International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://www.theaspd.com/ijes.php

A SALSA-Based Literature Review On Federated Learning: Taxonomy Of Challenges And Emerging Applications

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Abstract

Federated Learning (FL) has emerged as a transformative approach for privacy-preserving machine learning, enabling decentralized model training across distributed data sources. This survey presents a comprehensive and methodologically rigorous review of FL systems, employing the SALSA methodology to identify, evaluate, and categorize the primary challenges associated with FL implementations. Spanning literature from 2015 to 2025, the review covers both tradi- tional sectors such as healthcare, finance, IoT, and education, as well as underrepresented and emerging domains including smart agriculture, wildlife conservation, legal analytics, and space exploration. We introduce a structured taxonomy that classifies FL challenges into six key cate- gories: privacy and security, communication and infrastructure, data heterogeneity, algorithmic and optimization, fairness and participation, and evaluation and debugging. The qualitative findings reveal critical gaps in current research, especially regarding cross-domain applicabil- ity, fairness, client reliability, and scalable personalization. Additionally, the survey identifies significant under representation of FL in agriculture and low resource environments, proposing application specific adaptations to enhance deployment feasibility. Emerging opportunities are discussed in the context of intelligent edge systems, collaborative governance, and regulatory compliance. Comparative tables and domain specific summaries further enhance the practical value of this work. This review contributes actionable insights for researchers, developers, and policymakers seeking to design robust, inclusive, and secure FL frameworks. It establishes a foun- dation for future innovation and emphasizes the need for scalable, trustworthy federated systems across privacy-sensitive domains in the era of distributed artificial intelligence.

Keywords: *Federated Learning, Decentralized Machine Learning, Privacy-Preserving AI,Real-world applications, Distributed learning.*

1 Introduction

In the age of precision agriculture and digital farming, data-driven insights have become crucial for enhancing productivity, sustainability, and efficiency in agricultural practices [1]. The growing deployment of Internet of Things (IoT) devices [2], smart sensors [3], drones [4], and satellite-based systems [5] across farms has led to an exponential surge in agricultural data, ranging from soil and weather conditions to crop health and pest infestations. While such data holds immense potential for transforming decision-making in agriculture, its collection and centralization often raise significant concerns related to privacy, bandwidth limitations, data ownership, and regulatory compliance.

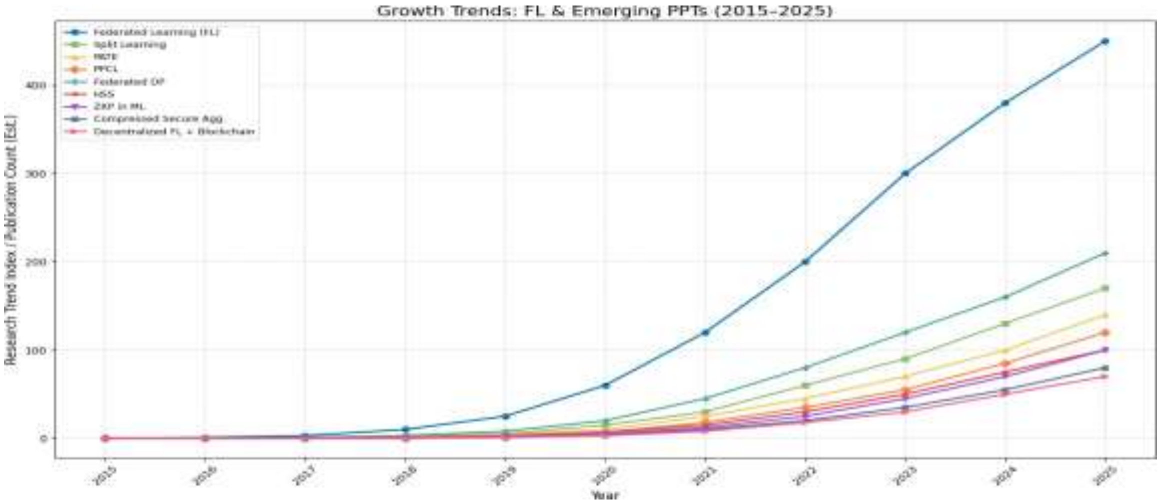

Fig. 1: Publication trends of FL and emerging Privacy-Preserving Technologies (PPTs)

FL [6] emerges as a transformative solution to address these challenges by enabling decentralized model training across multiple data-generating entities such as agricultural institutions, sensor networks, and research centers without the need to transmit raw data to a central server. In contrast to traditional centralized machine learning, FL allows data to remain local while collaboratively training global models using distributed updates, thus preserving privacy, reducing communication overhead, and accommodating region-specific data characteristics. These capabilities make FL particularly suited for modern agricultural systems, where data is sensitive, heterogeneous, and geographically dispersed [7]. Initially developed to address privacy concerns in mobile devices and healthcare applications, FL has now expanded into diverse sectors including finance [8], transportation [9], and more recently, agriculture [10]. The application of FL in agriculture enables smart systems to learn from distributed datasets such as soil profiles, climate variations, pest outbreaks, and disease symptoms, resulting in more adaptive, accurate, and localized models. For instance, smart irrigation systems can optimize water usage across regions, and disease detection models can become more robust by learning collaboratively from data collected across different agro climatic zones while keeping data securely within local sources.

Figure 1 represents the trend of FL estimated number of research activity or publications per technique and provide an idea about its increased or decreased significance in the field of machine learning. Remarkably, FL exhibits a sharp and exponentially increased trend that starts in 2018, and its publication index is expected to surpass 450 by the year 2025, and so it is the most popular method in the given category. This explosion is an indication of the growing need of decentralized privacy-sensitive learning environments posited by data governance models and the emergence of edge computing. Other related technologies like Split Learning, Federated Differential Privacy (DP), and Compressed secure aggregation are experience consistent growth and presumably reasons what complement technologies to improve the privacy and communication efficiency of FL. Although such methods as PATE, Homomorphic Secret Sharing (HSS), Zero-Knowledge Proofs (ZKP) in machine learning are developing more steadily, the increasing uptake suggests a growing interest in secure, explainable, and auditable deployment of FL. Also, the Decentralized FL that is combined with Blockchain also shows a strong increasing movement since 2021, indicating that there is an increasing mutual share between DLT and FI. Taken together, all these trends suggest a growing research environment interested not only in constructing robust, scalable, and reliable AI models without compromising user privacy but do this across multiple application domains.

The fusion of FL with agriculture not only enhances the capabilities of precision farming but also addresses critical limitations such as poor internet connectivity in rural regions, data silos between agricultural organizations, and the lack of standardized data sharing frameworks. With increasing concerns over data privacy and ethical AI practices in rural communities, FL presents a privacy-aware and scalable paradigm for enabling secure, collaborative intelligence in agriculture. This comprehensive review aims to examine the growing landscape of FL applications in agriculture, analyzing its benefits, limitations, and real-world deployments across various agricultural domains. By surveying state-of-the-art approaches, the paper provides insights into how FL is being used to address challenges such as non-IID data, communication bottlenecks, and model heterogeneity in agricultural contexts. Furthermore, this work identifies emerging opportunities and research directions, offering a structured perspective for future exploration at the intersection of FL and agriculture. Table 1 comparison of this survey in agriculture with the state of the art of other review works shows a comparative analysis of several survey papers in various application domains of FL, as well as their scope and domain coverage.

Table 1: Comparison of this survey in Agriculture with the state of the art of other review works

Survey	Year	Agriculture	Healthcare	Finance	Smart City	IoT	Education
[11]	2024	✓	–	–	–	✓	–
[12]	2025	✓	–	–	–	-	–
[13]	2024	✓	–	–	–	-	–
[14]	2025	✓	–	–	–	✓	–
[15]	2023	✓	–	–	–	✓	–
[16]	2025	✓	–	–	–	-	–
[17]	2022	✓	–	–	–	-	–
[18]	2025	✓	–	–	–	-	–
[19]	2023	–	✓	✓	✓	✓	–
[20]	2023	–	✓	✓	–	–	–
[21]	2021	–	–	–	–	✓	✓
[22]	2023	–	–	–	✓	–	–
Our Survey	2025	✓	✓	✓	✓	✓	✓

The rest of this paper is structured as follows: Section 2 presents the related literature, compar- ing previous survey efforts. Section 3 outlines the methodology used for paper selection and data synthesis. Section 4 introduces the foundational concepts of FL in agricultural settings. Section 5 categorizes the various FL applications of federated learning. Section 6 highlights the challenges and limitations associated with applying FL. Section 7 summarizes the key findings and contributions of the review. Section 8 discusses future directions, and Section 9 concludes the paper with reflections on the implications of FL for sustainable agriculture.

2 Related Work

In this section, we provide an overview of related works on FL in variety of sectors: agriculture, healthcare, finance, IoT, smart cities, and education. These surveys have discussed the evolution of FL frameworks, aggregation methods, optimization issues, domain-specific utilities, and deployment challenges. Comparison to such surveys locates the originality of this paper that is, concentrating on FL applications for smart agriculture systems.

Zheng et al. [23] provided a survey on a list of FL structures, like horizontal, vertical and transfer FL and aggregators, like FedAvg, FedProx, FedYogi. It examines practice implementations of smart contracts in the context of healthcare, finance, IoT, smart cities, education, and agriculture, studying data properties and privacy issues in the respective fields. The paper enters into optimization methods , security such as secure aggregation and DP , heterogeneity in the system. It shows profiling of such datasets as FLamby and Flower, and compares communications overhead in a variety of domains. Outstanding among those is its sector comparison model, which produces cross sector gaps in design and sets out future directions on personalization, incentive mechanism, and hybrid FL.

Nguyen et al. [24] this survey is interested in FL executed on resource-constrained hardware to be applied in healthcare, smart cities, autonomous, and unmanned aerial vehicles, smart industry application, such as agricultural sensors, powered by IoT. It examines such technological issues as two-layer FL architecture on edge servers, quantization and pruning compression, asynchronous updates, and privacy approaches like homomorphic encryption, secure aggregation. The authors survey sources of datasets from IoT sensors, medical wearable, drone images and review related challenges such as non-IID data, straggler effect and a bandwidth bottleneck. They give information on performance indicators such as latency, energy levels and model accuracy depending on the domain.

Olivares et al. [25] in this review, the intersection of IoT, edge intelligence, and FL can be realized between IoT through smart agriculture and other areas. It talks about FL-grounded utility sensors like soil moisture, NDVI, livestock, monitoring and edge ML models of crop and animal health. Technically the present paper reviews the two communication protocols which were LoRa, ZigBee, data fusion schemes, energy efficient FL scheduling. It works on domain-critical issues, such as rural connectivity, data disparity, and regulations. This is agriculture centered but provides potentials to compare the presence of FL in smart cities and health care, demonstrating a cross functional blueprint of architecture in a scalable, privacy sustaining, edge based data processing.

