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Bridging Gaps in Transport Demand Forecasting through Artificial Intelligence and Machine Learning

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ABSTRACT: Artificial Intelligence (AI) has emerged as a transformative tool for transportation demand forecasting, addressing the limitations of traditional statistical approaches. This study systematically reviews recent literature to evaluate AI methodologies, their applications, and the systemic factors that shape adoption. Peer-reviewed studies published between 2018 and 2025 were identified from Scopus, Web of Science, and Google Scholar. Findings reveal that AI techniques, particularly deep learning and ensemble models, consistently outperform conventional forecasting methods in predictive accuracy and adaptability. Integration of spatio-temporal and geospatial data further enhances model robustness, supporting more responsive strategies for sustainable urban mobility. Applications span passenger transport, freight logistics, public transit optimization, and electric vehicle charging demand. Nonetheless, challenges persist, including data scarcity, computational demands, interpretability concerns, and uneven adoption between developed and developing regions. The review underscores the need for supportive policies, collaborative data management, and fairness-aware models. Overall, leveraging AI in transport forecasting is essential to build efficient, adaptive, and inclusive mobility systems while aligning future research with long-term planning and sustainability goals.

Keywords: Artificial Intelligence, Transport Demand Forecasting, Machine Learning, Urban Mobility, Spatio-temporal Data, Sustainable Transportation, Deep Learning.

INTRODUCTION

Artificial Intelligence (AI) has rapidly become a transformative force across diverse sectors, including healthcare, finance, agriculture, and transportation. Within transportation, AI is increasingly recognized for its capacity to improve demand forecasting in complex and dynamic urban environments where population growth and rapid urbanization place mounting pressure on mobility systems (Çolak & Bayrak, 2025). Conventional forecasting methods, such as regression-based or econometric models, often struggle to capture the nonlinear and fluctuating patterns of modern travel behavior (Nguyên et al., 2018). These limitations have spurred interest in AI-driven approaches that can process large, heterogeneous datasets and generate more accurate and adaptive predictions.

Recent advances in deep learning and machine learning have already demonstrated significant potential. Neural networks, random forests, and optimization algorithms have been applied to enhance urban travel predictions, improve traffic flow management, and support freight logistics planning (Spanos et al., 2025; Regal et al., 2022). AI has also shown promise in optimizing multimodal transport systems and informing sustainable mobility strategies (Bansal et al., 2024). Despite these developments, most studies have concentrated on short-term or real-time traffic predictions, leaving long-term forecasting and strategic planning relatively underexplored (Khairi et al., 2023). This narrow focus limits the capacity of policymakers to design transport systems resilient to structural changes such as demographic shifts, climate impacts, and evolving mobility preferences.

In addition, challenges related to data availability, interpretability, and fairness remain unresolved. While advanced AI models deliver high predictive accuracy, their "black box" nature raises concerns about transparency and accountability. Moreover, empirical evidence suggests that reliance on biased datasets can inadvertently reinforce inequalities in transport accessibility (Yan & Howe, 2020). These issues highlight the need for models that are not only technically robust but also interpretable, equitable, and context-sensitive.

Against this backdrop, the present study systematically reviews recent research on the application of AI in transportation demand forecasting. It aims to evaluate the effectiveness of AI methodologies compared to traditional approaches, analyze their limitations, and identify opportunities for innovation. By addressing underexplored areas—such as long-term forecasting horizons, transfer learning in data-scarce environments, and integration with sustainability goals—this review contributes to advancing both the academic discourse and practical policy development in urban mobility systems.

METHOD

The methodology for this study was designed to ensure a systematic and comprehensive approach to the identification, selection, and evaluation of relevant literature on the application of Artificial Intelligence (AI) in transportation demand forecasting. The focus was to capture the breadth and depth of recent advancements in the field while maintaining strict adherence to academic standards of reliability, transparency, and reproducibility. This section provides a detailed explanation of the process undertaken, including the databases consulted, keywords applied, criteria for inclusion and exclusion, the types of studies considered, and the screening and evaluation procedures employed.

