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Federal AI for Indoor Localization

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Abstract

This paper examines the transformative role of Federal AI (FAI), particularly Federated Learning (FL), in advancing indoor localization systems. It addresses the increasing need for accurate and dependable positioning solutions while maintaining user privacy. The survey reviews various indoor localization technologies, analyzing their limitations and the specific challenges posed by indoor environments. It highlights the principles of FAI and its advantages, including user privacy preservation, scalability, and support for personalization. The paper also explores practical applications of FAI in areas such as personalized navigation, asset tracking, and other location-based services. It provides a detailed overview of existing FAI methodologies for indoor localization, discussing their key contributions. Finally, it identifies unresolved challenges and outlines potential research directions, emphasizing the promising future of FAI in this domain.

Keywords: Federated Learning; Indoor Localization; Privacy Preservation; Non-IID Data; Wi-Fi Fingerprinting.

1 | Introduction

Indoor localization focuses on identifying the specific position of items or people within enclosed areas such as galleries, medical facilities, or corporate buildings [1]. This concept is similar to navigating through a structure but without depending on Global Positioning System (GPS), which is commonly used outdoors [2]. Since barriers like walls and roofs obstruct satellite signals, indoor systems utilize alternative methods to determine your accurate location. It's essentially about identifying where you are inside a building's boundaries. Picture trying to navigate through a shopping mall, a healthcare facility, or even your residence. Indoor localization employs technology to help you understand your exact position within these environments. It does more than merely stating, "I'm on the top floor," offering instead a pinpointed spot inside the structure [3]. The approach to navigating an open field is quite distinct from maneuvering through a crowded hospital. Indoor localization solutions need to accommodate varying building architectures. Spacious areas with minimal hindrances support straightforward signal paths, while multi-story buildings with partitions may pose difficulties for these systems. Imagine accurately determining the position of not only individuals but also devices, robots, or tiny items [4]. That illustrates the capability of indoor localization. Beyond locating individuals, it can track their movements and even relay this data to others. This innovation finds extensive applications, such as aiding emergency responders in locating people, ensuring critical equipment is tracked in hospitals, and monitoring assets in factories [5]. It's a transformative system, enhancing how indoor spaces are managed.

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Imagine a scenario where navigating a bustling shopping mall is as effortless and precise as using GPS outside. This is the vision of indoor localization, a technology that's quickly gaining momentum [6]. However, the challenge of accurately identifying your position inside a building is more complex than it appears. Think of radio waves, like those enabling your Wi-Fi, bouncing off surfaces, ceilings, and even people, creating a tangled mix of signals. This multipath effect complicates indoor systems' ability to identify the correct signal, causing errors in positioning. Additionally, each building has unique characteristics—its structure, design, and the movement of crowds—all of which impact how signals behave [7]. To complicate matters further, there are concerns about energy usage in mobile devices, protecting user privacy, and the expenses associated with deploying these systems [8]. Despite these hurdles, the potential of indoor localization is vast. Envision a future where you're guided to a specific shop in a mall, receive tailored promotions based on your exact location, or effortlessly track critical medical equipment in healthcare settings [9]. The opportunities are boundless, but addressing these issues is essential to unlock the full potential of indoor localization and transform it into a revolutionary tool.

AI's capacity to transform industries is undeniable, but its dependence on centralized datasets raises significant privacy and security issues. Gathering massive amounts of information in one place increases vulnerability to breaches, exposes confidential data to unauthorized parties, and can create ethical quandaries surrounding the use of private information [10]. Federated Learning (FL) tackles these problems by facilitating collaborative AI model building across numerous distributed devices or servers, eliminating the need to share unprocessed data [11]. This distributed strategy not only safeguards sensitive data but also improves the safety, flexibility, and resilience of AI infrastructure. By allowing people and companies to maintain control of their information while contributing to AI progress, FL enables the creation of privacy-focused and secure AI methods [12]. This is especially important for indoor positioning, where the gathering and examination of location information raises special privacy issues. FL provides a strong solution for developing precise indoor localization systems while protecting user privacy, enabling uses like customized navigation in complicated buildings and tracking high-value assets in places like hospitals or storage facilities.

This research paper explores the developing area of FAI and its transformative capabilities for indoor positioning. Acknowledging the increasing need for precise and dependable indoor location systems, this work offers a thorough overview of FAI methods designed to tackle the specific difficulties of indoor spaces. The second section starts by building a fundamental knowledge of indoor localization technologies, encompassing frequently used approaches like Wi-Fi, Bluetooth, RFID, UWB, visible light communication, acoustic positioning, and ultrasound. It examines the merits and drawbacks of each method, emphasizing their constraints regarding accuracy, reliability, and privacy in complicated indoor settings. Section 3 examines the idea of FL and its distinct benefits for indoor positioning. It covers the advantages of FL in terms of privacy, security, scalability, and customization, highlighting how it overcomes obstacles presented by conventional centralized approaches. Section 4 presents a detailed review of current FAI strategies created for indoor location, evaluating diverse methods such as customized models, federated transfer learning, dynamic access point placement, and multi-level FL. It analyzes the pros and cons of each technique, describing their real-world uses and limitations. Section 5 pinpoints key obstacles and knowledge gaps that must be addressed to fully unlock FAI's potential in indoor localization. It examines promising future research avenues for improving the precision, dependability, and efficacy of FAI-based indoor positioning systems while tackling privacy and security issues, including managing non-IID data, enhancing communication efficiency, and creating robust privacy-protection methods.

