6G-DTFP: A Digital-Twin-Enabled Privacy-Preserving Federated User Prediction Framework for 6G Mobile Edge Computing

Cong Li, Lijing Zheng, Xinsheng Ji, Xingxing Liao, Zilong Wang, and Guoqiang Mao

Abstract

MEC is set to play a pivotal role in 6G, supporting the Internet of Everything. 3GPP has proposed user mobility analysis and prediction methods to manage vast user data. However, by bringing services closer to the network edge, MEC improves user access efficiency and exposes user predictions, including location data, to greater privacy risks and potential malicious attacks. Additionally, conducting experiments on large-scale user populations increases communication and training costs. To address these challenges, we propose the Digital-Twin-Enabled Privacy-Preserving Federated User Prediction Framework (6G-DTFP) for 6G MEC. This architecture incorporates a personalized model, enhances training efficiency, and strengthens privacy protection using differential privacy mechanisms. By leveraging Digital Twin technology, it maps real user entities to the virtual environment, improving insights into user characteristics and optimizing resource utilization. Experimental results show that this framework offers reliable user prediction and aligns with the sustainable development goals of 6G networks.

Introduction

With the advancement of research into sixth-generation (6G) mobile communication networks, the integration of Mobile Edge Computing (MEC) technology is increasingly recognized as crucial for 6G [1]. 6G maintains the cloud-edge-terminal collaborative architecture of 5G. However, 6G offers greater capacity, higher data rates, and lower latency [2]. It enhances connectivity among intelligent entities [3]. This creates a heterogeneous user dataset and introduces inter-network challenges, increasing response times and costs [4]. The 3rd Generation Partnership Project (3GPP) advocates introducing user prediction mechanisms to address efficiency and cost challenges [5]. TR 23.700-80 highlights that the requirements for user mobility prediction of the core network mainly focus on assisting the Application Function (AF) in selecting User Equipment (UE). TR 23.700-84 emphasizes that analyzing user mobility via Network Data Analytics Function (NWDAF) can capture UE location characteristics, helping optimize Quality of Service (QoS) strategies. These requirements are addressed in the UE mobility analytics of TS 23.288, which defines the format of mobility prediction outputs, including UE ID, time slot entry, duration, and other details.

In 3GPP standards, the RAN-Based Notification Area (RNA) user prediction mechanism reduces signaling overhead by configuring a set of Cells or TAs, allowing the UE to move within this area without frequent location updates. Cell-level prediction leads to excessive signaling in high-mobility scenarios, while TA-level prediction lacks accuracy for 6G services. We propose a compromise using gNodeB-level mobility analysis to balance positioning accuracy and signaling overhead, independent of the UE RRC connection state. Before user prediction, connection records between devices and gNodeB are collected and converted into sequential patterns to set initial conditions. This solution is a core network-layer prediction, while RNA is a passive optimization mechanism in the access network. The two mechanisms can complement each other through cross-layer interaction and do not serve as substitutes. To balance computation and transmission delays, user prediction is migrated from network nodes to MEC nodes, and multiple MEC nodes are adopted to enhance autonomy and improve the model efficiency. With massive heterogeneous data, MEC edge servers experience increased load, but gNodeB-level user prediction helps guide MEC operational decisions, distributing load pressure. This approach avoids traditional traversal mechanisms, offering efficient solutions for paging and improving network performance and service quality [6].

While efficient user prediction is critical, addressing the privacy exposure and security risks associated with aggregating user location information is equally important. The International Telecommunication Union's Radiocommunication Sector (ITU-R) underscores security, privacy, and resilience as fundamental principles in the design of 6G, prioritizing user safety [7]. In this context, Federated Learning (FL) [8] protects privacy by decentralizing model training and computation, making it ideal for MEC User Prediction. Local models are trained on clients, and their updates are aggregated into the global model, allowing for knowledge sharing across clients while ensuring privacy by avoiding raw data exchange. In

Cong Li, Lijing Zheng, Zilong Wang, and Guoqiang Mao are with Xidian University, China; Xinsheng Ji is with Tsinghua University, China; Xingxing Liao is with Purple Mountain Laboratories, China.

