European Research Studies Journal
Volume XXIX, Issue 1, 2026

pp. 432-447

Artificial Intelligence in the Management of Transportation Companies

Submitted 13/11/25, 1st revision 04/12/25, 2nd revision 15/12/25, accepted 20/02/26

Marx Davidson Nkonyam Ando[1], Bartosz Zakrzewski[2], Irena Dul[3]

Abstract:

Purpose: *This article examines the transformative impact of artificial intelligence (AI) on the management of transportation enterprises, with particular emphasis on enhancements in planning accuracy, operational efficiency, environmental sustainability, and strategic decision-making. As transport systems grow increasingly interconnected, dynamic, and data-rich, AI provides new capabilities that fundamentally reshape managerial practices.*
Design/Methodology/Approach: *The study employs an integrative synthesis of contemporary scholarly literature to identify and organize the mechanisms through which AI influences managerial processes in the transport sector. Drawing from state-of-the-art research, a four-layer conceptual framework comprising data acquisition, AI-driven analytics, decision-support functions, and operational execution is developed to systematize the multifaceted effects of AI on organizational management.*
Findings: *The analysis demonstrates that AI significantly enhances and strengthens predictive planning, route optimization, fleet maintenance scheduling, warehouse coordination, and risk mitigation. Beyond automating routine tasks, AI enhances managerial cognition by enabling rapid adaptation to uncertainty, supporting evidence-based decision making, and facilitating more environmentally responsible transport operations. These effects collectively contribute to the modernization and increased resilience of transportation companies.*
Practical Implications: *The proposed conceptual model offers managers, practitioners, and policy makers a structured tool for understanding and implementing AI solutions within transportation organizations. The findings highlight practical pathways for leveraging AI to improve operational performance, strengthen strategic planning, and advance sustainability objectives across the transport sector.*
Originality/Value: *By integrating and synthesizing current research, this article provides a comprehensive and analytically grounded framework that elucidates the complex, multidimensional role of AI in transport management. The study contributes original value by offering a coherent conceptual model that can guide future empirical research and inform policy and managerial practices in the rapidly evolving domain of intelligent transportation systems.*

[1]*Git-Go Technology, Maryland 21157, USA,*
ORCID: 0009-0007-0398-3013, e-mail: mdbih28@gmail.com;
[2]*Ph.D., Motor Transport Institute, Warszawa, Poland, ORCID: 0000-0001-9902-9759,*
e-mail: bartosz.zakrzewski@its.waw.pl;
[3]*Szczecińska Energetyka Cieplna, 70-653 Szczecin, Polska, ORCID:0000-0001-8182-8157,*
e-mail: dul.irena@gmail.com;

Keywords: *Artificial intelligence, transportation management, routing optimization, fleet operations, predictive analytics, decision support, sustainability, logistics systems.*

JEL code: *L9, L91, R41, R42, C45, H54.*

Paper type: *Research article.*

1. Introduction

Artificial intelligence has become a central pillar of contemporary management discourse, particularly within transport and logistics, where firms confront rising operational complexity, volatile demand patterns, and accelerating digital transformation. Transportation companies operate in environments characterised by network congestion, fluctuating fuel prices, supply chain disruptions, and increasingly stringent customer expectations.

As conventional planning tools struggle to process high-velocity and heterogeneous data, managers increasingly turn to artificial intelligence to enhance analytical and operational capabilities. Recent scholarship demonstrates that AI enables organisations to improve real-time decision-making, optimise routing processes, enhance fleet utilisation, and strengthen safety management, thereby positioning AI as an essential capability in transportation management (Abduljabbar *et al.,* 2019). Moreover, AI-driven systems increasingly complement managerial functions through predictive forecasting, optimisation algorithms, and integrated decision-support technologies.

A substantial body of empirical work highlights AI's contributions to multiple dimensions of transportation operations. Štencl and Lendel (2012) show that neural networks and fuzzy logic outperform conventional forecasting tools in modelling nonlinear transport patterns, improving predictive accuracy under uncertain conditions. Hu *et al.* (2020) developed an AI-based optimal route planning model integrating a multilayer perceptrons neutral network with a speed-weighted Dijkstra algorithm, demonstrating significant reductions in travel time and fuel expenditure.

Nozari *et al.* (2025) evaluate AIoT-enabled cold chain logistics in which genetic algorithms, particle swarm optimisation, and emperor penguin optimisation collectively reduce transportation costs by more than half in complex distribution systems. Chatzidimitriou and Zissis (2023) evaluate AI-based predictive maintenance in the maritime sector and find that machine learning improves equipment reliability and reduces unplanned downtime. Wright *et al.* (2025) analyse AI-based intelligent transport systems and show that integrating operational data with strategic planning enhances organisational resilience and long-term competitiveness.