2 | Fundamentals of Indoor Localization

Indoor localization has grown vital to numerous facets of contemporary life. Unlike outdoor positioning, which often relies on an unobstructed view of satellites, indoor settings introduce distinct challenges [13]. These spaces can vary from straightforward, open layouts with minimal barriers to intricate, multi-level structures filled with walls and other impediments. This variability makes achieving precise indoor positioning much more challenging than outdoor localization [14].

The main components of an indoor localization system are: sensors, which transmit signals and collect data; mobile devices, which receive signals from the sensors and then calculate their position based on these signals using a positioning algorithm; and a database, which contains all the information about the environment, such as sensor coordinates and routing information [15].

Navigating the complex labyrinth of indoor spaces has long been a challenge, but the emergence of sophisticated localization technologies is changing the game. Indoor localization, the ability to precisely pinpoint the location of objects or individuals within buildings, is rapidly transforming how we interact with our surroundings [16]. The rest of this section explores the diverse range of technologies that have been developed to address this challenge, each offering unique advantages and limitations.

2.1 | Using Radio Waves

Radio communication technologies have led the way in indoor positioning advancements, employing numerous standards and communication protocols for precise location within buildings[17].

The common Wi-Fi network, built on the IEEE 802.11 standard, has become a surprising tool in indoor positioning. Wi-Fi's broad availability and incorporation in most devices makes it a convenient and economical option. Utilizing existing network equipment, Wi-Fi positioning systems measure Wi-Fi signal strength (RSSI) to approximate a device's position [18]. As signal strength weakens with increased distance, triangulation methods can determine a device's location in relation to multiple access points. However, Wi-Fi positioning faces obstacles like signal interference, environmental conditions, and the intricacies of how signals spread inside structures.

Bluetooth, a short-range wireless technology, provides a different indoor positioning method, centered on proximity detection and object tracking [19]. Bluetooth beacons, compact gadgets that regularly transmit Bluetooth signals, serve as reference points inside. By gauging the intensity of Bluetooth signals from these beacons, a device can determine how close it is to them [20]. Bluetooth positioning is ideal for situations requiring accurate placement within a small area, such as shops, cultural institutions, or indoor guidance systems. But, the restricted reach of Bluetooth signals limits its usefulness in larger indoor areas [21].

Radio Frequency Identification (RFID) technology uses passive tags attached to items or people, enabling identification and tracking indoors. When scanned by an RFID reader, these tags send a special code used to find the tagged object. RFID positioning shines in inventory control, asset monitoring, and similar applications where keeping tabs on many objects is essential [22]. However, RFID requires installing readers and supporting infrastructure, reducing its flexibility compared to alternatives.

Ultra-Wideband (UWB) technology employs high-frequency radio pulses to determine the time-of-flight (ToF) between devices [23]. By accurately measuring the time it takes a signal to go from a UWB anchor to a device and return, the system can precisely calculate the distance between them. This precise distance data, combined with triangulation algorithms, enables highly accurate indoor location [24]. UWB offers substantial benefits in difficult settings with obstacles and signal reflections, making it suitable for applications needing pinpoint accuracy, like factory automation, medical care, and robotics.

2.2 | Using Light and Sound

Beyond radio waves, other technologies have emerged to tackle indoor location problems.

2.2.1 | Visible Light Communication (VLC)

VLC uses modified light from LED lamps to send data. This still-developing technology has the potential for indoor positioning by examining the arrival angle of light from LEDs acting as beacons [25]. The widespread adoption of LEDs makes VLC a promising possibility for indoor positioning systems.

2.2.2 | Acoustic Localization

Smartphone microphones can be used for indoor positioning by detecting sounds from specific sources or reference points [26]. By examining the time-of-flight or Doppler shift of sound waves, the system can approximate a device's location. Acoustic positioning benefits from using existing smartphone sensors, but its accuracy is affected by ambient noise and limitations of phone microphones.

2.3 | The Future of Indoor Localization

Several exciting new technologies are set to further revolutionize how we locate things indoors. These include:

- **Ultrasound**: Similar to UWB in its use of time-of-flight, ultrasound has shown considerable potential for highly accurate indoor positioning. Its capacity to track numerous devices at once with low power consumption and minimal signal bleed between rooms makes it a serious contender.

- **Artificial Intelligence (AI):** AI algorithms, particularly deep learning models, are being added to indoor positioning systems to boost accuracy, reduce reliance on specialized hardware, and improve adaptability to different environments [27].

Indoor positioning systems face unique hurdles that can greatly impact their precision. Signal propagation inside buildings is complicated by walls, ceilings, and other obstructions that warp and diminish radio waves. Signal fading, where strength decreases as signals penetrate materials like walls or floors, presents a significant obstacle, making it harder to estimate distance based on signal strength. Multipath propagation adds another layer of complexity; signals bouncing off various surfaces create multiple paths to the receiver, arriving at different times and disrupting the primary signal, introducing errors in time-based measurements.

