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Federated Machine Learning for Smart Logistics: A Comprehensive Survey

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ABSTRACT

Federated Machine Learning, or in short Federated Learning (FL), has emerged as a promising paradigm for decentralized, privacy-preserving machine learning, with significant potential in transportation and logistics. This survey provides a comprehensive review of FL applications in Smart Logistics such as supply chain optimization, warehouse management, and efficient delivery. We discuss core principles of FL, alongside challenges when applying to Smart Logistics domain. We provide a comprehensive clustering of methodologies to tackle the problem. Finally, we highlight future research directions, emphasizing the integration of FL with IoT and edge computing, personalized and adaptive models, privacy, security, and sustainability to enhance smart transportation systems.

1. Introduction

Federated Learning (FL) is a machine learning approach that enables collaborative training across entities while keeping sensitive data private. Clients or organizations train local models on their own datasets, sending only parameter updates to form a global model, preserving privacy. Unlike traditional distributed learning, which assumes uniform data, FL excels with heterogeneous datasets common in real-world scenarios. Its rise is fueled by privacy concerns, data minimization principles, and regulations like The EU general data protection regulation (GDPR), alongside edge computing's growth, which supports local processing [1].

Based on the system architecture, FL operates in either centralized or decentralized approach. In centralized FL, clients train local models and send to a server to aggregates updates into a global model. The global model is then redistributed until performance goals are met. In decentralized FL, clients directly interact, bypassing a central server. This suits transportation and logistics, where diverse, sensitive data from vehicle sensors, IoT devices, supply chain metrics varies widely and centralized collection is inefficient.

The transportation and logistics industries are characterized by the generation of vast quantities of data from a multiple sources, including vehicles equipped with sensors, infrastructure-based sensors, and various Internet of Things (IoT) devices [2]. A significant portion of this data is inherently sensitive, encompassing location information, detailed operational metrics, and potentially personal details, thereby necessitating the application of privacy-preserving techniques. Furthermore, the geographically dispersed nature of operations within these industries often renders the

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centralized collection of data challenging and inefficient tasks. FL emerges as a promising solution in this context, offering a framework for enabling collaborative learning and the development of robust machine learning models across these distributed data sources while effectively maintaining both privacy and security.

This survey aims to provide a comprehensive overview of the state-of-the-art in applying FL to the field of smart logistics. While prior surveys have explored FL in general contexts [3] or specific task like recommender systems [4], none have systematically addressed its intersection with smart logistics - a field with distinct operational and technical demands. We conducted the study by reviewing literature from prominent journals and conferences in Computer Science and Logistics, published since 2020. Our contributions are threefold:

(1) We summarize and organize existing approaches on FL;

(2) We analyze the methodologies and techniques tailored to smart logistics;

(3) We identify key challenges as well as applications and propose future research directions to FL on intelligent transportation systems and logistics.

The remainder of this paper is organized as follows. Section II provides background on FL and its relevance to smart logistics. Section III reviews the methodologies and techniques employed in this domain. Section IV explores specific applications, highlighting real-world use cases in the field of logistics. Section V discusses future directions. Finally, we summarize the insights and contributions.

2. Fundamental of Federated Learning

2.1. Core Principles

Federated Learning is built on key principles that set it apart from traditional machine learning. First, it emphasizes data localization, keeping raw data on local devices or within organizational boundaries, enhancing privacy. Second, each participant trains a model locally using its private dataset. Third, only model updates, i.e., gradients or weights, are shared, not the raw data, with a central server in centralized FL or among nodes in decentralized setups. Fourth, model aggregation combines these updates to form a refined global model, managed by a server or decentralized mechanism. Finally, this process iterates over multiple rounds until the global model achieves desired accuracy.

These principles tackle data privacy concerns effectively. By avoiding raw data sharing, FL reduces risks of breaches and unauthorized access, aligning with heightened data protection demands. Unlike centralized methods requiring data aggregation, FL focuses on localized data and model updates minimizes exposure of sensitive information. Its iterative nature supports continuous learning, adapting the global model as new data emerges. This is vital in dynamic fields like logistics, where demand and supply chain disruptions require ongoing model updates for accuracy and efficiency.

2.2. Comprehensive Categorization of Federated Learning Approaches

Approaches to the problem of FL are classified across multiple dimensions, each customized to meet the demands of application domains. This section focuses on two widely recognized categorizations: Data Partitioning and System Architecture, highlighting their relevance to the domain of Logistics.