Additional research reinforces these trajectories across diverse transportation contexts. Díaz and López (2023) show that machine-learning optimisation improves load balancing and multimodal network performance in logistics companies. Adeyemi *et al.* (2024) demonstrate that AI-driven predictive analytics enhance freight demand forecasting accuracy, reducing operational waste.

In aviation, Grigorescu *et al.* (2020) demonstrate that deep learning perception systems strengthen hazard detection and operational safety. In road freight transport, Marton *et al.* (2024) identify expert systems as central tools for risk management, process standardisation, and accelerate response times.

Finally, Hernandez (2024) provides evidence that AI–IoT integration reduces emissions and fuel use in commercial fleets by enabling continuous monitoring and adaptive routing. Collectively, these studies confirm AI's expanding role in shaping efficiency, safety, and strategic decision-making across transportation sectors.

Despite the expanding literature, several limitations remain. Most studies examine AI applications in specific modes, such as road freight, maritime operations, or cold chain logistics, rather than a holistic review at the organisational level of transportation company management.

Methodologically, many analyses emphasise technical optimisation models but provide limited insight into how managers integrate these tools into broader governance systems, organisational processes, or strategic architectures. This gap restricts understanding of the organisational mechanisms, contextual contingencies, and managerial capabilities required to embed AI effectively within transportation company management.

The present study addresses this gap by systematically examining how transportation companies adopt and utilise artificial intelligence within of their management systems. Focusing on the operational and strategic practices of transportation firms, the study examines how AI supports forecasting, routing, risk management, asset maintenance, and decision-making routines. By analysing managerial processes rather than isolated technical applications, the research provides a more systematic understanding of AI's organisational role and its implications for transportation company performance.

This study makes several contributions to management and transportation discourse. Theoretically, it advances knowledge on the integration of AI into organisational decision systems, extending the managerial perspective on intelligent transport technologies. Empirically, it offers context-specific insights that complement the predominantly technical literature, thereby enriching the understanding of how firms operationalise AI within real-world constraints.

Methodologically, the study provides an analytical framework for evaluating AI-enabled management practices across transportation sectors. For practitioners and international audiences, the findings highlight how transportation companies can leverage AI to enhance efficiency, resilience, safety, and competitiveness in increasingly dynamic logistics environments.

This paper is structured as follows: - Introduction, Literature review, Methodology, Conceptual Model, Discussion, and Conclusion.

2. Literature Review

The growing integration of artificial intelligence into transportation systems has attracted extensive scholarly attention, with research converging on the proposition that AI enhances operational precision, strategic decision quality, and organisational resilience. Across the literature, there is a consistent recognition that transportation systems are increasingly data-intensive and subject to variability in demand, environmental conditions, and network complexity, making AI a valuable tool for improving decision-making under uncertainty.

Early contributions to the field, such as those of Dia and Rose (1997), established the potential of artificial neural networks to outperform traditional rule-based approaches in incident detection, demonstrating AI's capacity to model nonlinear patterns in traffic systems. Subsequent studies build on this foundation, illustrating the growing sophistication of AI methodologies and their ability to address increasingly complex transportation challenges.

A dominant theme across the literature concerns the use of machine learning and predictive analytics to improve forecasting accuracy and real-time responsiveness in transport operations. Research by Štencl and Lendel (2012) found that neural networks and fuzzy logic provide superior predictive performance relative to classical statistical models, particularly in volatile environments characterised by fluctuating transport demand.

This aligns with the findings of Hu *et al.* (2020), who demonstrated that artificial intelligence-based routing, supported by multilayer perceptrons combined with a modified Dijkstra algorithm, reduces travel times and fuel consumption. These studies suggest a broad scholarly consensus that AI enhances forecasting quality and optimisation outcomes, though they differ in their methodological approaches and the specific transport modes analysed. For example, while Štencl and Lendel (2012) focus on general traffic forecasting, Hu *et al.* (2020) situate their analysis within route-level optimisation, indicating a shift from macro-level modelling toward more granular operational applications.

Comparative studies further reveal convergence in the benefits of AI across distinct transport sectors. In maritime transport, Chatzidimitriou and Zissis (2023) show that predictive maintenance systems powered by machine learning improve equipment reliability and reduce unplanned downtime. These findings are reinforced by the systematic review conducted by Carvalho *et al.* (2019), who demonstrate that predictive maintenance supported by AI enables transportation organisations to transition from scheduled servicing to condition-based maintenance, enhancing asset longevity and reducing operational disruptions.