Nguyen et al. [26] discusses FL frameworks and technical adaptations like FedProx, SCAFFOLD, secure multi-party computation, in the context of healthcare, IoT, smart cities, finance, and dabbles in agricultural health monitoring of soil and plant diseases. It looks into a variety of data types: medical images, wearable, sensors, and comments on model architectures of 3D-CNN and RNN, homomorphic encryption, and client-server heterogeneity. The paper also examines latency of the system, fairness metrics and compliance with GDPR. It combines applications such as disease detection, smart mon- itoring and resource management, and plots next requirements, such as cross-domain adaptation, trust, and incentive-aligned FL ecosystems.Such an authority survey discusses FL frameworks and technical adaptations like FedProx, SCAFFOLD, secure multi party computation.

Zheng et al. [27] capacities and restrictions of the concept of smart cities are extensively dis- cussed, whereas comparative overview of FL applications in other fields, including IoT, healthcare, finance, transportation systems, and agriculture e.g. pest monitoring systems, crop analytics using UAVs are also covered in this survey. It categorizes NLP driven tasks: data offloading, anomaly detection, location services, and agricultural sensor fusion of data. Technically, this paper evaluates the frameworks of FedAvg and FedAtt, secure aggregation protocols, and blockchain-based identity management. It compares communication strategies, device-heterogeneity as well as privacy enforce- ments between sectors. The cross-domain solution would make it possible to realize reuse of smart city design patterns like edge orchestration, incentive models in agricultural FL implementations.

Javed et al. [28] provide an extensive survey and framework proposal to combine blockchain technology and FL to develop trustful decentralized frameworks to support Internet of Things (IoT) conditions (smart cities and 6G networks). The authors bring up the reliance of traditional FL on centralized aggregators that can be a problem of trust and transparency on large scale, heterogeneous networks of IoT. To overcome it, they suggest a blockchain accessibly FL framework applying non- centralized records to aggregate safe models and select on-chain storage to benefit both performance and resource constraints. The paper also says a few words about reputation-based mechanisms that can be applied to validate client behavior and it aligns its architecture with some global standards, including 3GPP, ETSI, ITU-T, IEEE, and O-RAN. To support their design, the authors develop a simulation of the model on the IOTA Tangle platform and demonstrate that the offered system could demonstrate high throughput and consistent confirmation rate even as the workload was increasing. Such major issues as blockchain overhead, latency, and the ability of devices to work together are as well critically assessed. This piece of work is a good source of information into making further advancements in the reliability, auditability, and scale of FL implements in smart infrastructures of the next generation. Table 2 presents a detailed comparative summary of five key research papers that apply FL in agricultural contexts.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://www.theaspd.com/ijes.php

Table 2: Examination of the latest events in the application of federated learning

Paper	**Methodology Reviewed**	**Key Contributions**	**Limitations**
Puppala et al. [29]	The paper reviews cross-silo FL approaches deployed over heterogeneous rural networks. The authors focus on adaptive clustering tech- niques that integrate both sensor and satellite data (Sentinel-2, CropScape) to enable scal- able model training under connectivity and energy constraints.	The authors propose a self regulating FL framework that optimizes both communica- tion efficiency and energy consumption. The framework is validated using remote sensing data and highlights the feasibility of FL in decentralized agricultural systems.	
Aggarwal et al. [30]	This review evaluates resource efficient FL for agricultural IoT settings, focusing on CNN ensemble models for rice leaf disease clas- sification. Methods such as model pruning, quantization, and asynchronous updates are discussed for optimizing FL performance.	The paper presents a custom FL pipeline that improves model accuracy while sig- nificantly reducing communication cost. It demonstrates that FL can outperform central- ized approaches in constrained farm environ- ments.	
Žalik et al. [31]	The authors review horizontal FL architec- tures and their application in agriculture, especially those using FedAvg variants. The survey covers sensor and image data integra- tion, as well as a classification of FL types and aggregation topologies.	The work provides a clear taxonomy of FL strategies applicable to agriculture and dis- cusses communication bottlenecks and data heterogeneity in rural settings. It helps catego- rize deployment use-cases based on data types.	
Durrant et al. [32]	This paper explores cross-silo FL models applied to yield prediction in agri-food sup- ply chains using decision tree ensembles. The focus is on secure, collaborative model training among multiple institutions without sharing raw data.	The study demonstrates how FL enables privacy-preserving modeling for soybean yield prediction. It shows FL achieves similar perfor- mance to centralized models while maintaining data privacy and ownership.	

International Journal of Environmental Sciences
ISSN: 2229-7359
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The framework lacks on field deployment test- ing and does not address device-level process- ing efficiency or compatibility with low power edge devices.

agricultural domains or geographic regions.

FL strategies.

It is limited by the use of a small set of public datasets, lacks real world farm level deployment, and does not consider network heterogeneity or device variability.

While insightful, the review lacks algorithmic depth and does not provide performance met- rics or comparative results across multiple

The review is crop specific focused on rice and lacks generalizability or scalability anal- ysis across different

Vimalajeewa et al. [33]	The review presents a service-based FL frame- work for smart agriculture using microservice orchestration. Edge devices are configured to run modular models with support for updates and localized adaptation.	The approach supports remote model updat- ing and client personalization in greenhouse setups. It is designed for lightweight deploy- ment, enhancing the scalability and adaptabil- ity of FL in edge environments.	The framework is validated at prototype level only and lacks full scale deployment results. It also does not cover security robustness or long- term performance implications.

3 Study design and data collection

The present systematic review gives a detailed overview of the development, use, and current issues of FL in an extensive list of areas. It presents an examination of the developing, simulating and implementing of FL frameworks in real-world. The aim is to develop a synthesized opinion about the existing state of the FL research with respect to the architecture advancements, approach to algo- rithms, communication models, privacy strategies, and system capacity with respect to the strengths, weaknesses, and rising tendencies. This study adhere to the SALSA [34] (Search, Appraisal, Synthesis, and Analysis) methodology to make it methodologically rigorous, transparent, and interdisciplinary meaningful. The literature search was concentrated on the subline 2015-2025 and a huge number of searches were conducted on the key academic databases such as IEEE Xplore, SpringerLink, Science Direct, ACM Digital Library, Wiley Online Library, Scopus and Google Scholar. ArXiv and other preprint outlets were used to take into consideration grey literature. Such terms as the ones included in the following list: federated learning, decentralised learning systems, privacy-preserving machine learning, cross-silo FL, FL in edge computing, non-IID data management, and secure aggregation were used to create keyword combinations.

In this study, the methodology is hinged on the SALSA framework. Although the Systematic Literature Review (SLR) approach [36] is frequently implemented when collecting evidence in a struc- tured way, the nature of FL in the all domain needs to be less structured and more iterative. SALSA allows scholars to reflect the empirical advances as well as the theoretical ideas in a new area. The proposed methodology can be especially effective in synthesis works that run across subjects and disciplines, like in the case of such interdisciplinary as agriculture, machine learning, and edge com- puting, where the API set, deployment patterns, and application pattern differ considerably. SALSA enables one to develop a sophisticated sense of how to implement FL with regard to methodological clarity and scholarly rigor.

3.1 Search Strategy

The main objective of the search strategy was seeking a broad range of peer-reviewed and upcoming research papers in terms of concentration on FL. More attention was paid to the literature con- cerning the foundations of FL, the design of the system, optimization approaches, and their use in different real-life situations such as healthcare, IoT, financial, educational, and smart environments. Literature search was undertaken in high flying online libraries such as IEEE Xplore, SpringerLink, ScienceDirect, ACM Digital Library, Scopus, Wiley Online Library and Google Scholar. Also, arXiv was added to guarantee the inclusion of grey literature and the most innovative solutions that are yet to be reviewed. To ensure an all round coverage, search terms were formulated through the Boolean logic. Some of the example queries were the compoundings of terms like federated learning AND privacy, non, IID data AND FL optimization, edge devices AND FL deployment, and cross-device federated training. The publications available between 2015 and 2025 were put in the search box to obtain current and up to date studies. This time slot can be described as the time of the blistering growth of the FL research, as there is a growing need of privacy-aware, distributed AI.

3.2 Appraisal

The Preliminary search identified 3,401 records of which 3,373 records were obtained in the primary scholarly databases, i.e., IEEE Xplore, SpringerLink, ScienceDirect, ACM Digital Library, Scopus, Wiley Online Library, and Google Scholar, and 28 records in the grey literature sources: arXiv. Duplicate records were removed and 1,823 records were kept after the initial screening. Another 600 articles were eliminated via unaccessibility or irrelevancy depending on the title and the synopsis. This yielded 600 full-text papers that were checked in terms of their eligibility. Articles were selected due to applications to specific Federated Learning (FL), including the development of algorithms, systems, and implementation, privacy measures, optimization of communications or empirical eval- uation in the real world. Researches referring to FL briefly or dedicating their attention to other fields were excluded. After the appraisal of full-texts, 456 articles were excluded because of irrele- vance or inadequate contribution and 144 studies were included in this review. They comprised 46 papers using implementation and experimenting, 39 using simulation and modeling, 28 on architec- ture design and 24 on the subject of conceptual and thematic approaches to personalization, non-IID data processing, and efficiencies in communications. The whole process of article selection and filter- ing is visualized in We used specific Boolean search strings to search multiple academic databases for key Federated Learning concepts in order to make sure that the literature review was thorough and strong. In order to guarantee a solid and thorough literature review, various scholarly databases were searched with clear Boolean search terms centered on major Federated Learning themes. As shown in Table 3 reflecting the prominent presence of FL research in computer science and engineering- oriented journals. This initial dataset served as the basis for the following screening and synthesis phases according to the SALSA approach.

