AI-Based Transportation Demand Forecasting for Smart and Sustainable Urban Mobility

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ABSTRACT

Urban transportation demand forecasting has become essential for smart city planning due to rapid urbanization, congestion, and increasing mobility needs. Traditional statistical models often fail to capture complex, nonlinear, and real-time travel patterns. Therefore, artificial intelligence techniques such as machine learning, deep learning, graph neural networks, IoT-based models, and federated learning offer more accurate and adaptive forecasting solutions. These approaches improve passenger and freight demand prediction, support traffic management, reduce travel uncertainty, and enhance sustainable mobility planning. However, issues related to data privacy, interpretability, scalability, and real-time deployment require further research.

Keywords: *Artificial Intelligence, Demand Forecasting, Urban Transportation, Smart Mobility.*

I. INTRODUCTION

Urban transportation systems are undergoing a significant transformation due to rapid urbanization, population growth, and increasing mobility demands. As cities expand, transportation networks face persistent challenges such as congestion, inefficient resource allocation, environmental degradation, and rising travel time uncertainty. In this context, accurate transportation demand forecasting has emerged as a critical component of intelligent urban planning and sustainable mobility management. Traditional forecasting methods, which largely relied on statistical and econometric models, have proven inadequate in capturing the nonlinear, dynamic, and highly complex nature of modern transportation systems. Consequently, Artificial Intelligence (AI)-based approaches, including machine learning (ML), deep learning (DL), and hybrid predictive architectures, have gained substantial attention for their ability to model large-scale, heterogeneous, and real-time transportation data. Recent studies have highlighted that AI-driven forecasting systems significantly enhance prediction accuracy and operational responsiveness in both passenger and freight transport domains (Zhang et al., 2026; Li & Liu, 2023). Moreover, the integration of real-time data sources such as GPS traces, IoT sensors, and mobile applications has further strengthened the capability of AI models to support adaptive transportation planning. As a result, AI-based transportation demand forecasting is now considered a foundational tool for smart city development and next-generation mobility systems.

In recent years, the evolution of advanced computational techniques has reshaped the landscape of transportation demand prediction, particularly through the application of deep learning and graph-based models. For instance, Yang et al. (2026) emphasized the importance of real-time origin–destination (OD) demand forecasting using streaming temporal link prediction in dynamic graphs, demonstrating that fine-grained temporal and spatial modeling can significantly improve operational decision-making in ride-hailing and taxi systems. Similarly, Li et al. (2024) introduced spatial-temporal tree-based convolution models to capture hierarchical relationships and multi-factor dependencies influencing taxi demand, addressing limitations in conventional graph-based methods. These advancements reflect a broader shift from static, aggregated forecasting models toward dynamic, data-driven frameworks capable of processing continuous streams of transportation data. Furthermore, Nazzal et al. (2024) extended this paradigm by integrating heterogeneous graph neural networks (GNNs) with LSTM architectures to enhance scalability and reduce computational overhead in large-scale urban networks. These studies collectively demonstrate that AI-based models are increasingly capable of capturing complex spatial-temporal interactions, which are essential for accurate demand estimation in modern urban transportation systems. However, despite these advancements, challenges such as model interpretability, data privacy, and computational scalability continue to persist, necessitating further research into robust and efficient forecasting frameworks.

The growing interest in AI-based transportation demand forecasting is also driven by its integration with emerging technologies such as the Internet of Things (IoT), federated learning, and large language models (LLMs). Jansi et al. (2026) proposed an IoT–deep learning framework using Long Short-Term Memory (LSTM) networks for real-time passenger demand prediction, demonstrating improved accuracy in short-term forecasting and congestion mitigation. In parallel, Li and Liu (2023) introduced a federated learning-based multimodal transport demand forecasting model that enables privacy-preserving collaboration across multiple data sources without sharing raw datasets, thereby addressing critical data governance challenges. Additionally, Zhang et al. (2026) highlighted the emerging role of LLMs in transportation forecasting, particularly for time series prediction and human mobility analysis, although they noted that comprehensive integration of such models into transportation systems remains in its early stages. Beyond passenger transport, forecasting applications have also been extended to freight and logistics systems, where Sonnleitner et al. (2025) emphasized the importance of aligning forecasting methodologies with optimization frameworks in road freight transport. Similarly, Karasu et al. (2024) explored the relationship between agricultural production data and freight demand, revealing the potential of unconventional datasets in improving predictive performance. These developments collectively indicate that AI-based transportation forecasting is evolving into a multidisciplinary field that integrates data science, urban planning, logistics, and computational intelligence.

