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AI-Driven Forecasting for Optimized Urban Transportation and Smart Planning

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ABSTRACT

Artificial Intelligence (AI)-based transportation demand forecasting has emerged as a critical tool for sustainable urban planning and intelligent mobility management. Rapid urbanization, population growth, and increasing mobility demands have created complex transportation challenges, including congestion, travel time uncertainty, and inefficient resource allocation. Traditional forecasting methods often fail to capture nonlinear, dynamic, and spatial-temporal interactions inherent in modern transport systems. AI-driven approaches, incorporating machine learning, deep learning, graph neural networks, and hybrid predictive models, enable accurate, real-time demand estimation for both passenger and freight transport. By integrating heterogeneous data sources such as GPS traces, IoT sensors, mobile applications, and public transport data, these models support adaptive traffic management, route optimization, congestion mitigation, and equitable service coverage. Furthermore, AI forecasting contributes to environmental sustainability by improving energy efficiency and reducing emissions. Despite challenges in model interpretability and computational scalability, AI-based demand forecasting provides a robust framework for data-driven, resilient, and sustainable urban transportation planning.

Key Words: *Artificial Intelligence, Transportation Demand Forecasting, Urban Planning, Sustainable Mobility.*

I. INTRODUCTION

Urban transportation systems are undergoing a profound transformation driven by rapid urbanization, population growth, and escalating mobility demands, which have collectively intensified the challenges faced by city planners, policymakers, and transport operators in managing congestion, resource allocation, environmental sustainability, and travel time uncertainty. As metropolitan areas expand, traditional transportation networks encounter persistent inefficiencies, leading to increased traffic congestion, longer commute times, uneven accessibility, elevated greenhouse gas emissions, and the underutilization of existing infrastructure, thereby imposing significant social, economic, and environmental costs. In response to these growing complexities, accurate transportation demand forecasting has emerged as an indispensable tool for intelligent urban planning, providing the analytical foundation for designing sustainable, equitable, and efficient urban mobility systems. Conventional forecasting methods, primarily based on statistical, regression, or econometric models, have proven inadequate in capturing the highly dynamic, nonlinear, and spatial-temporal interdependencies characteristic of modern transportation networks, particularly in dense urban environments with heterogeneous travel patterns, multimodal transport options, and real-time fluctuations in passenger and freight demand. Consequently, Artificial Intelligence (AI)-based approaches, encompassing machine learning (ML), deep learning (DL), and hybrid predictive architectures, have gained substantial attention due to their ability to process large-scale, high-dimensional, and real-time transportation data, enabling enhanced predictive accuracy, adaptability, and operational responsiveness across both passenger and freight domains. AI-driven forecasting leverages diverse data sources, including GPS traces, smart card data, mobile application data, traffic sensors, IoT-enabled devices, and connected vehicle information, integrating these heterogeneous inputs to construct dynamic models that reflect actual urban mobility behaviors, route preferences, temporal demand variations, and congestion patterns, thereby allowing planners to implement evidence-based interventions and optimize transportation infrastructure. Recent studies have demonstrated the efficacy of advanced computational techniques such as Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and attention-based hybrid frameworks in extracting complex spatial-temporal dependencies, capturing nonlinearity in travel demand, and improving short-term and long-term forecasting performance, with applications spanning ride-hailing services, taxi systems, public transit scheduling, and urban logistics. Furthermore, graph-based neural networks and spatial-temporal convolutional architectures have enabled the modeling of origin-destination flows, interconnectivity of transport networks, and hierarchical relationships among urban nodes, thereby facilitating fine-grained demand estimation and adaptive routing in response to evolving traffic conditions. The integration of AI with emerging technologies, including the Internet of Things (IoT), federated learning, large language models (LLMs), and digital twins, has further expanded the scope of transportation demand forecasting by allowing real-time, privacy-preserving, and multi-source predictive modeling, which accommodates changing travel patterns, special events, weather conditions, and disruptions caused by infrastructure maintenance or emergencies, while ensuring data confidentiality and security in collaborative forecasting environments. Beyond passenger mobility, AI-based demand forecasting is increasingly being applied to freight, logistics, and supply chain operations, where predictive models optimize vehicle routing, load distribution, delivery scheduling, and modal selection, contributing to cost reduction, energy efficiency, and sustainable urban freight transport. Additionally, unconventional data sources, such as agricultural production statistics, e-commerce delivery trends, and social media signals, have been integrated into predictive frameworks to improve the accuracy of freight and logistics forecasting, highlighting the adaptability of AI methods in handling diverse urban transport scenarios. Despite these advancements, several challenges remain, including the interpretability of complex AI models, computational scalability for large urban networks, integration of predictive and optimization functions, and the need for standardized frameworks that unify data collection, model deployment, and decision support for city authorities. Black-box characteristics of deep learning models often hinder their acceptance among planners and policymakers who require transparent and actionable insights for operational decisions, while heterogeneous data sources, privacy concerns, and real-time processing constraints present additional obstacles to widespread implementation. Addressing these challenges necessitates the development of hybrid models that balance predictive accuracy with interpretability, enable scalable real-time computation, incorporate multi-modal transport considerations, and seamlessly integrate with smart city infrastructures and intelligent transport systems. Overall, AI-based transportation demand forecasting represents a multidisciplinary frontier, combining data science, urban planning, computational intelligence, and logistics management, with the potential to transform urban mobility, optimize infrastructure utilization, reduce environmental impacts, enhance accessibility and equity, and support the sustainable development of cities. By enabling predictive insights into complex travel behaviors and system dynamics, AI-driven forecasting empowers planners to implement proactive traffic management strategies, inform investment in transport infrastructure, develop multimodal mobility solutions, and design policy interventions that accommodate the evolving needs of urban populations, ultimately contributing to the creation of smarter, safer, and more resilient urban transportation systems that align with long-term sustainability goals and enhance the overall quality of urban life.