Table 3: Query search results of relevant content for data collection from each database

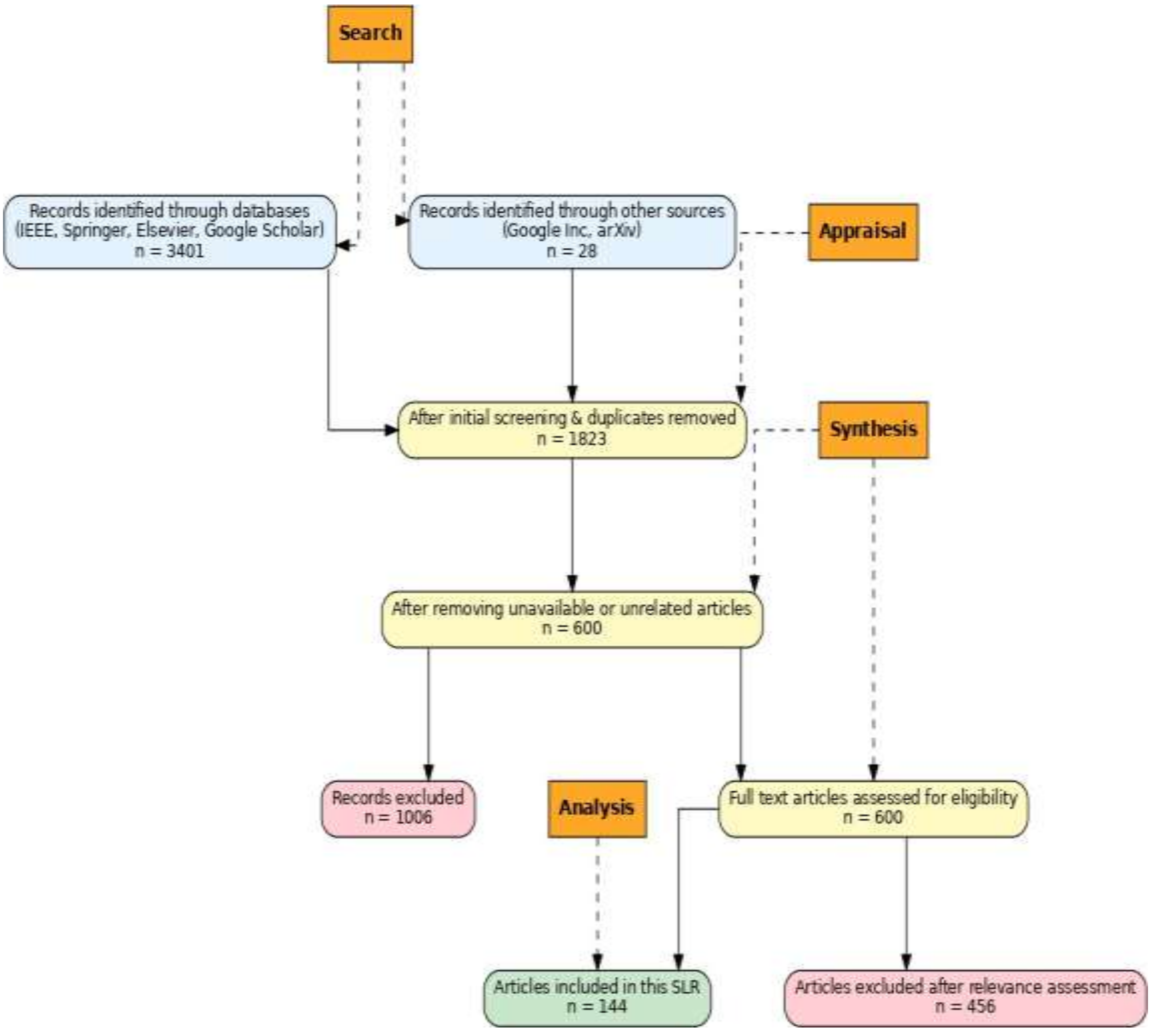
Database	**Example string**	**Total articles**
IEEE Xplore	("Federated Learning") AND ("privacy") AND ("aggregation") OR ("communication")	761
SpringerLink	("Federated Learning") AND ("optimization") OR ("non-IID") OR ("per- sonalization")	654
ScienceDirect	("Federated Learning") AND ("edge computing") AND ("deployment") OR ("scalability")	612
ACM Digital Library	("Federated Learning") AND ("secure aggregation") OR ("system design")	403
Scopus	("Federated Learning") AND ("IoT") AND ("decentralized learning")	327
Wiley Online Library	("Federated Learning") AND ("applications") AND ("deep learning")	241
Google Scholar	("Federated Learning") AND ("applications") OR ("challenges")	47
arXiv	("Federated Learning") AND ("survey") OR ("novel framework")	28

3.3 Synthesis

The synthesis stage was performed through an orderly structure of the chosen studies to reveal pre- vailing themes, novelty, and gaps with regard to FL research. A systematic template was used to read and analyze each article, and major details were captured including the kind of FL that was applied in the article (horizontal, vertical, cross-device or cross-silo), the learning model employed (e.g., CNNs, LSTMs, Transformers), privacy preserving mechanisms (e.g., differential privacy, homo- morphic encryption, secure aggregation) and the evaluation metric. Instead of categorizing the papers by a particular application domain, the synthesis was done in terms of a technical aspect which included handling non-IID, personalization strategies, aggregation method and deployment on edge devices. APTs such as FedAvg and FedProx were commonly found, and even architectures designed to operate in real-time or in low resources environments. The most common datasets included bench- marked image datasets, synthetic sensor data and federated healthcare data. The method used to classify the results thematically allows highlighting the way in which the whole framework of FL is changing, both theoretically and practically, notwithstanding the field.

3.4 Analysis

At the stage of analysis, the synthesized information was to be interpreted and key trends, strengths, and limitations, and gaps to conduct FL research were to be obtained. One of the more prevalent themes was the use of FedAvg as a basis of aggregation, even as an increasing amount of work focuses on personalizing aggregation in the non IID setting and convergence. Transformer-based models and CNNs were also common in the vision-based tasks and sequence-based tasks. The use of simulation environments in the process of evaluation was underlined in many cases, whereas valuable was the absence of full-scale implementation in the real world. These issues of communication overhead, model drift, hardware heterogeneity, and data imbalance among clients were constantly found. Moreover, there was no standardized procedure of benchmarking performance of different models across implementation, which aggravated comparability. Privacy and trust are the major themes around the idea of FL but there have been limited works providing end-to-end secure proposals which integrate cryptographic solutions and performance-efficient solutions. Furthermore, the gap between research and practice was an important issue, since not many systems were implemented in active edge or mobile settings. Figure 2 presents a flowchart illustrating the article selection process based on the SALSA methodology. It outlines the step-by-step filtration of articles starting from the initial retrieval of 3,126 records across multiple databases, followed by duplicate removal, title and abstract screening, full-text appraisal, and final inclusion of 137 relevant studies. This visual representation ensures transparency and reproducibility of the review process while demonstrating the rigor applied in curating the literature for comprehensive analysis.



International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://www.theaspd.com/ijes.php

Fig. 2: Flowchart of all the articles used in the SALSA

3.5 Insights and Implications

The current mini-review has a number of valuable insights as to what is going on and where FL research is heading. This is because, first there is an urgent need to have sensible, communication efficient aggregation mechanisms where aggregation can scale under low bandwidth or mobile net- works. Second, global models personalization in non-IID, multi cultural worlds is an open issue. Third, the lightweight models, energy efficient training techniques are imperative in the development of FL that requires edge devices with no strong computing capabilities. Fourth, to enhance repro- ducibility, and facilitate cross-community collaboration, open-source toolkit and established forms of evaluation need to become available. The review also indicates that there is still a need to perform more interdisciplinary work that unites distant systems and privacy and deep learning expertise with expertise in those fields where FL is deployed to bridge the gap between research prototypes and real-world practice. It is also necessary to integrate policymakers and technology developers to need to collaborate and eliminate legal and infrastructural obstacles, particularly when it comes to data regulation and robust collaboration on a big scale.

3.6 Reporting

In order to guarantee transparency and reproducibility, the whole review process was thoroughly reported. All the steps of SALSA methodology have been carried out through pre-defined templates and documentation instruments. All articles used in the research had been referenced accordingly through standardized citation methods. Data on the type of algorithm, the deployment model, the approach to privacy, and evaluation were represented in summarized form using comparative tables and depicted in visual graphs. The thematic structure of the review facilitates its usage by a general audience and serves as a practical resource to the readers who are researchers, engineers, educa- tors, and anyone working in the industry. This review will be used to establish the ground in the further development of federated intelligence systems by focusing on the aspects of methodological exactitude and cross-domain utility. Table 4 presents a structured overview of the reviewed liter- ature on federated learning spanning the years 2015 to 2025. A total of 144 articles were selected using the SALSA methodology, sourced from leading academic databases. The studies span a diverse range of application domains—including agriculture, healthcare, finance, smart cities, IoT, and more. The most common challenges identified across the literature include privacy risks, communication overhead, non-IID data, algorithmic instability, fairness issues, and difficulties in evaluation. Key findings emphasize the growing demand for scalable, privacy-preserving federated systems and high- light significant research gaps, particularly in underrepresented sectors like agriculture and mental health.

Table 4: Overview of Included Literature in the Review

Criteria	Details
Publication Year Range Considered	2015–2025
Total Articles Reviewed	144
Databases Used	IEEE Xplore, SpringerLink, ScienceDirect, ACM Digi- tal Library, Scopus, Wiley, Google Scholar, arXiv
Methodology Used	SALSA (Search, Appraisal, Synthesis, and Analysis)
Types of Applications Considered	• Smart Agriculture • Healthcare • Finance and Banking • Smart Cities

- Internet of Things (IoT)
- Education
- Legal Analytics
- Wildlife Conservation
- Space Exploration
- Mental Health Monitoring

Types of Challenges Faced

- Privacy & Security
- Communication Overhead
- Data Heterogeneity (Non-IID)
- Algorithmic Optimization
- Fairness & Participation
- Evaluation & Debugging

Key Findings (Short Keywords)

- Taxonomy of FL challenges
- Underrepresented domains (e.g., agriculture)
- Need for scalable, privacy-preserving FL
- Emphasis on cross-domain applicability
- Lack of standardized benchmarks
- Gaps in personalization and deployment

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4 Fundamentals of Federated Learning

4.1 Basic principle of federated learning

FL is a learning system that collaboratively models together and shares no raw data across several separate clients, which are independent of one another. Rather than that, all clients can run their data locally and share with a central server model parameters or updates only. This paradigm aids in maintaining data privacy and minimizes overhead in communication related to transmitting huge set of data.

In equation 1, Let K represent the total number of clients. Each client k possesses a local dataset of size n_k, and the global data size is $n = \sum_{k=1}^{K} n_k$. The global objective is to minimize the weighted average of each client's local objective function, defined as:

$$\min_{w} F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \quad (1)$$

Here, $F_k(w)$ denotes the local loss function for client k, which is given by:

$$i \qquad i$$
$$i=1$$
$$\overline{k} \qquad n_k$$

where $\ell(w; x_i^k, y_i^k)$ represents the loss function applied to the i-th data point of client k, and w are the model parameters.

During each communication round t, the following steps occur:

1. The server broadcasts the current global model w_t to all selected clients.
2. Each client performs local training on its private dataset and updates the model to w_t^k.
3. The server aggregates the clients' updates using a weighted average:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k \qquad (3)$$

This iterative process continues until convergence. FL is particularly effective for scenarios involving sensitive or distributed datasets, such as those in agriculture, healthcare, and IoT, where data-sharing constraints are critical.

4.2 Types of federated learning

FL has become one such magic bullet in the field of decentralized machine learning enabling many clients or organizations to train models in a coordinated manner without exchanging raw data. With the proliferation of application of FL in a variety of fields and spheres of life (agriculture, healthcare, finance, etc.), the typology of its implementation and design versions becomes relevant. The difference between these types depends on the data distribution nature, the relation between clients, and the involved learning strategies. The realization of such categories is critical to making a decision when adopting the appropriate FL framework to the domain of application, particularly in situations where data heterogeneity, device constraints, or privacy policies bring in special challenges.

Among the major divisions of FL, we suggest such viewpoints as Horizontal Federated Learning (HFL) [42], Vertical Federated Learning (VFL) [43] and Federated Transfer Learning (FTL) [44], and new models such as Cross-Silo [45] and Cross-Device Federated Learning [46]. All of them are used in solving different problems based on individual functions of whether the clients share features or even data samples or not and whether they are personal devices and institutional servers. These FL models are described in the subsections below as well as their relevance and usefulness in application, especially in agriculture.