Digital Object Identifier: 10.1109/MCOM.001.2400536

 0163-6804/25/$25.00 © 2025 IEEE

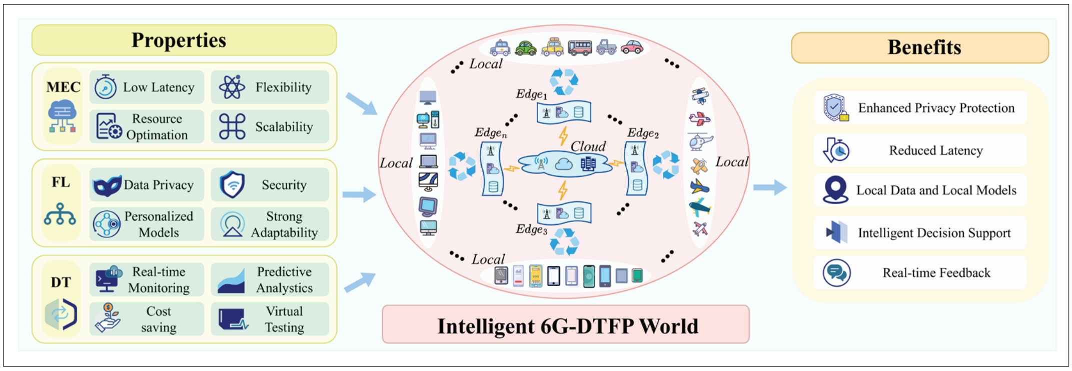

FIGURE 1. Benefits of Integrating MEC, FL, and DT.

Direct deployment of the global model leads to slower accuracy improvements and may not fully align with the current 6G MEC architecture.

the IID Scenario, the global model replaces local models for testing, leveraging shared knowledge for higher accuracy. FL enhances scalability and efficiency by allowing local learning and exchanging only model updates, making it well-suited for the dynamic 6G network environment. Furthermore, deploying computing resources close to FL clients within MEC environments significantly reduces communication delays traditionally associated with FL, facilitating large-scale learning in 6G networks. However, existing FL algorithms face challenges in managing diverse and heterogeneous datasets [9] in 6G edge network, where clients have distinct data distributions. Direct deployment of the global model leads to slower accuracy improvements and may not fully align with the current 6G MEC architecture. Therefore, a secure and efficient federated learning framework is urgently needed to develop one specifically designed to accommodate the diverse and heterogeneous user data of 6G MEC User Prediction. Such a framework would enable local clients to access global model knowledge without necessitating model transmission, effectively addressing the security concerns associated with model propagation in traditional FL approaches.

Given the increased scenario diversity and component heterogeneity in 6G networks, MEC User Prediction and FL interactions lead to significantly heightened communication and training costs. Digital Twin (DT)[10] technology provides a means to create virtual models that mirror the real world through data interactions, enabling the simulation and prediction of the 6G MEC network environment. DT facilitates real-time monitoring of the 6G network and leverages robust communication and computational capabilities to minimize resource expenditure while promoting energy efficiency and emission reduction[11]. However, the application of DT within MEC User Prediction for 6G networks remains in its nascent stages, primarily due to challenges related to trust and privacy concerns associated with the sharing of sensitive user location information. To address these challenges, integrating FL with DT technology offers a promising strategy for mitigating privacy risks and communication costs.

Despite the benefits of integrating MEC, FL, and DT technologies, the industry currently lacks practical and effective user prediction mechanisms for 6G MEC. These mechanisms should combine the three technologies and be compatible with the distributed architecture of 6G. Additionally, they must address diverse, heterogeneous, and privacy protection requirements for user prediction. This article proposes a practical Digital Twin-Enabled Privacy-Preserving Federated 6G MEC User Prediction Framework (6G-DTFP). The architecture uses DT to map the real world into a virtual space. This allows real user features to be integrated into the MEC network, effectively linking users with the MEC system. The 6G Federated User Prediction captures user data from the real world. It enables local prediction tasks as needed. Results are then sent to the service layer to meet user needs. This improves training efficiency and service quality.

To handle data heterogeneity among clients, the framework aggregates each client model. Differential Privacy (DP) [12] techniques are employed further to secure the models during the upload and download processes.

6G-DTFP is expected to bring numerous benefits to the intelligent world, as shown in Fig. 1. The main contributions of this article are summarized as follows:

- We propose a novel 6G Digital Twin Federated User Prediction Framework (6G-DTFP) that integrates Digital Twin technology with Federated Learning to achieve efficient and privacy-preserving user prediction.
- Our framework uniquely combines Digital Twin for real-time network simulation with Federated Learning for decentralized model training, effectively addressing the challenges of data heterogeneity and privacy in 6G networks.
- We enhance Federated Learning by incorporating differential privacy techniques, ensuring the secure aggregation of global models while allowing local retention of personalized models. This approach mitigates privacy risks and improves security in 6G MEC scenarios.