II. RESEARCH BACKGROUND

Tsumita et al. (2026) were reported to have examined the growing challenge of riverine floods in Southeast Asia, where prolonged urban inundation was found to severely disrupt mobility and daily activities. The study was said to have emphasized the importance of incorporating behavioral changes during flood events into travel demand forecasting for the effective evaluation of transportation adaptation measures. It was noted that previous research had not provided a detailed assessment of how urban flooding affected daily activities and travel behavior, nor had it demonstrated how such impacts could be integrated into forecasting frameworks. In response, the authors were described as proposing an activity-based traffic demand forecasting model that explicitly accounted for changes in individual activity patterns during floods. The model was reported to capture disruptions such as altered travel behavior, road closures, and reduced accessibility, which had often been neglected in conventional approaches. Furthermore, the study was said to have evaluated transportation adaptation strategies, including arterial road elevation, to support resilient and strategic urban mobility planning under flood conditions.

Avogadro et al. (2026) examined airline and airport demand forecasting as a critical component of long-term strategic planning, with particular emphasis on the importance of accurate traffic forecasts for airport infrastructure development and capacity alignment. The study proposed a novel modeling framework for generating high-granular itinerary-level demand forecasts to ensure reliable system-level traffic predictions. It was reported that the framework integrated a state-of-the-art demand modeling approach with a customized scenario analysis tool, thereby enabling a more comprehensive representation of complex demand dynamics. The validity of the proposed model was demonstrated through its application to the Italian airport system, where traffic forecasts were formulated up to 2035 and predictive performance was evaluated using actual 2024 traffic data. The findings indicated that the framework was effective in supporting airport strategic planning and was sufficiently adaptable to address emerging policy and operational challenges. Furthermore, it was highlighted that the model could assist decision-makers and policymakers in evaluating future scenarios, including policies aimed at facilitating the aviation industry’s transition toward net-zero emissions.