The collection of literature was conducted using a combination of reputable and widely recognized academic databases. Scopus and Web of Science were selected as primary sources due to their rigorous indexing processes and their coverage of peer-reviewed journals across diverse disciplines, including transportation, computer science, and artificial intelligence (Spanos et al., 2025; Regal et al., 2022). These databases are considered highly reliable for retrieving high-quality academic research, ensuring that the articles included in this review reflect scholarly contributions that have undergone rigorous peer evaluation. In addition, Google Scholar was used to complement the search strategy by capturing a broader scope of material, including conference proceedings, working papers, and other academic contributions not always indexed in more selective databases (Çolak & Bayrak, 2025). While Google Scholar offers less control over quality and indexing consistency, its inclusion ensured that potentially valuable sources from emerging fields or interdisciplinary studies were not overlooked.

The search strategy employed a series of carefully chosen keywords and Boolean operators to identify relevant studies. Core search terms included "Artificial Intelligence," "Transport Demand Forecasting," and "Machine Learning," which were selected based on their prevalence in the literature and their ability to capture the central theme of this research (Zambang et al., 2021; Liu et al., 2021; Daios et al., 2025). Boolean combinations such as "Artificial Intelligence" AND "Transportation Demand Forecasting" and "Machine Learning" AND "Traffic Prediction" were employed to refine results and focus on the most relevant works. Additional variations were also tested to capture specific dimensions of the topic, including "Demand Prediction," "Urban Travel Forecasting," and "Neural Networks," ensuring coverage of both general and specialized applications of AI within transportation systems. More targeted queries were applied to explore subdomains of the research field, such as "AI" AND "Urban Mobility" to identify studies on metropolitan travel demand, or "Machine Learning" AND "Freight Demand" for analyses related to logistics and freight forecasting (Regal et al., 2022; Alex et al., 2019).

To ensure rigor and relevance, the review employed clear inclusion and exclusion criteria. Studies were included if they directly addressed the application of AI, machine learning, or deep learning techniques in forecasting transportation demand. Eligible articles had to be published in peer-reviewed journals, conference proceedings, or other reputable academic outlets between 2018 and 2025, reflecting the rapid evolution of AI methods during this period. Only articles published in English were considered, in order to maintain consistency and facilitate analysis. Studies focusing exclusively on unrelated applications of AI, such as healthcare or finance, were excluded unless they provided transferable methodological insights directly applicable to transportation forecasting. Similarly, purely conceptual papers without empirical validation were excluded, as this review emphasized studies that presented concrete models, simulations, or case studies.

The types of research considered included a wide range of study designs, reflecting the interdisciplinary nature of the field. Empirical studies such as case studies of AI deployment in specific cities or transport networks, experimental designs testing the performance of different algorithms, and comparative analyses of AI and traditional forecasting methods were all deemed relevant. Simulation-based studies, where models were applied to synthetic or real-world transportation datasets, were also included due to their critical role in evaluating the robustness and scalability of AI approaches. Additionally, systematic reviews and meta-analyses were considered, provided they offered rigorous syntheses of AI applications in transportation demand forecasting. Excluded from this review were opinion pieces, editorials, and non-peer-reviewed reports, as these lacked the empirical or methodological rigor necessary for inclusion.

The process of literature selection unfolded in multiple stages. Initially, all search results were exported into reference management software to streamline the process of removing duplicates and organizing articles. Titles and abstracts were then screened for relevance based on the inclusion and exclusion criteria. At this stage, studies that clearly did not address transportation forecasting or lacked substantive AI applications were discarded. The remaining studies underwent full-text review to ensure methodological rigor, relevance to the research question, and sufficient detail to support comparative analysis. Articles were further evaluated according to their methodological transparency, dataset size and quality, and the extent to which their findings contributed to understanding AI applications in transportation demand forecasting.

Each study was then assessed for quality and reliability using a set of evaluative criteria designed to balance methodological rigor with practical relevance. Studies that employed real-world datasets, such as urban mobility surveys, traffic sensor data, or freight logistics records, were prioritized for their empirical grounding. The use of advanced algorithms, including neural networks, random forests, and multi-task learning approaches, was noted as a marker of methodological innovation (Liu et al., 2021). Additionally, studies were examined for the extent to which they considered contextual factors, such as spatial and temporal variability, demographic differences, and policy implications. Research that incorporated these dimensions was particularly valuable, as it aligned with the overarching aim of developing forecasting models that are adaptable, equitable, and scalable.

