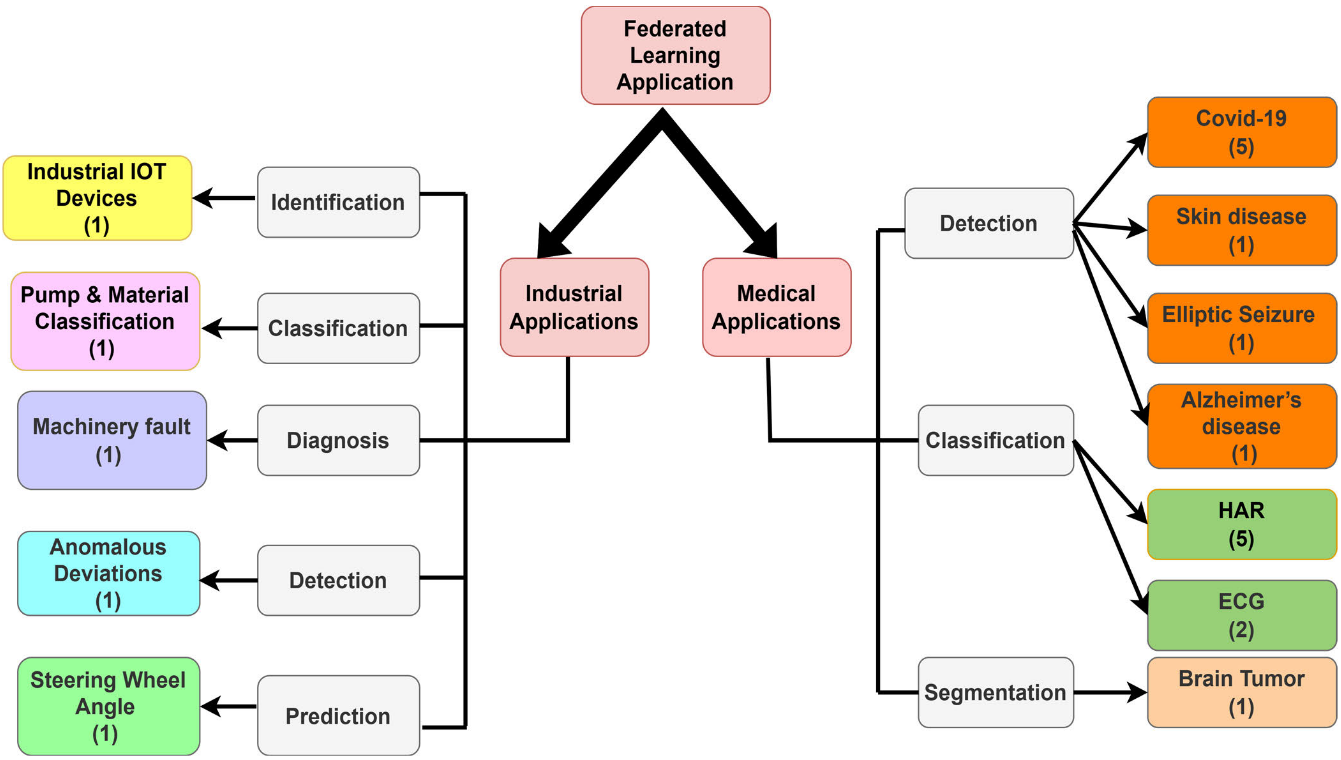

FIGURE 7. An overview of federated learning articles used in various applications.

TABLE 5. The computational complexity of some validity criteria for choosing an appropriate cluster method [93].

criteria	measurement	complexity
Dunn's index	measuring inter-cluster distance and intra-cluster diameter	$O(nN^2)$
Rand index	similarity between clustering	O(N)
Silhouette	how well objects lie within clusters	$O(nN^2)$
Simplified silhouette	The computation of all distances among all objects.	O(nN)
Davies–Bouldin	Ratio involving within-group and between-group distances.	$O(n(k^2 + N))$
Ball and Hall	group sum of distances	O(nN)

K is disjoint clusters, n is a dimensional vector of the sample, N is data object. O(n) is distance between different vectors

7) SKIN DISEASE

A study described how deep FL was used to identify skin disorders, and after several rounds, the results showed that the model's AUC percentage was greater [83].