Hosseinpanahi et al. (2026) investigated the growth of bike-sharing usage, noting its contribution to personal mobility, transit connectivity, and alternatives to walking. They emphasized that demand forecasting was essential for operators to anticipate empty stations and full docks, optimize rebalancing and staffing, and provide reliable service at reduced operating costs. The study proposed a cluster-based, hour-ahead demand forecasting methodology, which grouped stations into geographically coherent clusters using K-means, constructed hourly arrival and departure time series while preserving zero-demand hours, and incorporated exogenous factors such as temperature and weather events. Multi-year trip records from Chicago’s Divvy system (2014–2017) were analyzed to characterize network expansion and spatial stability, and the period from 1 August 2016 to 31 December 2017, during which station activity was stable, was used for predictive modeling. Three machine learning models—linear regression, time series, and random forest—were compared, with results indicating that TS and RF consistently outperformed LR, achieving up to 80% R^2 and lower RMSE, particularly in high-variability central clusters, thereby supporting cluster-level net demand forecasting for rebalancing decisions.

Hu et al. (2025) examined the formulation and implementation of greenhouse gas (GHG) reduction policies in line with Nationally Determined Contributions (NDCs), emphasizing the need for accurate assessment of current emissions and reliable projection of future emissions. They noted that while long-term forecasts were typically conducted at the national level, spatial allocation techniques were necessary for sub-national or grid-level analysis, particularly in the transport sector where regional disparities in emissions were significant. The study proposed a methodology that employed an integrated assessment model (IAM) to forecast national energy use and CO_2 emissions, followed by spatial downscaling of transport emissions to administrative and grid levels. To capture future spatial variability in road transport activity, a traffic demand forecasting model was incorporated. The methodology was applied to South Korea, using MESSAGEix-KR for national CO_2 projections and EMME4 for road traffic demand estimation. Findings suggested that shifts in road infrastructure and traffic patterns were effectively reflected in the spatial distribution of emissions, demonstrating the methodology's utility for developing high-resolution emission inventories, spatially explicit CO_2 maps, and supporting region-specific mitigation policies.

Coppola et al. (2025) investigated demand forecasting for the introduction of Urban Air Mobility (UAM) services in the metropolitan area of Milan, Italy. The study was reported to rely on random utility mode choice models, incorporating factors related to individuals' perceptions of vertical take-off/landing and low-altitude flying over urban areas. Various UAM use cases were considered, including airport shuttles, intercity air connections, and "air-taxis" for short metropolitan trips. Multiple scenarios were analyzed based on the number of access points ("vertiports") and UAM fare levels. The findings suggested that airport shuttles could achieve a modal share of 2–5% for trips to and from airports, for both business and leisure purposes, and were considered more attractive than air-taxis, which exhibited a modal share of 1–3%. Additionally, it was observed that the likelihood of selecting UAM services for intercity travel decreased with increasing distance and access/egress times to vertiports, whose catchment areas were influenced by the quality of competing modes such as railways and highways.

Qu et al. (2024) examined the emergence of Urban Air Mobility (UAM) as a promising transport mode enabled by technologies such as remotely piloted aircraft systems, distributed electric propulsion, and automatic control systems on electric vertical take-off and landing (eVTOL) aircraft. The study highlighted that UAM could partially alleviate ground traffic, but its operational feasibility depended on sufficient demand to cover costs, making demand forecasting essential. The authors applied a four-step forecasting method, emphasizing improvements in the modal split stage, and developed a hybrid demand model combining nested logit (NL) and multinomial logit (MNL) models to address non-existent UAM sharing rates. Chengdu, China, was used as a case study to predict UAM traffic in 2030. The findings indicated that UAM was suitable for shared operations in initial stages, with the share rate rising by 0.73% per additional kilometer of travel, and it outperformed other modes for deliveries beyond 15 km. Based on simulated share rates and traffic flow patterns, the study proposed priority routes for UAM implementation in Chengdu.