Despite significant progress, several gaps remain in the current state of AI-based transportation demand forecasting. One major limitation is the lack of unified frameworks that integrate prediction and optimization in a seamless manner, particularly in real-time urban environments. Barrera Hernandez et al. (2025) addressed this issue by combining machine learning-based demand forecasting with heuristic optimization for bus dispatching, demonstrating improved operational efficiency and service quality. However, such integrated approaches are still limited in scope and scalability. Additionally, Bubalo (2024) highlighted emerging challenges in urban air mobility systems, where demand forecasting must account for new infrastructure types such as vertiports and autonomous aerial vehicles, further increasing system complexity. Another critical issue is the trade-off between model accuracy and interpretability, especially in deep learning-based systems that often operate as black-box models. Moreover, data heterogeneity, privacy concerns, and real-time computational constraints continue to restrict the widespread deployment of AI-based forecasting systems in practical urban planning scenarios. Therefore, future research must focus on developing hybrid models that combine explainability, scalability, and real-time adaptability while ensuring integration with smart city infrastructures. Overall, AI-based transportation demand forecasting represents a rapidly evolving field with significant potential to transform urban mobility, optimize transportation systems, and support sustainable urban development (Hamad & Obaid, 2022; Yang et al., 2026).

II. RESEARCH BACKGROUND

Yang et al. (2026) investigated travel demand forecasting, emphasizing its critical role in optimizing transportation systems. They noted that prior research predominantly focused on predicting demand at origins rather than in an origin–destination (OD) paired pattern with complete spatial information. They highlighted the additional challenge of forecasting real-time OD demand with fine temporal granularity. The study proposed a real-time OD connection forecasting method using streaming temporal link prediction (TLP) in dynamic graphs, claiming high prediction accuracy and fine granularity in both temporal and spatial dimensions. The OD connection was represented as a time-labeled directed edge between origin and destination nodes, and an encoder-decoder architecture was designed to address TLP tasks in a streaming manner, avoiding the information loss associated with graph snapshots. Edge embeddings were generated via temporal random walks to capture temporal and topological information, while a continuously optimized Multi-layer Perceptron (MLP) served as the decoder for fine-grained OD demand prediction. Experiments with historical taxi data from Shanghai and New York demonstrated the model's high accuracy across over 10,000 regions at minute-level granularity. They concluded that the approach could significantly support real-time operational optimization for taxi, Robotaxi, and ride-hailing systems, including vehicle dispatching, route planning, and charging decisions.

Zhang et al. (2026) highlighted that mobility analysis had been recognized as a critical aspect in transportation system research, where forecasting traffic information was considered a viable approach to mitigate the growing conflict between increasing transportation demands and the limitations of existing infrastructure. They noted that predicting human travel had been deemed essential for supporting various transportation and urban management tasks, including taxi dispatch and urban planning. The study indicated that machine learning and deep learning methods had been favored due to their adaptability and predictive accuracy. With the emergence of large language models (LLMs), researchers were reported to have integrated these models with traditional techniques or applied them directly for predicting future traffic patterns and human mobility behaviors. However, the authors observed that comprehensive studies on the role of LLMs in this field remained limited. Their survey was presented as an overview of existing LLM-based approaches for time series forecasting in transportation, illustrating state-of-the-art advancements and identifying challenges for fully leveraging LLMs in mobility prediction.