2.2.1. Data partitioning

Data partitioning distinguishes FL types based on how data is distributed among clients [3]. As shown in Table 1, three key approaches are identified: (1) horizontal, (2) vertical, and (3) transfer. They are explained as follows.

Table 1. Categorization based on data partitioning

Approach to FL	Description	Application
Horizontal	Same features, different samples across clients	Fleet management, ITS with uniform sensor data
Vertical	Different features, overlapping samples	Supply chain integration across stakeholders
Federated Transfer	Different features and samples, uses transfer learning	Cross-regional or cross-modal applications

Horizontal FL involves clients with identical features but different samples, such as vehicles sharing sensor data for traffic prediction across varied trips. Vertical FL features different data types with overlapping samples, like logistics companies and retailers collaborating on customer demand using delivery and purchase records. Federated transfer learning adapts models across domains with dissimilar features and samples, as in applying urban traffic insights to rural logistics.

2.2.2. System Architecture

System architecture offers another perspective. Table 2 outlines four categories, including: (1)

centralized, (2) decentralized, (3) hierarchical, and (4) hybrid.

Centralized FL uses a server to aggregate updates, fitting intelligent transportation systems or corporate logistics managed centrally. Decentralized FL enables direct client coordination, ideal for vehicle-to-vehicle networks or independent warehouses. Hierarchical FL employs edge aggregators, enhancing scalability in large transportation networks, while hybrid FL blends these for flexibility in mixed scenarios.

This categorization highlights adaptability, enabling privacy-preserving, scalable solutions for transportation and logistics diverse, dynamic challenges.

Table 2. Categorization based on System Architecture

Approach to FL	Description	Application
Centralized	Central server aggregates updates	ITS, corporate logistics with central oversight
Decentralized	Direct client coordination, no server	V2V networks, distributed supply chains
Hierarchical	Intermediate aggregators (e.g., edge servers)	Scalable transportation networks
Hybrid	Combines centralized and decentralized elements	Mixed transportation-logistics scenarios

3. Federated Learning for Smart Logistics

This section presents a taxonomy that categorizes common FL algorithms by their core objectives, highlighting their mechanisms and relevance to transportation and logistics.

Federated Averaging (FedAvg) introduced by McMahan et al. [5], serves as a fundamental algorithm. It allows clients to train local models and periodically send weight updates to a central server, which then averages these updates to create a global model. Its simplicity makes it a baseline for horizontal FL, particularly useful in transportation for tasks like traffic prediction across vehicle fleets with uniform sensor data. However, FedAvg assumes that data is independently and identically distributed (IID), a condition often violated in logistics, where supply chain data varies significantly.

To address this data heterogeneity, Federated Proximal (FedProx) [6] extends FedAvg by adding a proximal term to the local objective. This term penalizes deviations from the global model, enabling FedProx to handle non-IID data. This makes it suitable for logistics applications like demand forecasting across retailers and suppliers with diverse feature sets, and in transportation, it stabilizes training for Intelligent Transportation System models when vehicle data differs by region or type.

In safety-critical transportation systems, where malicious or faulty updates pose a significant risk, Robust Federated Aggregation (RFA)[7] provides essential security. RFA employs geometric median aggregation, a technique that minimizes the impact of corrupted data, rather than simple averaging. This robust approach ensures reliable operation of Intelligent Transportation Systems, even in the face of spoofed vehicle data. Similarly, in logistics, RFA enables secure collaboration among supply chain partners who may not fully trust each other.

Table 3. Algorithm Categorization

Algorithm	Data Partitioning	System Architecture	Applied in
FedAvg [5]	Horizontal	Centralized	Traffic prediction
FedProx [6]	Horizontal	Centralized	ITS stabilization; Demand forecasting
RFA [7]	Horizontal	Centralized	ITS security; Secure collaboration
PerFL [8]	Horizontal	Hybrid	Fleet routing; Inventory models
Travelling FL [9]	Horizontal	Decentralized	V2V updates; Fleet data
SecAgg [10]	Vertical	Centralized	Driver data protection; Vertical FL security

Personalized Federated Learning (e.g., PerFL [8]) algorithms adapt global models to local client needs, balancing generalization and specificity. In transportation, PerFL optimizes routing for individual fleets while leveraging collective insights, while in logistics, it tailors inventory models to specific warehouses. This personalization enhances efficiency in dynamic, client-specific contexts.