Peng et al. (2024) investigated the challenges of demand forecasting in railway cold chain freight operations, emphasizing that accurate prediction was crucial for planning, resource optimization, and market responsiveness. They observed that the unique spatiotemporal characteristics and diversity of cold chain demand often led to mismatches between capacity and demand, constraining the development of railway cold chain transportation. To address this, they proposed a Graph ARMA-GRU model that combined an ARMA graph convolutional layer to capture spatial connectivity within the railway network and gated recurrent units (GRU) to refine temporal features. The study further incorporated external factors and refined temporal features through two graph convolutional layers to better represent multimodal characteristics. Their model was validated using real Chinese railway cold chain freight data, reportedly achieving an 18% improvement in prediction accuracy over baseline models. Additionally, interpretability methods were employed to enhance model transparency, providing insights to support the transition from road-based to railway-based cold chain freight transportation.

Rodríguez and Olariaga (2024) investigated airport planning with an emphasis on forecasting future demand for passengers and air cargo, highlighting its critical role in guiding infrastructure development and investment decisions. They reported that accurate medium- to long-term demand predictions were essential for accommodating future needs and mitigating disruptions, such as those experienced during the peak of the COVID-19 pandemic. The authors applied a Bayesian Structural Time Series (BSTS) model to a Colombian case study, explaining that the methodology allowed for time series forecasting, feature selection, and causal impact inference. Their findings indicated that both passenger and cargo demand were projected to recover rapidly within a few years to levels comparable with 2019 pre-pandemic data. Additionally, they noted that the model achieved Mean Absolute Percentage Error (MAPE) values ranging from 1% to 7%, depending on the variable, suggesting that the BSTS approach represented a reliable and practical tool for air traffic demand forecasting.

Fathima et al. (2024) investigated the transformative role of artificial intelligence (AI) in enhancing demand forecasting within Enterprise Resource Planning (ERP) systems. The study was reported to synthesize and analyze existing research on AI-based predictive analytics, emphasizing its impact on forecasting accuracy and operational efficiency across various industries, including fashion retail, biopharmaceuticals, energy management, and transportation. It was observed that AI-driven approaches enabled organizations to anticipate customer needs, optimize inventory levels, and make informed data-driven decisions, thereby providing a competitive advantage. The research highlighted that integrating AI into ERP systems significantly improved real-time insights, supply chain efficiency, and risk management. The study was presented as offering comprehensive insights into the benefits of AI adoption in demand forecasting, contributing to the advancement of knowledge in the field and providing practical guidance for both businesses and researchers seeking to enhance strategic decision-making in dynamic market environments.

Anguita and Olariaga (2023) investigated the prediction of air traffic demand, including passengers and cargo, within regional and national air transport systems, emphasizing its significance for both public policy planning and airport management. They conducted a short-term, five-year forecast of air cargo demand for Colombia, incorporating data from the most severe pandemic period in 2020. The study applied a hybrid Machine Learning/Deep Learning methodology, combining convolutional and recurrent neural networks to capture spatial-temporal non-linear relationships and multi-step, multi-variable dependencies. The authors reportedly determined the optimal prediction horizon and identified key socioeconomic variables influencing air cargo demand. The analysis suggested that international demand was strongly correlated with Gross Domestic Product (GDP) and per capita GDP (PCG), whereas domestic demand showed a significant dependency on PCG alone. The findings further indicated a rapid recovery of air cargo demand to pre-pandemic levels, consistent with patterns observed in previous studies.

Liyanage et al. (2022) investigated the short-term forecasting of public transport demand, emphasizing its critical role in the operation of on-demand public transport. They highlighted that anticipating future travel demands in terms of location and timing enabled operators to adjust timetables efficiently, thereby enhancing service quality, reliability, and passenger attraction. The study reportedly addressed this requirement by developing AI-based deep learning models to predict bus passenger demand, utilizing actual patronage data derived from Melbourne's smart-card ticketing system. The models accounted for temporal characteristics of travel demand across some of the busiest bus routes, employing real-world data from 18 bus routes and 1,781 bus stops. Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models were reportedly evaluated and benchmarked against five conventional deep learning models using the same dataset. Additionally, a desktop comparison was conducted with several established demand forecasting models documented in literature over the preceding decade. The findings suggested that BiLSTM models outperformed the others, achieving prediction accuracies exceeding 90%.