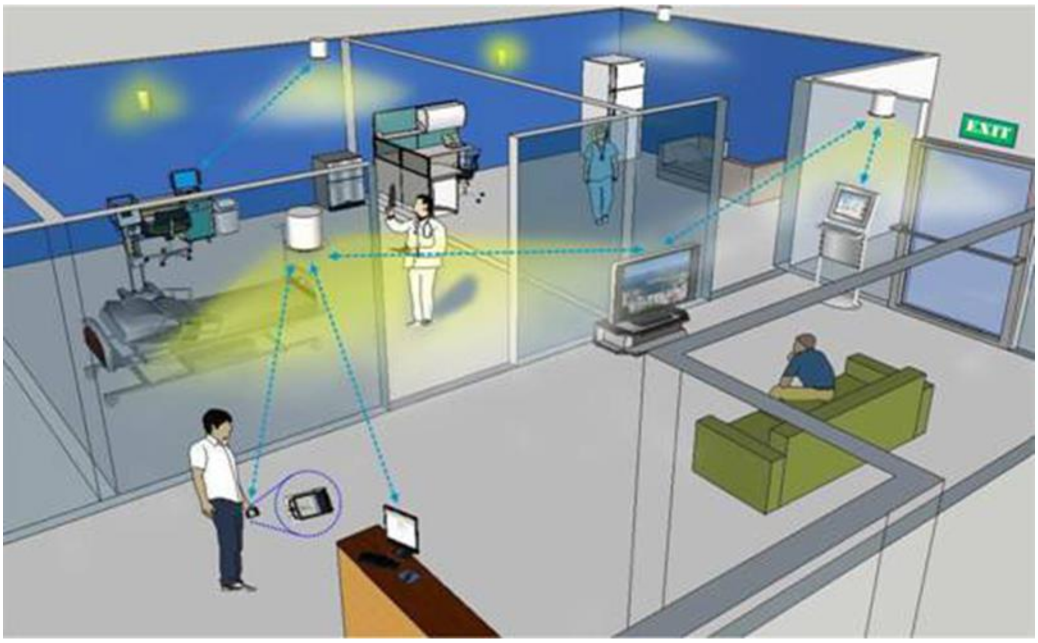
Privacy issues also emerge, as monitoring movement inside raises questions about information security and access control. Furthermore, combining location systems with existing building infrastructure, like security or facility management, can be a complex undertaking requiring specialized solutions [28]. Signal blockage, where objects obstruct the direct path between transmitter and receiver, further complicates matters by creating areas with faint or absent signals, reducing accuracy in those zones. Overcoming these obstacles requires sophisticated signal analysis techniques to sift out interference, compensate for signal loss, and pinpoint direct signal paths among numerous reflections. These advancements are essential for developing precise and reliable indoor location solutions while also considering the practicalities of implementation.

3 | Federal AI and its Applications in Indoor Localization

Artificial intelligence's power to reshape industries is undeniable, but relying on large, central datasets for AI training raises serious privacy and security worries. Gathering huge amounts of information in one spot creates vulnerabilities to security breaches, exposes private data to unauthorized access, and may lead to ethical conflicts about the use of personal information [29]. This is especially true for indoor positioning, where collecting and studying location information raises unique privacy issues. People are often reluctant to share their exact location due to valid privacy concerns.

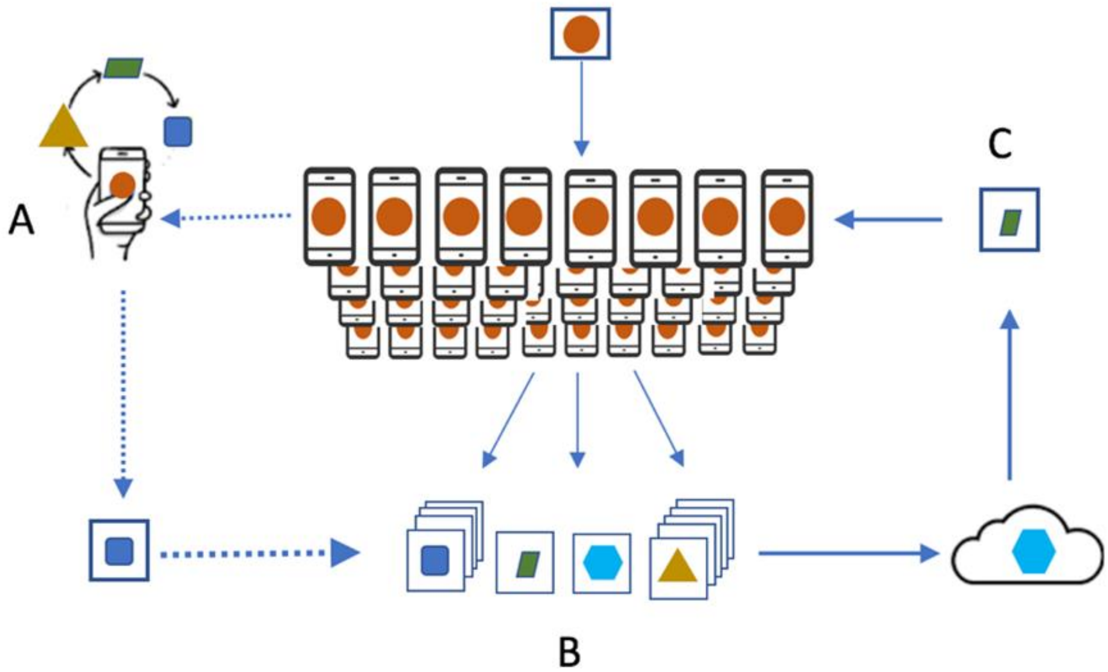
FAI, particularly FL, tackles these problems by enabling collaborative AI model development across many distributed devices or servers without sharing the original data. This innovative method, sometimes called "edge learning," protects sensitive information on individual devices while still allowing the creation of strong AI models [30]. By giving individuals and groups control over their information while still contributing to AI advancements, FAI enables privacy-preserving and secure AI development. This is especially relevant in indoor positioning, where location data collection and analysis are sensitive. FL offers a powerful solution: building accurate indoor location systems while protecting user privacy. This allows for applications like custom navigation in complicated buildings and tracking valuable equipment in hospitals and warehouses [31].