B. APPLICATION INDUSTRY ENGINEERING

For modern industries enabled by 5G, a hierarchical cloud-edge-end FL structure was suggested; numerous tests demonstrate that proposed model significantly outperforms non-IID, improving efficiency by 3.5% and reducing simulation running by approximately 59% [45]. Using two-time series-based industrial datasets, a researcher first described the design and execution of a service-based system before presenting the evaluation of an Industrial Federated Learning (IFL) system, and in IID and non-IID scenarios, the model performance following FL outcomes is shown and compared [46]. For the diagnosis of machinery faults, another paper [52] suggested an FL method based on DL, and the findings indicate that the suggested method is reliable for fault diagnosis and maintains data safety. A self-learning technique for spotting hacked devices in IoT networks was introduced [61]. When tested in a real-world deployment, the system detected 95.6% of threats in 257 msec and without generating any false alarms [61]. Another study evaluated the proposed model in his case of industrial use in the automotive field, focusing on steering wheel angle prediction for autonomous driving, and the results demonstrate the advantages of this model when trained utilizing the suggested technique [83].

TABLE 6. Comparison between existing studies.

H \ C	C1	C2	……….	Cn
H1	C1-H1	C2-H1		Cn-H1
….				
Hm	C1-Hm	C2-Hm	……….	Cn-Hm

VII. OPEN DIRECTIONS

A. HETEROGENEITY DATA

Many methods have been proposed for the FL on non-IID data, but some methods do not use certain criteria to verify

TABLE 7. Comparing federated learning algorithms: Description, code availability, weaknesses, use cases.

REFERENCE	ALGORITHM	DESCRIPTION	AVAILABLE CODE	WEAKNESS	USE CASE
[29]	FedHome	This approach enables the creation of personalized health monitoring models that are tailored to individual users, while preserving the privacy and security of their data.	-	requires significant computational resources, including powerful servers and edge devices	healthcare
[30]	FEDGAN-IDS	It is a privacy-preserving algorithm using GAN and FL to enable effective and accurate intrusion detection.	-	requires significant computational resources, including high-end servers and GPU	intrusion detection system
[31]	FedSS	It is an algorithm designed for efficient and effective Federated Learning in fog computing environments where data is heterogeneous and distributed.	-	requires a significant amount of communication between the fog nodes and the cloud server	Healthcare/Industrial
[33]	FL	It is federated learning.	-	Limited data availability	Healthcare
[24]	FL with MoE and adversarial domain	It is an algorithm that enables collaborative machine learning across multiple sites while preserving privacy and security.	https://github.com/xxlya/Fed _ ABIDE/	requires a significant amount of communication between the different sites and the central server	Healthcare
[20]	CSFedAvg	It is an algorithm that enables efficient Federated Learning across mobile devices with non-independent and identically distributed (non-IID) data.	-	Privacy	Healthcare/Industrial
[39]	FedDPGAN	It uses the training of Differentially Private Generative Adversarial Networks (DPGANs) to design and preserve the privacy of the training data.	-	high communication overhead and delay	Healthcare
[34]	FedMood	It is designed to preserve the privacy of user data while enabling collaborative learning across multiple mobile devices.	-	Quality of user-generated data	Healthcare
[35]	HPFL	It is an algorithm that enables personalized machine learning across multiple devices while preserving privacy and security.	https://github.com/bigdata-ustc/hierarchical-personalized-federated-learning	requires a significant amount of communication between the nodes in the network	Healthcare/Industrial
[40]	FLOP	It works by using partial networks to enable communication-efficient model aggregation, making it suitable for resource-constrained environments.	-	-	Healthcare
[36]	FL	It is federated learning.	https://github.com/med-air/FL-COVID	-	Healthcare
[45]	FEDGS	It is a machine learning approach that combines federated learning and group client selection	https://github.com/Lizonghang/fedgs	-	Industrial
[46]	FLaaS	It combines federated learning with cohort-based analysis	https://github .com /OpenMined /PySyft. https://github .com /OpenMined /PyGrid	-	Industrial
[52]	-	It is self-supervised learning method	-	-	Industrial