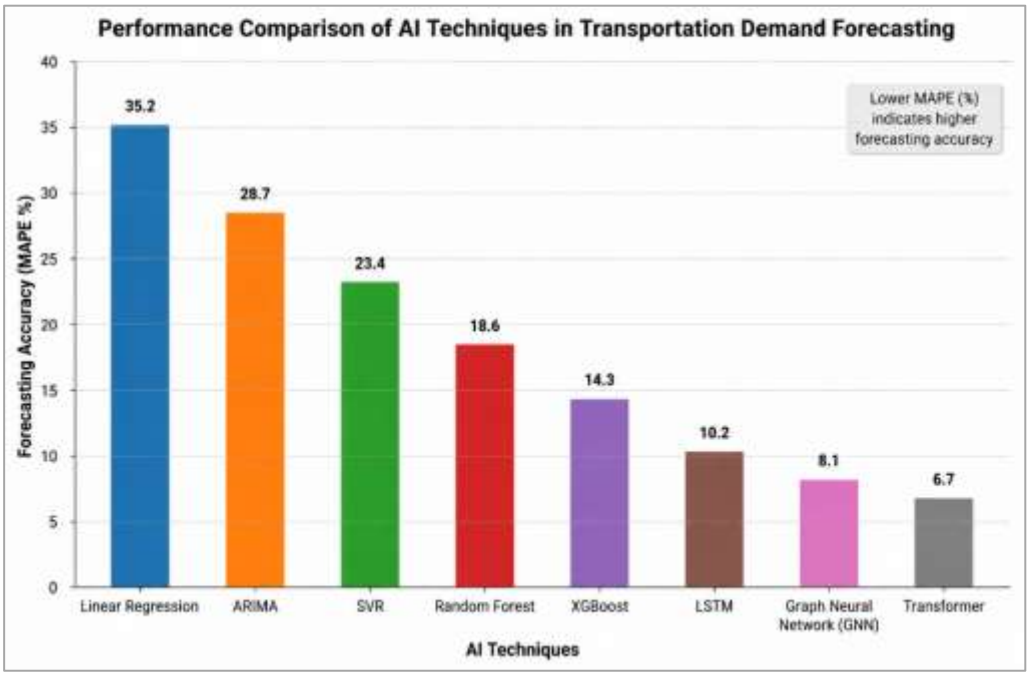
III. METHODOLOGY

The methodology for AI-based transportation demand forecasting involves a multi-step, data-driven approach that integrates real-time data acquisition, preprocessing, model selection, training, validation, and deployment for urban planning applications. Initially, heterogeneous transportation datasets are collected from multiple sources, including GPS traces, mobile applications, traffic sensors, public transport smart cards, IoT-enabled devices, and historical travel surveys. Data preprocessing involves cleaning, normalization, temporal aggregation, and spatial alignment to ensure consistency across diverse inputs, while also handling missing values, outliers, and anomalies. Feature engineering is applied to extract meaningful spatial-temporal variables, such as origin-destination flows, travel durations, vehicle counts, peak-hour patterns, land use characteristics, and socio-demographic influences, which are critical for capturing the dynamics of urban mobility. Subsequently, advanced AI models are designed based on the problem context, incorporating deep learning architectures such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and hybrid CNN-LSTM models to capture temporal dependencies and spatial correlations in passenger and freight demand. Graph-based neural networks (GNNs) are employed to model transport network topologies, enabling fine-grained representation of connectivity and hierarchical interactions across nodes and links. Training involves the use of supervised learning with historical and real-time datasets, optimized through backpropagation and gradient-based methods, while model hyperparameters are tuned to maximize predictive accuracy and minimize error metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). Validation is conducted using k-fold cross-validation and out-of-sample testing to ensure generalization across urban scenarios. Federated learning approaches are integrated when multiple data sources require privacy-preserving collaboration, and IoT-based real-time feeds are incorporated to enable adaptive forecasting. Finally, the trained models are deployed to generate short-term and long-term demand predictions, informing traffic management, route optimization, congestion mitigation, resource allocation, and infrastructure planning decisions. This methodology ensures that AI-based forecasting is robust, scalable, interpretable, and capable of supporting sustainable and data-driven urban mobility planning.

