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A Systematic Review of Artificial Intelligence in Transportation Systems: Methods, Applications, and Transport–Energy Integration for Sustainable Mobility

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ABSTRACT

Artificial Intelligence (AI) is transforming the transportation systems with autonomous, efficient, and sustainable mobility. The swift transformation of it into a data-driven intelligence rather than a rule-based one has opened new possibilities of interconnecting transportation systems with electrical power networks. This study is a systematic review of AI applications in autonomous and sustainable transportation systems. The major academic databases, such as Scopus, IEEE Xplore, Web of Science, ScienceDirect, and SpringerLink, were searched to retrieve literature that was published in 2015-2025. Peer-reviewed journal and conference papers were screened using a structured screening process, which led to the selection of 35 studies to be included in qualitative synthesis. The review framework was based on thematic analysis in the fields of evolution, applications, methodologies, and energy integration. Results indicate that machine learning and deep learning are the most prevalent in the current transportation AI studies, especially in traffic prediction, autonomous navigation, and infrastructure monitoring. The most developed application areas are traffic management and autonomous vehicle systems, and energy-aware mobility, especially electric vehicle charging optimisation and vehicle-to-grid coordination, is developing quickly but is less advanced. Major obstacles are the data quality constraints, the challenges of model interpretability, the constraints of infrastructure, cybersecurity threats, and disjointed regulatory frameworks, particularly in developing areas. The review confirms the evident shift towards combined transportation-energy intelligence, where AI can facilitate coordinated mobility and power system optimisation. The future directions are federated learning, digital twin systems, explainable AI, and multi-modal intelligent transport systems, which facilitate scalable and sustainable mobility development.

1. INTRODUCTION

The transport industry is undergoing a radical change, with the rapid adoption of Artificial Intelligence (AI) in autonomous and sustainable mobility systems. Transportation systems traditionally based on human decision-making and deterministic control systems are becoming more intelligent, data-driven, and adaptive ecosystems aimed at optimizing efficiency, safety, and environmental performance [1][2]. This change is not just a technological upgrade but a structural shift toward predictive, responsive, and interconnected mobility systems that can respond to the increasing complexity of urban transportation and support low-carbon development objectives [3]-[5]. The history of AI in transportation dates to the 1980s and 1990s, when rule-based and expert systems were developed to aid traffic signal control, route planning, and operational decision-making [6]. Early AI uses in transportation relied on rule-based systems that encoded expert knowledge into

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predetermined decision logic. Although successful in more formal settings, these methods could not cope with the uncertainty and dynamism of real-world traffic systems and were thus limited in scalability and adaptability [7]. To overcome these limitations, fuzzy logic and heuristic optimization techniques were proposed, allowing more adaptive reasoning in the presence of uncertainties and enhancing responsiveness in traffic control and routing issues [8]. Simultaneously, multi-objective transport optimization models were developed to support intermodal planning and system-wide efficiency as part of a broader shift toward integrated mobility management [9]. These advancements were also expanded through intelligent transport system models that integrated optimization methods and urban mobility planning to improve operational efficiency and economic performance [10]. Later developments in heuristic and fuzzy-based traffic flow modeling enhanced adaptive control further, especially in complicated and uncertain traffic scenarios [11]. These pioneering advancements are still essential in the context of the path to modern AI-based mobility. In current transport systems, AI methods have been applied in a broad spectrum of applications, such as traffic control, self-driving and connected cars, smart infrastructure, and safety optimization [12]-[15]. Traffic prediction and congestion control: Machine learning models, including support vector machines, random forests, and gradient boosting, are popular in this domain, whereas deep learning models, including convolutional and recurrent neural networks, allow more sophisticated perception in autonomous vehicles, including lane detection, obstacle recognition, and adaptive navigation [16]-[20]. Hybrid systems, which combine neural networks and fuzzy logic, also increase system robustness and understandability, especially in safety-critical systems [21].

Recent works also show the increasing complexity of intelligent traffic control systems. For example, Iyobhebhe et al. [22] note that adaptive and energy-efficient communication protocols in wireless sensor networks are important and form the basis of real-time data acquisition in intelligent transport systems. Similarly, Obari [23] proposes a dynamic congestion pricing model that uses fuzzy logic to combine traffic density and emissions, showing improved fairness and efficiency. These contributions support the importance of AI-based optimization in ensuring operational efficiency and environmental sustainability. Beyond operational benefits, the electrification of transport has introduced energy-aware mobility, with AI as a key element for optimizing energy use, controlling electric-vehicle charging, and coordinating with power systems [24]-[27]. AI-based predictive energy management models can predict EV demand and match transportation loads to grid conditions, minimizing peak demand and emissions. Moreover, optimization algorithms such as reinforcement learning and metaheuristics enable the integration of transportation and electrical systems [28]-[30], strengthening the dual purpose of AI mobility and sustainability. Spatial and infrastructural dynamics are also important factors of transportation efficiency at a bigger systems level. Ndzie Bitundu et al. [31] study port systems through spatial interaction and Bayesian modeling and point out inefficiencies in connectivity and infrastructure planning. This aligns with AI-powered transportation systems, where system-wide optimization is needed.

In developed economies like Europe, North America, and parts of Asia, AI-based transportation systems have been implemented at scale and shown to reduce congestion and increase efficiency [32]. Nevertheless, uptake in developing countries remains limited due to infrastructural constraints, regulatory fragmentation, and data issues [33]-[35]. These limitations are further exacerbated by ongoing energy supply challenges and infrastructural constraints in Nigeria and other African regions, especially in Nigeria, where energy reliability is a major impediment to technology-based mobility systems [36]. However, integrating with electrical power networks is becoming more important, with electrified mobility coordinated with grid stability, renewable energy integration, and smart charging. AI-based vehicle-to-grid systems, along with predictive energy management and intelligent routing schemes, can facilitate optimized charging behavior, minimized peak demand, and enhanced infrastructure resilience [37]-[39]. AI-based vehicle-to-grid coordination can optimize charging patterns and improve infrastructure resilience. Although these opportunities exist, challenges remain, including data quality issues, model interpretability, cybersecurity risks, and infrastructure preparedness. New research directions such as federated learning, explainable AI, and digital twin technologies offer avenues for a more transparent and scalable system [40][41]. Figure 1 provides a system overview of AI adoption in transportation, with North America and Europe as the most adopted, Asia-Pacific rapidly increasing, and Africa undergoing a new wave of digital transformation.