Key Design Requirements

In November 2023, Purdue University, in collaboration with Ericsson, Intel, Nokia, Qualcomm, Cisco, and Dell, released the 6G Global Roadmap: A Taxonomy [13], which highlights four critical issues in the development of 6G: scalability, sustainability, trustworthiness, and digital inclusivity. Among these critical challenges, we focus on scalability and sustainability, proposing a systematic 6G-DTFP (Distributed, Flexible, Trustworthy, and Personalized) framework. The key design requirements that this framework needs to meet are as follows:

Scalability: With 6G expected to support 125 billion devices by 2030[14], handling vast and diverse data is crucial. This progression drives the

The total accuracy is calculated based on this principle, determined by dividing the number of correct predictions by the total number of instances in the dataset.

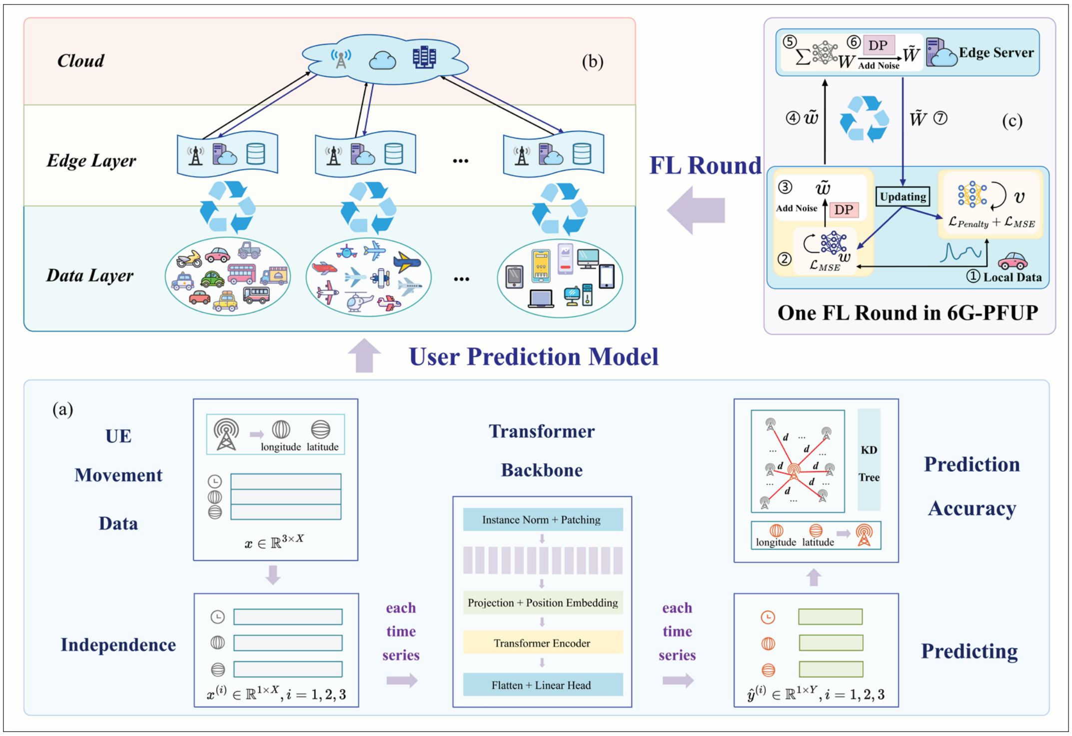

FIGURE 2. The Architecture of MEC with Personalized Federated Learning (6G-PFUP). (c) consists of seven key stages: ① Send Local Data to Local Model w and Personalized Model v. ② Local Model w use the Local Data to update. ③ Add Gaussian noise to Local Model w to obtain $\tilde{w}$. ④ Update the Noised Local Model $\tilde{w}$ to Edge Server. ⑤ Aggregate to produce Global Model W from $\tilde{w}$. ⑥ Add Gaussian noise to Global Model W to obtain $\tilde{W}$. ⑦ Download the Noised Global Model $\tilde{W}$, use $\tilde{W}$ to overwrite w for training on local data, and also use $\tilde{W}$ to calculate $\mathcal{L}_{Penalty}$ to assist v in training on local data.

transformation of 6G from a core communication technology to a foundational infrastructure for digital ecosystems. However, the devices' diversity and massive data heterogeneity present significant challenges for 6G. In the next section, we propose a Privacy-Preserving Federated User Prediction Framework to meet this requirement. This framework integrates FL with MEC, efficiently handling the heterogeneous data from clients while supporting devices' dynamic joining and departure, ensuring excellent scalability. Additionally, incorporating DP effectively reduces the risk of attackers inferring user information, fully meeting the requirements for trustworthiness.