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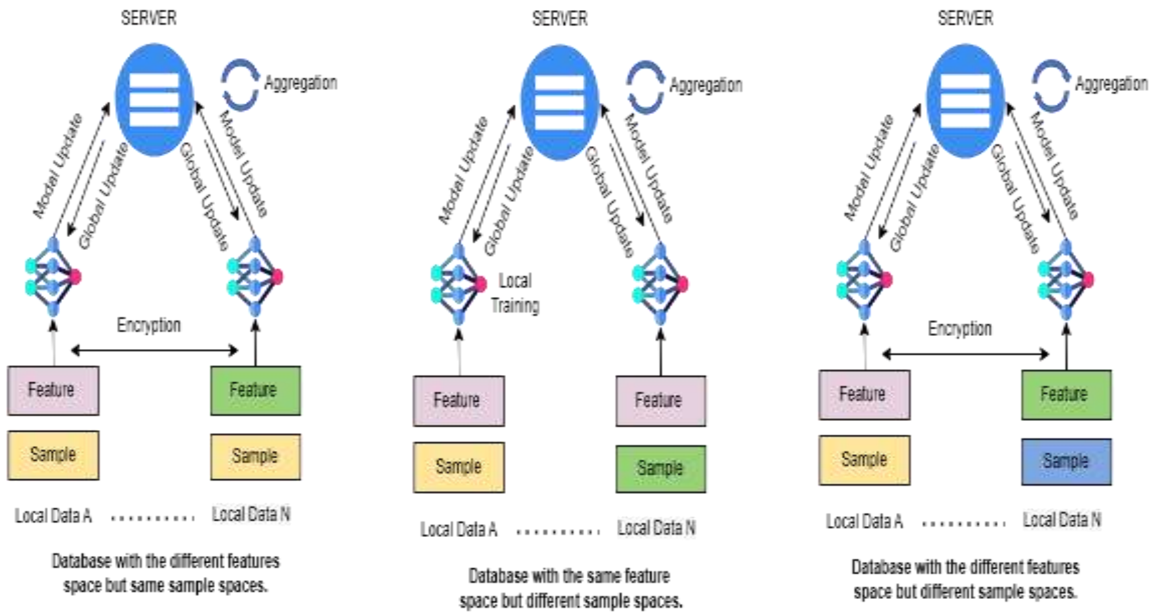
4.3.1 Horizontal Federated Learning

Horizontal Federated Learning is suitable when the data of diverse clients belong to the identical feature space but divergent sample space [45]. With reference to agriculture, this could occur whereby various farms can gather the same information as soil moisture, leaf images or weather but on a different piece of land or crops. Every farm learns about the same model structure on its data and transmits the updates to a central server. Weighted averaging is done to create a global model based on the server. HFL is especially successful where institutions or clients gather similar kinds of features but in separate operations. It assumes the homogeneity of data in regards to features and is mostly applied via FedAvg algorithm. Although HFL could be used to improve the privacy and collaborative modeling of data, it can encounter challenge when the local datasets are non-IID, and such cases can cause problematic convergence and performances among the clients.

4.3.2 Vertical Federated Learning

Vertical Federated Learning can be appropriate in situations in which various clients hold varying elements regarding a similar set of information images [46]. This category is particularly important when there are several agricultural stakeholders of that have complementary data of same entities. An example would be that a crop monitoring agency could have image data of plants and national weather service measures temperature and humidity on the same geographic locations. The clients do not share the data samples, but the data entities overlap, which is why VFL needs the ability to sufficiently conduct such techniques as secure entity alignment and homomorphic encryption that need to be in place to provide privacy assurance and faultless merge of features. This model can enable the cooperation between the institutions having different data capabilities and providing more complex training inputs. However, VFL at the cost of computation and communication overheads, requires secure matching of data and model updates. When it is to be used in agriculture, it will bring about more integrated and model-rich models of decision support, particularly when both governmental and non-governmental agencies are required to cooperate. The figure 3 illustrates the three main types of federated learning based on data partitioning.



(a) Vertical FL (b) Horizontal FL (c) Transfer FL

Fig. 3: Types of Data Partitioning Models

4.3.3 Federated Transfer Learning

Federated Transfer Learning deals with a case in which feature space and sample space vary across clients. This is usual in the case when institutions or farms are working under various environmental, technological or the data collection scenario [47]. As an instance, a research center engaged in wheat disease might be interested in cooperating with a regional center being engaged in rice disease with varied crop variety, climatic conditions, and characteristics. FTL uses the principles of transfer learning to transfer knowledge used for one domain and adjust it to the other using common intermediate representation or transfer modules. This renders it to be an effective instrument of the knowledge generalization in various farming environments [48]. FTL also generally assumes some small overlap in either data points or representation of the data features is possible. The principal complexities are domain adaptation and the necessity to compose semantic mappings. Nonetheless, the potential benefit in FTL to increasing the robustness of models in geographically and semantically heterogeneous farming systems that do not involve direct data sharing is obvious.

4.3.4 Cross-Silo Federated Learning

Cross-Silo Federated Learning allows a few trusted and high performance organizations namely universities, agricultural research centers or state agencies to work together [49]. The data stored in each silo is generally large volume of data and they also possess enough computational power to effectively train the models. This type of FL is based on the assumption of the relatively stable con- nection to the network and the consistent presence of the clients. When several institutions bring their local models to construct the common crop disease prediction model or selection of the common crop yield estimation model, It can be used in the agricultural field. Such configurations usually enable superior orchestration and version of the training pipeline. The FL model updates are aligned and jointed with regulated and secure protocols, and, therefore, a Cross-Silo FL is much easier to process, in respect of privacy, compliance, and audit [50]. It can also engage in more complicated model architectures as well as prolonged training periods because resources are abundant. Nevertheless, they have weak scalability and lack diversity of clients in comparison with Cross-Device FL. The structure of cross-silo Federated Learning is shown in Figure 4, in which a few trustworthy organizations, like hospitals, universities, or research centers, work together to jointly train a global model while maintaining decentralized data. This method permits high-performance model learning across separate silos while guaranteeing privacy, trust, and data ownership.

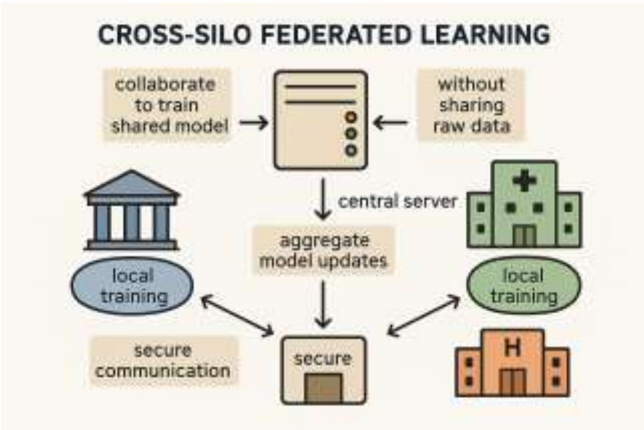


Fig. 4: Illustration of cross-silo Federated Learning architecture

4.3.5 Cross-Device Federated Learning

The Cross-Device Federated Learning works on a different scale on the edge devices e.g. mobile phones, IoT sensors, and agricultural drones [51]. Very little data is contained in each device and computing, storage and energy is scarce in each device. The given FL environment is perfect to work with smart farming where numerous sensing nodes are distributed to provide real time information about crop health, soil moisture, or micro climate variables. Some of the issues that may arise due to use of Cross-Device FL are latency in communication, heterogeneity of devices, and unstable network connections. In response, strategies such as asynchronous updates, compression algorithms and sparse communication protocols are used. The greatest benefit is that privacy is high because sensitive on-device data does not leave the local system. The aggregation is usually carried out applying algorithms such as FedAvg or federated dropout. Cross-Device FL can be scaled to field use, and can personalize and localize model updates, but it puts a strong requirement on distributed coordination that must be robust to allow effective and reliable work across a highly dynamic system of devices. Cross-device Federated Learning, where a large number of decentralized and frequently unreliable edge devices like smartphones, wearables, or IoT nodes participate in training a shared model, is demonstrated in Figure 5. This kind of FL puts user privacy and scalability first, but it also comes with drawbacks like device heterogeneity, limited bandwidth, and sporadic connectivity.

5 Applications of federated learning

5.1 Agriculture

FL takes a significant role in revolutionizing smart agriculture by providing data driven solutions with protecting privacy [52]. So the nature of agriculture is that the farms are geographically far apart and each produces a lot of potentially useful sensor data on soil condition, irrigation, crop health and pest trends. The concentration of such data may easily cause privacy issues and logistic problems. FL allows these distributed farms, research establishments, as well as agro tech enterprises to jointly train effective machine learning systems without moving any sensitive details. It is necessary

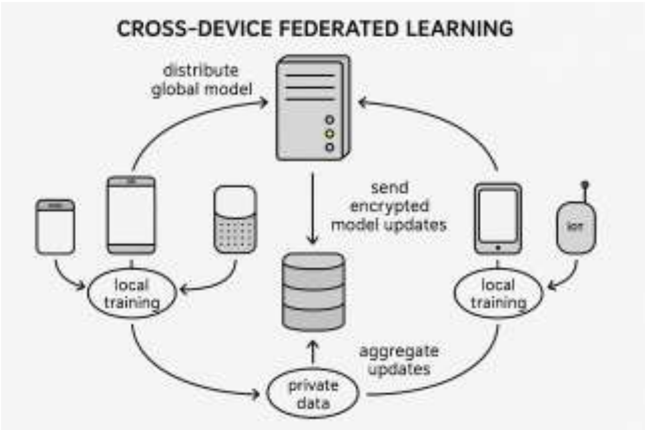


Fig. 5: Architecture of cross-device Federated Learning across decentralized user devices

in precision agriculture as a localized knowledge may greatly influence productivity. FL enables the detection of diseases via imagery of the leaf [53], optimizes the most appropriate time to make harvest, and optimizes the timing of an irrigation cycle, through sensor readings [54]. Also, FL is scalable in diverse environments that adjust to a region specific pattern and seasonal trend. Its decentralized structure matches the requirement of privacy, security and regulatory compliance that is demanded in agriculture [55]. In general, FL enables farmers and policy makers to have timely and actionable intelligence and yet owning the data and being considerate of regional differences. Numerous uses of Federated Learning in agriculture, such as crop disease detection, yield prediction, pest monitoring, and irrigation management, are depicted in Figure 6. FL facilitates scalable and privacy-preserving decision-making in contemporary agricultural practices by allowing cooperative model training across dispersed farms and research institutions without exchanging raw data.