This study advances the existing literature by providing a distinct, integrated view of Artificial Intelligence in transportation systems. First, it adopts a transport-energy integrated review lens that explicitly connects AI-based mobility to electrical power systems, especially for electric vehicles and smart grid coordination. Second, it builds a systematic taxonomy, which links AI methods with transportation uses and energy-aware mobility capabilities, providing a single classification system. Third, the paper offers a focused discussion of deployment issues in developing countries, specifically infrastructural, regulatory, and energy-related limitations in the African context. Lastly, it suggests a multi-layered conceptual model that logically connects data collection, AI processing, transportation applications, and system-level results. Collectively, these contributions elevate the paper beyond a descriptive review by providing a logical analytical framework for developing sustainable and intelligent transportation systems.

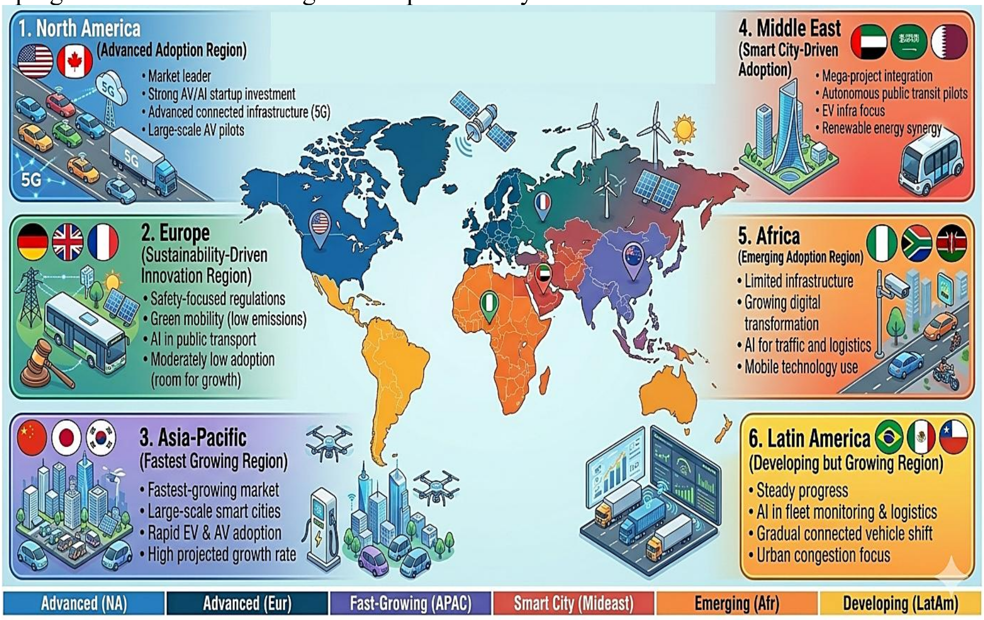

Figure 1. System Overview of AI in Autonomous and Sustainable Transportation

The remainder of this paper is organized as follows. Section 2 outlines the methodology used in the systematic review, including the search strategy, selection criteria, and analytical framework. Section 3 gives the results and discussion, which summarizes the development, uses, methodologies, and issues of AI in transportation systems. Lastly, Section 4 concludes the paper by summarizing the main findings and outlining future research directions.

2. METHOD

This study adopts a systematic review methodology to provide a structured, transparent, and reproducible synthesis of the literature on Artificial Intelligence (AI) in autonomous and sustainable transportation systems. The methodological approach is designed to ensure rigor in the identification, selection, and analysis of relevant studies, while capturing the interdisciplinary convergence between transportation systems and electrical power networks.

2.1 Research Design and Review Objectives

A systematic and evidence-based framework guides the review in order to answer the following research questions:

1. What has been the development of Artificial Intelligence in transportation systems over the years?
2. What are the current state-of-the-art applications of AI in autonomous and sustainable mobility?
3. What are the challenges and gaps in research, especially with regard to energy-aware transportation systems?

The areas of interest covered by the review are major areas such as traffic management, autonomous and connected vehicles, intelligent infrastructure, safety optimisation, and AI-enabled energy systems, and how they are integrated with smart grid technologies.

2.2 Data Sources and Search Strategy

The literature search involved a thorough search of various academic databases to ensure that peer-reviewed studies were sufficiently covered. The major databases to be used were:

- Scopus
- Web of Science
- IEEE Xplore
- ScienceDirect
- SpringerLink

The search was limited to English-language articles published between 2015 and 2025 to capture the latest developments while also including a small number of foundational studies that provide historical context.

The search queries were built using Boolean operators to combine the main thematic terms related to AI, transport, and energy systems. The main search term used in databases was:
(Artificial Intelligence OR Machine Learning OR Deep Learning)
AND (Transportation Systems OR Autonomous Vehicles OR Intelligent Transport Systems)
AND (Sustainability OR Energy Management OR Electric Vehicles OR Smart Grid)
The search was done iteratively, and the keywords were narrowed to enhance relevance and coverage. The database search took place from January 2025 to March 2025.