Sustainability: Climate change is one of humanity's major challenges, with electricity consumption being a significant source of greenhouse gas emissions. Additionally, the scarcity of critical metals limits hardware manufacturing. Relying solely on hardware innovation will not meet the future demands of 6G networks [15]. Thus, the new 6G framework must address sustainability requirements. We propose a Digital Twin-Enhanced Federated User Prediction Framework (6G-DTFP) to meet this requirement. It builds AI models for user prediction and integrates DT to optimize resource utilization and achieve sustainability goals.

Privacy-Preserving Federated User Prediction Framework

To meet the design requirements for scalability, as stated earlier, we propose a privacy-preserving personalized Federated User Prediction mechanism for 6G MEC, as illustrated in Fig. 2.

First, Fig. 2a presents the Trs-PRE architecture, an improved transformer model for user prediction in 6G edge networks. We extracted sequential data $x \in \mathbb{R}^{3\times X}$ from telecom network user data, where X is the sequence length. Then, the input sequence data $x \in \mathbb{R}^{3\times X}$ is divided into three independent sequences $x^{(i)} \in \mathbb{R}^{3\times X}$, i = 1, 2, 3, based on start time, gNodeB longitude, and latitude. This division helps mitigate overfitting. Each sequence is processed through a patch-based Transformer backbone during forward propagation, ensuring that the output from the Linear layers remains independent, thereby enhancing prediction accuracy. During this process, we use the Mean Squared Error (MSE) loss between the predicted values $\hat{y}^{(i)}$ and the actual values $y^{(i)}$ to guide the Trs-PRE model training. Finally, we input the predicted and actual values into a 2D KD-tree for the nearest neighbor search. If the nearest neighbor returned is the same, the prediction is considered correct. Otherwise, it is deemed incorrect. The total accuracy is calculated based on this principle, determined by dividing the number of correct predictions by the total number of instances in the dataset. Trs-PRE demonstrates substantial data collection and analysis capabilities, allowing it to accurately predict user locations even with an expanding user base, thus ensuring scalability. Given the large and diverse user population in 6G scenarios, centralized data processing can consume significant resources. It may not fully exploit the advantages of various data types, potentially leading to privacy breaches. Therefore, there is a pressing need for a highly trustworthy and adaptable 6G MEC user prediction mechanism.

Figure 2b illustrates the federated user prediction mechanism within the 6G MEC framework to integrate MEC and FL technologies. We deploy the 6G-DTFP within the 6G Core Network, where the Cloud Layer services are implemented on the Central NWDAF, the Edge Layer services operate on the Edge NWDAF, and each Data Layer component is deployed within the Local AMF. By leveraging MEC technology, computational and storage resources are shifted from the centralized cloud to the network edge, enabling function offloading, improving response times, and optimizing resource utilization. The Cloud Layer provides large-scale storage and computing in this framework, efficiently processing information from the Edge Layer while managing network resources. This ensures effective resource allocation and load balancing between edge nodes and terminal devices within the 6G network. The Edge Layer includes edge servers, geodes, and data centers that process requests from terminal devices in the data layer to optimize resource use. Edge servers aggregate local model parameters from terminal devices, forming a global model for collaborative training without revealing private data, thus enhancing privacy protection. The data layer plays a critical role by performing local data processing and modeling, improving computational efficiency, and reducing bandwidth reliance.

Finally, to create a trustworthy and sustainable federated user prediction mechanism within 6G MEC, we develop a personalized federated algorithm to tackle the heterogeneity of terminal data, as shown in Fig. 2c. Each client is assigned a local model w and a personalized model v in this mechanism. Both models, w and v, deployed the Trs-PRE model and are trained on the same data, which is the privacy data for their client. The core distinctions manifest in their loss function designs and parameter transmission mechanisms. For the local model w, in each communication round, w is initialized with the global model W from the edge server. Then, it is trained on the local dataset using MSE as the loss function, with updated parameters uploaded to the edge server for global model W aggregation and distribution, facilitating cross-client knowledge sharing. For the personalized model v, during communication rounds, v remains stored locally without being transmitted to the edge server and is not overwritten by the global model. It is updated using a composite loss function with MSE and a regularization term. Minimizing the parameter distance between the global model W and the personalized model v enhances prediction accuracy for user behavior. We retain local and global knowledge through the collaboration of three models.

Despite the high security of the personalized model v, which does not require transmission, local models w involved in aggregation still need to be transmitted. In the real 6G environment, this process could be susceptible to member inference attacks, model inversion attacks, and other threats. Such attacks may analyze model parameters or gradients to infer user information and reconstruct training data, potentially leading to privacy breaches. Therefore, we follow the privacy-performance-cost triangular balance principle when constructing model w and model v. By incorporating differential privacy during the model upload and distribution process, we apply Gaussian mechanisms to perturb the actual parameters of the model, obfuscating the specific details of the original parameters to ensure more secure transmission of model w and global model W. To calibrate the noise magnitude, we rigorously evaluate its impact on accuracy and communication rounds, achieving an optimal equilibrium among efficiency, security, and energy-saving.