Complementing these insights, Puthenkarayil *et al.* (2024) find that anomaly detection models trained on telematics data can identify irregularities in heavy vehicle fleets with high accuracy. Collectively, these studies affirm the value of AI-based maintenance systems, though they vary in their empirical scope, with some using experimental data and others relying on industry case studies. This variation suggests opportunities for future research to integrate these perspectives into a more unified, cross sector understanding of maintenance optimisation.

Parallel advancements are observed in fleet and logistics optimisation. Khaja (2025) demonstrates that integrating machine learning with Internet of Things data enables real-time fleet routing and resource allocation, reducing idle time and emissions. Similar benefits are reported Díaz and López (2023), who show that machine-learning-driven load balancing improves multimodal logistics coordination.

These findings align with the broader literature on dynamic routing, including studies by Pillac *et al.* (2013) and Li and Li (2022), which conclude that artificial intelligence-based algorithms outperform classical optimisation methods in large-scale, time-sensitive routing problems. While these studies differ in their modelling techniques, they collectively support the argument that AI enables transportation companies to better cope with uncertainty and dynamic conditions.

Another significant theme emerging from the literature concerns intelligent transportation systems. Research by Jevinger *et al.* (2023) and Hassan *et al.* (2025) shows that AI applications in intelligent transportation systems primarily focus on prediction, resource allocation, and real-time state estimation. Their analyses identify machine learning as the most widely used method in intelligent transportation systems research and reveal limitations in data quality, governance, and adoption challenges.

These findings are consistent with those of Vlahogianni *et al.* (2014) and Lv *et al.* (2015), whose earlier contributions emphasise the importance of high velocity data collection and the challenges of modelling complex spatial-temporal dependencies.

While technological advancements have significantly improved predictive modelling capabilities, the literature indicates ongoing barriers concerning data heterogeneity and the organisational adaptations necessary to support AI-enabled intelligent transportation systems.

In recent years, scholars have increasingly examined the role of artificial intelligence in supporting sustainable transportation. Chen *et al.* (2024) show that AI based optimisation can reduce emissions and energy consumption when sustainability criteria are embedded into routing and scheduling decisions.

Hernandez (2024) demonstrates similar effects within commercial fleets, where AI-supported telematics enhance fuel efficiency and reduce environmental impact. Wen *et al.* (2021) also conclude that AI contributes to sustainable mobility by reducing congestion and supporting low-carbon transport operations.

Collectively, these studies indicate strong alignment on the environmental benefits of AI, while also highlighting the need for improved organisational readiness and data integration to realise sustainability outcomes fully.

The literature further indicates that artificial intelligence is playing an increasingly important role in supporting managerial decision-making. Davenport and Ronanki (2018) argue that AI augments managerial cognition by improving the speed and accuracy of information processing, while Chae (2019) illustrates how AI-enriched decision support systems enhance coherence across the supply chain and reduce cognitive burdens on decision makers.

Dubey *et al.* (2020) extend this line of reasoning by showing that AI-enabled analytics improve organisational performance through enhanced risk identification and scenario modelling. Despite differences in disciplinary focus, these studies converge on the understanding that AI transforms decision making from reactive to proactive and from intuition-based to evidence-based.

Across the literature, however, several critical limitations persist. Hassan *et al.* (2025) and Jevinger *et al.* (2023) observe that research remains heavily skewed toward technical algorithmic performance rather than organisational adoption processes. This gap is echoed by Wright *et al.* (2025), who argue that integrating AI into strategic planning requires more than algorithmic sophistication and depends on governance structures, workforce capabilities, and institutional support.

Ivanov (2020) similarly emphasises the need for resilience-based frameworks that connect predictive analytics to strategic planning under uncertainty. These findings collectively suggest that while technical research on AI in transportation is mature, managerial research remains underdeveloped and requires further empirical exploration.

To sum it up, the literature demonstrates strong alignment on the operational and strategic benefits of AI, as well as shared concerns about data limitations, organisational readiness, and governance.

While the evidence base is robust across multiple transport modes, future research must address conceptual gaps in cross-sector integration, responsible AI deployment, and the organisational transformations necessary to support the widespread adoption of artificial intelligence in transportation management.

3. Research Methodology

To construct our comprehensive analysis and conceptual model, we adopt an integrative literature review methodology, which allows us to synthesize diverse theoretical and empirical insights across multiple academic and industry domains (Snyder, 2019). This methodology is suited to emerging, interdisciplinary topics such as artificial intelligence in transportation management, where evidence arises from logistics, engineering, computer science, sustainability studies, and operations research.