2.3 Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria were used to ensure the content was relevant and high quality. Both high-quality conference papers and peer-reviewed journal articles were included because AI research is rapidly changing. The criteria are as follows:

Inclusion Criteria:
- Peer-reviewed journal articles and conference papers.
- Research on AI applications to transportation systems.
- Studies on autonomous mobility, traffic control, infrastructure control, or energy control.
- Articles that are not older than the specified time frame (20152025)

Exclusion Criteria:
- Opinion papers, non-peer-reviewed articles, and editorials.
- Research that is not directly connected with transportation or energy-aware mobility.
- Records in multiple databases.
- Articles that are not adequately detailed in terms of methodology or technicality.

2.4 Study Selection Process

To ensure transparency, reproducibility, and methodological rigor, the study selection process followed a multi-stage screening process in line with PRISMA guidelines. The selected academic databases were first searched to retrieve 162 records. After removing duplicates, 138 distinct records remained for screening. Title screening was applied to remove records clearly outside the research scope, and 92 records were retained for further evaluation. They were then screened abstractively to assess thematic relevance to artificial intelligence use in transportation systems, narrowing down the dataset to 58 studies. Next, a full-text eligibility review was conducted to ensure methodological and contextual fit with the inclusion criteria. This final step identified 35 studies, which were used to conduct a thorough qualitative synthesis and thematic analysis in this review. This systematic process ensures a transparent, replicable, and bias-reduced selection of literature, as shown in Figure 2.

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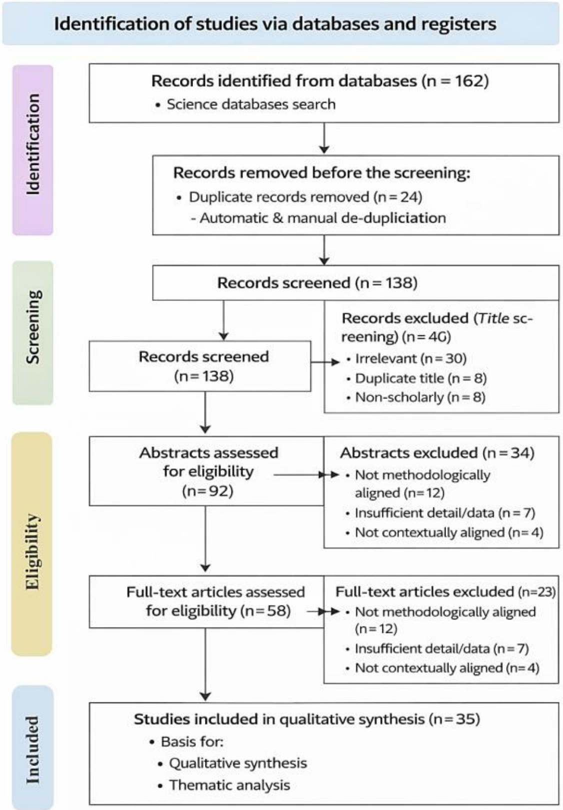

Figure 2. A diagram illustrating the identification, screening, and inclusion of relevant studies.

2.5 Quality Assessment of Studies

A qualitative evaluation of the chosen studies was made to increase the credibility of the review according to the following criteria:

- Transparency of research purposes.
- Suitability of AI methodologies employed.
- Quality of data and relevance of the datasets.
- Validation and evaluation techniques
- Donation to transportation and/or energy systems.

A qualitative scoring system (Low, Medium, High) was used to assess each study according to the established criteria. Only studies rated as medium to high quality were retained for final synthesis.

Table 1. Quality Assessment of Selected Studies

Study	Clarity of Objectives	AI Method Appropriateness	Data Quality & Relevance	Validation Technique	Transport-Energy Relevance	Overall Quality Rating
[1]	High	High	High	Strong	Medium	High
[7]	High	High	Medium	Moderate	Medium	High
[8]	High	High	High	Strong	Medium	High
[11]	High	High	High	Strong	High	High
[15]	High	High	Medium	Strong	Medium	High
[19]	High	High	High	Strong	High	High
[24]	High	High	High	Strong	High	High
[25]	High	High	High	Strong	High	High
[26]	High	High	High	Strong	High	High
[27]	High	High	Medium	Strong	Medium	High
[40]	High	Medium	Medium	Moderate	Medium	Medium
[42]	High	High	High	Strong	Medium	High

Table 1 shows a representative sample of 12 best-quality studies used to illustrate the quality assessment framework. Nevertheless, all 35 studies were critically analyzed using the same criteria, such as clarity of objectives, methodological suitability, data quality, strength of validation, and transport-energy applicability. This guarantees uniformity and openness in the appraisal process. The selected works are high-impact and methodologically sound in major thematic areas, such as traffic intelligence, autonomous systems, and energy-aware mobility integration.

2.6 Data Extraction and Synthesis Approach

It used a systematic data extraction system to provide uniformity in all the chosen studies. The main characteristics that were noted include:

- Study objectives
- AI techniques applied
- Application domain (e.g., traffic management, autonomous vehicles, energy systems)
- Key findings
- Identified limitations

A thematic analysis method was applied to extract and synthesize data, allowing identification of recurring patterns, methodological trends, and research gaps. The synthesis is structured around three dimensions:

- Development of AI in transport systems.
- Existing applications and approaches.
- Challenges, limitations, and future research directions.

Moreover, special attention is given to the combination of AI and electrical power systems, which is associated with the increasing significance of energy-aware transportation. The synthesis also includes a comparative and critical analysis of the studies, focusing on methodological trends, performance measures, and domain-specific constraints.

2.7 Analytical Framework

The review is guided by a multi-layered analytical framework that links:

- Data acquisition (sensors, vehicles, infrastructure, and energy systems)
- AI processing techniques (machine learning, deep learning, hybrid models)
- Application domains (transportation operations and energy management)
- System-level outcomes (efficiency, safety, and sustainability)

This framework supports the development of a taxonomy of AI techniques and informs the conceptual model presented in the subsequent section.