The Proposed 6G-DTFP

To meet design requirements for sustainability, we propose a Digital Twin-Enhanced Federated User Prediction Framework (6G-DTFP), as illustrated in Fig. 3. By leveraging the capabilities of digital twins, this framework enhances awareness of network conditions and effectively reduces environmental simulation costs associated with a large user base. This integration strengthens the federated user prediction mechanism and promotes sustainability and digital inclusivity through optimized resource allocation and equitable access to network services.

The 6G-DTFP framework designed in this article comprises three layers: the Physical Layer, the Digital Layer, and the Service Layer.

Physical Layer

In the 6G-DTFP framework, the physical layer collects diversified and heterogeneous data from user terminals, serving as the most direct interface for real-world environmental interaction. In this layer, physical entities in the real world (e.g., base stations and servers) are mapped into digital models while aggregating data D_j from user devices, where j represents the total number of users. Given our focus on predicting users' future gNodeB access patterns, the digital twin of user u_j is denoted as DT_j, which is composed of the collected data D_j and real-time dynamic state R_j. The feedback mechanism incorporates Data Flow and Information Feedback, ensuring bidirectional information exchange between the Physical and Digital Layers. In the Data Flow phase, the Physical Layer transmits all digital twins DT_j containing user data to the Digital Layer, where subsequent computational tasks are executed. The virtual mapping construction and the Data Flow component enable efficient data processing with minimized resource consumption. Leveraging DT, we eliminate the need for resource-heavy physical experiments by creating accurate virtual replicas for predictive modeling and scenario simulation, thus enabling more energy-efficient infrastructure optimization in the 6G network.

Digital Layer

The Digital Layer is res ponsible for structuring the data transmitted from the physical layer, parsing it into data-label pairs. We implement sequence length normalization to ensure that data of varying scales are suitable for model construction and real-time analysis. However, directly synchronizing raw data to the digital twin system would introduce significant communication load and data leakage risks. To address this issue, we designed a Privacy-Preserving Federated User Prediction Framework (6G-PFUP) within the 6G MEC scenarios. Under the 6G-PFUP, local models are continuously trained in a digital twin environment while maintaining privacy, simulating the likelihood of users connecting to gNodeBs at the next moment. Each client obtains a personalized model v retained locally to mitigate privacy risks.

In the 6G-DTFP framework, the physical layer collects diversified and heterogeneous data from user terminals, serving as the most direct interface for real-world environmental interaction.

The framework improves user prediction capabilities, which is expected to promote the development of intelligent services and support dynamic network optimization.

