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Federated Learning for 6G Networks: A Comprehensive Review of Challenges, Techniques, and Future Directions

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A R T I C L E I N F O

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A B S T R A C T

The convergence of Federated Learning (FL) and sixth-generation (6G) communication systems promise to revolutionize distributed intelligence by addressing emerging demands for data privacy, real-time processing, and massive connectivity. However, integrating FL within 6G introduces complex challenges ranging from heterogeneous data and devices to communication bottlenecks, energy constraints, and stringent security demands. This review provides a comprehensive examination of FL techniques and their applicability in terms of 6G communication models. The review also emphasizes how these technologies are used in real-world fields like healthcare, autonomous systems, and digital twins—areas where privacy, reliability, and latency are mission-critical. Unlike earlier surveys that treat FL and 6G as separate research tracks, this paper critically reviews their convergence, identifying how FL techniques must evolve to meet the architectural, functional, and regulatory demands of 6G systems. It discusses ongoing challenges and emerging directions such as quantum-safe protocols, interpretable federated learning, and energy-aware orchestration. By synthesizing cross disciplinary insights and mapping current gaps, this review aims to guide future research in developing robust, adaptive, and secure FL frameworks.

1. Introduction

The rapid advancement in wireless communication technologies is ushering in the era of sixth-generation (6G) networks. These next-generation networks aim to provide ultra-fast data speeds over 1 terabit per second along with near-zero latency, and the ability to connect a massive number of devices simultaneously [1]. These capabilities are essential for enabling emerging applications like holographic communication, digital twins, extended reality (XR), and autonomous systems all of which require highly reliable, secure, and adaptable connections. To reach these goals, researchers are focusing on key technologies such as Terahertz (THz) communication, intelligent reflecting surfaces (IRS), edge artificial intelligence (AI), distributed intelligence, and block-chain as fundamental parts of the 6G infrastructure [2]. Historically, distributed learning systems have always been known to go through a process of being divided into centralized and decentralized approaches. Centralized training is where the raw data is collected at a central server for model training. This method of training is efficient; however, it poses a lot of privacy issues, causes bandwidth congestion and creates a single point of failure. The practices of decentralized approaches like peer-to-peer and fully

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decentralized algorithms let the system work with no dependency on the central server, however, they face challenges like scalability, convergence in heterogeneous environments, and that of being invulnerable to adversarial attacks. Federated Learning (FL) is a model that allows for the combination of decentralization, which means that models will be trained on edge devices without the data being transferred. Privacy of the data during training is also taken into consideration [3, 4]. This approach naturally helps protect privacy, reduces the amount of data that needs to be transmitted, and adapts well to environments that are constantly changing and spread out over large areas making it especially suitable for 6G networks, which are expected to be extremely dense and filled with a wide variety of devices. Despite all these benefits, using federated learning in 6G systems introduces several challenges. These include the high costs of communication because of sending lots of model updates often, differences between devices and data, and security threats such as malicious attacks [5, 6]. To address these issues and unlock the full potential of FL, Researchers have proposed a range of intelligent strategies to enhance communication efficiency among distributed nodes. These include creating layered system architectures that allow for better information flow, enabling devices to send updates asynchronously thus avoiding delays, and data compressing techniques to minimize bandwidth usage. Concurrently, considerable efforts are being made to improve privacy protection in federated learning systems. Techniques such as secure data protocols and differential privacy, which introduces controlled noise to prevent personal disclosure of sensitive data. These techniques are being developed to ensure robust privacy guarantees. Several model compression techniques such as SVDFed [7] use low-rank approximations via Singular Value Decomposition (SVD) to compress model parameters before transmission. This strategy effectively reduces communication costs while maintaining model accuracy. Collectively, these initiatives aim to establish a federated learning environment that is not only more secure, faster, and more flexible but also meets the practical requirements of 6G networks [5, 8]. While several prior works have surveyed federated learning (FL) or 6G communication separately, few have thoroughly explored their intersection with sufficient depth and critical analysis. Most existing studies usually give a general overview or focus on the technical details of algorithms, but they often don't look closely at how everything fits together as part of the bigger 6G system. In addition, limited attention has been paid to the joint implications of privacy, scalability, and latency under real-world constraints such as edge-cloud coordination, device heterogeneity, and quantum-safe communication protocols. Unlike existing surveys that primarily catalog algorithms and architectures, this review provides several new insights into the role of federated learning (FL) in 6G networks. The main contributions are as follows:

1. Systematic evaluation framework: We introduce a structured protocol for assessing FL in 6G environments, incorporating quantitative metrics such as communication cost, convergence speed, robustness to non-independent and identically distributed (non-IID) data, and computational overhead. Explicit thresholds for Low/Medium/High performance levels are provided, enabling reproducible and comparable assessments.
2. Refined taxonomy: A novel taxonomy is proposed that distinguishes the functional roles of edge, fog, and cloud layers. This taxonomy maps representative FL algorithmic strategies to 6G enablers, including ultra-reliable low-latency communication (URLLC), terahertz (THz) connectivity, and reconfigurable intelligent surfaces (RIS).
3. Identification of underexplored challenges: We highlight issues insufficiently addressed in prior surveys, such as quantum-resilient privacy preservation, cross-layer orchestration of resources, and large-scale scalability across heterogeneous devices.
4. Evidence-based recommendations: A systematic comparison of representative FL algorithms (FedAvg, FedProx, SCAFFOLD, and FedNova) is presented under 6G-like conditions. Based on this evaluation, we provide practical guidelines and recommendations for algorithm selection and deployment in next-generation wireless systems.