3. RESULTS AND DISCUSSION

3.1 Study Selection Results

The systematic review procedure found 162 records in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. After eliminating duplicates, 138 records were filtered based on relevance in the title and abstract. This step filtered out studies not aligned with artificial intelligence use in transportation systems, leaving 92 studies. The dataset was further narrowed through full-text eligibility assessment to 58 studies, and 35 studies were ultimately included in the synthesis process because they satisfied all inclusion criteria. The chosen papers cover the major areas such as traffic management, autonomous and connected vehicles, intelligent infrastructure, safety systems, and energy-aware mobility. Machine learning and deep learning methods predominate in AI use in transportation across the dataset, indicating a transition to data-driven and predictive mobility systems [1][15]. Another emerging body of research is concerned with the interconnection between transportation systems and electrical power systems, especially in the optimization of electric vehicle charging, vehicle-to-grid systems, and smart grid coordination [24][26]. This attests to a new convergence between mobility systems and energy infrastructure.

3.1.1 Quality Assessment of Included Studies

The quality of the chosen studies' methodologies was evaluated based on criteria including the clarity of objectives, the appropriateness of AI methods, data quality, the strength of validation, and relevance to transport and energy. Overall, most studies were high quality, indicating strong methodological design and validation procedures aligned with best practices in systematic reviews in the AI transportation literature. Nevertheless, fewer studies were considered medium quality because of constraints in dataset completeness and validation depth. These constraints are largely linked to limited data availability or the use of simulations for evaluation rather than real-world implementation. Overall transport energy integration in the reviewed studies was moderate, suggesting that this field is still in its infancy compared with fundamental transportation AI applications. Although electric mobility and energy-aware optimization are increasingly researched topics, full integration with power systems remains a research frontier. In general, the final dataset provides a valid and methodologically consistent basis for synthesis and interpretation, enabling strong cross-thematic analysis of AI applications in transportation systems, as shown in Table 2.

Table 2: PRISMA-Based Synthesis of Selected High-Quality Studies in AI for Transportation Systems

S/No.	Study	Thematic Area	AI Methods / Focus	Transport Domain	Key Contribution	Quality Rating
1	[1]	Foundational AI in Smart Mobility	ML, DL overview, mobility systems	Smart mobility systems	Comprehensive synthesis of AI roles in transport evolution	High
2	[15]	Autonomous Transport Systems	Autonomous systems, AI frameworks	Autonomous transport	Development trends and enabling technologies for autonomy	High
3	[7]	Traffic Control Systems	Adaptive signal control, ML	Urban traffic management	AI-based adaptive traffic signal optimization	High
4	[8]	Real-time Traffic Optimization	Reinforcement learning, optimization	Traffic signal systems	Real-time traffic flow optimization strategies	High
5	[11]	Traffic Flow Modelling	Fuzzy logic, heuristic AI	Traffic flow control	Uncertainty handling in traffic modelling systems	High
6	[19]	Autonomous Vehicles & UAVs	Deep learning, perception systems	Connected autonomous mobility	AI-enabled perception and navigation in autonomous systems	High
7	[25]	EV Energy Management	AI-based optimization models	Electric vehicle systems	Intelligent EV energy management strategies	High
8	[27]	EV Routing Optimization	AI routing, optimization algorithms	EV transport systems	AI-driven route and charging optimization models	High
9	[26]	Grid–Vehicle Integration	Smart grids, EV coordination	Transport–energy systems	Integration of electric mobility with grid systems	High
10	[24]	EV Charging Optimization	Optimization, predictive AI	EV charging infrastructure	Optimal charging strategy for electric vehicles	High
11	[40]	Digital Twins & Cybersecurity	Digital twins, cybersecurity AI	Smart transport infrastructure	Secure and intelligent cyber-physical transport systems	Medium
12	[42]	Traffic Prediction Systems	Machine learning models	Traffic forecasting	ML-based predictive traffic modeling framework	High

3.2 Thematic Synthesis of AI in Transportation Systems

The development of artificial intelligence in transportation systems is clearly presented in five stages: rule-based systems, fuzzy logic and heuristic methods, machine learning, deep learning, and energy-aware intelligent systems. The initial rule-based systems relied on deterministic logic, which limited flexibility in dynamic and complex traffic environments. To overcome these shortcomings, fuzzy logic and heuristic optimization techniques have been proposed to improve uncertainty management and adaptive traffic control [10][21]. The advent of machine learning signaled a shift toward predictive and data-driven transportation systems [30]. Deep learning also advanced the field by enabling real-time perception and decision-making in autonomous vehicles. The latest trend is the convergence of transportation and energy systems, especially through optimization and control-based solutions [24][26].

3.3 Applications of AI in Transportation Systems

- Traffic Management and Prediction
  AI-powered traffic systems rely on real-time data from sensors and connected vehicles to optimize traffic flow and reduce congestion. Machine learning models prevail because they offer high predictive accuracy, while reinforcement learning is becoming popular for adaptive traffic signal control [7][43].
- Autonomous and Connected Vehicles
  Autonomous vehicle systems rely on deep learning to support perception, navigation, and decision-making. LiDAR, radar, and camera sensor fusion enhances environmental awareness and safety [18][19]. Although this has improved, decision-making in uncertain, complex urban settings remains a major challenge.
- Smart Infrastructure and Predictive Maintenance
  AI is also extensively used in infrastructure surveillance of roads, railways, and bridges, allowing to detect faults early and lower the costs of operation. Energy system integration also helps coordinate infrastructure use with electric vehicle charging demand [25][26].
- Safety and Risk Management
  Machine learning models predict accidents and assess risk using past data, driver behavior, and environmental factors [16][44]. These systems support preventive measures such as speed regulation and hazard warnings. Nonetheless, the generalisability is still poor because of the geographical, infrastructure, and data availability variations between regions.
- Energy-Aware and Sustainable Mobility

A fast-growing application area is energy optimization. AI assists with scheduling electric vehicle charging, predicting energy demand, and coordinating vehicle-to-grid. Reinforcement learning and optimisation algorithms minimise energy usage and enhance grid stability, but their implementation is limited in areas with poor infrastructure [24][26].