Imagine your phone navigating a hospital, guiding you to the correct clinic without sharing your location with a central server. Or envision a warehouse where valuable assets are tracked in real time to optimize operations, all without compromising employee privacy.



The rise of Federated AI represents a major shift in AI development. By using a distributed training approach, Federated AI empowers individuals and organizations to control their information while still using AI for innovation. This move toward decentralized learning not only addresses critical privacy and security concerns but also opens up exciting new avenues for using massive amounts of data previously isolated in separate systems. As Federated AI matures, it has the capacity to transform AI, creating a future where AI applications are both robust and ethical, driving advancement while protecting fundamental privacy rights.

FAI presents several promising solutions to indoor positioning challenges. A key benefit is its ability to protect user privacy. By letting devices train models locally and share only updates, FAI eliminates concerns about sending sensitive location information to central servers. FAI's scalability is another major advantage. Indoor environments are incredibly varied, and traditional methods struggle to capture this diversity. FL allows us to use data from many devices in different locations, creating more reliable and precise positioning models. Personalization is also improved with FAI. People have unique movement habits and device settings, and FL can adapt to these individual differences while benefiting from shared insights. Integrating data from various sensors is another indoor positioning challenge. FAI creates a framework to combine diverse data sources without centralizing raw data, potentially boosting location accuracy. Indoor spaces are dynamic, constantly changing, posing a continuous challenge for positioning systems. FAI's capacity for continuous learning allows it to adapt to environmental changes, like furniture rearrangements. Practically speaking, FAI significantly reduces data transmission needs by processing information locally and only sharing model updates. This is crucial for real-time indoor positioning. FAI also holds promise for building more adaptable models. By learning from diverse environments and users, it can create location models that work well in various settings. Finally, federated AI addresses data imbalances common in indoor positioning. Some building areas may have more data than others, and federated learning can balance these contributions, improving the overall model.



4 | Existing Federal AI Approaches for Indoor Localization

Liu et al. [32] proposed an innovative indoor localization system named Floc which introduce a groundbreaking approach to indoor localization that prioritizes both accuracy and privacy. FLoc leverages the power of Federated Learning to update fingerprinting-based localization models without requiring users to share their raw location data. This innovative system tackles the critical challenges of dynamic environments, unstable signals, and the ever-present threat of privacy breaches. By incorporating homomorphic encryption, FLoc ensures that model update parameters are securely transmitted between mobile devices and a central server, safeguarding user location information. Through rigorous experiments conducted in a laboratory corridor, FLoc demonstrates its effectiveness in adapting to changing environments and maintaining accurate localization performance. FLoc's ability to achieve comparable accuracy to traditional Deep Learning approaches while offering enhanced privacy and robustness makes it a significant advancement in the field of indoor localization.

Li, Zhang, and Tanaka [33] tackle two major hurdles faced by RSS fingerprint-based indoor localization systems: the demanding calibration process and privacy concerns. Their innovative solution, CRNP (Centralized indoor localization method using Pseudo-label), utilizes a clever combination of limited labeled data with vast amounts of unlabeled data, significantly reducing the effort required for data collection. To address privacy concerns, they integrate Federated Learning with CRNP, enabling decentralized training where location data remains on individual devices. Model updates are then securely aggregated, protecting user privacy while reducing network overhead. Their extensive experiments confirm the effectiveness of this approach, demonstrating improved localization accuracy and robustness, highlighting the potential of this novel method to revolutionize indoor localization while safeguarding user privacy.

Bekir Sait Ciftler et al. [34] present a novel approach for indoor localization leveraging federated learning to enhance privacy and accuracy. They propose a system where Received Signal Strength (RSS) fingerprint-based localization is performed using a multilayer perceptron (MLP) model trained in a decentralized manner. This method preserves user privacy by keeping local data on edge devices and only sharing model updates with a central server. Their experimental results demonstrate that this approach achieves improved localization accuracy while maintaining data privacy, showing up to a 1.8 meter improvement in localization accuracy when combined with centralized learning and satisfactory accuracy when used independently.