The data collection approach involved conducting structured searches using keywords including artificial intelligence in transportation management, fleet optimization machine learning, predictive maintenance transportation, routing algorithms artificial intelligence, sustainable transportation and artificial intelligence, and decision support systems logistics, with sources drawn from peer reviewed journals indexed in Scopus, Web of Science, and Google Scholar to ensure comprehensive coverage and high academic quality of the literature.

Clearly defined eligibility criteria guided the selection of the literature to ensure relevance and academic quality. It included studies focused on artificial intelligence applications in transportation operations such as forecasting, routing, predictive maintenance, logistics, intelligent transportation systems sustainability and decision support.

Only English language peer-reviewed journal articles indexed in Scopus Web of Science and Google Scholar were considered, including conceptual studies, systematic reviews, modelling-based research, and bibliometric analyses. At the same time, preprints and unpublished works were excluded.

Analysis Process to analyse the collected literature, we applied a thematic coding process, a qualitative method widely used to identify and interpret patterns across heterogeneous data sources (Braun and Clarke, 2006; Saldaña, 2016). This approach is particularly appropriate for integrative reviews, where conceptual insights must be extracted from diverse empirical studies, theoretical contributions, and technical models. The analysis progressed through six iterative stages:

Familiarization with the literature involved thoroughly reading studies to gain a detailed understanding of their research aims, methodologies, and findings. During this stage, preliminary notes were made on recurring concepts related to AI's operational, strategic, and managerial roles in transportation. This aligns with Braun and Clarke's (2006) emphasis on deep immersion as the foundation for robust qualitative analysis.

Initial code generation involved highlighting key textual segments such as descriptions of outcomes, technological capabilities, or managerial implications and assigning them initial descriptive codes. These codes captured references to efficiency impacts, predictive modelling capabilities, sustainability outcomes, and risk-related insights. First cycle coding followed Saldaña's (2016) guidance on maintaining an open and inclusive coding structure.

Codes were reviewed to eliminate redundancies and to cluster conceptually related elements through a systematic process of refinement and consolidation. This process employed constant comparison techniques to ensure consistency and conceptual clarity across the dataset. Overlapping codes were merged into broader analytical categories that represented shared meanings across studies, thereby strengthening the coherence and interpretive robustness of the analysis.

The validation and interpretation themes were re-examined across the entire dataset to ensure adequate evidential support and alignment with the theoretical and practical concerns of transportation management. Following Saldaña's (2016) second-cycle coding principles, attention was directed toward conceptual integration and the identification of overarching patterns across studies.

The final themes served as the structural foundation for the layered conceptual model developed in this study, with each theme representing a critical dimension through which artificial intelligence shapes transportation management across operational, tactical, and strategic levels. These themes collectively provide a comprehensive framework for understanding how emerging technologies can transform decision-making, resource allocation, and strategic planning in transportation systems.

An integrative review was adopted because AI in transportation spans multiple disciplines, with evidence scattered across academic and industry sources, and because transportation organizations require system-level perspectives to understand how AI shapes both operational and strategic dimensions.

Traditional systematic reviews may limit the ability to uncover cross-cutting conceptual connections. In contrast, an integrative approach enables a holistic and flexible synthesis that captures the complex, multi-level impacts of AI, offering insights that advance scholarly understanding while informing the practices of transportation professionals.

4. Research Results and Discussion

This study investigates how artificial intelligence transforms management practices in transportation companies through a systematic organizational process. Based on an integrative review, a four-layer conceptual model is proposed, comprising data collection, artificial intelligence analytics, decision support, and operational execution. The model demonstrates how information from fleet, warehouse, environmental, and enterprise systems is processed to generate actionable insights that support forecasting, routing, maintenance, risk management, and sustainability strategies.

Findings indicate that artificial intelligence enhances managerial cognition, operational efficiency, and strategic decision-making while promoting organizational adaptability and environmental performance. Despite challenges such as fragmented data systems, skill gaps, cybersecurity risks, and regulatory uncertainty, artificial intelligence emerges as a critical enabler of intelligent, resilient, and sustainable transportation management.

4.1 Conceptual Model of Artificial Intelligence in Transportation Company Management

Based on the expanded integrative review, we introduce a four-layer conceptual model that captures how artificial intelligence transforms data into coordinated managerial action. The model aligns with both technological architectures and managerial workflows, ensuring applicability to real-world practice. We describe the model in Figure 1 below.