Communication-Efficient FL algorithms, like TravellingFL [9], reduce bandwidth demands by transmitting only significant updates. These are vital for real-time transportation applications, such as V2V networks updating navigation models under connectivity constraints, and logistics networks managing large-scale fleet data.

An approach, called Secure Aggregation (SecAgg) [10], employs cryptographic techniques to ensure privacy during model updates, complementing privacy mechanisms like differential privacy. SecAgg is particularly relevant in logistics for vertical FL, where stakeholders (e.g., manufacturers and distributors) share sensitive data, and in transportation for protecting driver information in centralized systems.

We summarize the above algorithms with the categorization based on data partitioning and the system architecture as shown in the Table 3.

4. Application in Smart Logistics

This section identifies the most common field that FL can be efficiently apply in Logistics.

4.1. Supply Chain Optimization

The logistics industry, with its complex networks of suppliers, manufacturers, distributors, and retailers, can greatly benefit from the application of Federated Learning for supply chain optimization [11]. FL enables collaborative training of machine learning models for critical tasks such as demand forecasting and inventory optimization across various stakeholders in the supply chain. This allows different entities within the supply chain to contribute their data to train more accurate and robust models without the need to share sensitive proprietary information like sales figures or production capacities. For instance, suppliers can share insights about their production capabilities and potential disruptions without revealing exact output numbers, while retailers can contribute demand data without exposing specific customer details. The aggregated knowledge can lead to more precise demand forecasts, allowing for better inventory management across the entire supply chain, reducing stockouts and minimizing waste. Furthermore, FL can be used for collaboratively predicting and mitigating supply chain risks. By training models on the collective data of supply chain partners, potential disruptions such as supplier failures or transportation delays can be identified earlier, enabling proactive risk management strategies without compromising the confidentiality of risk assessment data from of individual partners.

Federated Learning presents a transformative approach to supply chain management by fostering collaboration and enhancing predictive capabilities while safeguarding sensitive business information. The ability of diverse entities within a supply chain to collectively train AI models on their local data, without direct data exchange, allows for a more holistic and accurate understanding of the entire system. This can lead to significant improvements in efficiency, resilience, and responsiveness throughout the supply chain, ultimately benefiting all participating stakeholders and the end consumers.

4.2. Warehouse Management

Federated Learning can be effectively applied to optimize various aspects of warehouse management within the logistics industry. By leveraging data collected from a multitude of sensors and devices deployed within a warehouse, such as inventory tracking systems, robotic material handlers, and environmental sensors, FL can enable the training of models that optimize warehouse operations [12]. For example, FL can be used to improve inventory placement strategies, determining the most efficient locations for different products based on historical demand patterns and picking frequencies, without requiring individual warehouses within a large logistics network to share their detailed operational data with a central system. Similarly, FL can enhance the efficiency of inventory retrieval processes by learning optimal picking routes for warehouse personnel or automated systems based on the collective data from various warehouse environments. This collaborative learning approach can lead to significant reductions in operational costs, improved throughput, and better utilization of warehouse space by allowing different warehouses or departments within a logistics company to learn from each other's experiences and best practices without centralizing potentially sensitive operational data.

The implementation of Federated Learning in warehouse management offers a privacy-preserving pathway to achieving greater operational efficiency and cost savings. By enabling different warehouse facilities or departments to collaboratively train AI models on their local data, logistics companies can identify and implement best practices for inventory management, space utilization, and material handling [13]. This decentralized learning approach fosters a culture of continuous improvement and knowledge sharing across the organization while ensuring that sensitive operational data remains secure within each individual facility.

4.3. Efficient Delivery and Fleet Management

The logistics industry relies heavily on efficient delivery operations and effective fleet management, both of which can be significantly improved through the application of Federated Learning [14]. FL enables logistics companies to optimize delivery routes by training models on the aggregated data from their fleet of vehicles, taking into account factors such as real-time traffic conditions, road closures, and delivery time windows, without needing to track and store the precise location data and routes of individual drivers on a central server. This collaborative learning approach can lead to more efficient routing algorithms that minimize travel distances, reduce fuel consumption, and improve on-time delivery rates. Furthermore, FL can be utilized for predictive maintenance of delivery fleets by training models on the sensor data collected from vehicles, allowing for the prediction of potential mechanical failures and the scheduling of proactive maintenance to minimize vehicle downtime and ensure operational reliability. In the context of electric delivery vehicle fleets, FL can facilitate intelligent charging schedule optimization, learning from the usage patterns and charging needs of the entire fleet to minimize energy costs and maximize vehicle availability without compromising the privacy of individual vehicle usage data.