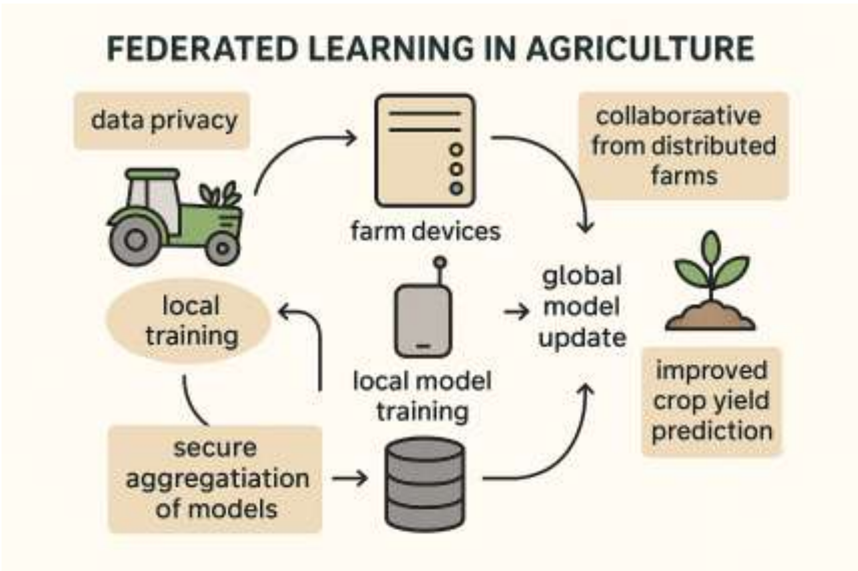


Fig. 6: Applications of Federated Learning in smart agriculture systems

5.2 Healthcare

FL is deemed to be one of the most important areas to apply to healthcare since all medical-related data is sensitive and confidential [56]. Medical data that include imaging scans, genetic information, and client reports are collected in huge volumes in hospitals, diagnostic labs, and clinics. Because of strict privacy laws (HIPAA and GDPR), it is difficult to share this data in various institutions. FL enables such a distributed model development by enabling decentralized learning the raw data does not leave the local location [57]. This offers privacy and promotes innovation on medical research. The applications of FL include constructing systems to detect diseases, updating radiology images classification [58], anticipating the shift in patient condition, and inventing personalized treatment advises. It also supports multi institutional research that is quite important in solving rare diseases and characteristics of different populations. Making the model more general, de biasing, and preserv- ing the identity of the patient, FL is substantial in advancing more ethical and safe AI tools in the current healthcare contexts.

5.3 Finance

Data security, along with the derivation of meaningful business intelligence is of high importance in the financial sector. The excellent solution to this problem is federated learning, which will allow banks, insurance companies, and fin-tech platforms to learn collectively in machine learning mod- els without compromising any confidential data [59]. Financial institutions handle sensitive data of credit histories, log of transactions and account balances. When this data is shared even to analyt- ics, it brings both regulatory and competitive issues to the fore. By participation in decentralized collaboration, FL enables the construction of models of detection of fraudulent operations, credit risk scoring and systems of prevention of money laundering. These models have the advantage of diversity of data on the institutional level, and they adhere to the laws of protection of data, such as GDPR, CCPA, and PCI-DSS [60]. FL also increases the customization of services in the banking sector since it is possible to run behavior-based recommendation engines but without getting access to the individual users profile centrally. Its distributed structure makes its models robust, the sys- tem less biased, and cybersecurity in financial systems. Therefore, FL guarantees new advancement in the world of finance without sacrificing privacy, compliance, or the integrity of an institution.

5.4 Smart city

The creation of smart cities is inseparable with FL since streams of large data are being rung out by a network of distributed sensors and IoT devices (which exist). Those are surveillance systems, environmental monitors, traffic sensors, and utility meters. Such huge and sensitive data cannot be amalgamated at a central point and this presents a privacy issue. The FL solution is scalable and secure because it allows the local models to be trained at the edge and precisely update the at-a-central-server [61]. This solution keeps data locally and yet contributes to a smart system worldwide. The FL is utilized in smart cities to optimize traffic, anticipate infrastructure maintenance, analyze energy efficiency, and emergency response systems. The role of FL is associated with the decrease in latency, reduction in bandwidth utilization, and maintaining the individual privacy without compro- mising real time decision making. In addition, it enables municipalities to use the information on the insight of heterogeneous data streams without jeopardizing security, resulting into a robust, adap- tive, and privacy-conscious urban ecosystem. It plays a significant role in streamlining the movement of traffic, saving energy, and analyzing the safety of people. The added value of FL is the creation of smart infrastructure that changes in real time, has low latency and does not violate the privacy of citizens [62].

5.5 IoT devices

Industrial Internet of Things (IoT) involves the deployment of sensors and devices across manu- facturing units, energy plants or supply chain facilities [63]. These systems produce high frequency sensitive data about machine performance, environmental conditions, and system health.electronics. This data is centralized, which can lead to operational leakage and cyber attacks. These issues are addressed by federated learning, which allows for the direct training of models at the edge. The use of FL enables accurate identification of machinery failure patterns for predictive maintenance, improves production efficiency, and enhances quality assurance without the disclosure of proprietary data. The development of AI models can be undertaken collaboratively by manufacturers across multiple facilities or companies, while maintaining minimal industrial confidentiality. Its localization of data benefits real-time analytics and reduces network overhead. The impact of it is felt in areas such as enhanced operational resilience, cost reduction, and smarter automation across industries, which spurs innovation while maintaining data sovereignty in competitive markets, energy plants, & supply chain facilities [64]. These systems produce high frequency sensitive data about machine per- formance, environmental conditions, and system health electronics. The concentration of data can lead to operational leakage and cyber attacks. FL addresses these issues by facilitating direct model training at the edge. Moreover, FL facilitates predictive maintenance by identifying failure patterns in machinery and improving production processes while maintaining proprietary data. Manufactur- ers have the ability to collaborate on developing AI models across multiple facilities or companies without breaching industrial confidentiality. The ability to keep data locally helps support real time analytics and reduce network overhead.

5.6 Education

In the education industry, where student data distribution is among schools, universities, and internet sites, FL is a rather important aspect [65]. Individual institutions collect massive data on student and learning performance, behavioral information including engagement. The shared trait is the privacy issue and the policies of data governance do not allow sharing such data to perform large scale analytics. FL allows one to train predictive models in a decentralized way that may predict the results in academic performance and identify the learning challenges and personalize the educational information. These frameworks utilize a rich set of educational data, and also satisfy student privacy laws such as FERPA. FL enables equity since the underrepresented or distant institutions can share their insights, but they do not have to reveal sensitive information [66]. It also gives a hand to adaptive learning systems whereby the delivery of content is customized according to the regional learning contexts. On the whole, FL provides better decision-making to educators, supports scalable e-learning infrastructure, and popularizes equity in academic AI systems, which makes it a decisive instrument of digital change in education. Federated Learning is being used in the education sector to facilitate decentralised academic data sharing, personalised learning models, and privacy-preserving analysis of student performance, as shown in Figure 7.

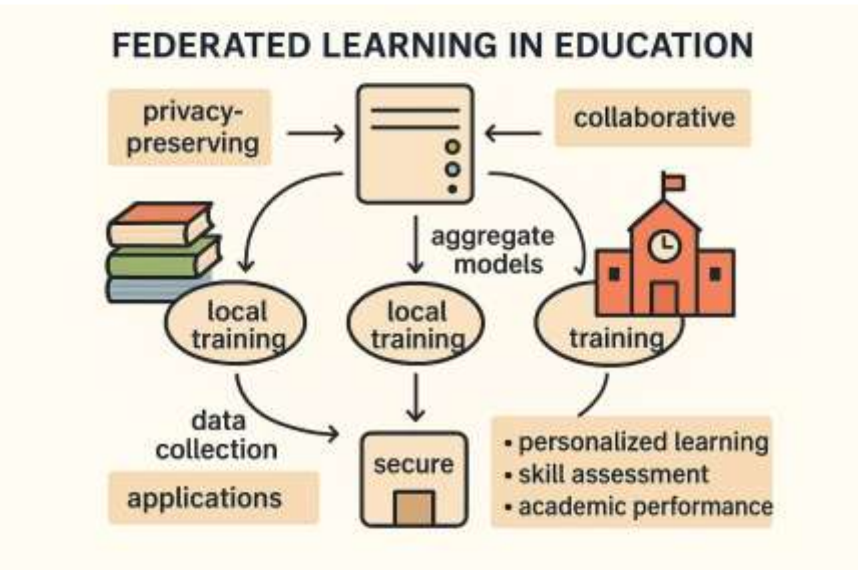


Fig. 7: Applications of Federated Learning in the education sector

6 Challenges faced in federated learning system

The real life application of FL is full of challenges manifesting as a result of the type and distributed nature of the constituents of the process. These difficulties cut across concerns on privacy and security, limited communications, data heterogeneity, instability on the algorithm, and fairness. A proper comprehension and taxonomy of these issues can guide in the creation of scalable, secure, and effective FL systems. A detailed classification and deep analysis of the main challenges encountered in FL systems are presented as below.

6.1 Privacy and security challenges

FL is planned as a system that aims at preserving the privacy of the users, keeping their data in one place, but still leaves their privacy and security at severe risks. As the updated model is shared rather than raw information, it is possible to draw adversaries to deduce some sensitive information or corrupt the model via malicious activities. These threats are important to be addressed to assure FL deployments of trust, reliability, and safety. Though FL has a decentralized characteristic, still it has privacy and security risks. The purpose of these threats is to reveal some confidential data or destroy the integrity of the model.

6.1.1 Information Leakage Attacks

This is an attack whose goal is to infer sensitive information using the shared parameters of the model. The updates used to modify data samples may be discarded through gradient leakage exposing all of the data samples. Membership inference determines whether particular information was included in training. Model inversion attacks attack data elements based on inferences of the models. These attacks affect the confidentiality of data stored about the clients, although raw data may never be presented. [67] demonstrates how gradients shared during FL can be used to reconstruct original training inputs. It evaluates multiple scenarios and mitigation techniques.

6.1.2 Poisoning Attacks

Poisoning takes place whenever the opponents inject some poisonous updates or data into the system. Information contamination skews local information to deceive global learning. Backdoor attacks are performed as model poisoning, where misclassification triggers are embedded. Sybil attacks imply training models by several bogus clients to take control. Such threats compromise the performance of models as well as generate used-attacker mistakes or inability to trust the system. [68] introduces model replacement as a form of backdoor attack in FL. It shows that a single malicious client can manipulate the global model while remaining undetected.

6.1.3 Lack of Secure Aggregation

Central servers are capable of reading or tinkering with client updates without cryptographic protections in place. Lack of a safe aggregation method like homomorphic encryption or secure multi-party computation puts the clients at the risk of monitoring or alteration. The vulnerability goes against the privacy goal of FL and can cause adversaries to make inferences about client behavior or model input using aggregated statistics. [69] presents a secure aggregation protocol designed to protect model updates in federated learning while ensuring efficiency and scalability.