The four-layer conceptual model illustrates the organisational process through which artificial intelligence becomes embedded in transportation company management. Each layer represents a distinct yet interconnected domain of activity that collectively explains how data is transformed into managerial insight and operational action.

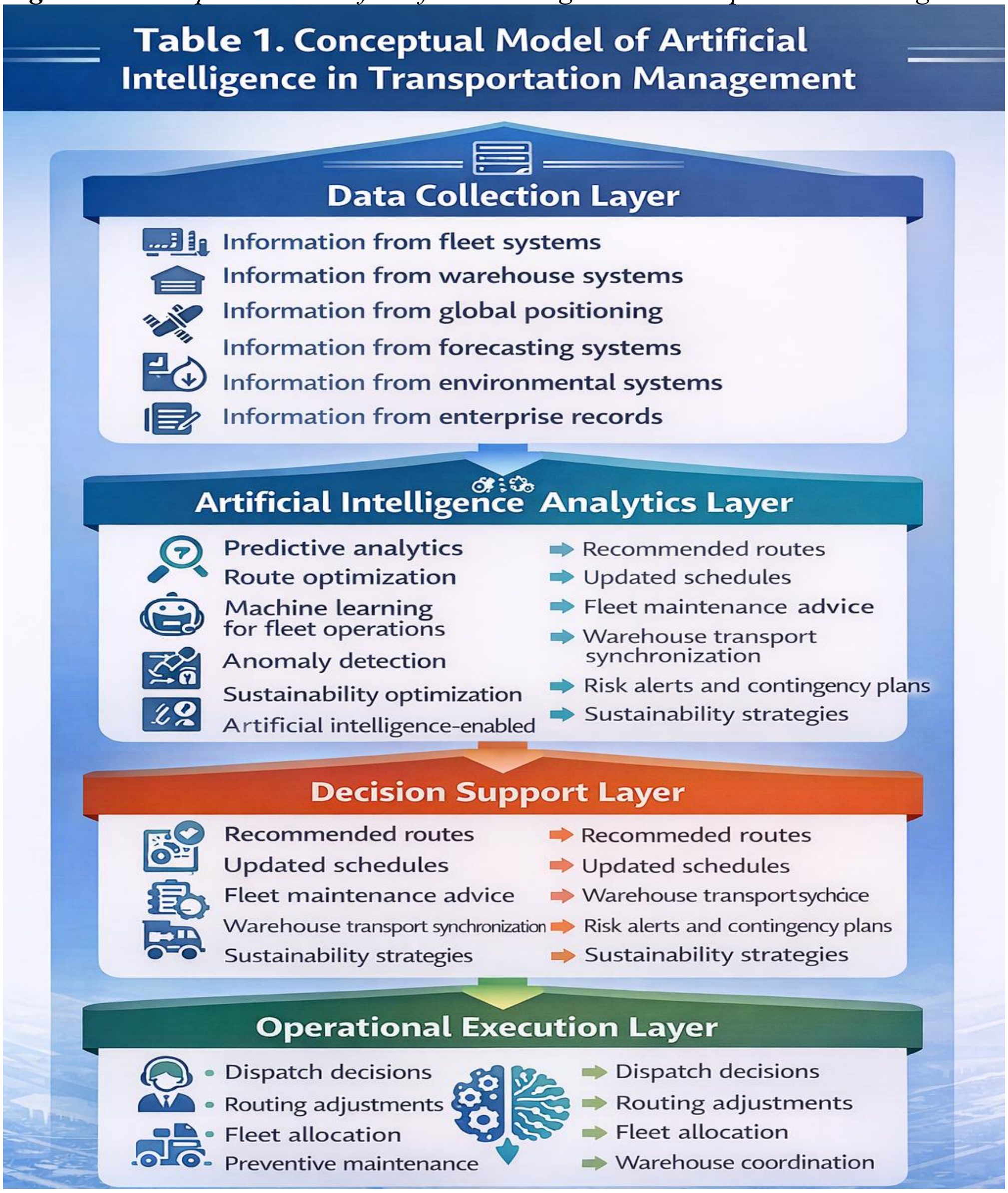
By describing these layers, the model addresses the research objective by demonstrating the pathways through which AI supports forecasting, routing, maintenance, risk management, and strategic decision-making within transportation firms.

4.2 Data Collection Layer

The first layer, the Data Collection Layer, forms the foundational infrastructure required for AI-enabled management. Transportation companies generate vast quantities of information from telematics systems, warehouse operations, navigation interfaces, environmental sensors, planning software, and diagnostic tools. This layer emphasises that AI adoption begins with the ability to capture and consolidate high-quality, high-frequency, and contextually rich data across organisational subsystems.