Yin et al., [35] present a comprehensive overview of Federated Learning (FL) as a powerful tool for enhancing localization and location data processing while safeguarding user privacy. They introduce the FedLoc framework, a novel approach that empowers mobile users to collaboratively train global AI models for localization without sharing raw data, effectively addressing the limitations of traditional centralized data collection and processing methods. The researchers examine several practical uses of FedLoc, demonstrating its capacity to transform location-based services in diverse areas, such as stationary positioning, vehicle navigation, tracking pedestrians indoors, and predicting wireless network traffic over space and time. Their work also explores the advantages and disadvantages of various learning models, like Deep Neural Networks (DNNs) and Gaussian Processes (GPs), emphasizing the benefits of GPs for handling uncertain input, incorporating existing knowledge, and providing stronger generalization abilities. Beyond examining different learning models, they investigate distributed training methods, comparing various strategies like FedAvg, FedProx, and ADMM-based techniques. This detailed analysis highlights key factors for optimizing learning models in distributed environments. Recognizing the importance of privacy in federated learning, they also discuss several privacy-protection methods, including secure multi-party computation, homomorphic encryption, and differential privacy, which can be incorporated into the FedLoc framework to protect sensitive user information. Through real-world evaluations of the FedLoc framework for static localization and vehicle navigation, the authors demonstrate the practical effectiveness of their approach. Their findings highlight the potential of Federated Learning to achieve high accuracy, particularly when using GPs for modeling location data, while respecting user privacy.

Wu et al. [36] address a critical challenge in FL for indoor localization: the presence of non-IID data. To overcome this, they propose a novel approach that trains personalized models for each user, tailored to their unique data distribution, and then optimally fuses these predictions using Bayesian rules. Their research demonstrates the effectiveness of this strategy through simulations based on real-world information, showing its capacity to surpass existing methods in both accuracy and reliability. This study emphasizes the vital role of personalization in FL for creating effective, privacy-focused, and robust indoor location systems, opening doors for more accurate and adaptable positioning solutions in various environments.

Wu et al. [37] address the challenges of privacy and real-time deployment in FL for indoor localization. Their proposed framework, OPFL, utilizes an online personalized approach where users update model parameters while simultaneously collecting new labeled samples. OPFL employs a Differential Privacy mechanism to add artificial noise, making it more difficult for attackers to infer sensitive information. To mitigate the potential deterioration of the model caused by noise perturbation, they integrate a personalized algorithm that further enhances accuracy. Their experiments demonstrate that OPFL, even with noise added, achieves significantly better performance on local test sets than conventional FedAvg algorithms, even approaching the accuracy of centralized training. This research highlights the potential of OPFL to provide a practical, privacy-preserving, and efficient solution for real-time indoor localization systems.

Li et al. [38] investigate the feasibility of using FL to enhance indoor localization while protecting user privacy. The author acknowledges the limitations of GPS indoors and highlights the increasing reliance on Wi-Fi fingerprinting for accurate positioning. The paper explores the challenges of traditional crowdsourced data collection, which can expose sensitive user location data. Federated Learning, with its ability to train models locally on user devices and transmit only model parameters, emerges as a promising solution for addressing these privacy concerns. They conduct a comparative analysis of mainstream Federated Learning frameworks, ultimately choosing TensorFlow Federated (TFF) for its ease of use and suitability for indoor localization simulations. The research then examines the performance of Federated Learning on a real-world Wi-Fi fingerprint dataset, specifically considering the scenario of Non-IID (Non-Independent and Identically Distributed) data, common in indoor environments. The results demonstrate that Federated Learning can achieve good training performance and prediction results, comparable to non-federated learning, while ensuring data privacy.

Gao, Yang, Cui, Xiong, Lu, and Wang [39] present FedLoc3D, a groundbreaking FL framework designed for robust indoor localization in complex multi-building and multi-floor environments. Recognizing the challenges of non-IID data, they introduce specialized techniques, FedDSC-BFC for building-floor classification and FedADA-LLR for latitude-longitude regression, to address data heterogeneity and enhance both localization accuracy and learning efficiency. Through rigorous experiments on real-world WiFi fingerprint data, they demonstrate the effectiveness of their approach in navigating the complexities of multi-building and multi-floor scenarios, highlighting the potential of FedLoc3D to revolutionize indoor localization while prioritizing user privacy.

Park, Moon, Kim, Wu, Imbiriba, Closas, and Kim tackle a crucial challenge in [40] FL for indoor localization: overcoming the performance degradation caused by non-IID data. Their innovative approach addresses this by incorporating model reliability into the weight update process. They propose a novel method that considers the uncertainty of local models, which are trained on individual user data, to improve the accuracy of the global model. To efficiently quantify this uncertainty, they leverage the power of Monte Carlo (MC) dropout, a technique that approximates Bayesian uncertainty with minimal computational overhead. Their simulation results demonstrate that this approach, compared to traditional FedAvg methods, significantly improves localization performance, even approaching the accuracy of centralized learning.