6.1.4 Trust Management

All the participants are assumed to be honest in FL, but not always this is the case. The free-riding clients reap the benefits of the global model and they do not provide quality upgrades. In addition, unverifiable training causes server to doubt whether a particular client indeed did computation, or whether it indeed provided synthetic updates. This increases the need of scoring reputation and verification mechanism of contributions. [70] explores how trust and accountability can be managed in distributed systems where multiple autonomous entities collaborate without a central authority. Figure 8 shows the main problems that come with FL.These problems make it very hard to use FL in the real world, especially in places with limited resources or where people are spread out. They are also important areas of ongoing research and improvement.

6.2 Communication and Infrastructure Challenges

The FL systems involve regular communication and infrastructure from decentralize to the central server. Nonetheless, there are considerable impediments brought by the fact that the hardware, network bandwidth, and participation capabilities would vary across participating clients. These problems lead to coordination headaches, unbalanced input and poor model. The nature of such communication and infrastructure challenges is important to predict how resilient and scalable FL systems can be designed. These are attributable to the reliance to network availability, device capacity and communication overhead. [71] provides a comprehensive review of techniques to improve communication efficiency, highlighting methods like model compression, client selection, and asynchronous updates while outlining ongoing challenges such as bandwidth constraints and client heterogeneity.

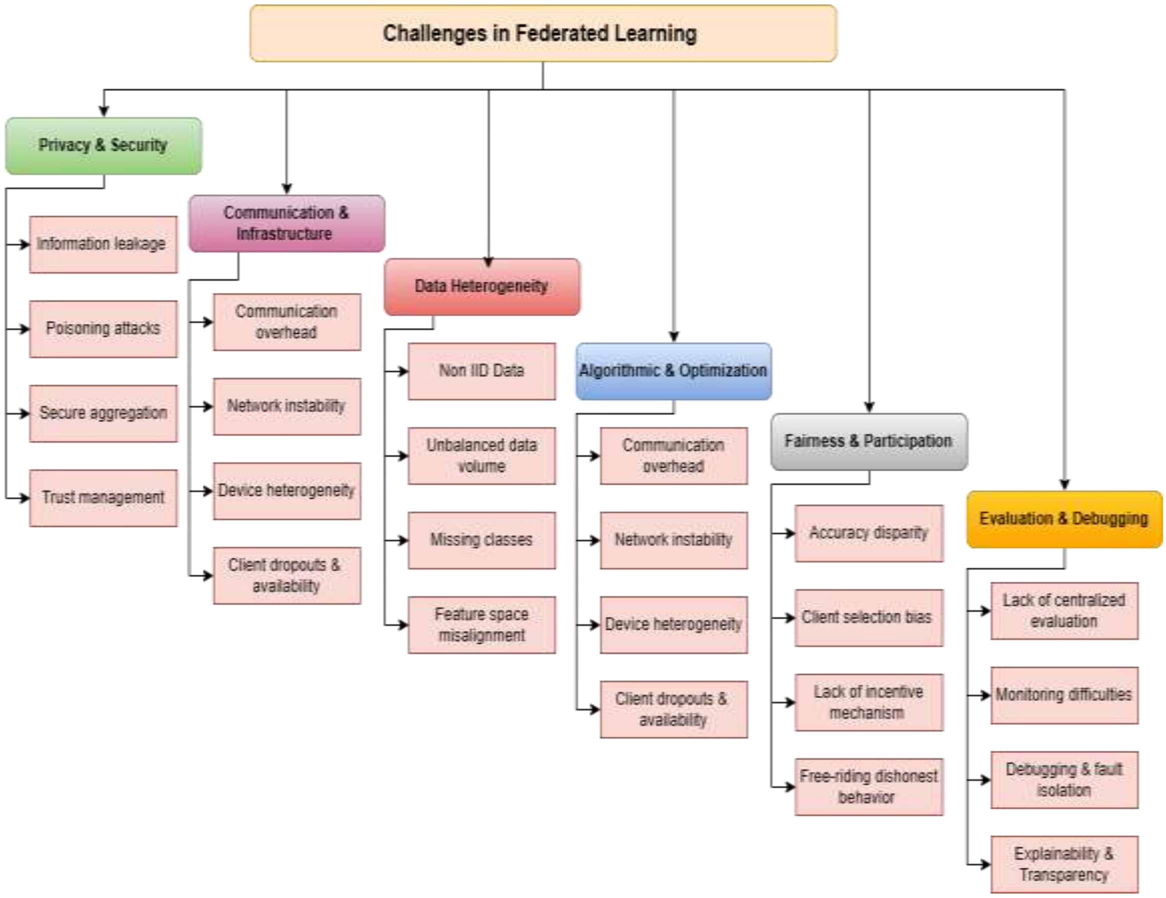


Fig. 8: Key challenges in the implementation and deployment of Federated Learning syst

6.2.1 Communication Overhead

A continuous transport of large model parameters between customers and the server strains the communication infrastructure. Training rounds multiply the network load more so in a large scale deployment. Such overhead is expensive in those places where connectivity is not so good and the overall training may be hampered. [72] define the concept of the federated optimization that is a paradigm of training centralized machine learning models over massively distributed, non-IID, and unbalanced data, including mobile phone data with communication efficiency as the main bottleneck, and the novel algorithm in this unique environment.

6.2.2 Network Instability

FL can be implemented in an edge or rural setting where the presence of the internet is sporadic. Weak signals may also make the clients miss or lack the ability to send and receive information on time leading to their partial or late contribution. Unstable network causes de synchronization and poor accuracy and reliability of the model. [73] introduce a federated PAC-Bayesian learning model that generalizes traditional PAC-Bayesian theory to any non-IID federated application that conceptualizes tight generalization bound designed to work with decentralized data and metric. They provide client- specific priors and aggregation weights of variables, estimate a new Gibbs-based algorithm minimize the PAC-Bayesian bound and cross check its utility on practical datasets through resource efficient federated updates .

6.2.3 Device Heterogeneity

Clients of FL are highly diversified in terms of computational capacity, memory and battery life. The low-resource devices might not be able to do training tasks which results in either client dropouts or rounds skipped. This disparity influences equity, delays convergence and it creates glitches when aggregation is accomplished. [74] address the problem of federated optimization in resource-limited edge settings through a dual direction; first, derive bound of convergence in distributed gradient descent over non-IID edge data, and then design a control algorithm that strategically trades off local updates and global aggregation in a resource-bounded local setting. Their approach thus reaches near-optimal model performance with both prototype and large scale simulations that not only reduce communication expense but also reduce training duration as well, and thus it is applicable in IoT and edge computing applications.

6.2.4 Client Dropouts and Availability

Every client can participate in FL on a voluntary basis and depending on his or her availability. The devices can easily be disconnected during training or can be nonreactive due to power limits or way of connections. Dropping out causes unequal participation and may severely cause them to slow down a learning process all altogether. [75] introduce FedCS, a client selection algorithm to federated learning on heterogeneous mobile edge systems, which selects clients to maximize client participation in a round with consideration to computational capabilities and network conditions to decrease the amount of training time and remove the impacts of dropout.

6.3 Data Heterogeneity Challenges

Rare and non-homogeneous nature of distributed data on the clients is one of the fundamental confusions of FL. In contrast to centralized learning, non-IID data, imbalanced sample size, and the discrepancy of features apply to FL. Such heterogeneity may prevent convergence, make the models less accurate, and be subject to biases. The solution to data heterogeneity is the key to making the FL systems generalizable and fair in their performance. Such category includes challenges brought by diversity of local datasets.

6.3.1 Non-IID Data

The data are normally non-identical and independently distributed in FL. Various distributions of classes or patterns of data may be observed by clients. This disparity between client information and the worldwide model goal leads to low generalization as well as draggy convergence. [76] present a comprehensive survey on the effects of non-IID data in federated learning, analyzing its impact on both horizontal and vertical FL, reviewing mitigation strategies, and outlining future research directions.

6.3.2 Unbalanced Data Volume

There are clients who obtain and collect thousands of samples whereas there are few ones. This tilt betrays the model in terms of data rich clients and undermining the global model representation of underrepresented clients, which lowers model fairness and robustness. [77] the objective inconsistency issue has been discussed in the paper, which occurs in heterogeneous federated learning due to differences among local updates among clients, leading to global level convergence to an unwanted surrogate objective. The authors suggest fixing this with FedNova, a normalized gradient aggregation scheme that guarantees convergence of the global, true objective that shows increased performance in non-IID and resource-varying environments.

6.3.3 Label Scarcity and Missing Classes

In most regions, some of the clients do not have labeled data or their data are not all the classes. This imbalance has an impact on classification, including skew global model decision boundaries. [78] FedGroup proposes a clustered federated learning scheme which dynamically clusters the clients together according to affinities in their local model updates- using a new data-driven distance- such that they can carry out client-clustered specific federated training to enhance robustness given non-IID data, gaining accuracy in non-IID data over regular FedAvg by a big margin.

6.3.4 Feature Space Misalignment

Under vertical FL or multi-source, the customers should be able to capture different characteristics of the same entities. Incorporating in such sets of diversified features sets entails complex transformation or matching of entities processes which render the system complex and computationally expensive. [79] Fed2 mitigates the structural feature misalignment induced by using local models in federated learning by presenting feature oriented structure adaptation, a process to divide neural network into grouped modules corresponding with individual structures, and a feature-paired averaging scheme that only semantically coherent parameters are averaged. This achieves a more stable convergence, greater accuracy (2.52-4.6 percent improvements), and lower computational and communication expenditure than FedAvg particularly when facing both IID and non-IID data distributions

6.4 Algorithmic and Optimization Challenges

The FL version of system types of distributed optimization typically get tangled up with various algorithmic difficulties faced in non-IID data, device disconnection and non- synchronous updating. These complicate convergence and stability of training. As well, the optimization trade-offs between the generalization of a model that should be used worldwide and the personalization of models on a client-to-client basis exist. These challenges should be addressed to develop such a FL algorithm that is strong and effective. Some of them are model training, convergence and aggregation.

6.4.1 Slow Convergence

The convergence of FL models usually needs much more training rounds to converge than that of centralized models owing to the heterogeneity of data, incomplete participation by the clients, and the non-synchronous update process. Incremental progress slows down the full functionality of the system and minimally increases the deployment. Optimizers such as FedDyn and FedNova are designed to stabilize convergence in this phenomenon. [80] poses a combined optimization problem based on user selection, wireless resources block allocation and global model aggregation to minimize convergence time and training loss of FL of wireless network. They propose a probabilistic client selection methodology and use neural networks to guess updates of omitted customers so that they can achieve up to 56 percent faster convergence and 3 percent superior precision in comparison with standard FL guidelines

6.4.2 Model Personalization Trade-off

Global models can fit badly on distributions that are client specific. The methods of personalization such as meta learning, local fine tuning learning enable models to be adjusted locally but remain a part of a global model. The main FL challenge is finding the perfect measure between generalization and personalization. [81] discusses the model generalization-personalization trade-off in federated learning so as to curb the effects of data heterogeneity among clients. The authors exemplify their strategy by presenting a privacy-preserving heterogeneous fall detection system and explain that a balanced trade-off between the two objectives can considerably enhance the robustness and accuracy of a system in realistic settings.