The integration of diverse data streams ensures that managers are not constrained by fragmented information, a limitation frequently highlighted in the existing literature. By structuring and harmonising data inputs, this layer directly supports the research objective by showing how transportation firms build the informational base necessary for AI-driven managerial practices.

Figure 1. *Conceptual Model of Artificial Intelligence in Transportation Management*



Source: *Model - own elaboration; Graphics – ChatGPT.*

4.3 Artificial Intelligence Analytics Layer

The second layer, the Artificial Intelligence Analytics Layer, explains how computational techniques transform raw operational data into meaningful analyses that improve managerial reasoning. Within this layer, algorithms for predictive analytics, route optimisation, machine learning, and anomaly detection process the collected data to reveal patterns, forecast disruptions, and identify operational inefficiencies. The inclusion of sustainability optimisation and risk modelling illustrates that AI extends beyond efficiency to address broader strategic priorities, such as environmental performance and organisational resilience.

This layer addresses the research objective by demonstrating how firms utilise AI to enhance forecasting accuracy, routing efficiency, and maintenance planning, thereby supporting more informed and proactive management processes.

4.4 Decision Support Layer

The third layer, the Decision Support Layer, highlights how analytical outputs are translated into managerial recommendations that guide organisational action. At this point in the model, AI-generated insights are synthesised into practical decision aids, such as updated schedules, maintenance advisories, optimal routing proposals, warehouse coordination suggestions, and risk alerts.

These outputs help managers evaluate alternatives, anticipate operational consequences, and coordinate decisions across departments. By outlining how AI improves managerial cognition, reduces uncertainty, and supports scenario-based reasoning, this layer directly responds to the research objective's focus on understanding how decision-making routines evolve with the integration of AI systems.

4.5 Operational Execution Layer

The fourth and final layer, the Operational Execution Layer, illustrates how AI-informed decisions are enacted in practice. Once managers interpret the decision-support outputs, transportation companies implement concrete actions such as dispatching vehicles, adjusting routes, allocating fleet resources, conducting preventive maintenance or coordinating warehouse flows.

This layer demonstrates the tangible organisational impact of AI, showing how digital intelligence is converted into real-world operational adjustments that shape performance outcomes. It also completes the feedback loop, as executed actions generate new data that feeds the system, allowing AI models to become more accurate and adaptive over time. This cyclical relationship between decision and execution is central to answering the research objective because it clarifies how AI ultimately enhances efficiency, safety, sustainability, and resilience within transportation organisations.

Together, these layers demonstrate that AI adoption in transportation management is not a single technological action but a systemic organisational process. By linking data collection, analytical modelling, decision support, and operational execution into a coherent structure, the model provides a comprehensive explanation of how transportation companies institutionalise AI within managerial systems. It therefore directly addresses the research objective by offering a structured, theoretically grounded understanding of the mechanisms through which AI contributes to improved planning, operations, and strategic capability in the transportation sector.

Furthermore**,** this integrative review demonstrates that artificial intelligence (AI) is reshaping the strategic, operational, and organisational dynamics of transportation firms. The evidence indicates that AI's value lies not only in task automation but in its capacity to enhance managerial intelligence and enable data-driven reasoning in complex decision environments.

As Davenport and Ronanki (2018) argue, AI augments managerial cognition by generating timely insights, forecasts, and scenario analyses, reducing reliance on intuition and strengthening anticipatory decision-making, an increasingly vital capability in turbulent transport markets. Studies such as Chae (2019) reinforce this view by showing how data-centric decision processes improve responsiveness and strategic coherence. General aspects of the considerations regarding changes in logistics processes caused by the implementation of automation and AI in transport are described by Zakrzewski and Szopik-Depczyńska (2022).

Operationally, AI enhances efficiency through predictive analytics, dynamic optimisation, and adaptive control systems. This review confirms the effectiveness of these models in improving routing, scheduling, and fleet utilisation, consistent with findings by Li and Li (2022). Such capabilities reduce delays, minimise fuel consumption, and improve asset productivity, thereby strengthening service reliability and economic performance.

At the same time, AI contributes to sustainability objectives by supporting low-carbon logistics strategies, optimising energy use, and improving the operational viability of electric fleets (United Nations, 2021; Wen *et al.,* 2021). These developments align transportation organisations with emerging environmental standards while promoting long-term ecological resilience.