Collectively, these contributions demonstrate how the paper goes beyond literature compilation by providing benchmarks, clarifying taxonomies, and outlining concrete research directions.

2. Background and Foundations

2.1. Evolution to 6G Networks

The transition to 6G networks is being driven by emerging communication paradigms, increasingly intelligent network design, and the rising demand for data-intensive applications. AI-powered networks are the basis of this transformation. These networks offer the ability to autonomously learn, make quick decisions, and use resources more efficiently to ensure seamless operations [9, 10]. New ideas like quantum information processing, integrated sensing and communication, and very high-frequency bands like terahertz are paving the way toward data speeds exceeding 1Tbps. These techniques also enable ultra-reliable and low latency connections, which are really important for time-critical applications [11]. This evolution signifies a future where networks are becoming more decentralized and autonomous, focusing on edge intelligence to minimize latency and maximize bandwidth efficiency. Technologies like fog and edge computing will become essential enabling distributed processing and scalable, privacy-protecting. AI models particularly federated learning, which is well-suited for deployment at the network edge [9, 12, 13]. Federated learning's ability to allow devices to collaboratively train models without sharing raw data aligns with 6G's core objectives of data control, security, and privacy protection. It helps build a strong and reliable foundation for future smart services. Furthermore, the proliferation of intelligent, context-aware, and adaptive IoT systems like holographic communication, digital twins, and the tactile internet require extremely high levels of network reliability, scalability, and security that have never been needed before [10, 14]. Addressing these requirements necessitates the integration of advanced physical-layer technologies like terahertz communications with smart AI-driven network management and lightweight, secure ways for devices to learn and collaborate, such as federated learning [15, 16]. Consequently, federated learning is expected to become a key technology in 6G networks, helping to create sustainable, privacy-focused, and highly flexible systems that can support the wide variety of new and emerging applications. Table1 summarizes various FL techniques and their applicability in 6G environments.

Table1. Key Enabling Technologies in 6G and Their Roles

Technology	Description	6G Role and Benefits	References
Terahertz (THz) Communication	Operates at 100 GHz–10 THz frequency bands.	Supports ultra-high data rates (>1 Tbps) for XR, holograms, and digital twins.	[1], [8], [15]
Intelligent Reflecting Surfaces (IRS)	Reconfigurable surfaces that control signal propagation.	Enhances spectral efficiency, coverage, and energy savings.	[2], [9]
Edge AI and Distributed Intelligence	Embeds AI at edge nodes for local processing.	Reduces latency and enables real-time decision-making.	[9], [14]
Quantum Communication	Uses quantum mechanics to encode and transmit information.	Provides ultra-secure communication channels.	[3]
Integrated Sensing and Communication (ISAC)	Combines radar and communication functionalities.	Enables environment-aware and context-adaptive services.	[9], [10]
Blockchain for Trust and Privacy	Distributed ledger ensuring transparent and tamper-proof records.	Facilitates secure FL, data sharing, and decentralized identity.	[17]

2.2. Principles of Federated Learning

Federated Learning (FL) is a collaborative way of training machine learning models where many devices such as smartphones, IoT sensors, or autonomous vehicles, work together to improve a shared model without sharing their private data. This approach is perfectly suited for 6G networks, as it helps ensure privacy, reduces delays, and can scale to support the huge number of connected devices. The core FL process typically involves the following iterative steps [18].

1. Model Initialization

A central server initializes a global model and distributes it to selected edge clients.

2. Local Training

Clients perform local training on their private data and generate updated model weights or gradients.

3. Model Upload

Clients send only model updates (not raw data) to the server.

4. Aggregation

The server performs model aggregation (commonly using FedAvg) to update the global model:

$$w^{(t+1)} = \sum_{k=1}^{k} \frac{n_k}{n} . w_k^{(t+1)} \tag{1}$$

Where w_k is the local model from client *k, and* n_k is its dataset size.

5. Redistribution

The updated model is redistributed to clients for the next round. This process is repeated until convergence. While the FedAvg algorithm is simple and widely used, it faces limitations in 6G scenarios with high device mobility and intermittent connectivity, where convergence slows and global models may become biased under non-IID data [19]. In addition, the computational complexity of local training is a concern, since even lightweight CNNs may exceed the memory and energy budgets of IoT sensors [20]. To consolidate the discussion of representative FL algorithms, Table 2 summarizes their computational complexity and communication characteristics, highlighting the trade-offs between local training cost, communication overhead, and suitability for 6G devices.