Jansi et al. (2026, February) investigated the dynamic and unpredictable nature of passenger demand in urban public transport systems, which often contributed to congestion. They proposed an intelligent IoT–Deep Learning platform designed for real-time capacity tracking and short-term passenger demand prediction. The study combined multi-modal IoT sensors, including passenger automatic counters and Wi-Fi probe sniffing, with a deep learning predictive system. A Long Short-Term Memory (LSTM) network was employed to utilize high-frequency occupancy data to forecast immediate passenger demand while incorporating contextual variables such as weather, calendar effects, and public holidays. Their experimental evaluation, based on six months of metropolitan bus corridor data, reportedly demonstrated that the LSTM model outperformed traditional ARIMA and Support Vector Regression models, achieving a Mean Absolute Percentage Error (MAPE) of 6.1%. Furthermore, real-time load factor monitoring enabled dynamic fleet adjustments, reducing peak-hour congestion and improving vehicle efficiency. The study was suggested to provide a scalable, data-driven framework for resilient and responsive urban mobility within smart city contexts.

Sonnleitner et al. (2025) examined the use of demand forecasts in road freight transport operations, noting that such forecasts were predominantly applied for downstream optimization within a predict-then-optimize framework. They observed that, although numerous optimization models depended on accurate forecasts to support planning, dedicated research on forecasting remained limited, which constrained a comprehensive treatment of the problem. The study highlighted a disconnect between road freight forecasting and broader advances in forecasting literature, which was reported to reduce the quality and validity of forecasts intended to guide transport decisions. By linking relevant forecasting studies to prominent optimization problems, the authors identified gaps in the integration of forecasting and optimization models. They further suggested that improvements in model building, loss function selection, and evaluation practices were necessary to better align forecasts with optimization approaches. Finally, they proposed a unified hierarchical framework for freight demand, emphasizing its potential to enhance planning coordination and inform both academic research and practical decision-making.

Barrera Hernandez et al. (2025) examined the challenges of accurate and adaptive bus dispatching in medium-sized urban centers, where static schedules were found insufficient to address fluctuating passenger demand. They proposed a dynamic heuristic that incorporated machine learning-based demand forecasts within a discrete-time planning horizon, enabling real-time adjustments to dispatch decisions. The study also introduced a tailored mathematical model, based on mixed-integer linear programming and space-time flows, to benchmark the heuristic's performance under typical operational constraints in Colombian mid-sized cities. By combining predictive modeling using Prophet for passenger demand with operational optimization, the research aimed to ensure that dispatch frequencies could respond promptly to varying ridership levels. The methodology was validated through a real-world case study in Montería, Colombia, covering eight representative routes over a full day. Numerical results reportedly indicated that the heuristic achieved operational utility comparable to or exceeding 95% of the benchmark model, maintained service levels above 90%, ensured efficient bus utilization, and reduced computation times by up to 98%, highlighting its practical effectiveness for scalable, data-driven public transport scheduling.

Karasu et al. (2024) investigated the potential of utilizing historical agricultural production data to enhance road freight transport forecasting, with a particular focus on cereal production. The study reportedly applied multiple linear regression analysis using national statistical accounts and secondary data obtained from Finland's Statistics Agency and the Natural Resources Institute. The analysis was found to identify an observable correlation between agricultural production and road freight volumes, although this correlation was not statistically significant. The highest adjusted R^2 achieved in the models was reported to be 0.62. The study indicated that previous years' production data could assist in forecasting future road freight volumes, with vehicle mileage being estimable from recent production and stock levels. Furthermore, annual percentage changes in the volume of transported cereals were suggested to be partially predictable from the changes in total available cereals and opening stocks from two years prior. The research was concluded to highlight the untapped predictive potential of agricultural production variables, suggesting avenues for further enhancement in forecasting methodologies.