Federated Learning offers a powerful tool for logistics companies to enhance the efficiency and reliability of their delivery operations and fleet management. By enabling the collaborative training of AI models on the distributed data generated by their fleet, logistics providers can optimize routing, predict maintenance needs, and improve energy efficiency in a privacy-preserving manner. This leads to reduced operational costs, improved service quality, and a more sustainable logistics ecosystem.

4.4. Efficient Route Planning

Federated Learning can contribute to the development of more efficient and sustainable transportation systems through optimized route planning. By leveraging real-time traffic information, road conditions, and other relevant data from a distributed network of vehicles and infrastructure, FL can enable the training of models that provide more efficient delivery route planning for logistics operations [15]. This collaborative learning approach allows logistics companies to benefit from the collective experience of their entire fleet, optimizing routes to minimize travel time, fuel consumption, and operational costs without the need to centralize sensitive data about individual drivers or routes. Furthermore, in the context of electric vehicle fleets, FL can be utilized for intelligent charging schedule optimization, taking into account factors such as vehicle usage patterns, battery levels, and charging infrastructure availability across the fleet to minimize energy costs and maximize vehicle uptime. The aggregation of data from multiple vehicles through FL can also lead to the development of collaborative learning models aimed at improving overall energy efficiency in transportation, identifying and promoting best practices for fuel-efficient driving and vehicle operation across a fleet.

Federated Learning offers a unique opportunity to enhance the efficiency and sustainability of transportation through intelligent route planning and resource management. By enabling a fleet of vehicles to collaboratively learn from their collective operational data, FL can facilitate the identification of optimal routes, efficient charging strategies for electric vehicles, and best practices for energy conservation. This collaborative intelligence, achieved without compromising the privacy of individual vehicle data, can lead to significant reductions in operational costs, improved service delivery, and a more environmentally friendly transportation sector.

4.5. Traffic Flow Prediction and Optimization

Federated Learning holds significant promise for revolutionizing traffic management through enhanced prediction and optimization of traffic flow [16]. By training machine learning models on data collected from a distributed network of sensors, vehicles, and roadside units, FL can enable more accurate forecasting of traffic conditions. This approach allows for the aggregation of insights from diverse and geographically dispersed data sources without the need to centralize sensitive information such as GPS trajectory data [17], thereby addressing critical privacy concerns. The resulting models can then be utilized to optimize traffic light timings in real-time, dynamically adjusting to predicted congestion levels and improving the overall flow of traffic in smart cities. The integration of FL with edge computing in traffic management systems further enhances their capabilities. By deploying FL-trained models on edge devices located closer to the data sources, such as roadside units, real-time processing and decision-making become possible. This reduces latency in analyzing local traffic data and allows for quicker adjustments to traffic signals or the provision of timely routing recommendations to drivers.

The application of FL in traffic flow prediction enables the creation of more accurate and localized models by leveraging the collective intelligence embedded within the distributed data. Unlike traditional centralized approaches, FL can capture traffic patterns specific to different locations and times without requiring the direct sharing of potentially sensitive user data. This capability can lead to substantial improvements in urban mobility, reducing travel times and alleviating traffic congestion, which in turn can contribute to a decrease in fuel consumption and environmental impact. The synergy between FL and edge computing in this domain is particularly noteworthy. By pushing the computational workload to the edge of the network, closer to where the traffic data is generated, FL facilitates rapid analysis and response to changing traffic conditions. This decentralized processing not only improves the speed and efficiency of traffic management systems but also enhances their resilience by reducing reliance on a central server.

5. Future Directions and Research Opportunities

The field of FL in Transportation and Logistics is rapidly evolving, presenting numerous promising future directions and research opportunities. The following list outlines key future directions to enhance impact on efficiency, resilience, and sustainability of FL in logistics.