Figure 3 provides a structured overview of AI applications in transportation, combining traffic optimization, autonomous mobility, intelligent infrastructure, safety systems, and energy-aware solutions to improve operational efficiency, system stability, and long-term sustainability.

3.4 Taxonomy of AI Techniques in Transportation

The review singles out four key categories of AI methods applied to transportation systems:

- Machine learning algorithms are commonly used in predictive applications such as traffic and accident prediction.
- Deep learning methods support perception and real-time decision-making, especially in autonomous systems.
- Hybrid and ensemb1le techniques: Hybrid and ensemble techniques combine multiple models to enhance robustness and interpretability.
- Energy-aware AI models are concerned with energy consumption optimization and power system integration.

One major observation is that hybrid solutions are becoming increasingly popular because of the complexity and safety-critical nature of transportation systems. Figure 4 shows a taxonomy of AI methods in transport and energy, including simple machine learning methods, hybrid methods, energy-aware methods, and methods that bridge approaches like CNNs and ensemble learning with traffic management, autonomous vehicles, and grid-integrated electric systems.

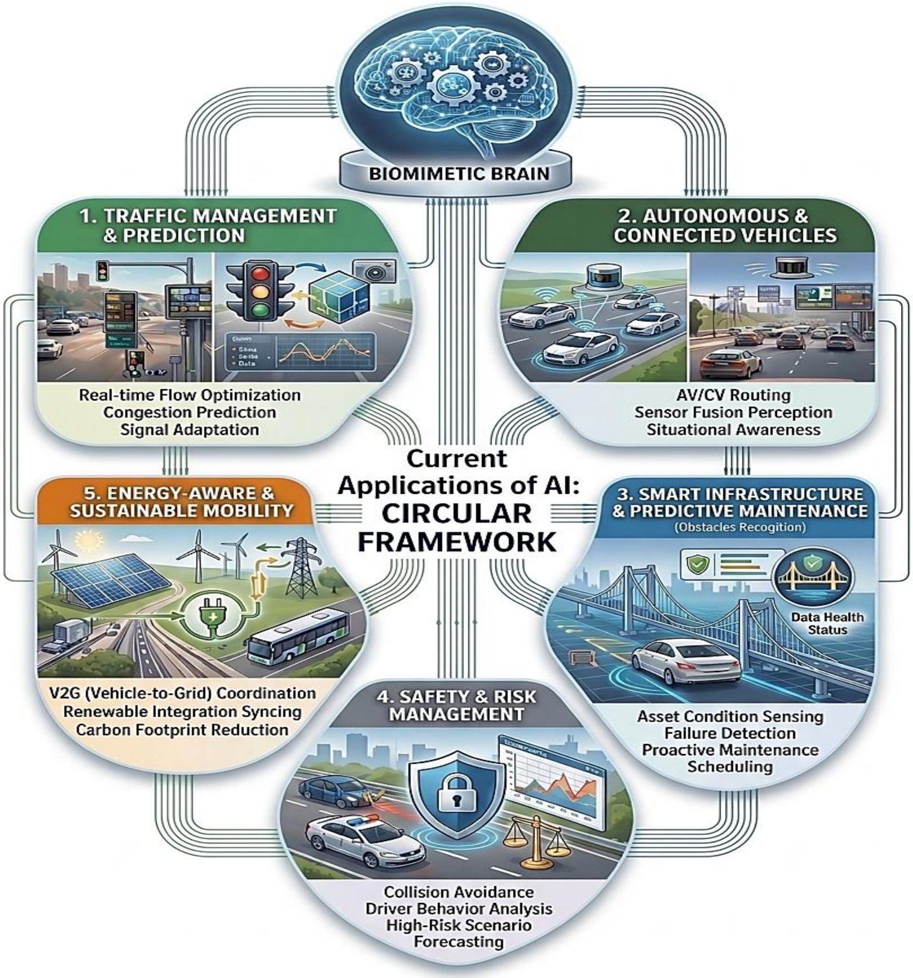

Figure 3. Current Applications of AI in Autonomous and Sustainable Transportation

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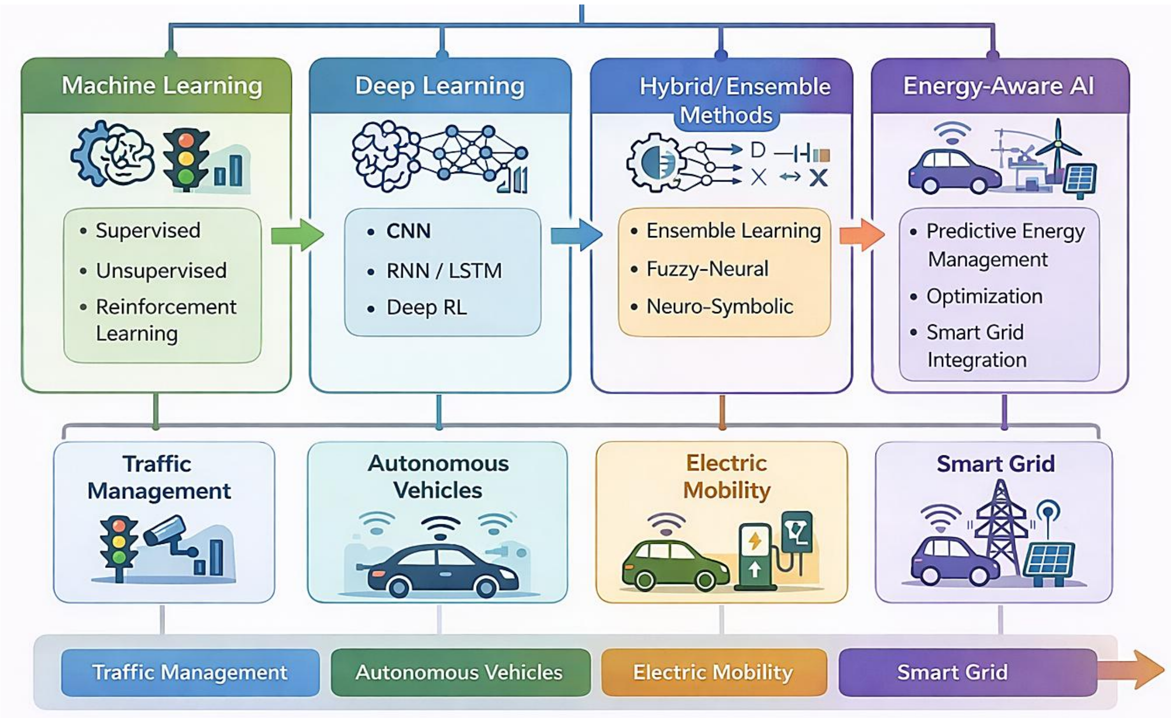