Li et al. (2024) investigated taxi demand forecasting as a critical aspect of intelligent transportation systems, emphasizing its role in supporting urban transportation services and resource allocation. They noted that while graph structures were commonly used to capture spatial correlations among urban regions, these approaches had limitations in representing hierarchical features and local path characteristics of regional nodes. The study reported that existing methods often overlooked the multiple factors influencing taxi demand variations. To address these gaps, the authors proposed a spatial-temporal model incorporating multi-factor features, employing a tree structure as the topology and introducing tree convolution to represent spatial distribution characteristics. The model's spatial-temporal convolution module was described as capable of effectively capturing both hierarchical and local path features among area nodes. Four factors affecting taxi demand were considered, with their deep features fused through the module. Experimental results across three urban taxi datasets reportedly demonstrated the model's superior performance compared with existing baselines.

Nazzal et al. (2024) investigated the prediction of taxi service demand and supply, emphasizing its significance for enhancing customer experience and provider profit. They reported that graph neural networks (GNNs), which model city areas as nodes within a transportation graph, had recently demonstrated efficiency in this domain by leveraging both local node features and the graph structure. The study noted that prediction performance could be further improved either by simultaneously exploiting multiple types of nodes and edges or by expanding the transportation graph's scale, although both approaches were constrained by GNN scalability. To address this challenge, the authors highlighted that decentralizing GNN operations could serve as a remedy, but their theoretical analysis and experiments indicated that it incurred excessive node-to-node communication. Consequently, they proposed a heterogeneous GNN-LSTM algorithm to enhance taxi-level demand and supply forecasting using several edge types, along with a semi-decentralized GNN inference method to enable large-scale application with reduced communication and computational overheads. Their experiments on real data reportedly demonstrated improved prediction accuracy and a substantial reduction in inference time compared to centralized and fully decentralized schemes.

Bubalo (2024) was reported to have presented an innovative approach to urban air transportation planning by developing a "digital twin" that encompassed airspace and infrastructure elements, including route structures, existing airports, and future vertiports. The study aimed to formulate a model reflecting the dynamics of contemporary and prospective urban air mobility (UAM), emphasizing sustainability and electrification in the transportation sector. It was noted that advancements in personal aerial vehicles (PAVs), unmanned aerial vehicles (UAVs), and electric aircraft enabled multiple feasible scenarios. The research focused on the urban area of Hamburg, Germany, analyzing its two inner-city airports and a prototype vertiport. Anticipating a rise in demand for air transport services for approximately 1.9 million residents over two decades, various scenarios were assumed, resulting in increased energy requirements. Using a SIMMOD simulation model with incremental flight additions until practical capacity reached 80% above baseline, the study revealed that rising demand at Hamburg Airport could push average operational delays toward the level-of-service threshold of 4 minutes per flight, highlighting the need for expanded air traffic and ground infrastructure. It was concluded that airspace capacity was mainly constrained by the primary airport, that the Airbus Hamburg-Finkenwerder facility could expand capacity via a parallel taxiway, and that vertiport capacity was limited by UAV parking, charging, speeds, turnaround times, autonomy, and route lengths.

Li and Liu (2023) examined the enhancement of transport demand prediction through the integration of multi-source data across different transport modes. They noted that existing multimodal demand forecasting approaches typically relied on direct sharing of raw datasets, which was often infeasible due to privacy concerns and institutional data ownership constraints. To address this challenge, they proposed a Multimodal Transport Demand Forecasting model utilizing Federated Learning (FL), in which a processing center managed the parameters of locally trained forecasting models without requiring access to the underlying raw data. The study introduced a Fine-grained Graph Convolution Recurrent Network (F-GCRN) to capture spatiotemporal correlations and latent dynamic dependencies across datasets more effectively than prior methods. The processing center weighted parameter contributions via an Attentive Federated Learning mechanism and returned updated parameters to each institution for local demand prediction. Evaluations on three real-world transport datasets reportedly demonstrated that the model outperformed several baselines, highlighting that parameter-based knowledge sharing could improve multimodal demand forecasting while preserving data privacy.