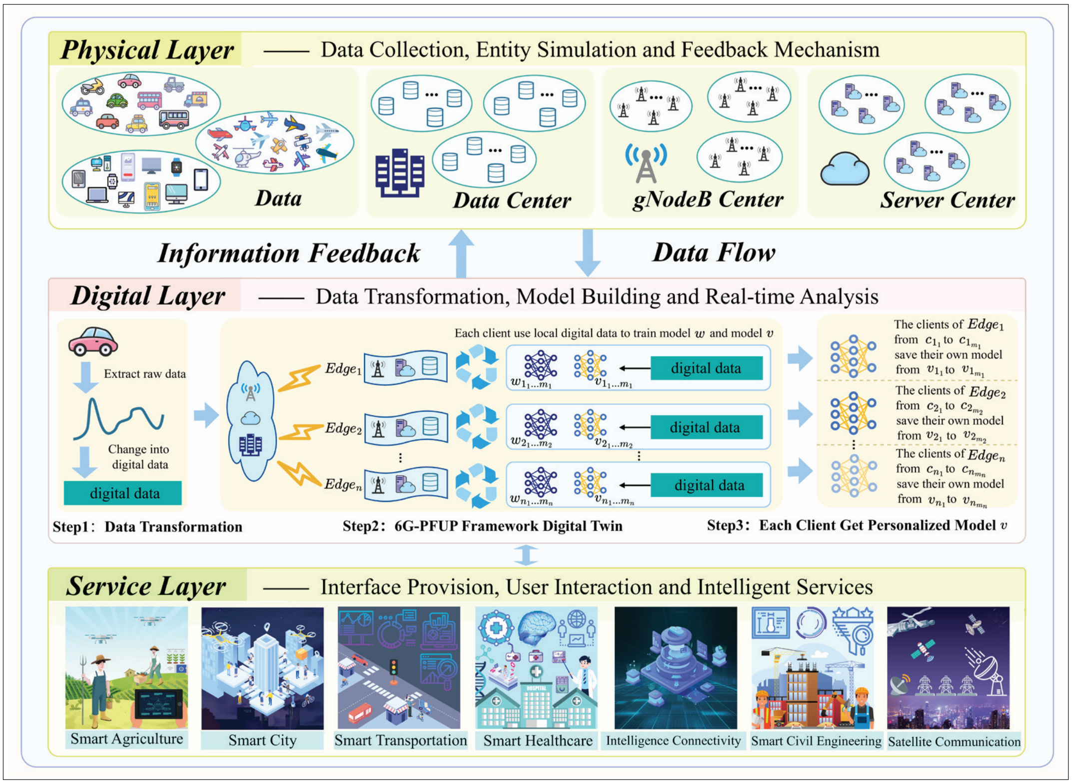

FIGURE 3. The architecture of 6G-DTFP.

This model incorporates local knowledge and integrates global insights from other clients, achieving high-precision user prediction services. Notably, the Information Feedback in the Digital Layer is a crucial component of the feedback mechanism. Specifically, the system records the gNodeB information currently connected by user u_j as R_j. In the Information Feedback phase, R_j is returned and combined with D_j to update the sequence state. This mechanism enables real-time feedback, continuously optimizing the prediction model by comparing the actual connected gNodeB with the system prediction results. Based on 6G-DTFP, we can obtain real-time status information about the gNodeB the user is connected to and make optimization decisions accordingly, significantly improving the performance of downstream services such as paging.

Service Layer

The Service Layer provides interfaces, user interactions, and intelligent services. It offers personalized, ready-to-use models for each client, facilitating interactions between users and administrators while delivering innovative services. This article integrates the user-prediction-centric 6G-PFUP framework within the 6G-DTFP for accurate forecasting of user location. Notably, the 6G-DTFP can transform into a versatile, digital-twin-enhanced federated architecture that adapts to various scenarios, including smart cities, transportation, healthcare, and satellite communications. It supports prediction, analysis, diagnosis, and simulation, optimizing the 6G network and advancing intelligent services, thus contributing to digital transformation and sustainable development.

The 6G-DTFP framework offers an innovative solution for the complex application scenarios of 6G networks by integrating digital twin technology with federated learning mechanisms. Its multi-layered design enables real-time monitoring and optimization of network resources, enhances user experience, and safeguards user privacy. The framework improves user prediction capabilities, which is expected to promote the development of intelligent services and support dynamic network optimization. We hope this architecture can contribute to sustainable development in the future.

Numerical Results

First, we utilize a comprehensive Shanghai Telecom dataset comprising over 7.2 million user paging access records. This dataset covers six months and documents interactions with 3,233 gNodeB instances across 9,481 mobile devices. Specifically, it includes the month, date, start time, end time, gNodeB longitude, gNodeB latitude, and user ID. To simulate real-world data distribution, we construct the Non-IID dataset by Dirichlet Distribution and allocate 150 clients to edge servers, with the number of users in each client ranging from 2815 to 4508. Utilizing this dataset, we conduct experiments to rigorously evaluate the proposed framework's efficacy and assess the personalized model's performance v.

Figure 4 evaluates the performance of Trs-PRE, showing the test accuracy changes of the Trs-PRE model compared to other predictive models (including LSTM_FCN, FCN, LSTM, ResCNN, and TST) on the test set. As communication rounds increase, Trs-PRE exhibits lower volatility and outperforms other models. In the 41st round, Trs-PRE achieved an accuracy of 60.40 percent, surpassing LSTM_FCN, FCN, LSTM, ResCNN, and TST by 2.18 percent, 2.03 percent, 2.04 percent, 3.39 percent, and 2.04 percent in accuracy. This performance is attributed to Trs-PRE's Transformer-based architecture, which effectively captures long-range dependencies in time series and employs the channel independence mechanism. Additionally, compared to TST, the patching operation used in Trs-PRE improves the efficiency of attention calculations. As a result, Trs-PRE demonstrates faster convergence and superior accuracy.

Figure 5 illustrates a comparative analysis of 6G-DTFP and the only local method (without employing FL or MEC) regarding test accuracy on the test set. The 6G-DTFP framework demonstrates a rapid increase in accuracy during the early communication rounds, maintaining a high level of performance thereafter, achieving an accuracy of 62.42 percent by the 79th round. In contrast, the Local model exhibits considerable fluctuations in testing accuracy, consistently remaining below 62 percent, with certain rounds even dipping to 60 percent.