- **Personalized and Adaptive FL Models**: One significant area of focus is personalized and adaptive FL models. Logistics operations often vary by region, company, or customer base, necessitating models that adapt to specific contexts. Future efforts could refine personalized FL techniques, such as PerFL [8] or FedMSplit [18], to dynamically adjust to fluctuating demand patterns or localized disruptions (e.g., weather impacts on shipping). This adaptability could improve last-mile delivery efficiency and warehouse management, enhancing customer satisfaction without compromising collaborative benefits;
- **Integration with IoT and Edge Computing**: As logistics increasingly relies on IoT devices, such as smart sensors in warehouses, GPS trackers on delivery vehicles, and RFID tags in supply chains, FL can harness real-time data at the edge. Training models directly on these devices could optimize inventory tracking, predict delivery delays, and reduce latency, all while preserving data privacy. Research into lightweight FL algorithms tailored for resource-constrained IoT devices will be critical to enable this shift;
- **Enhanced Privacy and Security**: Privacy and security enhancements also warrant exploration. With logistics stakeholders including suppliers, distributors, retailers, robust protection against data inference attacks becomes more and more important. Advancing secure aggregation with quantum cryptography or blockchain-based trust mechanisms could safeguard sensitive data like pricing or inventory levels, fostering greater adoption of FL across competitive supply chains;
- **Sustainability-Focused FL**: Logistics contributes significantly to carbon emissions, and FL could optimize resource use by training models on distributed fleet data to minimize fuel consumption or coordinate electric vehicle charging schedules. Future research might integrate FL with green logistics strategies, aligning operational efficiency with environmental goals.

The above directions require overcoming challenges like computational overhead, data heterogeneity, and regulatory compliance. Addressing these will position FL as a cornerstone of next-generation logistics, enabling smarter, more secure, and eco-friendly supply chains.

6. Conclusion

Federated machine learning presents a transformative approach for the Transportation and Logistics industries, enabling collaborative model training while prioritizing data privacy. It is especially significant in industries defined by the need to protect sensitive data across a broad geographic area. FL can be applied to improve supply chain efficiency, warehouse management and enable predictive maintenance for infrastructure and vehicles.

The core strength of FL lies in its ability to leverage vast datasets without centralizing sensitive information, thus addressing critical privacy concerns. This distributed learning paradigm allows for the creation of robust models that benefit from diverse data sources, improving generalization and accuracy. Furthermore, FL minimizes communication costs and facilitates compliance with stringent data regulations. By maintaining collaborative intelligence, FL promises to drive significant advancements in efficiency, safety, and sustainability, ultimately reshaping the future of transportation and logistics.

Contributions of authors in this article

Le Van Quoc Anh: Methodology, Formal analysis, Investigation, Validation, Visualization, Feedback on peer review, Writing – original manuscript. **Nguyen Van Chien**: Data analysis, Investigation, Verification, Writing – original manuscript. **Nguyen Thi Giang:** Methodology, Manuscript Editing.

Declaration of competing interest and dedication to copyright

We have no conflicts of interest to disclose and confirm that this work has not been previously published.

Data available

Data will provided upon request.

References

[1] D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li, and H. Vincent Poor, "Federated Learning for Internet of Things: A Comprehensive Survey," *IEEE Commun. Surv. Tutorials*, vol. 23, no. 3, pp. 1622–1658, 2021, doi: 10.1109/COMST.2021.3075439.

[2] F. Islam, A. S. Raihan, and I. Ahmed, "Applications of Federated Learning in Manufacturing: Identifying the Challenges and Exploring the Future Directions with Industry 4.0 and 5.0 Visions," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Houston, USA: IEOM Society International, Jun. 2023. doi: 10.46254/NA8.20230219.

[3] J. Wen, Z. Zhang, Y. Lan, Z. Cui, J. Cai, and W. Zhang, "A survey on federated learning: challenges and applications," *Int. J. Mach. Learn. & Cyber.*, vol. 14, no. 2, pp. 513–535, Feb. 2023, doi: 10.1007/s13042-022-01647-y.

[4] D. Javeed, M. S. Saeed, P. Kumar, A. Jolfaei, S. Islam, and A. K. M. N. Islam, "Federated Learning-Based Personalized Recommendation Systems: An Overview on Security and Privacy Challenges," *IEEE Trans. Consumer Electron.*, vol. 70, no. 1, pp. 2618–2627, Feb. 2024, doi: 10.1109/TCE.2023.3318754.