Table 2. Computational Complexity and Communication Characteristics of Representative FL Variant.

FL Algorithm	Local Training Complexity	Communication Cost per Round	Suitability for 6G Devices
FedAvg [21]	$O(E.n.d)$	High (full model, size = d)	Limited under non-IID, high mobility
FedProx [22]	$O(E.n.d) + proximal\ term$	High	More stable under heterogeneity
SCAFFOLD [22]	$O(E.n.d) + control\ variates$	Medium	Faster convergence, extra device-side memory
Quantized FL [20]	$O(E.n.d)$	Low (compressed gradients)	Energy-efficient, slight accuracy drop
Hierarchical FL [23]	$O(E.n.d)$ per tier	Medium (multi-tier aggregation)	Scalable for massive 6G deployments

Where E is the number of local epochs, n is the number of samples per device, and d is the model dimension (parameters) [21].

2.3. Types of Federated Learning

Federated Learning can be categorized based on how the data is distributed among the participants [21]**:**

- Horizontal FL, different clients have similar types of data features but different data samples (e.g., smart phones with similar applications collecting different user information).
- Vertical Federated Learning is like two companies (e.g., a bank and a retailer) working together on the same group of customers. The bank and retailer each have different types of information about these customers, but they share the same data samples. They collaborate to learn from each other's data without giving away their private details.
- Federated Transfer Learning, on the other hand, is useful when businesses have disparate data and feature sets, which makes cooperation more challenging. It focuses on a limited number of shared characteristics that enable both sides to modify their models and collaborate productively in spite of their differences.

2.4. Advanced Variants and Enhancements

To make Federated Learning more effective and better suited to real-world situations; it has developed into several different forms:

- Asynchronous Federated Learning allows clients to send their updates at varying times, instead of waiting for all devices to finish. This reduces delay from slow or unreliable devices and improving scalability [21].
- Personalized FL, where each client gets a tailored version of the model optimized for its unique data distribution [24].
- Hierarchical FL introduces an intermediate step where nearby edge servers gather and summarize updates before sending them to the central server, which helps reduce the overall communication workload and improving scalability [25].

These advancements enhance FL's ability to function efficiently in dynamic and resource-constrained environments typical of 6G networks.

2.5. Relevance of FL to 6G Networks

Federated Learning aligns closely with architectural vision and functional requirements of 6G networks as outlined in Table 3, FL offers distinct advantages aligned with 6G’s key features, including edge computing, privacy, scalability, and AI-native networking [14, 19, 22].

Table 3. Advantages of Federated Learning in Relation to Key 6G Features.

6G Feature	Federated Learning Advantage
Edge computing & low latency	Local training reduces cloud dependency and supports real-time tasks
Privacy & data sovereignty	Raw data remains on-device, enhancing user privacy
Ultra-massive device connectivity	Scales to billions of heterogeneous edge devices
AI-native networking	Supports decentralized, adaptive, and privacy-preserving intelligence

Figure 1 show how FL fits into the emerging 6G network environment. It enables intelligent decision-making while maintaining data privacy and minimizing redundant data transmission. This approach helps safeguard sensitive information and reduce network congestion, making the process more efficient and secure. The ability of FL to support scalable, on-device learning is especially critical in ultra-dense 6G environments. In addition to supporting secure and efficient network operations, FL enables real-time collaboration among smart vehicles, urban infrastructure, and various IoT devices**.** Collectively, these attributes position FL as a foundational element for the implementation of AI-driven applications in future 6G systems. To provide further context, Figure 2 presents a timeline showing the major milestones in the development and adoption of FL in wireless communication systems.

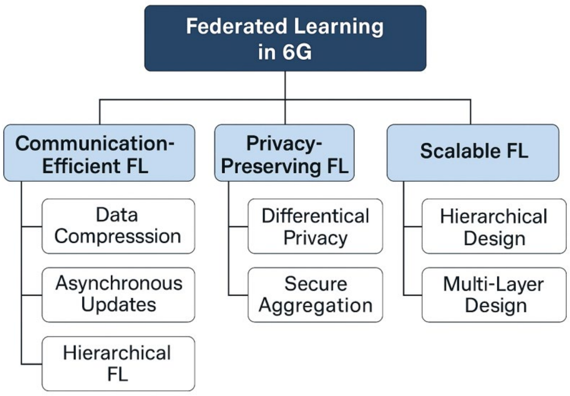

Figure 1. **Taxonomy of Federated learning in 6G: communication strategies, system architectures, privacy Techniques.**

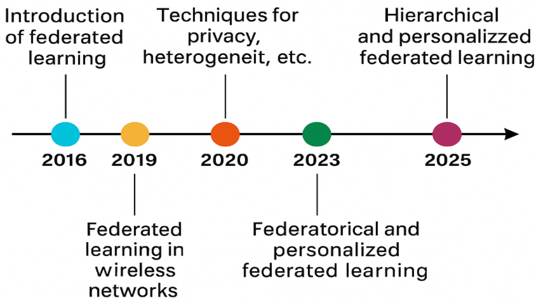

Figure 2. Timeline of FL in Wireless Networks.