The final selection of articles represented a diverse cross-section of research efforts, spanning multiple regions, modes of transport, and methodological approaches. Studies conducted in developed countries, particularly in Europe and Asia, often emphasized the integration of AI forecasting into smart city initiatives and advanced mobility systems (Spanos et al., 2025). In contrast, research from developing contexts focused on overcoming data scarcity and infrastructural limitations, highlighting the adaptability of machine learning techniques in resource-constrained environments (Zambang et al., 2021). The inclusion of freight-related studies (Regal et al., 2022) and community-aware forecasting models (Liu et al., 2021) further expanded the scope, demonstrating the breadth of AI's applicability across passenger and logistics domains.

In conclusion, the methodology for this review was intentionally comprehensive, designed to balance depth with breadth. By combining multiple databases, employing a wide but precise range of keywords, and enforcing rigorous inclusion and exclusion criteria, the process ensured that only the most relevant and methodologically sound studies were included. The reliance on empirical and simulation-based studies provided a strong foundation for analysis, while the emphasis on contextual and global diversity ensured that the findings of this review are broadly applicable. This methodology not only facilitates an accurate synthesis of current knowledge but also establishes a transparent framework that can be replicated or expanded upon by future researchers examining AI applications in transportation demand forecasting.

RESULT AND DISCUSSION

The analysis of the literature revealed a number of recurring themes that provide a comprehensive understanding of the role of Artificial Intelligence (AI) in transportation demand forecasting. The themes are organized under model and methodological innovations, the significance of spatio-temporal factors, and applications across different transportation contexts, followed by a comparative global perspective. Together, these findings underscore the transformative potential of AI while also highlighting its contextual dependencies and limitations.

One of the most prominent findings relates to the advancement of AI models and methodologies in transportation forecasting. Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), Random Forest algorithms, and more recently Transformer-based approaches have been widely utilized in capturing both temporal and spatial dependencies in transport data. LSTM and CNN models, in particular, have been shown to significantly outperform traditional approaches such as linear regression and autoregressive integrated moving average (ARIMA) models, largely due to their capacity to model nonlinear dynamics and high-dimensional data inputs (Spanos et al., 2025; Nguyên et al., 2018). A notable example is the Principal Component Random Forest (PCRF) model proposed by Spanos et al., which demonstrated high effectiveness in predicting passenger demand within cooperative and automated mobility contexts, with an average normalized error of approximately 15% (Spanos et al., 2025). Such evidence illustrates the capacity of ensemble learning methods to incorporate dimensionality reduction techniques while maintaining predictive strength.

Comparative analyses across AI and traditional models further validate these findings. In freight transport demand forecasting, Regal et al. (2022) highlighted the superior performance of neural network-based models in predicting long-horizon demand for loading zones in urban environments. Their findings suggest that AI-based models are not only capable of short-term optimization but also extend their utility to strategic planning horizons, outperforming linear models in capturing latent interactions within freight demand data. Additionally, Daios et al. (2025) and Kondratenko et al. (2023) reinforce this point, demonstrating that AI's ability to process complex multivariate inputs significantly enhances predictive performance beyond what classical statistical models can offer. Collectively, these studies emphasize that while econometric and statistical models laid the groundwork for transport forecasting, AI methods provide a new benchmark in terms of accuracy and adaptability.

The second theme relates to the pivotal role of spatio-temporal factors in shaping transport demand predictions. Literature consistently identifies that the integration of spatial variables—such as geographical location, land use, and community characteristics—with temporal data greatly enhances model performance. Liu et al. (2021) developed the Multi-task Spatio-Temporal Network (Ada-MSTNet), which successfully captured the complex interrelationships between regions and communities, resulting in substantial improvements in predictive accuracy. Similarly, Çolak and Bayrak (2025) emphasized the integration of urban community-specific attributes into demand forecasting models, demonstrating how local context significantly influences predictive outcomes.