TABLE 7. *(Continued.)* **Comparing federated learning algorithms: Description, code availability, weaknesses, use cases.**

[47]	AutoCFL	It involves clustering clients	-	communication overhead	Healthcare/Industrial
[48]	SS-FedCLAR	It combines Federated clustering and semi-supervised learning	-	need of storing labeled and unlabeled feature vectors, since it may not be sustainable in the long term on a mobile device.	Healthcare
[37]	FLY-SMOTE	It utilized federated learning and the SMOTE algorithm to improve model performance.	https://github.com/anonymousger/FLY-SMOTE	computationally expensive sensitive to the choice of hyperparameters, such as the number of neighbors	Healthcare/ manufacturing
[28]	-	It used data sampling	-	computationally expensive sensitive to the choice of hyperparameters,	Healthcare/ manufacturing
[49]	WSCC	It involves clustering the clients	-	not be scalable to large-scale federated learning	Healthcare/ Financial
[41]	FedMGD	It is a global Generative Adversarial Network	GitHub - Sheng-T/FedMGD: Modeling Global Distribution for Federated Learning with Label Distribution Skew	it requires the estimation of the global label distribution based on the distribution of labels across local datasets	Healthcare/ industrial
[50]	-	It used Model Distillation Update		Need several steps therefore more complexity	Healthcare
[51]	-	It used irrelevance sampling technique.		Scalability	Healthcare/ manufacturing
[22]	-	-	may available in future	require additional computational resources and time to align the outputs of the local model	Healthcare/ industrial
[32]	2DFL	It is 2D Federated Learning approach used to train the model for personalized human activity recognition	-	It operates on image and sometimes it is difficult represent motion in a 2D image	Healthcare/ industrial
[43]	DFL	It used Invariant aggregation and diversity transferring	-	It assumes the data can be easily disentangled	Healthcare/ industrial
[26]	CFL	It is variant of federated learning	-	require more communication and computational resources	Healthcare/ industrial

them or are taken at random. The figure 8 displays a categorization of these different challenges related to heterogeneity data along with the proposed solution.

Few studies have focused on time skew. Owing to the significant effect of time skew on healthcare, evaluating the actual effectiveness of those proposed innovative methods is not easy, especially in diseases such as COVID-19 and smallpox. Thus, an effective and efficient mechanism must be suggested to capture the time skew of data. Sharing data is not recommended because it contradicts the basic idea of