3. Challenges of FL in 6G Environments

Despite its promise, the deployment of FL in 6G networks faces several critical challenges due to the intrinsic characteristics of decentralized learning and the demanding nature of 6G environments. These challenges must be systematically addressed to realize efficient, secure, and scalable FL systems in next-generation networks.

3.1. Communication Efficiency

Communication overhead remains one of the most pressing limitations in FL, particularly in large-scale 6G networks. Frequent transmission of model updates can overwhelm bandwidth-constrained links and increase latency [25, 26]. Strategies to improve communication efficiency include gradient compression, update sparsification, and periodic averaging [27, 28]. Reducing duplicate traffic is another potential benefit of hierarchical federated topologies that make use of client-edge-cloud coordination [10].

3.2. Device and Resource Heterogeneity

In 6G environments, devices exhibit considerable disparities in processing capabilities, memory, energy availability, and network bandwidth. This heterogeneity complicates synchronization and may lead to clients dropping out during training. Lightweight model designs, efficient client selection algorithms, and asynchronous training strategies have been proposed to accommodate such variability [13, 10, 24]. In addition, adaptive techniques like model pruning and quantization are critical for enabling edge devices with limited resources to participate meaningfully in FL tasks [27].

3.3. Latency Sensitivity

Timing is also critical in FL because the process depends on regular updates from devices to keep the system synchronized. In scenarios that require ultra-reliable, low-latency communication like those expected in 6G delays in receiving model updates can hurt performance. To minimize these issues, approaches such as asynchronous learning, where devices send updates whenever they can, and event-triggered methods, which only communicate when a significant change occurs, are being explored to help reduce the impact of delays. [13, 29].

3.4. Privacy Preservation and Security Threats

While FL inherently improves privacy by avoiding raw data transmission, it remains vulnerable to a range of privacy and security threats. Gradient leakage, model inversion, and membership inference attacks can reveal sensitive user information [3, 16, 18]. Researchers widely study privacy-preserving techniques such as differential privacy [16], secure aggregation [3], and federated encryption protocols to combat these risks. In addition, the threat of poisoning attacks, where compromised clients intentionally corrupt global model updates, necessitates reliable defense mechanisms and anomaly detection algorithms [30, 31].

3.5. Data Imbalance and Non-IID Distribution

The main challenge in FL is the presence of non-independent and equally distributed (non-IID) data across participating devices. Each client may have limited and biased local datasets, leading to models that generalize poorly when aggregated globally. This statistical heterogeneity results in slower convergence, reduced accuracy, and inconsistencies in training outcomes [6, 9, 32]. Techniques such as hierarchical clustering [33] [34] and personalized FL approaches [28] aim to mitigate this issue by customizing models to local data distributions or grouping similar clients.

3.6. Scalability and System Management

With the rise of 6G networks and billions of interconnected devices, maintaining accurate and reliable federated models becomes increasingly complex. Many devices may join or leave unexpectedly, creating a highly dynamic and unstable environment. To handle these issues with scaling and keeping everything running smoothly, researchers are investigating solutions such as hierarchical (layered) architectures and cross-device learning paradigms, aiming to ensure FL remains reliable as network conditions change [12, 27]. Also, Blockchain integration [17], incentive mechanisms [35], and policy-based orchestration are proposed to enhance trust, transparency, and scalability in decentralized FL environments.

3.7. Standardization Roadmap and Interoperability

As FL moves from theoretical research to practical deployment in 6G environments, interoperability across devices, platforms, and communication protocols becomes essential. The sheer scale and heterogeneity of 6G networks spanning smart phones, IoT sensors, edge servers, autonomous vehicles, and more necessitate standardized frameworks for model exchange, privacy preservation, device authentication, and communication orchestration. Emerging initiatives are addressing these challenges:

- The IEEE P4006 standard [36] defines models for personal data AI agents, promoting responsible handling
- The ETSI ISG PDL working group focuses on using permission distributed ledgers to ensure auditability and trust in federated training and aggregation workflows [37].
- The ITU-T FG-AI4H (Focus Group on Artificial Intelligence for Health) recommends interoperability protocols and model validation pipelines specifically for FL-based medical applications [38].
- Industry-backed platforms such as FATE (Federated AI Technology Enabler) and Intel's OpenFL are pioneering cross-platform FL orchestration using gRPC APIs, secure aggregation, and modular architecture [39, 40].

However, several gaps persist, including:

- The lack of common formats for transmitting models (e.g., ONNX, TF Lite).
- No unified API standards for FL orchestration across heterogeneous clients.
- Limited benchmarked testbeds to validate cross-vendor compatibility.

Future research and industry collaboration are needed to define standards that address:

- Privacy-compliant model sharing.

- Protocols for trust, explainability, and reproducibility.
- Secure FL deployment over satellite and mobile 6G links.