Figure 4. Taxonomy of AI Techniques in Transportation

Table 3: Taxonomy of AI Techniques and Their Applications in Transportation Systems [1][15][19][24][41][45].

AI Category	Core Techniques	Primary Transportation Applications	Functional Role in System	Maturity Level
Machine Learning	SVM, Random Forest, Gradient Boosting, k-Means	Traffic prediction, congestion forecasting, accident risk analysis	Prediction and classification of transportation patterns	High (widely deployed in studies and pilots)
Deep Learning	CNN, RNN, LSTM, DNN	Autonomous driving, object detection, traffic flow prediction	Perception, temporal modelling, decision support	High (core technology in autonomous systems)
Reinforcement Learning	Q-learning, Deep Q Networks, Actor-Critic models	Adaptive traffic signal control, route optimisation, EV charging control	Dynamic optimisation and real-time decision-making	Medium to High (rapidly growing adoption)
Hybrid AI Systems	Neuro-fuzzy systems, ensemble models, neuro-symbolic AI	Complex traffic environments, safety-critical systems, infrastructure management	Robust decision-making under uncertainty	Medium (emerging but increasingly relevant)
Energy-Aware AI Models	Predictive energy models, optimisation algorithms, V2G learning systems	EV charging optimisation, vehicle-to-grid integration, smart grid coordination	Energy efficiency and transport-energy integration	Emerging (fast-growing research frontier)
Edge and IoT-Driven AI	Lightweight ML models, federated learning, edge inference systems	Real-time traffic monitoring, smart infrastructure sensing, connected vehicles	Distributed intelligence and low-latency decision-making	Emerging to Medium (context dependent)

The taxonomy of applications in Table 3 goes beyond the traditional classifications by directly connecting AI techniques to energy-aware mobility functions and system-level transportation goals. It offers a more comprehensive view of the interaction between AI techniques in transportation and power systems by combining predictive, perceptual, optimization, and energy management in one framework. This cohesive view is especially useful in informing method choice in real-world, complex deployments where energy sustainability and operational efficiency are both paramount.

3.5 Conceptual Framework Synthesis

The synthesis of the reviewed studies helps develop a multi-layered conceptual framework, one of the unifying contributions of this review. The framework conceptualizes AI-based transportation systems as a networked ecosystem that incorporates data collection, intelligent processing, application areas, and system-level outcomes. Unlike traditional models, which consider transportation and energy systems separately, this framework explicitly includes electrical power systems to provide a holistic view of energy-aware mobility.

- The data layer comprises vehicle, sensor, infrastructure, and energy system inputs.
- The AI processing layer utilizes machine learning, deep learning, and hybrid models to derive insights and optimize decisions.
- The application layer consists of traffic management, autonomous vehicles, infrastructure monitoring, and energy systems.
- The outcome layer indicates improvements in efficiency, safety, and sustainability.

The main characteristic of this framework is the integration of electrical power systems, which enables the coordination and optimization of transportation and energy networks, especially in electric mobility systems. Figure 5 illustrates a multi-layered AI in a transportation system, where energy and sensing systems are supplied by intelligent processing layers that support applications such as fleet management, to produce sustainable output via an ongoing adaptive feedback loop.

3.6 Challenges and Limitations

Despite significant progress, implementing AI in the transportation system still faces important challenges, which are especially acute in developing countries. The literature review shows that infrastructural constraints, data constraints, regulatory fragmentation, and energy-system instability impede large-scale implementation. These are not just technical challenges but also socio-economic ones, and solutions must be context-sensitive and scalable to meet the needs of different operational settings. Data quality and availability are also significant limitations, especially in developing countries where sensor networks are scarce. Model interpretability is also a concern, particularly in deep learning systems deployed in safety-critical applications. Large-scale deployment is constrained by infrastructure constraints such as poor communication networks and a lack of computational power. The interconnectedness of systems is also putting transportation and energy systems at risk because of cybersecurity threats. Regulatory fragmentation and socio-economic.