6.4.3 Aggregation Bias

Such aggregation methods as FedAvg favor different clients with greater data or hardware. It causes over representation and ineffective generalization on clients who are smaller or minority. Work such as weighted averaging, data-aware selection and fairness-aware aggregation are meant to address this. [82] contain a thorough literature review and taxonomy of 27 federated learning aggregation algorithms and evaluation of best practices like model averaging methods, client weighting, secure aggregation and even personalization approaches. They categorically discuss the contributions and drawbacks of all of the methods concerning issues such as efficiency of the communication, scalability, resilience, and privacy, and identify research directions toward standardization, homogeneity, defense against security attacks, and quantum-conscious aggregation.

6.4.4 Stale Updates

Nevertheless, asynchronous clients can send updates after some rounds and this can cause using out-dated gradients. Such uninspiring updates will undo new learning and unsteady the model. Such techniques as staleness-aware aggregation address this issue. [83] propose FedStale, a federated learning algorithm that is better than FedAvg and FedVARP in that its weighting scheme intelligently leverages both fresh updates supplied by the participating clients and stale updates supplied by the non participating ones, using a weighting scheme that is tunable to the perceived relevance of updates across the clients. This suffers the impact of homogeneous participation and data distributions quite passingly, providing improved and more consistent convergence, and beating baseline methods in a wide variety of experimental configurations.

6.5 Fairness and Participation Challenges

The situation with fair participation of diverse clients and equity of model performance is always a dilemma in FL. Unequal data quality, availability, and systems resources may result in unequal patterns in which it may profit some clients at the expense of the others. Besides, there are no well-developed incentives related to participation and ways to detect dishonest behavior. This is to be tackled comprehensively in a fair and inclusive FL system. These deal with fair model results and equal attendance of clients.

6.5.1 Accuracy Disparity

Global FL models might not equally work on all clients. The low accuracy can be encountered when users have minority or out-lier data distributions. This compromises the principles of fairness, particularly in the context of software such as healthcare tools or agriculture, where predictions have to be accurate to the marginalized population. Individualized FL algorithms and fairness consideration optimization algorithms help curb that gap. [84] that suggests the FOCUS framework to address poor quality labeling among clients by more keeping the small and clean benchmark dataset on the server. To update each client, FOCUS calculates that client credibility as a comparison of local model accuracy relative to this standard, and uses these credibility metrics to weight client updates, which has the effect of allowing noisy label participants greater weight or influence in traditional FedAvg, and greatly increases model accuracy.

6.5.2 Client Selection Bias

The clients that are usually chosen using FL frameworks tend to have good network connections or high reliability at the expense of slower or less available nodes. This causes biased training and decreased generalization of a model. System efficiency ought to be matched with statistical fairness performed through selection mechanisms, such as FedCS and Oort. [85] offer an overview of client selection methods in federated learning, and groups them according to system and data heterogeneity and discuss how they can differently affect performance, fairness, and resource consumption. They provide major limitations, which are resource limits, confidentiality, and equity, and future aspects of research are outlined, where these are dynamic selection, theoretical propositions, and large-scale benchmarks.

6.5.3 Lack of Incentive Mechanisms

Clients who have valuable data or those that possess high computation power might be reluctant to engage in FL without incentive. It is important to develop incentives that encourage honest, productive contributions. Reputation-based scoring, token systems and game-theoretic reward models can be used as solutions. [86] gives a broad survey of the 27 federated learning aggregation algorithms based on their strategies like secure aggregation, weighted averaging, and personalization and evaluates their ability in terms of diverse proxy measures like communication efficiency, robustness, scalability, and privacy. Main constraints on current methods and directions of future research, as identified by the author of the review, include standardization, a better way to handle the issue of data heterogeneity, and integration with secure aggregation methods to provide a higher degree of trustworthiness.

6.5.4 Free-Riding and Dishonest Behavior

Clients that are bound to cheat to score points of the global model without contributing to its training will involve themselves by giving the outdated, noise, or fabricated updates. This is against equity and it makes people lack trust. Such behavior can be detected and mitigated with the help of auditing and trust-based filters. [87] makes a credible analysis of free-rider attacks in blockchain assisted decentralized federated learning and quantifies how free-riders can undermine system performance. The authors prove the vulnerability to free-riders and the effectiveness of credibility enablers in maintaining the integrity and solidity of federated learning by testing the resilience of network, in terms of 6G-type topologies.

6.6 Evaluation and Debugging Challenges

Equal participation in the model performance and the involvement of the different clients is assured by fair means and that is the ever-present problem in FL. Data quality, availability or even the source system resources may be biased which may lead to the gains of some clients at the expense of other clients. Moreover, participation in incentives and the methods of determining unethical behavior are also not achieved successfully. These concerns should be addressed comprehensively and fairly in an inclusive manner in FL system. They concern just outcomes of the models and reasonable participation of clients.

6.6.1 Lack of Centralized Evaluation

The evaluation of the model performance is not carried out with the help of a common global dataset in FL, and it is challenging to trace the consistency of the model behavior among the clients. This is a drawback in reproducibility and reliability particularly when clients have very disparate data. There is no shared test set hence distributed validation policies are needed. [88] categorizes the

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://www.theaspd.com/ijes.php

studies on federated learning based on system design, application vertical, privacy/security protocols, and resource management that it highlights its transition out of a centralized model to a distributive, on site model of the IoT. They further determine some of the most pressing unresolved issues that include client heterogeneity, safe aggregation, communication efficiency, and regulatory compliance when they project future research directions on more resilient and more scalable FL frameworks.

6.6.2 Monitoring Difficulties

Given that training is carried out on-site, the server finds it difficult to track the action of the client, whether data is corrupted, over fitted or under-trained. Revealed a lack of transparency makes models subject to failures that are difficult to detect with FL systems. [89] perform an in depth survey of 27 federated learning aggregation algorithms and group them according to approaches such as weighted averaging, secure aggregation and personalization. They compare these approaches along the main performance axes, such as communication efficiency, scalability, robustness, and privacy and recommend remaining open questions and research directions, referred to as standardized benchmarks, heterogeneity, and security.

6.6.3 Debugging and Fault Isolation

In case of a decline in the performance of global models, it is hard to determine the root cause of error because of the decentralized solution of FL. The model can be disrupted by one bad client or update, and it will be necessary to do complex diagnostics on the client level and upgrades to figure out the offender. [90] FedDebug provides an end-to-end model of debugging federated learning programs by representing the simulation and replay execution together with automated fault identification to detect malicious clients without having access to test information or labels whilst vendorizing up to 100% precision in the single client fault identify and 90.3 percent accuracy in the multiple defective client situation, with just a 1.2 delay per round of training data. Its fine grained inspection and break point based interface allow developers to step through federated rounds and client states without interruption and significantly increase efficiency and reliability of their debugging and debugging of distributed systems of a privacy-sensitive nature.

6.6.4 Explainability and Transparency

FL models can be black boxes, meaning that the training data, as well as the behavior of the model locally, is not accessible to server. This explainability constrains stakeholder confidence, particularly in the regulated industries. On the one hand, explainable methods in FL remain in their infant stages.

[91] the author proposes a unified model in which FL is integrated with Explainable AI (XAI) to identify financial fraud among banks without sacrificing privacy. The system increases transparency, regulatory compliance, and accuracy of detection results training on realistic dataset of transactions by applying FL and using XAI to explain model decisions, without sharing raw data.

7 Results and discussion

This literature review was started because the investigator wanted to comprehend the complex nature of the issues of FL systems, as well as point out knowledge gaps by means of the published articles during the period between 2015 and 2025. Our qualitative research results demonstrate a certain pattern: although FL has been heralded as the paradigm that offers privacy-preserving education, its real-life application is hampered by numerous structural, operational, and ethical issues. We could see that most of the studies are domain specific i.e. they dwell on the areas of agriculture, healthcare, IoT, finance, or smart cities but few provide cross domain generalizations. More to the point, most of the papers do not thoroughly classify the problems they discuss, usually restrict their premise to a technical solution and do not consider its different repercussions.

One more critical point is that review articles concerning FL tend to make biased use of health-care or IoT and highly underrate smart agriculture in comparative papers. Moreover, even though most papers refer to data heterogeneity, privacy, or communication bottleneck, they usually do not attribute these issues to real-life deployment cases and do not provide scalable countermeasures. The inconsistency in reporting and bench marking of FL challenges also appeared as one of the gaps. Most of the papers examine the performance measures but missed out on long-term aspects such as fairness, trust dynamics, system robustness, or governance. This survey contribution is three-fold. We have first hand-picked and reviewed an impartial collection of FL review studies and articles that cut across fields. Second, we presented a well-organized taxonomy of dividing FL issues into six general categories with specifically delimited subcategories. This group helps scholars to get an organized knowledge about at which points the existing literature is focused, and which areas still have not been covered by it. Third, our survey is the first to emphasize comparative under representation of the agriculture domain and consequently the need to focus on a more inclusive research in which low resource and high variance settings like farms and their rural data networks get represented. Figure 9 shows how Federated Learning (FL) research is spread out across different application areas. The chart shows the main areas where FL has been used, including healthcare, finance, smart cities, edu- cation, IoT, and agriculture. Healthcare and IoT seem to be the most popular, which makes sense given the growing need for data analytics that protect privacy in sensitive and distributed settings. This breakdown by sector shows how flexible FL is and how it is becoming more useful in fields that cross disciplines.

Further, the survey can be considered an added benefit, since it contains a cross-domain comparative table, an SALSA inspired review methodology, as well as paper overviews with sources. This renders the paper not only tale of synthesis, but also of reference to practitioners, researchers, and policymakers, who seek to utilize the FL systems in the real-world environment. We based our hypothesis on the fact that although FL is presented with a solution to the issue of dependence on centralized data, it invokes a set of distinct issues that are fundamentally rooted together. They are not merely the technical ones like optimization instability or the cost of communication but also ethical, infrastructural and methodological. In a methodical evaluation of the existing literature, our theory is confirmed: FL does impose its own type of challenges that need to be approached in a much more comprehensive way than the one that is employed in the majority of the research stud- ies. Whether or not future FL systems will be successful also relies on how well these issues will be comprehended and mitigated.

8 Future prospects of federated learning

FL has huge potential as a privacy-preserving system of collaborative machine learning over distributed data assets. Since the concern of data privacy is gradually gaining prominence among industries, FL is likely to be the central aspect of intelligent systems expanding to cover other fields such as healthcare, agriculture, finance, and IoT. In the future, its improvement is based on the personalization enhancements, scaling through improvements, and advanced security. As edge computing develops, as privacy-enhancing technologies are improved and as governance protocols are imple- mented, FL will no longer be a dream, but will become a standard model of ethical and distributed machine learning.