As FL systems scale across 6G networks, standardization will be pivotal in ensuring interoperability, accountability, and secure collaboration at the edge.

4. Enabling Technologies for Communication-Efficient FL in 6G

The integration FL into 6G networks relies on multiple enabling technologies that collectively address the challenges of computation, communication, scalability, and privacy. This section outlines key pillars including distributed computing, secure coordination mechanisms, intelligent orchestration, and communication-efficient protocols while emphasizing their roles within the 6G–FL ecosystem.

4.1. Edge and Fog Computing

Edge and fog computing provide the computational backbone for FL in 6G systems by processing data close to its source, thereby minimizing latency and bandwidth usage. In an FL context, edge servers act as local aggregators, coordinating decentralized training and sending intermediate models to higher-tier nodes or the cloud [10, 12, 14]. A hierarchical edge–cloud architecture allows computationally intensive tasks to be offloaded to intermediate fog layers, enabling energy efficiency, scalability, and context-aware model specialization [29, 41]. This multi-tier design aligns well with 6G's distributed architecture, supporting applications such as autonomous vehicles and remote healthcare that require ultra-reliable, low-latency communication (URLLC).

4.2. Blockchain and Distributed Ledger Technologies

Blockchain provides a decentralized trust layer for FL by ensuring immutability and transparency in model update logging, participation tracking, and incentive distribution [42]. The integration of smart contracts can automate reputation scoring, penalize malicious behavior, and enforce access control. For resource-constrained edge devices, permissioned blockchains defined by bodies like ETSI [38] can offer lightweight, energy-efficient solutions without compromising auditability critical for sensitive domains such as healthcare or financial services.

4.3. Artificial Intelligence and Automation

Artificial Intelligence (AI) enhances the orchestration of FL in 6G networks by enabling intelligent client selection, adaptive learning rate scheduling, and personalized model delivery [3, 9]. Advanced AI techniques, such as reinforcement learning and meta-learning, allow the FL system to adapt dynamically to fluctuating device availability, non-IID data distributions, and varying network conditions [7, 28]. Embedding these AI functions into the 6G management plane improves both resource allocation and fault tolerance.

4.4. Communication-Efficient FL Protocols

Communication overhead remains one of the main bottlenecks in large-scale FL deployments, particularly in bandwidth-constrained 6G edge environments. Several strategies have been developed to address this challenge:

4.4.1. Dimensionality Reduction with SVD (SVDFed Framework)

A notable approach, SVDFed, employs Singular Value Decomposition (SVD) to compress model updates at both the server and client sides [7, 28]. The global model is decomposed before distribution, with only a low-rank approximation sent to clients. Clients train locally and apply SVD again to compress their updates before transmission. This bidirectional compression reduces communication costs by 40–60% while maintaining accuracy in tasks such as image classification and anomaly detection. Figure 3 illustrates this process, where high-dimensional parameter matrices are transformed into compact representations.

4.4.2. Asynchronous and Event-Driven Updates

To mitigate the straggler effect in synchronous FL, asynchronous protocols enable clients to upload updates at different times, reducing idle periods [32, 43]. Event-driven FL triggers communication only when local models exceed a divergence threshold or exhibit a significant drop in loss. Asynchronous SGD (AsyncSGD) accommodates intermittent connectivity and mobility, making it well-suited for URLLC applications in 6G.

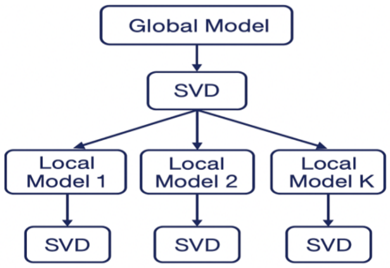

Figure 3. Dimensionality reduction in SVDFed using Singular Value Decomposition (SVD) at both global and local levels.

4.4.3. Hierarchical and Multi-Tier FL Architectures

Hierarchical FL introduces intermediate aggregation points, such as base stations or fog servers, before updates reach the central server [13, 44]. This reduces core network congestion and accelerates model convergence. Such multi-tier designs complement 6G's inherent fog–edge–cloud structure, enabling scalable deployment in high-density IoT and smart city environments.

4.5. System-Level Integration

The enabling technologies discussed above are interdependent and should be viewed as components of a unified 6G–FL architecture:

- Edge/fog computing reduces latency and distributes training loads.
- Blockchain secures interactions between distributed nodes.
- AI enhances orchestration and adaptability.
- Communication-efficient protocols ensure scalability in bandwidth-limited environments.

These technologies operate within a multi-layered network in which edge nodes perform localized learning; fog servers coordinate regional aggregation, and cloud or satellite layers conduct global optimization. By incorporating lightweight AI models, privacy-preserving protocols, and energy-aware designs, such systems can meet 6G's strict performance and sustainability goals. The full interaction of these components is depicted in Figure 4.