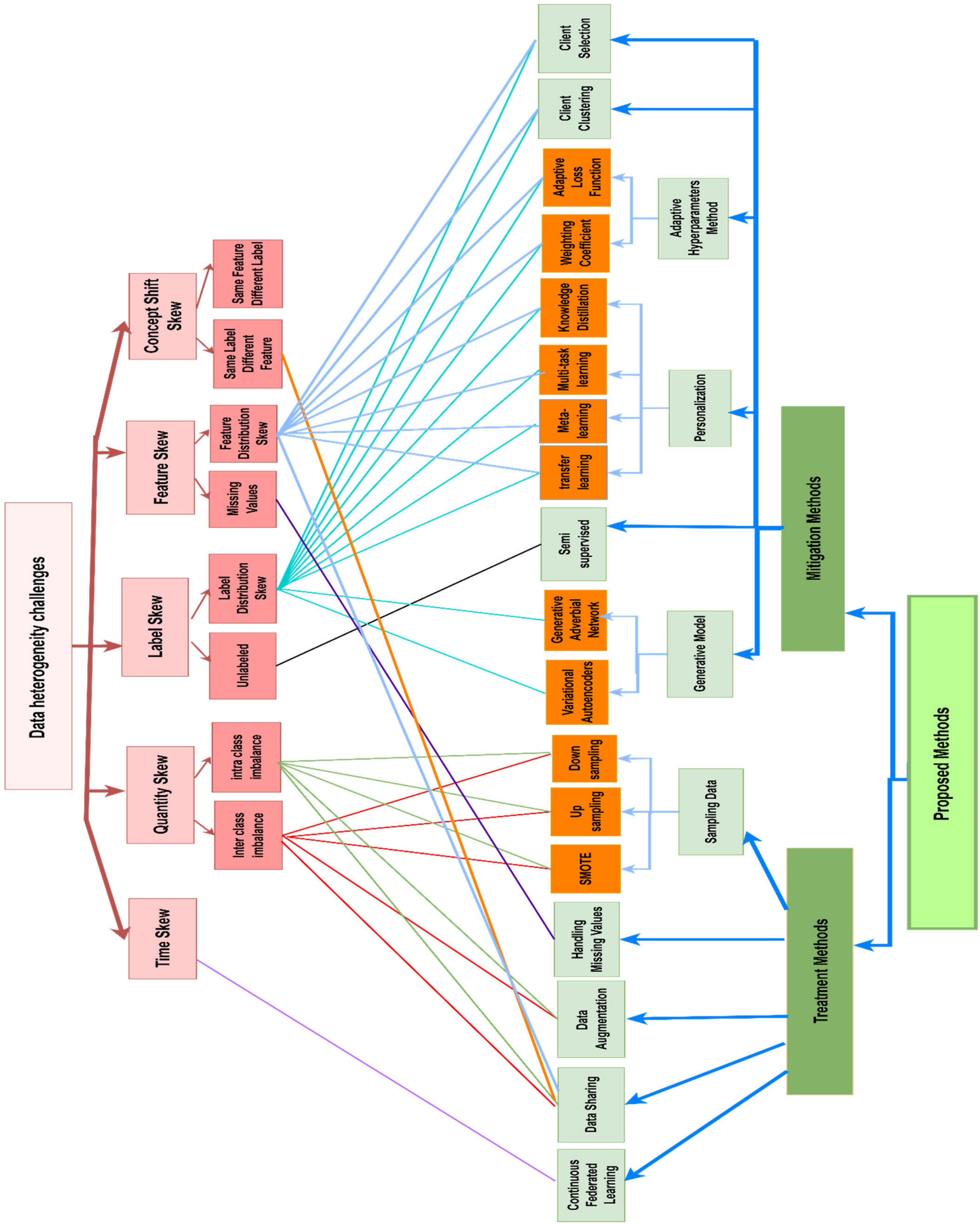

FIGURE 8. **The crossover among proposed methods for dealing with heterogeneous data challenges.**

FL, which is to protect the privacy of the user. Unbalanced data can be fixed with techniques like data augmentation, handling missing values, and sampling techniques. The adaptive hyperparameter method works well when dealing with the skewed properties of experimental label distributions in research [89], [90].

The personalization methods can mitigate the challenges of drift data, but they may affect other challenges like privacy and communication. Some personalization strategies deal with many issues with data skew, but they converge very slowly on large-scale datasets.

Many algorithms have been proposed for client clustering [48], [91]. However, only a limited amount of research discussed the criteria for clustering data. For example, a previous study proposed a clustering optimization method based on FL, in which the author utilized similarity to divide the clients into groups and then choose representative workers that communicate with a server; silhouette validation was used to ensure that the main workers are close to their current cluster. [92]. Depending on the complexity of the calculation and the type of data, there are many different criteria for validating the clustering algorithm, including optimization- and difference-like criteria [93]. The following table 5 displays the relationship between criteria and complexity:

Two or more skews were used to select a client with a lower degree of non-IID to participate in model training [20], [45], [51], [94]. Multi-criteria decision-making (MCDM) will be proposed to determine the similarity between clients as presented in table 6. The proposed MCDM method assigns m choices to each MCDM issue. H1,..., Hm presented hybrid models as well as a set of decision criteria. C1,..., Cn denoted evaluation criteria.