8.1 Space Exploration and Planetary Research

As space missions are becoming more independent, intelligent collaborative learning between satellites and planetary systems are in demand. Large amounts of localized information like orbital telemetry, thermal imagery or surface terrain distribution are frequently gathered by satellites or rovers and, since real-time transmission of this information to earth to be used in centralized training is usually constrained by latency, energy and bandwidth, the information will usually remain localized. FL

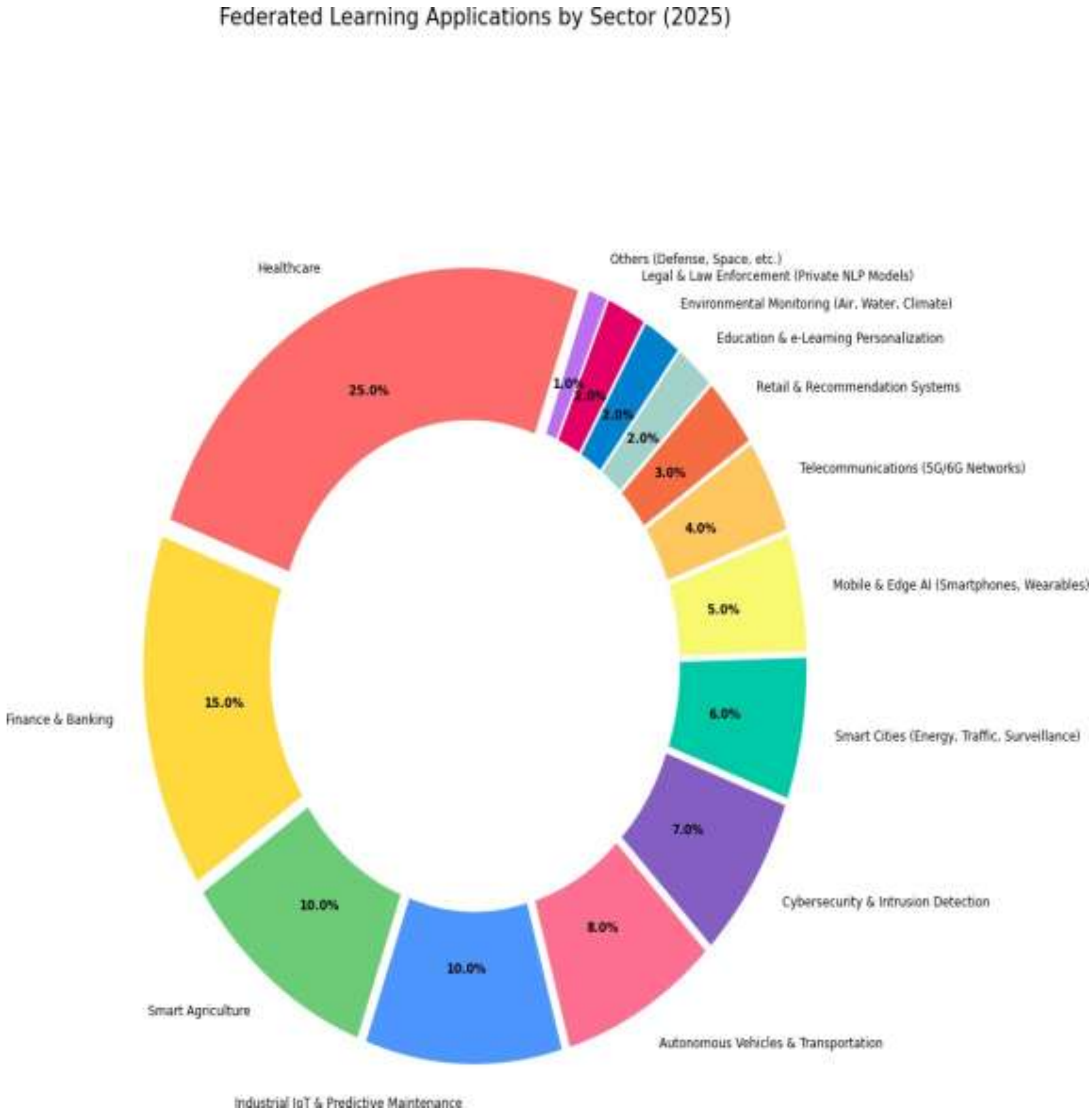


Fig. 9: Distribution of federated learning across different sectors

provides a potential solution since they allow these dispersed entities to jointly train the models without sharing their raw data. To take one example, satellites might create joint predictions of their orbital patterns, whilst deep space rovers might train themselves using each-others travel trends. The communication dependency is overcome in terms of the fact that the skill to train in situ not just diminishes communication dependency it also facilitates on-board intelligence which would enable real time decisions. [92] mentioned FedSecure, the LEO satellite federated frame worked by a group that is decentralized to generate keys and secure gradient aggregation, is presented in the paper. It makes learning computations on satellites with local image data rather than the traditional Earth-based orchestration. Through their experiments, convergence is faster and the robustness of their models is very powerful with less bandwidth. This confirms the viability of FL as a learning paradigm of orbital and interplanetary systems.

8.2 Mental Health and Behavioral Monitoring

The diagnostics of mental health become more and more dependent on such sensitive and personal data as voice patterns, keyboard use, sleeping, and smartphones usage. The conventional cloud- based systems pose significant privacy threats, which demoralize patients to engage in online mental health tracking. The privacy aware alternative offered by FL proposes to run the processing of the behavioral information locally, and only updates to the updated model are sent to be aggregated. This allows keeping confidential information on the device of a user but facilitates significant model optimization. FL has the potential to assist in mood monitoring, early intervention, identification of stress, and individualization of the therapeutic content. These strategies become essential when it is concerning the young population, susceptible consumers, or persons in prejudicial surroundings, where credibility as well as confidentiality are essential. The incorporation of context aware modeling in context of speech tone, typing delay or on screen usage increases the precision of mental health analytics without interfering with the freedom of the user. [93] FedTherapist is a smartphone-based FL framework that collects voice and text signals from users to predict psychological states. It leverages natural language processing to infer depression and anxiety while maintaining on device privacy. The system demonstrated improved AUROC and mean accuracy, validating FL's viability in mobile mental health contexts.

8.3 Legal and Judicial Systems

The confidentiality of information that law firms deal with is so high in areas like classified case files and verdicts, communications with client as well as litigation tactics among others. The most critical questions that concern the way such data, as the result of the machine learning process, is centrally processed refer to divergence with the question of confidentiality, regulatory requirement, and the ethical boundaries. When dealing with records owned by law firms, governmental or judicial institutions, FL offers one alternative of how to train a model in a collaborative fashion without being compelled to expose its raw documents. Applications Potential deployment could include the forms of outcome-prediction according to precedents, blinded evaluation of contracts, or automatic privilege-scrubbing of privileged objects within legal documents. Additionally, FL can promote global judicial cooperation, where the national laws on privacy will protect the privacy of legal information. Nevertheless, FL is an insufficiently examined domain in respect of this topic and is usually attributed to the fact that legal text is a complex structure, and legal datasets are extremely dismantled. The use of FL in judicial analytics would eliminate opaqueness, injustice and mistrust, and would not undermine privacy. Future research will be able to merge blockchain with the creation of auditable, secure multiparty computation to validate proofs, and recipe use the models of domain specific language and comprehend examples, all trained end-to-end across legal entities. [94] FedJudge is a practical federated learning framework that aim at fine-tuning big legal language models (LLMs) in various legal institutions without the exchange of sensitive data. It combines parameter efficient tuning (LoRA) and continual learning so that it can achieve high performance when it works on tasks such as the generation of court views, and legal consultation without compromising user privacy and compliance with regulatory rules.

8.4 Wildlife Conservation and Poaching Prevention

The conservation areas and wildlife parks use a combination of motion sensors, unmanned aerial drones, acoustical traps, and infrared cameras in ensuring that biodiversity is checked and species are not poached illegally. Much of this data, though, is location specific, and it is hard to centralize because of power limitations, poor connectivity and ecological sensitivities. fl can revolutionize the way wildlife is monitored as the collective training of models to differentiate human encroachment, poaching, or unusual animal behavior can be done in an edge setting without the need to exchange raw videos or geo location metadata. It is a privacy preserving method suitable to sensitive ecosystems and has the resilience against weather or interference induced data loss. In addition, models that are trained with FL can be customized according to the location, thus making the detection more accurate due to the use of local trends. [95] it proposes a new method of protecting the wild life in that wireless acoustic sensors actually differentiate between animal and human footsteps in real time and hence, an automatic notification of potential poaching activities are sent keeping the natural habitats healthy. Their system applies the machine learning method where the audio information is preprocessed, noise eliminated, and footstep events detected, to find useful intruders in distant wildlife reserves .

9 Conclusion

The research is the systematic and comprehensive literature review that explores the concept of FL based on the SALSA approach and supplemented by the resources accessed through DOI verified and peer-reviewed channels. As opposed to previous surveys, which are either more specific, targeting only the field of healthcare or the Internet of Things, this study is more universal covering both established and novel fields, such as agriculture, smart cities, FinTech, education, legal frameworks or environmental measurements. One of the main contributions is the formulation of a structured taxonomy in which all FL challenges are segregated into 60 significant classes: privacy and security, communication and infrastructure, data heterogeneity, algorithmic and optimization, fairness and participation, and evaluation and debugging. Qualitative analysis through this survey reveals the tendencies, the boundaries, and gaps in current literature that are underrepresented. It is important to note that it distinguishes smart agriculture as a substantially underserved area with a great potential of decentralized learning. The survey also underlines topic of site specific solutions, including privacy-preserving model sharing in wildlife surveillance and safe teamwork-related systems in space travel. These various implementations provide a basis by which the study enriches the insight of the behavior of FL in various heterogeneous environments with limited resources.

The possible practical applicability of this work is another major contribution to it. Coupled with full comparative tabulation, future mapping and mapping of barriers to deployment in the real world, the twofold actionable output assists academic researchers, as well as system constructors, in addition to their function of performing the initial stages of future app design. It has been established that the work suggests new spheres of implementations of FL, including judicial analytics, mental health monitoring, and biodiversity protection spheres that have not been actively covered during previous surveys. The implication of this study is great. It challenges the research community to concentrate on designing scalable, inclusive and secure FL frameworks that can suit a diversity of deployment environments. It also attracts to the acute necessity of benchmark datasets, interpret ability tools, incentive mechanisms, and edge-ready optimization algorithms.

To sum it all up, this survey is not only complementary to the scholarly concept of federated learning but also preconditions meaningful practical insight. With further maturity of FL, the spec- ified shortcomings will be crucial to overcome to achieve the potential of becoming an enabler of collaborative intelligence in the decentralized world.

Acknowledgments

Authors wish to thank Dr. Manasi Gyanchandani and Dr. Akhtar Rasool for their valuable guidance and support.

Funding

Not Applicable

Data Availability

Not Applicable

Concent for publication Not Applicable

Declarations

Author Contribution

D.R. developed and executed the study, analyzed the data, and authored the first draft. M.G. guided the research work, offered professional guidance on execution, and reviewed the work for scien- tific substance. A.K. coordinated this research work, gave professional guidance, and reviewed the manuscript .

Conflict of interest

The authors declare that they have no competing interests.

Ethical Approval

Not Applicable

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