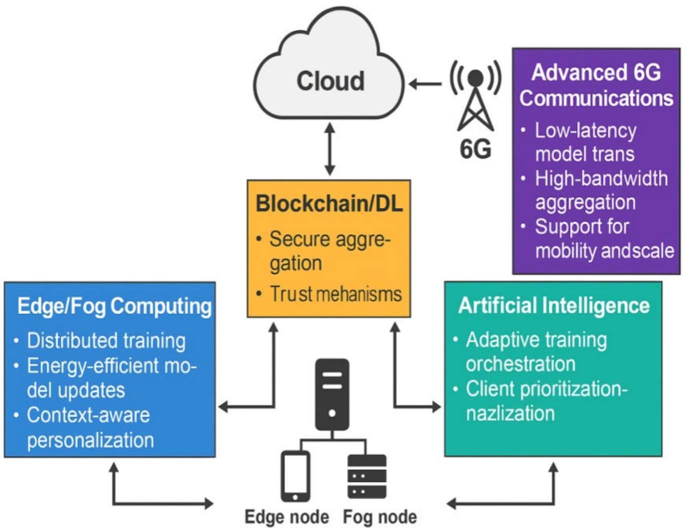

Figure 4. System architecture for federated learning in 6G networks integrating edge/fog computing, blockchain, and AI orchestration.

5. Federated Learning in 6G Networks

5.1. Application Domains of Federated Learning in 6G Networks

The integration of FL with 6G technologies presents transformative potential across a wide range of application domains. By enabling collaborative training directly on devices, FL supports privacy-preserving intelligence in ultra-dense, latency-sensitive, and data-rich environments all hallmarks of future 6G ecosystems. Table 4 presents the main application domains of FL in 6G, empathizing benefits and domain-specific challenges.

5.1.1. Autonomous and Connected Vehicles (V2X)

FL enables cooperative training among vehicles, roadside units (RSUs), and cloud platforms, facilitating tasks such as obstacle detection, route planning, and traffic pattern recognition. Its decentralized nature ensures that sensitive sensor data remains localized, enhancing privacy and responsiveness in real-time decision-making scenarios [10].

5.1.2. Smart Healthcare and Internet of Medical Things (IoMT)

Hospitals, wearable devices, and health-monitoring sensors can use FL to collaboratively train models for disease diagnosis, anomaly detection, and remote patient monitoring. This approach enables compliance with data privacy regulations (e.g., HIPAA, GDPR), while reducing latency in diagnostics [14].

5.1.3. Industrial IoT and Smart Manufacturing

In smart factories, distributed edge nodes can train models for predictive maintenance, fault detection, and quality control. FL helps preserve operational data confidentiality and supports real-time responses in mission-critical environments [31].

5.1.4. Extended Reality (XR), Augmented Reality (AR), and the Metaverse

FL provides personalized model training on user preferences, gestures, or visual input, enhancing immersive experiences. In the context of the metaverse, it allows scalable and secure learning for real-time avatar rendering, behavior prediction, and network adaptation [10, 39].

5.1.5. Smart Cities and Infrastructure

Urban infrastructure (e.g., smart traffic lights, surveillance, and environmental sensors) can participate in federated training to optimize energy use, improve traffic flow, and enhance public safety. This localized learning reduces communication overhead and complies with local data policies [9, 44].

5.1.6. Agriculture and Environmental Monitoring

Sensor networks in agriculture and remote ecosystems can collaboratively learn models for crop yield prediction, soil health assessment, and pollution tracking. FL avoids the transmission of sensitive geospatial data and supports deployment in bandwidth-constrained rural areas [12, 33].

Table 4. Application domains of federated learning in 6G.

Domain	Key Benefits of Using Federated Learning	Main Challenges in 6G Environments
Autonomous Vehicles	Enables real-time model updates and privacy-preserving vehicle-to-vehicle (V2X) learning	Managing constant mobility, unreliable connections, and keeping updates synchronized
Smart Healthcare	Protects patient privacy, supports distributed diagnostics, and keeps data localized	Must follow strict regulations (like HIPAA/GDPR), handle varied data formats, and work on low-power devices with secure protocols
Industrial IoT	Allows fast, on-site learning and keeps sensitive company data secure	Devices often vary by factory, and syncing data across sites is complex
AR/VR & Metaverse	Offers personalized experiences, supports smooth rendering, and saves bandwidth	Requires ultra-low latency, consistent high frame rates, and handles fragmented user data
Smart Cities	Supports decentralized decision-making, reduces dependence on cloud, and respects public data privacy	Balancing energy use, device diversity, and large-scale coordination while keeping data meaningful but private
Agriculture & Environmental Monitoring	Trains models locally even in remote or offline areas, with minimal risk of data leaks	Limited connectivity, unreliable sensors, and energy limitations are common issues

5.2. Comparative Evaluation of Federated Learning Algorithms in 6G Contexts

Although many FL algorithms have been developed, their performance in real 6G scenarios can vary greatly based on factors like network conditions, device diversity, and privacy requirements [3]. Table 5 enabling an informed choice of algorithms for various 6G deployment scenarios. It focuses on aspects such as overall suitability for 6G environments, privacy protections, device-to-device data differences, and communication efficiency. This comparison is intended to assist in choosing or developing FL techniques that satisfy the needs of ultra-dense, low-latency, and privacy-sensitive applications.