Wu, Wu, and Long [41] address the dynamic nature of indoor localization by introducing PSO-PFL, a novel FL framework designed to provide personalized localization services. PSO-PFL embraces online learning, allowing users to continually update the model while collecting new unlabeled data, thereby reducing dependence on extensive initial data collection. This framework also tackles the challenge of non-IID data, common in indoor environments, by considering diverse user needs and data distributions. To enhance accuracy and efficiency, they employ a prediction-based client selection strategy that prioritizes users with a higher probability of requiring localization services. Their experiments, conducted on real-world datasets, demonstrate the effectiveness of PSO-PFL, showcasing its ability to achieve superior personalization accuracy compared to centralized training and conventional FedAvg while effectively utilizing unlabeled data.

Ibnatta, Khaldoun, and Sadik [42] address a critical challenge in the realm of indoor localization: mitigating the detrimental effects of multipath interference on Received Signal Strength (RSS)-based positioning systems. Their proposed approach leverages the power of FL, a revolutionary paradigm in machine learning, combined with the well-established mathematical model of RSS, facilitated by UWB-OFDM communication. This synergistic combination tackles the problem from multiple angles, offering several key advantages. First, the authors recognize the significance of safeguarding user data privacy in indoor localization. Traditional centralized approaches often require sensitive location data to be shared with a central server, raising concerns about data breaches and unauthorized access. Second, their approach offers a robust solution to the multipath interference problem, which can drastically reduce the accuracy of RSS-based indoor positioning. By decentralizing the learning process through FL, they limit the negative impact of multipath on the system's performance, ensuring greater accuracy and stability. To validate the effectiveness of their proposed system, the authors employ a comprehensive simulation environment incorporating three powerful platforms: MATLAB, MySQL, and a Java interface. This robust setup enables them to simulate various scenarios and conduct rigorous evaluations, showcasing the system's capabilities. Their analysis explores the impact of different factors on localization accuracy, including the number of training rounds, the number of users participating in the system, and the quality of the data. They also compare their proposed approach with other established methods, highlighting its advantages in terms of accuracy and resilience to multipath interference. Furthermore, the authors emphasize the importance of adhering to real-world criteria for a successful indoor localization system, including precision, energy consumption, cost, ease of deployment, stability, and adaptation to dynamic environments. Their choice of tools – Federated Learning, RSS, and UWB-OFDM – effectively addresses these concerns, demonstrating the practical viability of their solution. The research culminates in an average error of 148.9 cm, achieved with 10 users and 5 training rounds, signifying promising accuracy. Their analysis demonstrates the influence of data quality on system performance, highlighting the need for robust data acquisition and preprocessing. Through their comprehensive approach, Ibnatta, Khaldoun, and Sadik offer a compelling demonstration of the potential of FL to overcome the limitations of conventional indoor localization methods.

Tasbaz, Moghtadaiee, and Farahani [43] address a key challenge in the field of indoor localization: safeguarding user privacy in FL systems. While FL offers a decentralized approach to model training, protecting sensitive location information during gradient transfer remains a concern. The authors propose a novel zone-based FL method that prioritizes privacy by determining user zones rather than their precise location. This clever approach ensures that even with potential gradient leakage, the user's exact location remains concealed, effectively preserving privacy. The paper demonstrates the effectiveness of their proposed method through experiments conducted using two real-world datasets. They compare the accuracy of their zone-based FL approach with a non-FL baseline, analyzing the impact of various factors, including the number of communication rounds, clients, and data per client. Their findings demonstrate that while protecting user privacy, the zone-based FL approach achieves localization accuracy that is remarkably close to the non-FL baseline. This research significantly contributes to the development of privacy-aware indoor positioning systems. The authors' work highlights the importance of strategically designing FL approaches to address privacy concerns and demonstrates the practicality of their zone-based method in achieving accurate indoor localization while safeguarding user data. This paves the way for more secure and user-friendly indoor positioning systems in smart cities and smart homes.

Wu, Wu, and Long [44] introduce a multi-level federated graph learning approach to capture the intrinsic features of RSS data, enabling more accurate model training for diverse indoor environments. This technique takes advantage of the inherent structure and relationships within the RSS data to enhance model performance. To further improve personalized accuracy, they introduce a self-attention mechanism to learn the optimal way to aggregate information shared by different clients in the Federated Learning process. This personalized aggregation strategy allows the system to adapt to the unique characteristics of each user's data and environment. These innovations, validated through simulations, demonstrate that their approach achieves significantly higher personalized localization accuracy than other personalized federated learning (PFL) methods, showcasing the importance of both graph learning and self-attention for tackling data heterogeneity in Federated Learning.

Gufran and Pasricha [45] tackle the challenges of device heterogeneity and dynamic environments in indoor localization. They propose FedHIL, a novel embedded ML framework that leverages FL to enhance localization accuracy while preserving user data privacy. Their approach incorporates a strategic data augmentation technique using a custom stacked autoencoder to address variations in Wi-Fi RSS fingerprints across heterogeneous devices. FedHIL further employs a lightweight neural network within an FL setting, continually updating the model to maintain accuracy and robustness. A unique selective weight adjustment method is introduced to filter out noisy data during aggregation, preventing model degradation. Extensive real-world evaluations across multiple heterogeneous devices and diverse building environments demonstrate FedHIL's superiority over state-of-the-art FL and non-FL frameworks, achieving a significant improvement in localization accuracy.