Evidence from empirical studies underscores the growing importance of geospatial artificial intelligence (GeoAI) in this domain. Liu et al. (2021) reported that incorporating high-resolution geospatial data alongside conventional traffic datasets substantially improved the accuracy and reliability of transport demand models. Such integrations have allowed predictive systems not only to anticipate mobility trends but also to contribute to environmentally sustainable transport strategies. Alzahrani et al. (2024) observed that GeoAI-driven forecasting approaches enabled the design of adaptive strategies that align with sustainability goals, particularly in rapidly urbanizing regions. These findings demonstrate that spatio-temporal modeling, enriched by geospatial data, represents a critical advancement in forecasting, offering insights that traditional datasets cannot capture.

The application of AI across different transportation contexts provides further evidence of its versatility and transformative capacity. Within urban passenger mobility, AI models such as neural networks and Random Forest have proven effective in capturing diverse and complex travel behaviors. Çolak and Bayrak (2025) showed that AI integration into urban demand forecasting not only improved predictive accuracy but also enhanced the capacity for long-term infrastructure planning. These models facilitated a nuanced understanding of intra-city travel patterns, thereby supporting the development of efficient and responsive transport systems.

In the domain of freight transport, Regal et al. (2022) demonstrated that AI-based machine learning algorithms could predict demand for urban loading zones with significant accuracy. Their findings revealed how predictive analytics can provide city planners and logistics managers with actionable insights into freight movement patterns, enabling more efficient allocation of urban space for loading and unloading operations. Such improvements in freight management highlight AI's potential to optimize not only passenger flows but also goods distribution within congested urban landscapes.

Public transit systems have also benefited from AI-enabled forecasting. Khairi et al. (2023) noted that machine learning models were increasingly being deployed to predict public transit demand and optimize service routes. By dynamically adjusting schedules and capacities in response to predicted demand, AI-powered systems improved service reliability and user satisfaction. In parallel, applications in electric vehicle (EV) charging demand prediction have emerged as a critical area of interest. Although not as extensively studied as passenger or freight transport, research suggests that AI techniques can support the optimal placement of charging stations and anticipate usage patterns, thereby facilitating the transition to sustainable mobility infrastructures.

A comparative analysis between developed and developing countries highlights both the opportunities and challenges associated with AI adoption. In developed contexts, particularly across Europe and Asia, robust datasets and advanced digital infrastructures provide a fertile ground for deploying complex AI forecasting models. Daios et al. (2025) reported that such conditions enabled significant improvements in transport efficiency and congestion reduction, with AI systems delivering actionable insights at both operational and strategic levels. Similarly, studies from smart city initiatives reveal that AI forecasting contributes to the optimization of multimodal systems, thereby enhancing sustainability and resilience.

Conversely, research in developing countries underscores significant barriers to the effective application of AI in transport forecasting. Zambang et al. (2021) highlighted that data scarcity and inadequate infrastructure in regions such as sub-Saharan Africa limit the extent to which AI can be effectively applied. In such contexts, models often rely on small-scale, fragmented datasets that constrain their predictive capacity. Consequently, the outcomes of AI forecasting in these settings are less accurate and reliable compared to those in data-rich environments. Nevertheless, even in resource-constrained conditions, AI has shown promise in bridging gaps left by traditional statistical methods, offering more adaptive solutions when tailored to local conditions.

Several systemic factors explain these differences in AI performance across contexts. First, disparities in data availability and quality directly influence model performance. Developed nations often possess extensive traffic sensor networks, real-time mobility tracking systems, and integrated digital infrastructures, while developing countries may lack such resources. Second, policy environments and governance structures play a role in shaping adoption. Alzahrani et al. (2024) found that proactive policy integration of AI into urban mobility strategies enabled more effective outcomes, whereas weak policy support in other regions hampered adoption. Finally, sociocultural factors, including variations in travel behavior and public engagement with data collection initiatives, further contribute to cross-country differences (Spanos et al., 2025).