In Table 5, the classification into Low, Medium, and High levels is based on quantitative thresholds defined in this study to ensure consistent interpretation of results. Communication overhead is categorized as Low (<10 MB per round), Medium (10–50 MB), and High (>50 MB). Convergence speed is classified as Low (<50 global rounds to reach target accuracy), Medium (50–150 rounds), and High (>150 rounds). Robustness to non-IID data is evaluated on a 0–1 scale, where values below 0.4 indicate Low robustness, 0.4–0.4

correspond to Medium, and values above 0.4 denote High robustness. Similar ranges are applied to computational overhead (<1 GFLOP = Low, 1–5 GFLOPs = Medium, >5 GFLOPs = High) and scalability (<1,000 clients = Low, 1k–100k = Medium, >100k = High). By applying these thresholds, the comparative analysis in Table 4 offers a reproducible benchmark that highlights not only absolute performance values but also the relative efficiency and practicality of each algorithm in 6G-like environments. Due to their simplicity and scalability, classic algorithms like FedAvg [3] are frequently used; however, they suffer under non-IID distributions, which is a common occurrence in 6G networks with billions of diverse devices.

Table 5. Comparison of Federated Learning Techniques in 6G Contexts

FL Method	Communication Overhead	Robustness to Non-IID Data	Privacy Mechanisms	Scalability	6G Suitability	Key Limitations
FedAvg [3]	Medium	Low	None – Baseline	High	Moderate	Sensitive to data heterogeneity
FedProx [9]	Medium	Medium	None – Regularized	Moderate	Good	Requires tuning of regularization term
FedNova [24]	Low	High	None	High	Good	Less explored in cross-device FL
FedMA [3]	Medium	High	None	Moderate	Moderate	Complex model alignment process
FedDF [3], [16]	High	High	Differential Privacy	Low	Limited	High server-side computation cost
SCAFFOLD [3], [25]	Medium	High	None	Moderate	Good	Requires correction terms at clients
FedSGD [3]	High	Low	None	Moderate	Limited	High communication per round
Secure Aggregation [16], [18]	Medium	N/A	Homomorphic Encryption	Moderate	Good	Adds cryptographic overhead

By adding a proximal term that restricts model divergence during local updates, FedProx [9] enhances convergence and provides moderate robustness to data heterogeneity. FedNova [24] addresses the issue of update normalization, reducing the adverse effects of partial client participation. Methods like SCAFFOLD [45] use control variates to correct client drift caused by non-IID data, while FedMA [3] aligns layers across models rather than aggregating weights, which improves accuracy but requires model architecture consistency. On the other hand, FedDF [3], which makes use of knowledge distillation, offers robustness and privacy preservation but comes at a high computational and communication cost. Although client updates are encrypted during transmission thanks to privacy-preserving methods like Secure Aggregation [16, 17], they come with cryptographic overhead that can be significant for low-power devices. Figure 5 shows relative communication overhead of common FL algorithms. FedAvg exhibits high overhead due to frequent full-model updates, while asynchronous and hierarchical FL approaches reduce this burden by leveraging partial or delayed communication. Although conceptually simple, FedSGD requires a frequent bidirectional communication for every update, which limits its practicality in 6G networks [3]. In general, there's no one-size-fits-all algorithm that can handle every need of 6G on its own. Moving forward, the most promising approach will be to blend different strategies combining techniques that are efficient with communication, adjust to individual users, and respectful of privacy to create a more effective and flexible FL system for the future of 6G.

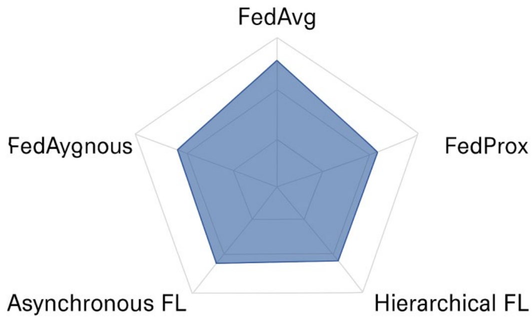

Figure 5. Relative communication overhead of common FL algorithms, comparing FedAvg, FedProx, FedSGD, and hierarchical methods.

6. Open Research Directions and Opportunities

The integration of FL into 6G networks presents a rich avenue for research, with several open challenges that must be addressed to realize its full potential. This section outlines critical areas for future exploration, emphasizing their importance to emerging 6G scenarios. Table 6 summarizes the key research directions discussed in this section, along with representative works addressing each theme.

6.1. Cross-Layer System Integration in 6G

Conventional FL primarily operates at the application layer, but 6G's stringent performance demands require tight cross-layer integration involving the physical, MAC, network, and transport layers. Cross-layer optimization can jointly address spectral allocation, energy efficiency, and model update scheduling, leading to improved convergence speed and reliability. For instance, adaptive resource allocation strategies have been shown to reduce FL convergence delays by up to 55% in mobile network scenarios [33]. The primary challenge lies in dynamically adapting training schedules to fluctuating wireless conditions, including channel fading and intermittent connectivity in terahertz (THz) frequency bands [1, 27].