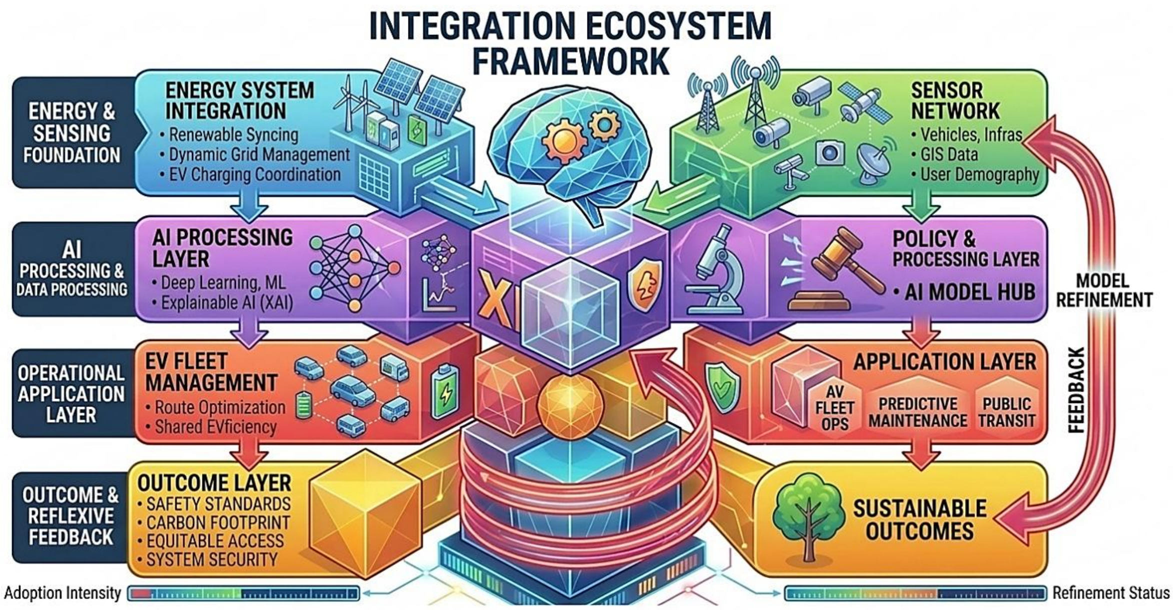

Figure 5. Integrated AI–transport–energy framework model

Table 4: Gap Analysis of AI in Transportation Systems

Thematic Area	Current Literature Focus	Key Limitation Identified	Research/Practical Implication
Traffic Management and Prediction	Machine learning and deep learning models for congestion prediction, adaptive signal control, and flow optimisation [7][16].	Limited transferability across cities due to differences in traffic patterns and data quality	Need for adaptive, location-aware models and transfer learning approaches for cross-city generalisation
Autonomous and Connected Vehicles	Deep learning-based perception systems using CNNs and sensor fusion (LiDAR, radar, cameras) for navigation and obstacle detection [18][19][46].	Weak robustness in complex urban environments and limited decision-making under uncertainty	Development of hybrid reasoning systems and explainable AI for safer autonomous navigation
Smart Infrastructure and Predictive Maintenance	AI-based structural health monitoring and predictive maintenance of roads, bridges, and rail systems [40][47][48]	Lack of standardised datasets and inconsistent infrastructure monitoring systems	Need for unified sensing frameworks and scalable infrastructure data platforms

Safety and Risk Management	Machine learning models for accident prediction, driver behaviour analysis, and risk forecasting [16][44]	Poor generalisability across regions and socio-economic contexts	Context-aware safety models and integration of local driving behaviour datasets
Energy-Aware Mobility and EV Systems	AI-driven EV charging optimisation, vehicle-to-grid coordination, and energy demand forecasting [24][25][26][49]	Weak integration with real-time grid constraints in developing regions	Stronger coupling of transport and power system models for grid-responsive mobility planning
Hybrid and Optimisation Models	Reinforcement learning, metaheuristics, fuzzy-neural systems for multi-objective optimisation [9][10][21][50].	High computational complexity and limited real-time deployment in low-resource environments	Development of lightweight optimisation models for edge and real-time applications
Data and System Integration	Multi-source data fusion from sensors, vehicles, and smart grids [34][36][45][51].	Data heterogeneity, incompleteness, and lack of interoperability standards	Establishment of unified data architectures and interoperable transport-energy data ecosystems

As Table 4 indicates, AI is extensively used in various fields of transportation, but major gaps remain. These include poor model generalisability, poor integration with real-world constraints, a lack of standardized datasets, and high computational requirements. The results highlight the importance of adaptive, context-sensitive, and lightweight AI systems, enhanced data integration models, and enhanced integration between transportation and energy systems.

3.7 Future Research Directions

Based on the gaps and limitations identified, the following research directions offer specific directions for developing AI-based, energy-aware transportation systems.

- Energy-aware AI systems: State-of-the-art models to optimize charging of electric vehicles, energy demand prediction, and grid integration.
- Federated learning methods: Privacy-aware distributed learning models that enable training of models without providing raw data.
- Digital twin technologies: Transport and energy system real-time optimisation simulation models.
- Multi-modal mobility systems: Public transport, autonomous vehicles, and shared mobility are combined into single AI-driven systems.
- Explainable AI models: Improving transparency, interpretability, and trust in AI decision-making processes, particularly in safety-critical applications.