This phenomenon primarily stems from data distribution bias caused by individual client users' behavioral patterns and environmental states. In such cases, pure local training tends to cause overfitting. Furthermore, when the number of users with small-sample clients is insufficient, low-accuracy clients are likely to occur, adversely impacting all clients' overall performance and resulting in significant performance fluctuations. The good performance of 6G-DTFP can be attributed to the constraints of the optimization objective and the knowledge transfer capability inherent in FL. Since the global model aggregates the parameters of all local models, the overall optimization objective is constrained by both the aggregation strategy and the local model optimization goals. This facilitates the global model in implicitly extracting common patterns from the data of individual client users through weighted aggregation. Additionally, knowledge transfer is realized through aggregating parameter spaces, endowing the global model with global knowledge, and compensating for the knowledge that individual clients may not have learned but that exists in practice.

The analysis reveals that 6G-DTFP not only outperforms the local training results in terms of accuracy but also demonstrates superior convergence properties, indicating a tendency toward stability over prolonged training periods. Compared to purely local approaches, this framework offers enhanced efficiency. These findings validate the effectiveness of integrating federated learning, mobile edge computing, and data transmission techniques within the 6G core network architecture, highlighting the significant impact of distributed learning strategies on improving model performance and generalization capabilities.

We also evaluate the performance of the personalized model v. Figure 6 illustrates the variations in test accuracy on the test set for the personalized model v and the local model w within the 6G-DTFP framework after applying Differential Privacy (DP) with Gaussian noise for privacy protection. The results indicate that the testing accuracy of model v consistently exceeds that of model w, reaching a peak accuracy of 63.26 percent by the 79th round, while model w fluctuates around 62 percent. This demonstrates the effectiveness of the personalized model design.

Furthermore, model v exhibits a greater specificity in leveraging local data knowledge, enabling

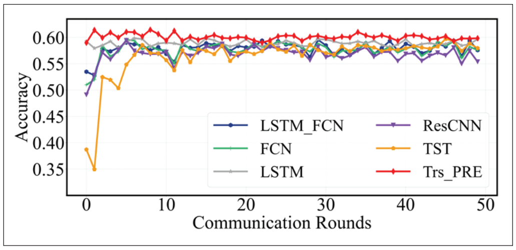

FIGURE 4. The test accuracy comparison between Trs-PRE and other models.

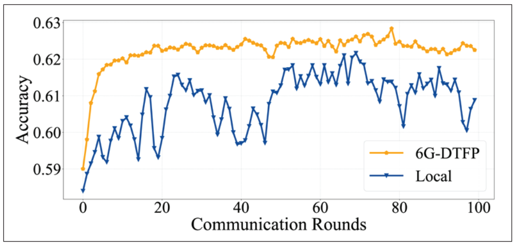

FIGURE 5. The test accuracy between 6G-DTFP model *w* and only local.

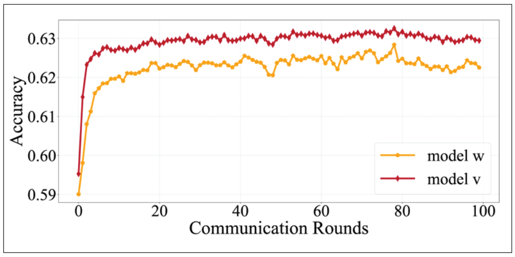

FIGURE 6. The test accuracy of 6G-DTFP Between model *w* and model *v*.

it to more effectively adapt to the unique needs of specific users or scenarios. The superior performance of model v may stem from its ability to fully utilize local data characteristics while also indirectly learning from the data features of other clients on a global scale. This approach allows model v to capture the diversity of user behavior and requirements while maintaining a strong focus on security.

Conclusion

This article presents the Digital-Twin-Enabled Privacy-Preserving Federated User Prediction Framework for 6G Mobile Edge Computing (6G-DTFP), which features low communication costs and strong privacy protection. To address the high costs of communication and training in real-world scenarios, we leverage digital twin technology to connect physical and virtual environments, avoiding resource wastage through blind experimentation. By incorporating Federated Learning (FL) and differential privacy techniques, we propose a distributed architecture for 6G MEC User Prediction, ensuring the security of model parameters during communication. The personalized model *v* further improves the model's performance. Simulation results demonstrate that 6G-DTFP enhances security and efficiency, significantly improving accuracy, and shows potential for deployment in 6G networks. In the future, we plan to optimize the user prediction model and refine the federated aggregation schemes to establish a more efficient and fair architecture for 6G MEC. This will require close collaboration between the system's AI components and network management aspects.

Simulation results demonstrate that 6G-DTFP enhances security and efficiency, significantly improving accuracy, and shows potential for deployment in 6G networks.