6.2. Hierarchical and Decentralized FL Architectures

The centralized aggregate used in traditional FL designs has the potential to become a bottleneck. Device-edge-cloud tiers are used by newly developed hierarchical federated learning (HFL) frameworks to increase fault tolerance, scalability, and latency [10, 44]. In addition, by removing the sole point of failure, decentralized aggregation techniques like blockchain-based FL allow safe cooperation in insecure situations [39, 40]. In 6G settings, multi-tier aggregation and dynamical task partitioning can maximize resource usage and model correctness

6.3. Quantum-Resistant and Privacy-Preserving FL

With the advent of quantum computing, existing cryptographic precautions in FL, such as differential privacy (DP) and homomorphic encryption (HE), may be compromised. Post-quantum cryptography (PQC) approaches, such as lattice-based encryption schemes, are being studied to secure FL models from quantum-capable adversaries [46]. Integrating PQC with privacy-preserving approaches while maintaining training efficiency and accuracy is a major challenge, especially in heterogeneous data situations [17, 47].

6.4. Cross-Silo and Cross-Device Collaboration

In 6G, FL must operate smoothly across cross-silo (e.g., hospitals, enterprises) and cross-device (e.g., IoT nodes, smartphones, vehicular systems) settings [6]. These environments differ in trust levels, computational capabilities, and data volumes, making fairness and personalization key research priorities. Benchmarks such as the LEAF dataset are instrumental in evaluating the robustness of FL algorithms under these heterogeneous conditions.

6.5. Integration of FL with Core 6G Technologies

The successful adoption of FL in 6G will depend on its integration with emerging enablers, including:

- **Terahertz (THz) communication** for ultra-high-speed model updates exchanges [1, 26].
- **Reconfigurable Intelligent Surfaces (RIS)** to dynamically manage propagation environments and enhance communication reliability [2, 15].
- **Ambient backscatter communications** for energy-constrained FL deployments.

Recent studies demonstrate how RIS can be employed to optimize user-side energy consumption while maintaining learning performance [47].

6.6. Explainable and Auditable Federated Learning

Given the increasing use of FL in safety-critical domains such as healthcare, explainability and auditability have become vital requirements. Techniques such as SHAP and LIME can provide model interpretability while safeguarding data privacy [48]. The integration of explainable AI (XAI) into FL pipelines is necessary to ensure transparency, trust, and compliance with ethical and regulatory frameworks.

6.7. Standardization and Real-World Testbeds

Even though there's been a lot of progress in the theories, we still don't have a clear, standard platform for 6G FL. Initiatives such as FATE [49], OpenFL [50], and IEEE P4006 [51] are working toward platform standardization, privacy protection, and interoperability. However, large-scale, latency-aware 6G-specific testbeds and simulators are still underdeveloped, representing a key opportunity for future research [52].

Table 6. Key Research Directions and Representative Works

Research Direction	Focus	Representative Works
Cross-Layer FL Integration	Joint optimization of communication and learning parameters	[34]
Hierarchical / Decentralized FL	Multi-tier and blockchain-enabled FL	[17], [25], [39], [42]
Quantum-Safe FL	Post-quantum cryptography and privacy preservation	[18], [26], [50]
Cross-Silo & Cross-Device FL	Fairness, personalization, and heterogeneity handling	[8]
FL with Emerging 6G Technologies	THz, RIS, and energy-efficient communication	[1], [2], [46]
Explainable and Auditable FL	Interpretability and compliance	[50]
Standards and Platforms	Standardized frameworks and testbeds	[40], [41], [51], [52]

7. Conclusion

This paper looks at both the design of 6G systems and how to include federated learning, unlike previous research that usually focused on just one part. It covers the key technologies like edge and fog computing, blockchain, and AI management, while also tackling big-picture issues such as security, how well the system can grow, and making communication more efficient. The analysis further identifies several critical avenues for future research. These include the development of quantum-resistant privacy-preserving mechanisms, the design of energy-efficient training paradigms, and the implementation of scalable multi-tier architectures that align with the inherently distributed characteristics of 6G. Such research directions represent significant opportunities for innovation that may shape the evolution of next-generation intelligent wireless communication systems. These research areas present significant opportunities for innovations that could fundamentally transform future smart wireless communication systems. As 6G develops, FL is likely to become a key way to enable smart, private cooperation right at the network's edge. Addressing the identified challenges through advanced enabling technologies and interdisciplinary approaches will be essential to establishing secure, sustainable, and high-performance AI-driven communication ecosystems. In essence, combining FL with 6G represents more than a technological upgrade. It's a big step toward creating AI that's more centered on people, more trustworthy, and built so that's decentralized. This shift will be a key part of the super-connected digital world we're heading into.

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