Etiabi, Njima, and Amhoud [46] introduce a novel approach to indoor localization that leverages FL and a hierarchical deep neural network to improve accuracy in complex multi-building and multi-floor environments while addressing privacy concerns. Their framework capitalizes on the inherent hierarchy between floors and buildings to enhance localization precision. Through an extensive performance evaluation, they demonstrate that their hierarchical learning scheme significantly boosts accuracy, achieving a 24.06% improvement over non-hierarchical approaches. Furthermore, they achieve remarkable building and floor prediction accuracies of 99.90% and 94.87% respectively. Notably, the proposed FL framework delivers performance comparable to centralized training with a minimal increase in localization error, highlighting its effectiveness in protecting user privacy. Their scalability study further confirms that the FL system's accuracy improves as more devices participate in the training process. This research offers a valuable contribution to the field of indoor localization, showcasing the potential of Federated Learning and hierarchical models to create more accurate, robust, and privacy-aware positioning systems in multi-building and multi-floor environments.

Kumar et al. [47] address the growing need for accurate and scalable indoor localization. They propose a federated learning-based framework designed to enhance location classification using Wi-Fi fingerprinting while prioritizing data privacy. Their approach leverages a distributed client-server architecture where each client trains a model locally on their own data, and only the trained model weights are shared with the central server. This ensures that sensitive location information remains on individual devices. The effectiveness of this framework is demonstrated through experiments conducted with both IID and non-IID datasets, comparing its performance to traditional distributed deep learning models. Results show the framework excels in accuracy and loss while maintaining data security. This innovative design, coupled with its superior performance and emphasis on data privacy, positions it as a promising solution for future indoor localization applications, particularly in edge computing environments.

Dou et al. [48] address the challenges of limited network connectivity and heterogeneous data in FL for indoor localization. They propose a personalized Federated Reinforcement Learning approach that enables each client device to learn an action policy for efficient target searching based on their unique local data. This allows for more accurate and robust localization, even with limited communication and diverse data distributions. The framework then leverages a central server to communicate only model updates from these clients, creating a global model that closely aligns with individual client models. Their experimental results showcase the superiority of this method in terms of localization accuracy and stability compared to existing approaches. Furthermore, they extend their framework to few-shot learning, allowing for fast and efficient localization of new users with limited data. This research offers a promising solution for privacy-preserving and personalized indoor localization, particularly in environments with resource constraints and diverse user needs.

Guo et al. [49] propose FedPos, a federated transfer learning framework for CSI-based Wi-Fi indoor positioning that addresses the limitations of traditional machine learning and cloud-based federated learning approaches. FedPos leverages a novel position estimation method that focuses on building a robust and versatile encoder on a cloud server by aggregating non-classification layer parameters from models trained in different environments. This approach ensures user privacy while allowing for the aggregation of diverse classifiers and the subsequent creation of personalized models for new users through fine-tuning. Their work highlights the transferability of a lightweight convolutional neural network to unfamiliar environments, demonstrating that FedPos can be incrementally updated and is highly extensible. They validate the performance of FedPos using real-world data from various indoor environments, achieving an impressive mean localization error of 42.18 cm in a 64-position living room. Their results further show that FedPos can significantly boost localization performance by 5.22% on average and reduce model training time by 34.78% compared to traditional methods. Additionally, FedPos enables the reuse of trained feature extractor layers, reducing the need for extensive training data and achieving similar performance to baseline models. Finally, the proposed position estimation method outperforms seven other existing CSI-based methods, confirming the efficacy of their approach. This research significantly contributes to the field of indoor localization by introducing a practical and scalable Federated Learning framework that prioritizes privacy, improves accuracy, and optimizes model training, making it a promising solution for a wide range of indoor positioning applications.

Varma et al. [50] present a novel approach to indoor positioning that balances user privacy with accurate location determination. Their federated KNN-based system uses discrete coordinate encryption to protect the exact location of target nodes, safeguarding user privacy. However, recognizing that privacy-enhancing techniques can sometimes compromise accuracy, they introduce a dynamic access point deployment strategy based on Hausdorff distance. By adjusting the placement of access points in response to user movements within convex hull regions, they significantly improve localization accuracy without requiring additional hardware. This research highlights the importance of balancing privacy with accuracy in indoor positioning, demonstrating a practical and adaptable approach for building cost-effective and robust indoor positioning systems for diverse consumer applications.

Paulavičius at al. [51] investigate the application of FL to RSSI-based indoor localization in a real-world multiple residential house scenario. They demonstrate that while FL with minimal fine-tuning can achieve strong performance across different houses, it falls short of individual learning methods. To bridge this performance gap, they propose a client-tuned FL approach where, in each round, only a subset of client parameters are fine-tuned while a common backbone remains unchanged. Clients then have the flexibility to accept or revert the tuned weights based on their local validation sets. This client-tuned approach significantly reduces the performance gap between completely individual machine learning and traditional FL methods, highlighting the potential of adapting FL for robust and personalized indoor localization in diverse environments.