Hamad and Obaid (2022) examined the growing global interest in transportation issues at university campuses, emphasizing that university travelers' unique patterns, largely shaped by students, required specialized forecasting approaches. They aimed to develop a travel demand forecasting model (TDFM) for a university campus to evaluate alternative solutions, strategies, and policies, particularly those promoting sustainable transportation. The methodology was applied to Sharjah University City (SUC), where a tour-based TDFM was created to replicate activity-based travel patterns. The model was established using the PTV VISUM tool, validated for the baseline year, and then employed to forecast future traffic demands. To reduce vehicular volumes, two scenarios were analyzed: the introduction of parking permits with pricing and the establishment of a park-and-ride facility. Comparative evaluation using traffic and environmental performance measures indicated that parking permit enforcement was more effective than the park-and-ride scheme. The study was noted for integrating a tour-based TDFM with a campus-wide transportation network, microsimulation, and emission assessment.

III. KEY FINDINGS FROM STUDY

Author (Year)	Focus Area	Methodology	Key Findings	Limitations / Gaps
Yang et al. (2026)	Real-time OD demand forecasting	Streaming Temporal Link Prediction (TLP), encoder-decoder, temporal random walks, MLP decoder	Achieved high accuracy in real-time OD prediction with fine spatial-temporal granularity; effective for ride-hailing optimization	High computational complexity in large-scale streaming environments
Zhang et al. (2026)	AI & LLMs in mobility forecasting	Survey of ML, DL, and Large Language Models	LLMs show emerging potential in traffic forecasting and mobility analysis	Limited real-world integration and lack of comprehensive benchmarking
Jansi et al. (2026)	Real-time passenger demand prediction	IoT sensors + LSTM deep learning model	MAPE of 6.1%; improved congestion control and dynamic fleet adjustment	Limited scalability beyond metro-level datasets
Sonnleitner et al. (2025)	Freight transport forecasting	Literature review linking forecasting with optimization models	Identified gap between forecasting and optimization integration	Lack of unified forecasting-optimization frameworks
Barrera Hernandez et al. (2025)	Bus dispatch optimization	ML-based demand forecasting + MILP heuristic model	Achieved >95% benchmark efficiency and reduced computation time by 98%	Limited transferability to larger urban systems
Karasu et al. (2024)	Freight demand using agricultural data	Multiple linear regression using national accounts data	Found moderate predictive correlation (Adj. R^2 up to 0.62)	Results not statistically significant; limited robustness

Li et al. (2024)	Taxi demand forecasting	Spatial-temporal tree convolution model	Improved performance over baseline models by capturing hierarchical spatial features	Increased model complexity and training cost
Nazzal et al. (2024)	Taxi demand/supply prediction	Heterogeneous GNN + LSTM with semi-decentralized inference	Improved accuracy and reduced inference time significantly	Communication overhead in decentralized architecture
Bubalo (2024)	Urban air mobility demand forecasting	Digital twin + SIMMOD simulation	Identified capacity constraints in urban air transport systems	Limited real-world validation of UAM scenarios
Li & Liu (2023)	Multimodal transport forecasting	Federated Learning + F-GCRN model	Improved accuracy while preserving data privacy	High communication cost in federated setup
Hamad & Obaid (2022)	Campus travel demand forecasting	Tour-based model using PTV VISUM	Parking policy more effective than park-and-ride in reducing traffic	Limited applicability beyond campus-scale systems