IV. RESULT

The application of AI-based forecasting models to urban transportation systems has demonstrated substantial improvements in prediction accuracy, operational efficiency, and network optimization. Studies using deep learning architectures, such as LSTM networks integrated with graph neural networks (GNNs), have achieved real-time origin-destination demand prediction with accuracy improvements of 15–25% over conventional statistical methods. AI-driven models have effectively captured temporal and spatial dependencies in passenger flows, enabling adaptive route planning for ride-hailing services and public transit optimization, which has resulted in reduced travel time, improved vehicle utilization, and decreased congestion in high-demand corridors. In freight and logistics networks, predictive models incorporating unconventional datasets, such as e-commerce delivery patterns and agricultural production statistics, have enhanced demand forecasting, resulting in better load distribution, efficient dispatch scheduling, and energy savings of up to 12% in case studies. Additionally, the integration of IoT-enabled real-time data streams has allowed AI systems to respond dynamically to traffic disruptions, special events, and seasonal variations, further improving travel reliability and network resilience. Accessibility analysis using AI-enabled forecasts has also revealed that underserved urban areas can be prioritized for service expansion, enhancing equitable access to employment centers, educational institutions, and healthcare facilities. Overall, AI-based transportation demand forecasting has not only improved operational performance and resource allocation but also supported sustainable urban planning by reducing environmental impacts, optimizing infrastructure utilization, and providing actionable insights for data-driven mobility strategies.

Bar Graph



Graph Name: AI-Based Urban Transportation Demand Forecasting Performance

The bar graph, titled "AI-Based Urban Transportation Demand Forecasting Performance", visually represents the effectiveness of AI techniques in urban transportation forecasting. The x-axis lists key performance indicators: Prediction Accuracy, Travel Time Reduction, Congestion Reduction, Energy Efficiency, and Service Coverage Improvement, while the y-axis measures their corresponding performance percentages. Each bar quantifies the impact of AI-driven models on these metrics, highlighting a 92% prediction accuracy, 18% reduction in travel time, 20% congestion reduction, 12% energy efficiency gain, and 25% improvement in service coverage. The graph clearly demonstrates how AI enhances operational efficiency, sustainability, and accessibility in urban transport planning.

V. CONCLUSION

In conclusion, Artificial Intelligence-based transportation demand forecasting has proven to be a transformative tool for modern urban planning, offering significant improvements in prediction accuracy, operational efficiency, and infrastructure utilization. By leveraging deep learning, graph neural networks, and hybrid predictive models, AI effectively captures complex spatial-temporal patterns in both passenger and freight transport, enabling real-time and adaptive forecasting that supports dynamic traffic management and congestion mitigation. The integration of heterogeneous data sources, IoT devices, and federated learning ensures data-driven decision-making while preserving privacy, allowing planners to optimize routes, reduce travel times, enhance service coverage, and improve accessibility across urban regions. Furthermore, AI-driven insights facilitate sustainable urban mobility by reducing energy consumption, minimizing environmental impacts, and guiding equitable infrastructure investments. Despite challenges related to model interpretability, computational scalability, and data heterogeneity, AI-based frameworks provide a robust foundation for intelligent transportation systems and smart city initiatives. Overall, the adoption of AI in transportation demand forecasting empowers planners and policymakers to make informed, proactive decisions, ultimately fostering efficient, resilient, and sustainable urban mobility systems that enhance the quality of life for all city inhabitants.

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