Zhang et al. [52] tackle the challenge of effectively safeguarding privacy while maintaining high accuracy in Federated Learning (FL) for indoor localization. Traditional approaches using differential privacy (DP) often compromise model performance due to the noise added to protect data. They propose ACDP-Floc, an adaptive clipping differential privacy FL method that overcomes this limitation by implementing a finer-grained gradient clipping mechanism. ACDP-Floc dynamically adjusts the clipping threshold based on the training process, ensuring that less noise is added as the model converges. This approach strikes a balance between safeguarding privacy and maintaining high localization accuracy. Their research highlights the importance of adaptive privacy protection for real-world applications, particularly in resource-constrained scenarios. Through comprehensive experiments on three practical datasets, they demonstrate that ACDP-Floc achieves significantly higher accuracy compared to existing DP-based FL methods, while incurring minimal additional training time. This work sets the stage for future research on asynchronous FL, focusing on improving the communication efficiency and real-time performance of wireless indoor localization services.

Chen, Chang, and Poor [53] address the challenge of high data-labeling and training costs in deep learning-based device-free indoor localization, particularly when adapting to multiple environments. They propose a federated meta-learning framework, where clients representing different environments collaboratively train a general, environment-agnostic model while ensuring data privacy. This general model can be downloaded by new clients and quickly adapted to new environments using only a small amount of labeled data. The proposed approach demonstrates significant reductions in data-labeling and training costs while maintaining accuracy across heterogeneous environments.

Tasbaz et al. [29] address the limitations of current indoor positioning systems (IPS) in terms of accuracy and privacy. They propose a comprehensive solution that leverages the strengths of both RSS and channel state information (CSI) to improve localization accuracy while ensuring user privacy through FL. Their approach tackles the inherent instability and inaccuracy of RSS by fusing it with CSI, creating a more robust and reliable system. To safeguard user privacy, they integrate FL into the IPS framework, allowing for collaborative model development while keeping data decentralized. Through extensive evaluation, they demonstrate the effectiveness of their solution, showing significant enhancements in accuracy and privacy compared to methods that rely solely on RSS or CSI.

Yan, Cui, and Wang [31] introduce a novel three-level FL framework for CSI fingerprint-based indoor localization, designed for multi-server environments. This framework addresses data privacy by implementing FL across multiple levels, involving communication between clients and intermediate servers, intermediate servers and other intermediate servers, and finally intermediate servers and a global server. This distributed approach minimizes the risk of privacy breaches by limiting data sharing at each level and extends the global server's coverage area by distributing the processing workload. To maximize localization accuracy, the authors propose a training accuracy-based model aggregation strategy for the first and second levels of FL, and an inner product-based aggregation rule for the final level to accelerate convergence. Through simulations conducted in two different scenarios, they demonstrate that their three-level FL framework surpasses the performance of existing approaches, highlighting its effectiveness in improving localization accuracy.

Yu, Liu, and Chen [54] explore the potential of CSI for indoor positioning, developing a complex-valued neural network (CVNN) based FL algorithm. This approach offers a significant advantage over traditional real-valued centralized machine learning methods by directly processing complex-valued CSI data without requiring data transformation. Furthermore, their FL framework operates in a decentralized manner, ensuring user privacy by preventing users from sharing their CSI data with the central server. The CVNN model can perform two key tasks: directly outputting estimated user positions and predicting CSI features like line-of-sight/non-line-of-sight classification and time of arrival (TOA) for use in traditional positioning algorithms. Simulation results demonstrate the superior performance of their CVNN-based FL approach, achieving a notable reduction in mean positioning error compared to an RVNN-based FL method that requires data transformation. This research underscores the potential of complex-valued neural networks and federated learning for improving the accuracy and privacy of indoor positioning systems.

5 | Open Challenges and Future Research Directions

Despite significant advancements in Federated AI (FAI) for indoor positioning, several obstacles remain:

- **Non-IID Data:** Managing non-IID data (data not identically distributed across users) continues to be a major hurdle. Indoor settings are often varied, causing differences in data gathered by various devices. Developing efficient methods to handle these variations and enhance model accuracy in such situations is crucial.
- **Efficient Communication:** Minimizing data transfer overhead is essential for real-time indoor location applications. Creating efficient techniques for compressing model data and reducing communication frequency is critical.
- **Enhanced Privacy:** While FAI excels at protecting privacy, further improvements in security measures are necessary. Creating strong privacy-preserving methods that can withstand various attacks and guarantee the confidentiality of user location information is vital.
- **Hardware/Software Integration:** Integrating FAI with diverse hardware and software is essential for practical use. Advancements in mobile AI processors and optimized Federated Learning frameworks for different devices are crucial for wider implementation.
- **Technology Fusion:** Investigating the combination of FAI with other indoor positioning technologies, like visual and acoustic positioning, could create more robust and comprehensive location systems.

6 | Conclusion

Federated AI, especially FL, offers a powerful approach for addressing the difficulties of indoor positioning, including data privacy, scalability, and adaptability. By allowing collaborative learning across numerous distributed devices while protecting user information, FAI can usher in a new generation of precise, reliable, and privacy-respecting indoor location systems. The research examined in this paper demonstrates FAI's considerable potential to transform indoor navigation and location-aware services. Overcoming the discussed challenges will require continued research and development efforts, particularly in areas such as managing non-IID data, improving communication efficiency, and developing robust privacy-protection methods. As FAI progresses, it will undoubtedly play a vital role in shaping the future of indoor positioning, enriching how we engage with the built world around us.

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Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors

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