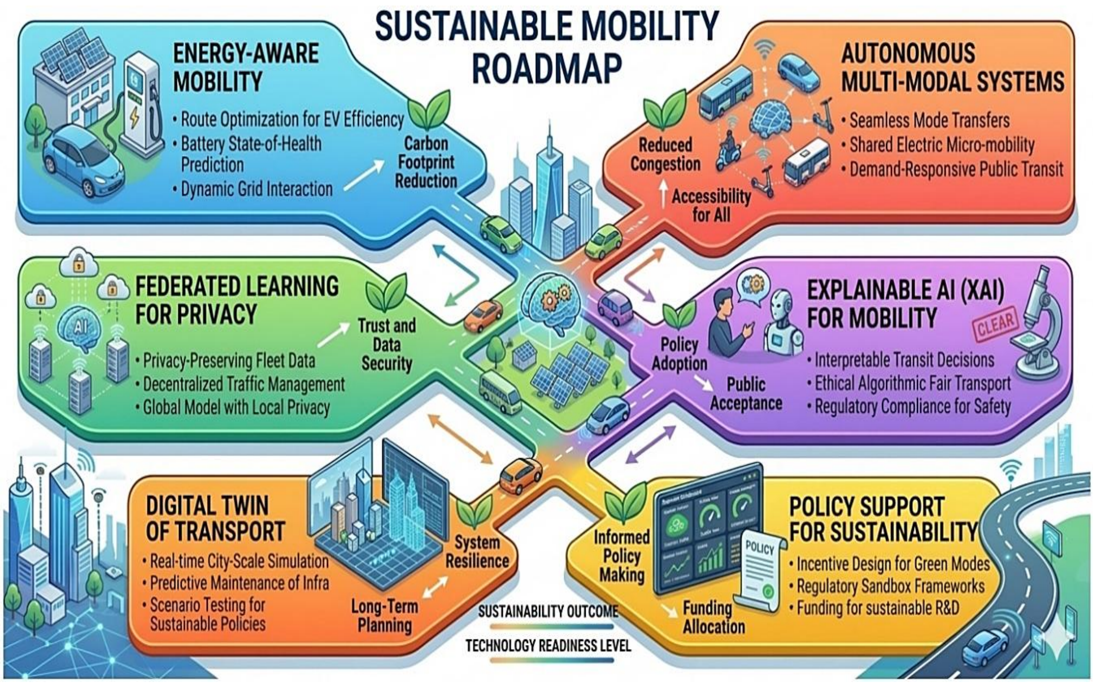

Figure 6. Research roadmap toward intelligent mobility systems

Figure 6 shows a prospective roadmap for AI in sustainable mobility, depicting the transformative directions that will define the future of transportation systems. It describes the key trends that incorporate federated learning to preserve data privacy, digital twins to enhance system resilience and real-time optimization, and explainable AI to enable easy policy adoption. Together, these innovations support the transition to a seamless, ethical, and carbon-neutral transportation ecosystem.

Table 5: Challenges Versus Future Research Solutions in AI-Driven Transportation Systems [1][26][52][53].

Challenge Area	Observed Limitation in Literature	Future Research Direction / Solution	Expected Implication
Data quality and availability	Many studies rely on incomplete, noisy, or region-specific datasets, limiting generalisability	Development of standardised datasets, data augmentation techniques, and cross-regional data sharing frameworks	Improved model robustness, transferability, and reproducibility across regions
Model interpretability	Deep learning and hybrid models operate as black-box systems with limited explainability	Integration of explainable AI (XAI) techniques and interpretable hybrid architectures	Increased trust, regulatory acceptance, and deployment in safety-critical systems
Infrastructure limitations	Limited sensing, connectivity, and computational infrastructure, especially in developing regions	Edge computing, lightweight AI models, and scalable IoT-based transport sensing systems	Broader deployment in low-resource environments and real-time decision support
Cybersecurity risks	Increased connectivity exposes systems to cyberattacks and data manipulation	AI-driven intrusion detection systems and blockchain-enabled secure communication	Enhanced system resilience, data integrity, and operational safety
Regulatory fragmentation	Lack of harmonised policies for autonomous systems and AI-enabled mobility	Development of international standards and adaptive regulatory frameworks	Faster adoption and safer deployment of autonomous transport systems
Energy system integration complexity	Weak coordination between transport systems and power grids	AI-enabled vehicle-to-grid optimisation and integrated smart grid frameworks	Improved energy efficiency and grid stability
Multi-modal integration gaps	Fragmented research across transport modes (road, rail, EV, public transport)	Unified AI-driven multi-modal mobility platforms	Seamless mobility ecosystems and improved urban transport efficiency

The Table 5 matrix reflects the shift from current constraints to action research directions, and how gaps in methodology, infrastructure, and governance can be systematically filled using emerging AI paradigms.

3.8 Implications for Policy and Practice

The findings of this review have important implications for policy and practice. The need for coordinated regulatory frameworks that combine transportation and energy systems under single governance structures, with specific investment in digital infrastructure, interoperable data ecosystems, and computational capacity to support the successful implementation of AI in transportation systems, is evident. Developing countries, especially in Africa, should adopt context-specific AI solutions to overcome long-standing issues of data scarcity, lack of infrastructure, and energy insecurity. The reviewed literature indicates that strategically incorporating AI into transport and energy systems can enable adaptive routes to sustainable mobility, especially through intelligent optimization and system-level coordination of infrastructure and energy networks [36][52].

4 CONCLUSIONS

This systematic review examined the use of Artificial Intelligence (AI) in autonomous and sustainable transportation systems, focusing on methodological evolution, application areas, and integration with energy. The fact that 35 of the selected studies were synthesized suggests that machine learning and deep learning are the most prevalent AI families, with supervised learning models most common in traffic prediction and risk analysis, and convolutional and recurrent neural networks forming the foundation of perception and decision-making in autonomous vehicles. In application fields, traffic management and autonomous mobility are the most developed, especially in congestion prediction, adaptive signal control, and sensor-based navigation systems. Conversely, energy-aware mobility and vehicle-to-grid optimization are the fastest-growing yet least developed research frontiers, as the convergence between electrical power networks and transportation systems accelerates. The review also notes that there are chronic structural impediments, such as data quality, model interpretability, infrastructure, cybersecurity threats, and fragmented regulatory landscapes, and all these issues are more acute in developing areas where digital and energy infrastructure is uneven. Future research directions include energy-aware AI optimization, federated learning to use data privately, digital-twin simulation, explainable AI for safety-critical decisions, and multimodal intelligent transport systems. Together, these directions point to a shift from individual predictive models to integrated, adaptive, system-level intelligent mobility ecosystems. In general, the evidence shows that AI is moving beyond task-specific optimization tools to an enabling platform of coordinated, energy-aware, and scalable transportation systems, especially when coordinated with smart grid integration and sustainability goals.

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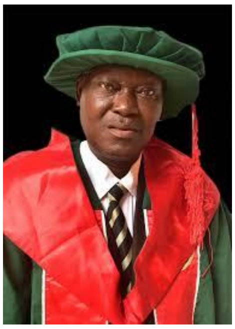

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