[5] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, A. Singh and J. Zhu, Eds., in Proceedings of Machine Learning Research, vol. 54. PMLR, Apr. 2017, pp. 1273–1282. [Online]. Available: https://proceedings.mlr.press/v54/mcmahan17a.html [Accessed: March, 25 2025]

[6] P. Zheng, Y. Zhu, Z. Zhang, Y. Hu, and A. Schmeink, "Federated Learning in Heterogeneous Networks with Unreliable Communication," in *2021 IEEE Globecom Workshops (GC Wkshps)*, Madrid, Spain: IEEE, Dec. 2021, pp. 1–6. doi: 10.1109/GCWkshps52748.2021.9682052.

[7] K. Pillutla, S. M. Kakade, and Z. Harchaoui, "Robust Aggregation for Federated Learning," *IEEE Trans. Signal Process.*, vol. 70, pp. 1142–1154, 2022, doi: 10.1109/TSP.2022.3153135.

[8] A. Z. Tan, H. Yu, L. Cui, and Q. Yang, "Towards Personalized Federated Learning," *IEEE Trans. Neural Netw. Learning Syst.*, vol. 34, no. 12, pp. 9587–9603, Dec. 2023, doi: 10.1109/TNNLS.2022.3160699.

[9] V. Gupta, A. Luqman, N. Chattopadhyay, A. Chattopadhyay, and D. Niyato, "TravellingFL: Communication Efficient Peer-to-Peer Federated Learning," *IEEE Trans. Veh. Technol.*, vol. 73, no. 4, pp. 5005–5019, Apr. 2024, doi: 10.1109/TVT.2023.3332898.

[10] K. H. Li, P. P. B. De Gusmão, D. J. Beutel, and N. D. Lane, "Secure aggregation for federated learning in flower," in *Proceedings of the 2nd ACM International Workshop on Distributed Machine Learning*, Virtual Event Germany: ACM, Dec. 2021, pp. 8–14. doi: 10.1145/3488659.3493776.

[11] H. Wang, F. Xie, Q. Duan, and J. Li, "Federated Learning for Supply Chain Demand Forecasting," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–8, Nov. 2022, doi: 10.1155/2022/4109070.

[12] T. M. Ho, K.-K. Nguyen, and M. Cheriet, "Federated Deep Reinforcement Learning for Task Scheduling in Heterogeneous Autonomous Robotic System," *IEEE Trans. Automat. Sci. Eng.*, vol. 21, no. 1, pp. 528–540, Jan. 2024, doi: 10.1109/TASE.2022.3221352.

[13] K. I.-K. Wang, X. Zhou, W. Liang, Z. Yan, and J. She, "Federated Transfer Learning Based Cross-Domain Prediction for Smart Manufacturing," *IEEE Trans. Ind. Inf.*, vol. 18, no. 6, pp. 4088–4096, Jun. 2022, doi: 10.1109/TII.2021.3088057.

[14] A. Angelopoulos, A. Giannopoulos, N. Nomikos, A. Kalafatelis, A. Hatziefremidis, and P. Trakadas, "Federated Learning-Aided Prognostics in the Shipping 4.0: Principles, Workflow, and Use Cases," *IEEE Access*, vol. 12, pp. 6437–6454, 2024, doi: 10.1109/ACCESS.2024.3350777.

[15] T. Ding, L. Liu, Z. Yan, X. Lu, and J. Hu, "Federated Reinforcement Learning for Intelligent Route Planning in Aerial-Terrestrial Network," *IEEE Internet Things J.*, pp. 1–1, 2024, doi: 10.1109/JIOT.2024.3492215.

[16] T. Qi, L. Chen, G. Li, Y. Li, and C. Wang, "FedAGCN: A traffic flow prediction framework based on federated learning and Asynchronous Graph Convolutional Network," *Applied Soft Computing*, vol. 138, p. 110175, May 2023, doi: 10.1016/j.asoc.2023.110175.

[17] C. Nguyen, T. Dinh, V.-H. Nguyen, N. Tran, and A. Le, "Histogram-based Feature Extraction for GPS Trajectory Clustering," *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, vol. 7, no. 22, p. 162796, Jan. 2020, doi: 10.4108/eai.13-7-2018.162796.

[18] J. Chen and A. Zhang, "FedMSplit: Correlation-Adaptive Federated Multi-Task Learning across Multimodal Split Networks," in *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, Washington DC USA: ACM, Aug. 2022, pp. 87–96. doi: 10.1145/3534678.3539384.