The review further emphasises that AI adoption triggers broader organisational transformation. As Waller and Fawcett (2013) note, data-driven operations demand new structures, competencies, and patterns of coordination, reshaping how information flows and decisions are distributed across the organisation. AI, therefore, functions as both a technological innovation and a catalyst for strategic renewal.

The conceptual model developed here illustrates this dynamic: data, analytics, decision processes, and operational execution form an interdependent system that continuously evolves as learning accumulates, consistent with Zhang et al. (2020). Through this lens, AI becomes an organisational capability rather than a discrete tool.

Nonetheless, transportation organisations continue to face challenges, including fragmented data systems, skills shortages, cybersecurity vulnerabilities, regulatory uncertainty, and ethical questions around algorithmic transparency. Addressing these barriers is essential to fully realise AI's strategic potential. At the same time, the literature highlights promising directions for further investigation, such as multimodal AI optimisation, AI-enabled digital twins, and governance frameworks that enhance fairness and accountability.

Overall, the findings suggest that AI is driving a substantive shift toward more intelligent, integrated, and sustainable transportation systems. By enhancing managerial insight, operational precision, environmental performance, and organisational adaptability, AI is emerging as a foundational capability for the future competitiveness and resilience of transportation organisations.

5. Conclusion

This study set out to examine the multifaceted role of artificial intelligence in the management of transportation companies and to synthesize existing knowledge into a cohesive conceptual framework. The integrative review demonstrates that AI is not merely an operational add-on but a transformative managerial capability that reshapes how transportation firms plan, analyse, decide, and execute their activities.

By consolidating the literature across intelligent transportation systems, fleet management, routing optimisation, decision-support technologies, and sustainability-driven logistics, the analysis reveals a consistent trajectory: AI strengthens the cognitive, operational, and strategic foundations on which transportation organisations compete.

The four-layer conceptual model developed in this article, comprising data collection, AI-driven analytics, decision-support functions, and operational execution, provides a structured understanding of how AI-generated intelligence moves through an organisation and ultimately informs managerial action.

This model advances existing scholarship by linking technical mechanisms to managerial processes, thereby addressing a persistent gap in the literature, which often isolates algorithmic performance from organisational realities. It emphasises that AI's value emerges not solely from predictive accuracy or optimisation efficiency, but also from its integration into decision routines, coordination mechanisms, and organisational learning systems.

The review further highlights that AI significantly enhances operational efficiency through improved routing, predictive maintenance, and real-time fleet optimisation, while simultaneously supporting strategic adaptation by enabling scenario modelling and risk-aware decision making. Significantly, AI contributes to environmental sustainability by reducing emissions, optimising energy use, and facilitating evidence-based climate strategies, imperatives that are increasingly central to regulatory compliance and corporate responsibility.

These findings demonstrate that AI strengthens not only economic performance but also ecological and organisational resilience, aligning transportation firms with the broader transition toward intelligent and sustainable mobility systems.

Despite these benefits, the study underscores persistent challenges that warrant further scholarly and managerial attention, including fragmented data infrastructures, limited organisational readiness, skill deficits, ethical risks, and uneven adoption across global regions and firm sizes.

Addressing these constraints is essential for realising AI's full transformative potential. Future research would benefit from empirical examinations of organisational adoption pathways, governance frameworks for responsible AI use, comparative analyses across transport modes, and studies in emerging-market contexts where digital maturity and institutional conditions differ substantially from technologically advanced economies.

In conclusion, AI is poised to redefine the competitive logic of transportation management by enhancing visibility, responsiveness, resilience, and sustainability. The conceptual model introduced here provides a foundation for understanding these dynamics and offers a roadmap for both researchers and practitioners seeking to implement AI in ways that reinforce strategic coherence and operational excellence.

As transportation systems become increasingly data-intensive and interconnected, the integration of AI into managerial practice will be central not only to organisational performance but to the broader evolution of intelligent, sustainable, and adaptive mobility ecosystems.

References:

Abduljabbar, R., Dia, H., Liyanage, S., Bagloee, S.A. 2019. Applications of artificial intelligence in transport. Sustainability, 11(189).

Adeyemi, O., et al. 2024. AI-Driven Predictive Analytics to Enhance Freight Demand Forecasting Accuracy. World Journal of Innovation and Modern Technology.

Agarwal, R., Dhar, V. 2014. Editorial: Big data, data science, and analytics. Information Systems Research, 25(3), pp. 443-448.

Amini, S., Tavana, M., Gholami, R. 2023. Machine learning approaches for transport optimization. Expert Systems with Applications, 219, 119658.

Baryannis, G., Dani, S., Antoniou, G. 2019. Predictive analytics and artificial intelligence in supply chain management. Computers and Industrial Engineering, 137, pp. 106024.