References

[1] Z. Liao *et al.*, "Distributed Probabilistic Offloading in Edge Computing for 6g-Enabled Massive Internet of Things," *IEEE Internet of Things J.*, vol. 8, no. 7, 2020, pp. 5298–5308.

[2] P. Ahokangas, M. Matinmikko-Blue, and S. Yrjölö, "Envisioning a Future-Proof Global 6g From Business, Regulation, and Technology Perspectives," *IEEE Commun. Mag.*, vol. 61, no. 2, 2022, pp. 72–78.

[3] K. B. Letaief *et al.*, "The Roadmap to 6G: AI Empowered Wireless Networks," *IEEE Commun. Mag.*, vol. 57, no. 8, 2019, pp. 84–90.

[4] M. Polese *et al.*, "Toward End-To-End, Full-Stack 6G Terahertz Networks," *IEEE Commun. Mag.*, vol. 58, no. 11, 2020, pp. 48–54.

[5] M.-A. Garcia-Martin, M. Gramaglia, and P. Serrano, "Network Automation and Data Analytics in 3GPP 5G Systems," *IEEE Network*, vol. 38, no. 4, 2024, pp. 182–89.

[6] M. Li *et al.*, "Intelligent Resource Optimization for Blockchain-Enabled Iot in 6g via Collective Reinforcement Learning," *IEEE Network*, vol. 36, no. 6, 2022, pp. 175–82.

[7] G. Liu *et al.*, "Senscap: A Systematic Sensing Capability Performance Metric for 6G ISAC," *IEEE Internet of Things J.*, vol. 11, no. 18, 2024, pp. 29,438–54.

[8] B. McMahan *et al.*, "Communication-Efficient Learning of Deep Networks From Decentralized Data," *Artificial Intelligence and Statistics*, PMLR, 2017, pp. 1273–82.

[9] P. Xu *et al.*, "Deep Learning Driven Buffer-Aided Cooperative Networks for B5G/6G: Challenges, Solutions, and Future Opportunities," *IEEE Wireless Commun.*, 2024.

[10] H. X. Nguyen *et al.*, "Digital Twin for 5G and Beyond," *IEEE Commun. Mag.*, vol. 59, no. 2, 2021, pp. 10–15.

[11] F. Tao *et al.*, "Digital Twin Modeling," *J. Manufacturing Systems*, vol. 64, 2022, pp. 372–89.

[12] M. Abadi *et al.*, "Deep Learning With Differential Privacy," *Proc. 2016 ACM SIGSAC Conf. Computer Commun. Security*, 2016, pp. 308–18.

[13] P. University *et al.*, "6G Global Roadmap: A Taxonomy," Report, 2023.

[14] Z. Yang *et al.*, "Federated Learning for 6G: Applications, Challenges, and Opportunities," *Engineering*, vol. 8, 2022, pp. 33–41.

[15] Y. Xiao *et al.*, "Toward Self-Learning Edge Intelligence in 6G," *IEEE Commun. Mag.*, vol. 58, no. 12, 2020, pp. 34–40.

Biographies

Cong Li received a B.Eng. degree in Electronic Information Technology from Xidian University in 2019. He is currently pursuing a Ph.D. in Cyber Engineering at Xidian University, focusing on next-generation mobile communication and privacy preservation.

Lijing Zheng received a B.S. degree in computer science from Henan Normal University, China, in 2023. She is currently pursuing an M.S. degree at the Key Laboratory of Intelligent Perception and Image Understanding at Xidian University, focusing on federated learning and privacy preservation.

Xinsheng Ji received a B.S. degree from Fudan University in 1991 and an M.S. degree from the National Digital Switching System Engineering and Technological Research Center in 1994. He has been a Professor at NDSC since 2005, with research interests in next-generation mobile communication and cybersecurity.

Xingxing Liao received a Ph.D. in Circuits and Systems from the University of Chinese Academy of Sciences, China, in 2017. His research interests are in the areas of B5G/6G security and network resilience.

Zilong Wang received B.S. and Ph.D. degrees in mathematics from Nankai University (2005) and Peking University (2010), respectively. He was a Visiting Ph.D. Student at the University of Waterloo from 2008 to 2009. he has been a Professor at the State Key Laboratory of Integrated Service Networks at Xidian University. His research interests include sequence design, cryptography, and information security, and is a Member of IEEE.

Guoqiang Mao earned his Ph.D. in telecommunications engineering from Edith Cowan University in 2002. He is a distinguished professor and dean of the Research Institute of Smart Transportation at Xidian University. His research interests include intelligent transport systems, the Internet of Things, and wireless localization techniques. He has published over 200 papers, cited more than 10,000 times, and is a Fellow of IEEE.