In sum, the findings of this narrative review indicate that AI has established itself as a transformative tool in transportation demand forecasting. From the deployment of deep learning models capable of capturing nonlinear mobility dynamics to the integration of spatio-temporal and geospatial data for context-sensitive predictions, AI significantly outperforms traditional forecasting methods. Applications across passenger, freight, public transit, and EV charging contexts demonstrate the versatility of these technologies. However, the global comparison reveals that successful implementation is contingent on local conditions, particularly the availability of quality data and supportive infrastructure. While developed nations reap the benefits of advanced AI integration, developing regions face challenges that require context-specific strategies and investments to harness AI's full potential. The evidence thus points to both the promise and the limitations of AI, underscoring the necessity for adaptable, inclusive, and globally informed approaches to transportation demand forecasting.

The results of this review confirm that Artificial Intelligence (AI) has advanced the field of transportation demand forecasting in ways that traditional methods have been unable to achieve. Deep learning approaches such as Long Short-Term Memory (LSTM) networks and ensemble-based methods like Random Forests consistently outperform econometric models such as linear regression or ARIMA in both accuracy and adaptability (Nguyên et al., 2018; Alzahrani et al., 2024). These findings are consistent with prior literature that emphasized the limitations of statistical models in capturing the nonlinear and dynamic characteristics of transportation data. By contrast, AI has demonstrated the ability to uncover complex relationships within data, providing forecasts that align more closely with the observed variability of urban mobility and freight logistics (Spanos et al., 2025; Khairi et al., 2023). The example of the Principal Component Random Forest model, which achieved strong predictive performance in cooperative and automated mobility contexts, illustrates the capacity of AI to address modern challenges that arise in technologically integrated transportation systems (Spanos et al., 2025).

A significant dimension of these findings is the recognition of systemic factors that influence the effectiveness of AI deployment. High-quality and comprehensive data remain the cornerstone of predictive accuracy. Without sufficient granularity or reliability, AI models risk producing results that fail to represent the realities of urban mobility (Alzahrani et al., 2024). This issue is particularly salient in developing regions, where digital infrastructure is insufficient and data collection processes are fragmented or inconsistent (Khairi et al., 2023). In such settings, the disparity between the theoretical potential of AI models and their real-world applicability becomes evident. Conversely, in data-rich environments such as Europe or Asia, the integration of AI into transport planning has delivered measurable improvements in congestion reduction and service optimization, illustrating how systemic support in data infrastructure and governance amplifies the effectiveness of AI solutions.

The importance of supportive policy frameworks also emerges as a consistent theme. Governments and transport authorities that actively invest in digital infrastructure, facilitate data sharing across sectors, and implement regulations encouraging innovation are better positioned to reap the benefits of AI-driven forecasting. By contrast, regions lacking such policy commitments often encounter significant barriers to adoption, leaving AI applications underdeveloped or ineffective despite their potential. Literature highlights that the capacity of AI to transform transportation systems is not solely a technical question but one deeply embedded in broader institutional and societal systems (Daios et al., 2025). The successful adoption of AI thus requires an interplay of technological readiness, policy support, and social acceptance.

Several studies propose potential solutions to mitigate the obstacles that hinder AI adoption in transport forecasting. Collaborative approaches to data collection and management are frequently cited as essential. Partnerships between government agencies, private sector entities, and research institutions can lead to the development of more comprehensive and diverse datasets, enhancing model robustness and generalizability (Nguyên et al., 2018; Daios et al., 2025). This type of multi-stakeholder collaboration is particularly crucial in contexts where fragmented or incomplete data sources pose significant challenges. Equally important is the establishment of standardized data protocols that ensure interoperability across regions and platforms, enabling models to be tested, validated, and adapted across multiple contexts.

The literature further suggests that investments in digital infrastructure are indispensable to unlocking AI's potential. Without adequate computational resources and connectivity, the deployment of advanced AI algorithms remains impractical. This gap is most pronounced in developing countries, where infrastructural shortcomings constrain the scalability of AI solutions. Addressing this issue requires deliberate policy interventions that prioritize digital infrastructure as a foundation for sustainable urban mobility. By investing in these systems, governments can provide the structural conditions necessary for AI to contribute meaningfully to transport demand forecasting.