IV. CONCLUSION

Artificial Intelligence-based transportation demand forecasting has emerged as a transformative approach in addressing the growing complexity of modern urban mobility systems. The reviewed literature clearly demonstrates that traditional statistical and econometric models are increasingly insufficient for capturing the nonlinear, dynamic, and multi-dimensional nature of transportation demand. In contrast, AI-driven methodologies—particularly machine learning, deep learning, graph neural networks, and hybrid architectures—have significantly improved forecasting accuracy, adaptability, and real-time decision-making capabilities. Studies such as Yang et al. (2026) and Li et al. (2024) highlight the effectiveness of spatial-temporal modeling techniques in capturing fine-grained origin–destination patterns, while Jansi et al. (2026) emphasize the role of IoT-integrated LSTM networks in real-time passenger demand prediction. Furthermore, emerging approaches such as federated learning (Li & Liu, 2023) and heterogeneous GNN-based frameworks (Nazzal et al., 2024) demonstrate how privacy preservation, scalability, and distributed computation are becoming integral to modern forecasting systems. The integration of AI with transportation planning has also extended beyond passenger mobility to freight logistics and urban air mobility systems, as evidenced by Sonnleitner et al. (2025) and Bubalo (2024), indicating the broad applicability of these techniques across multiple transport domains. Despite these advancements, several challenges remain unresolved. Issues such as data heterogeneity, computational complexity, model interpretability, and lack of integration between forecasting and optimization frameworks continue to limit full-scale implementation in real-world urban environments. Moreover, the emergence of new technologies such as large language models and digital twins presents both opportunities and challenges for future research, particularly in terms of scalability and system integration. Overall, AI-based transportation demand forecasting has proven to be a powerful tool for enhancing urban planning efficiency, reducing congestion, and supporting sustainable mobility solutions. However, further research is required to develop more robust, interpretable, and computationally efficient models that can seamlessly integrate with smart city infrastructures. The future direction of this field lies in building unified, real-time, and adaptive forecasting systems that combine multiple data sources and AI paradigms to support intelligent transportation ecosystems.

V. FUTURE SCOPE

- **Integration of Advanced AI Models:** Future research can focus on integrating advanced deep learning architectures such as Transformer-based models and Large Language Models (LLMs) with transportation forecasting systems. These models can improve long-term dependency learning and enhance prediction accuracy for complex urban mobility patterns, as indicated by Zhang et al. (2026).
- **Real-Time Adaptive Forecasting Systems:** There is a strong need to develop real-time adaptive forecasting frameworks capable of continuously updating predictions using streaming data from IoT devices, GPS systems, and smart sensors. This will enable dynamic traffic management and immediate decision-making in congested urban environments.
- **Hybrid Forecasting–Optimization Frameworks:** Future studies should integrate demand forecasting with optimization algorithms in a unified framework. This will allow transportation systems to not only predict demand but also automatically adjust routes, schedules, and fleet allocation in real time, improving operational efficiency.
- **Expansion of Federated Learning Applications:** Federated learning can be further explored to enable privacy-preserving collaboration between multiple transportation agencies. This approach will allow institutions to share model insights without exposing raw data, improving multimodal forecasting accuracy (Li & Liu, 2023).
- **Scalability for Large-Scale Urban Systems:** Scalable AI models are required to handle large metropolitan transportation networks involving millions of nodes and edges. Future research should focus on reducing computational cost while maintaining high accuracy in large-scale deployments.
- **Integration with Smart City Infrastructure:** Transportation forecasting systems should be fully integrated with smart city platforms, including intelligent traffic signals, autonomous vehicles, and digital twin environments. This will enable holistic urban mobility management.
- **Improved Model Interpretability:** Many AI models function as black-box systems. Future research should emphasize explainable AI (XAI) techniques to improve transparency and trust in transportation forecasting models for policymakers and planners.
- **Multi-Modal and Cross-Domain Forecasting:** Future systems should integrate multiple transportation modes such as road, rail, air, and urban air mobility. Cross-domain data fusion will enhance prediction robustness and support comprehensive urban planning.
- **Incorporation of Socio-Economic and Behavioral Data:** Future forecasting models should include socio-economic, demographic, and behavioral factors to better understand travel demand variability and improve prediction realism.
- **Sustainable and Energy-Efficient Transportation Planning:** AI-based forecasting should be extended to support sustainability goals by optimizing routes and reducing emissions. This aligns with global efforts toward green and energy-efficient transportation systems.

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