Carvalho, T.P., Soares, F.A.A.M.N., Vita, R., Francisco, R.D., Basto, J.P., Alcalá, S.G. 2019. A systematic literature review of machine learning methods applied to predictive maintenance. Computers and Industrial Engineering, 137, 106024.

Chae, B. 2019. A framework for artificial intelligence in supply chain management. Journal of Business Logistics, 40(2), pp. 120-137.

Chatzidimitriou, X., Zissis, D. 2023. AI-based Predictive Maintenance in the Maritime Sector. Journal Applied Sciences, vol. 14, issue 20.

Chen, C., Demir, E., Huang, Y., Scholts, S. 2022. Big data and AI in sustainable transportation systems. Transportation Research Part E, 159.

Davenport, T.H., Ronanki, R. 2018. Artificial intelligence for the real world. Harvard Business Review, January-February.

Dia, H., Rose, G. 1997. Development and evaluation of neural network freeway incident detection models. Transportation Research Part C: Emerging Technologies, 5(5), pp. 313-331.

Díaz and López. 2023. Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation. November, 101896. Information Fusion.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Fosso Wamba, S. 2020. Big data analytics and artificial intelligence pathway to operational performance. Production Planning and Control, 31(2-3).

Gen, M., Cheng, R. 2020. Evolutionary algorithms and optimization in transportation systems. Springer.

Grigorescu, S., et al. 2020. Deep Learning Perception Systems in Aviation for Hazard Detection and Operational Safety. Computer Science, Machine Learning.

Hernandez, G. 2024. Telematics and AI in modern fleet management. Journal of Intelligent Mobility, 6(1), pp. 44-59.

Ivanov, D. 2020. Predictive and prescriptive analytics for supply chain resilience. International Journal of Production Research, 58(10), pp. 3535-3548.

Jevinger, Z. 2023. Artificial intelligence for improving public transport: a mapping study.

Khaja, 2025. Artificial intelligence-powered advancements in atrial fibrillation diagnostics: a systematic review. The Egyptian Heart Journal.

Li, Z., Li, X. 2022. Reinforcement learning approaches for real time routing optimization. Transportation Research Part C, 138.

Lv, Y., Duan, Y., Kang, W., Li, Z., Wang, F. 2015. Traffic flow prediction with big data: A deep learning approach. IEEE Transactions on Intelligent Transportation Systems, 16(2), pp. 865-873.

Nozari, H., Rahmaty, M., Foukolaei, P.Z., Movahed, H., Bayanati, M. 2025. Optimizing Cold Chain Logistics with Artificial Intelligence of Things (AIoT): A Model for Reducing Operational and Transportation Costs. Future Transportation. 5(1). DOI:10.3390/futuretransp5010001.

Pillac, V., Guéret, C., Medaglia, A.L. 2013. A review of dynamic vehicle routing problems. European Journal of Operational Research, 225(1), pp. 1-11.

Puthenkarayil, K., Singh, R., Kumar, V. 2024. AI driven anomaly detection for heavy vehicle fleets. International Journal of Transportation Science and Technology, 13(2).

Snyder, H. 2019. Literature review as a research methodology. Journal of Business Research, 104, pp. 333-339.

Štencl, M., Lendel, V. 2012. Application of Selected Artificial Intelligence Methods in Terms of Transport and Intelligent Transport Systems. Periodica Polytechnica Transportation Engineering. 40(1), 11-16. DOI:10.3311/pp.tr.2012-1.02.

United Nations. 2021. Sustainable Transport Report. New York: UN Publications.

Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C. 2014. Short term traffic forecasting. Transportation Research Part C, 43, pp. 3-19.

Waller, M.A., Fawcett, S.E. 2013. Data science, predictive analytics, and big data. Journal of Business Logistics, 34(2), pp. 77-84.

Wen, J., et al. 2021. Artificial intelligence for sustainable transport systems. Sustainable Cities and Society, 74.

Wright, H. 2025. Artificial intelligence and competition policy. International Journal of Industrial Organization.

Yang, K., Wong, C., Chan, S. 2021. AI based routing for sustainable logistics. Transportation Research Part D, 93.

Zakrzewski, B., Szopik-Depczyńska, K. 2022. Changes in Logistics Processes Caused by the Implementation of Automation in Transport. European Research Studies Journal, XXV, 24-34. DOI:10.35808/ersj/2933.

Zhang, Y., Wang, L., Zheng, Y. 2020. Deep learning for intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems, 21(1), pp. 11-26.