Transfer learning has also been identified as a promising avenue for overcoming the disparity in data availability between developed and developing contexts. Liu et al. (2021) argued that models trained on robust datasets from developed countries could be adapted for use in resource-constrained settings, even when only limited data are available locally. This methodological innovation offers the possibility of narrowing the global gap in AI adoption, enabling developing regions to benefit from models that have already proven successful elsewhere. However, adapting these models requires careful contextualization to ensure that localized variables—such as cultural norms of transport use and infrastructural constraints—are adequately reflected.

The broader implications of these findings reinforce the necessity for ongoing research that adapts AI forecasting models to diverse contexts. Spanos et al. (2025) emphasized the need for frameworks that can systematically integrate spatio-temporal and community-specific data, recognizing that transport demand is deeply shaped by localized dynamics. Alex et al. (2019) similarly highlighted that without contextual adaptation, the predictive value of AI models is diminished, particularly in urban environments where travel behavior is highly heterogeneous. The emphasis on contextual sensitivity aligns with global calls for more sustainable and equitable transport systems that serve not only technologically advanced cities but also regions facing infrastructural and socioeconomic constraints.

Despite these advances, notable limitations persist in the current literature. Many studies remain narrowly focused on short-term forecasting, prioritizing real-time traffic management over long-term planning horizons (Khairi et al., 2023). This gap reduces the ability of AI models to support strategic policymaking that anticipates demographic shifts, climate change impacts, and broader urban development trends. Furthermore, issues of model interpretability continue to be a challenge. The reliance on black-box approaches, particularly in deep learning, limits transparency and hinders trust among policymakers and the public. As AI is integrated into decision-making processes with high societal stakes, questions of explainability and accountability will become increasingly critical.

In addition to interpretability, there is an underrepresentation of ethical considerations in current studies. Research has shown that AI-based demand forecasting may inadvertently reinforce inequities by reflecting biases in the underlying data (Yan & Howe, 2020). Addressing these issues requires deliberate efforts to design fairness-aware models that mitigate socioeconomic biases and promote inclusivity in urban transport systems. At the same time, concerns about privacy and data security must be addressed, particularly as AI models increasingly rely on granular mobility data collected through sensors, smartphones, and connected vehicles.

Moving forward, literature indicates the need for research that broadens the scope of AI forecasting beyond technical optimization to encompass broader societal objectives. Alzahrani et al. (2024) stressed the importance of aligning AI adoption with sustainability goals, including reductions in emissions, improvements in energy efficiency, and the promotion of public transit systems. Incorporating such priorities into AI model development requires interdisciplinary collaboration that bridges the fields of computer science, urban planning, and environmental policy. By embedding AI forecasting within a holistic vision of sustainable urban mobility, researchers and practitioners can ensure that technological advances contribute meaningfully to broader social and environmental goals.

CONCLUSION

This review highlights the significant contributions of Artificial Intelligence (AI) to transportation demand forecasting, demonstrating its superiority over traditional statistical approaches in capturing nonlinear, dynamic, and context-sensitive travel patterns. Models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Random Forest, and Transformer-based methods consistently achieved higher predictive accuracy and adaptability than regression or ARIMA-based models. The findings also underscore the importance of integrating spatio-temporal and geospatial data, which enhanced predictive precision and allowed for more responsive and sustainable transport strategies. Applications across urban passenger mobility, freight logistics, public transit, and electric vehicle charging illustrate the versatility of AI and its potential to transform diverse transport systems. However, systemic factors such as data availability, digital infrastructure, and supportive policy frameworks significantly influence the effectiveness of AI implementation. While developed regions benefit from rich datasets and advanced infrastructures, developing countries face substantial barriers that limit model accuracy and applicability. Addressing these challenges requires investment in digital infrastructure, multi-stakeholder collaboration in data sharing, and the adoption of fairness-aware and interpretable AI models. Future research should prioritize long-term forecasting horizons, transfer learning for data-scarce environments, and interdisciplinary frameworks that align AI with sustainability and equity goals. Overall, the integration of AI in transportation forecasting is both urgent and necessary, offering a pathway to more efficient, adaptive, and inclusive urban mobility systems.

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