The table 7 provides important information about previous studies that have dealt with non-iid data but suffer from many weaknesses that make the framework ineffective in real-life situations. Researchers can use the descriptions to understand the main features and strengths of each algorithm and develop new algorithms that are successful in specific missions. For example, you can use the description to choose algorithms that are better suited to handle non-iid data or algorithms that are most effective at ensuring privacy. The researcher can use an ensemble learning or clustering algorithm with domain adaptation, a GAN, or a generative convolutional autoencoder to deal with more kinds of skew. It can use compression techniques with fedHome, FEDGAN-IDS, or other algorithms to reduce the size of the transmission between the server and clients. It can also mix SS-FedCLAR or CSfedAvg with differential privacy techniques to ensure the privacy of the data. The availability code [24], [35], [36], [37], [41], [45], [46], helps researchers accelerate progress and proposes a proficient framework to deal with multiple challenges in FL. It can be used to test and evaluate different algorithms on different datasets and open opportunities to deal with new challenges at the same time.

B. PERFORMANCE COMMUNICATION COST

High communication overheads due to frequent gradient transmissions decelerate FL. Various techniques could aid in improving communication to reduce the overheads. These schemes include local updating, client selection, fewer model updates, decentralized training, and peer-to-peer learning, all of which are used to cut down on communication costs [95], [96]. The studies mostly focus on determining the best way to balance communication expense with computational/precision pressure.

C. PRIVACY-PRESERVING AND VERIFIABLE

Most of the researchers focused on algorithms that provide safeguarding the privacy of user data. The popular techniques are differential privacy, secure multi-party computing, and cryptography. However, there remain security and privacy concerns with FL because hackers can monitor and steal information about individual learners based on the data they generate in the form of models. To guarantee user privacy, one author proposed a grouped verifiable chained privacy-preserving FL scheme (G-VCFL), and a verifiable proposed secure aggregation protocol [97]. Another researcher proposed VerifyNet, an FL architecture that ensures security and can be independently verified [98]. To be more precise, a double-masking approach is proposed to ensure the privacy of users' local gradients throughout the FL process, and the server must then give each client evidence supporting that its aggregated findings are accurate [98]. Verified FL [99] with preserving privacy is suggested for massive data in industrial applications, which was also proposed; to meticulously select interpolated points for confirming the accuracy of the aggregated gradients, Lagrange interpolation was specifically used.

VIII. CONCLUSION

With an aging population, it is essential to have effective telemedicine services that can meet their demands at an acceptable cost and preserve user privacy. When presenting the results, researchers all over the world have started to move away from machine learning or deep learning and toward federated learning. With this method, there is no need to store or transmit sensitive data over an insecure network or share it with unreliable third parties. This paper provided a thorough analysis of how FL enhances patient confidentiality and improves patients' quality of life without tracking all user movements in a central database. In addition, the study presented the advancement of FL growth in the context of healthcare applications over the last five years from a data perspective. We provided the current state-of-the-art approaches that handle FL-related issues, such as statistical data heterogeneity, privacy and security concerns, expensive communications, limited resources, and efficiency. We comprehensively analyzed some studies to highlight challenges, the publicity of data, the percentage of challenges that are solved/unsolved, limitations, and recommendations, and found certain gaps. The analyses were then presented in dedicated tables and figures. These analyses are essential to provide readers with a clear vision of how to handle and overcome FL-based data problems. Next, existing studies are discussed on FL for various applications, organized by learning application task types such as prediction, diagnosis, and classification. This paper draws a road map for researchers on how to utilize the approaches that solve or mitigate all types of skew data, balancing communication, and privacy-preserving and verifiable FL for patients with special increased diseases like COVID-19, monkeypox, and black fungus.

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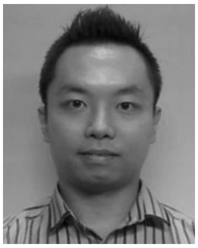

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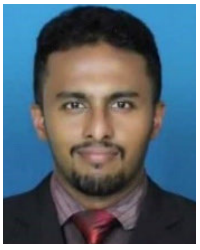

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