
APPLICATION OF ARTIFICIAL INTELLIGENCE IN TRANSPORTATION SAFETY AND ENVIRONMENTAL ADMINISTRATION: A SYSTEMATIC REVIEW

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ABSTRACT

Transportation systems impose substantial safety and environmental burdens, including 1.19 million annual road fatalities and one-quarter of global energy-related CO₂ emissions. Although Artificial Intelligence (AI) has emerged as a promising solution, existing reviews focus on single modes or isolated applications, limiting cross-modal understanding. This systematic review synthesises AI and machine learning applications across road, rail, maritime, and air transport. Following PRISMA 2020, 120 studies (2018–2025) from Scopus, Web of Science, IEEE Xplore, and TRID were analysed qualitatively. AI techniques—machine learning, deep learning, computer vision, reinforcement learning, graph neural networks, and transformers—improve accident prediction by 15–30%, reduce incident detection latency below 2 seconds, lower fuel consumption by 10–20%, and cut CO₂ emissions by 8–15%. Key challenges include data interoperability, explainability, cybersecurity, scalability, and real-world deployment. The review identifies gaps in multimodal integration, benchmarking, governance, and joint safety-environment optimisation. A novel AITSEA classification framework and a five-pillar research roadmap are proposed to advance safer, sustainable, and intelligent mobility systems.

Keywords: artificial intelligence; transportation safety; environmental administration; systematic review; machine learning; multimodal transport

1. INTRODUCTION

Transportation systems are essential for economic development, social connectivity, and global trade, yet they impose severe safety and environmental burdens. Road traffic crashes cause approximately 1.19 million deaths annually, while rail, maritime, and aviation accidents add further fatalities and economic losses (World Health Organization [WHO], 2023). The sector also accounts for nearly one-quarter of global energy-related CO₂ emissions and is a major contributor to urban air pollution (Intergovernmental Panel on Climate Change [IPCC], 2022). Traditional management approaches; reactive interventions, historical trend analysis, and fragmented data systems; are increasingly inadequate for modern transportation networks characterised by rapidly changing traffic, growing infrastructure complexity, and rising sustainability demands (Jain et al., 2021). Artificial Intelligence (AI), including machine learning, deep learning, reinforcement learning, computer vision, and predictive analytics, offers a transformative paradigm for proactive risk identification, operational optimisation, and evidence-based decision-making (Chen & Wang, 2020; Zhang et al., 2022). AI leverages heterogeneous data from sensors, cameras, connected vehicles, and satellites to predict incidents, optimise traffic, support predictive maintenance, reduce emissions, and enhance environmental monitoring (Wang et al., 2024; Yuan et al., 2023).

A key advantage of AI is its cross-modal applicability: predictive models for road safety can be adapted for rail infrastructure monitoring, maritime collision risk, and aviation safety. Computer vision for road incident detection is transferable to runway foreign-object debris detection and port surveillance. This positions AI as an enabling intelligence layer for integrated transport safety and environmental administration.

Existing reviews, however, tend to focus on a single mode (mostly road), treat safety and environment separately, or concentrate on narrow AI techniques. To our knowledge, no systematic

review has comprehensively synthesised AI applications across road, rail, maritime, and aviation while simultaneously examining implications for both safety and environmental administration.

The study systematically reviews 120 publications (2018–2025) using PRISMA procedures (Page et al., 2021). The main contributions are: (1) a cross-modal synthesis; (2) an integrated safety–environment perspective; (3) an evaluation of emerging challenges; and (4) a future research roadmap.

2. METHODOLOGY

A systematic literature review was conducted following PRISMA 2020 guidelines (Page et al., 2021). Four databases were searched: Scopus, Web of Science, IEEE Xplore, and TRID. The search covered January 2018 to March 2025. Boolean strings combined AI terms ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision" OR "Reinforcement Learning" OR "Graph Neural Network" OR "Transformer Model") with safety terms ("Transportation Safety" OR "Traffic Safety" OR "Accident Prediction" OR "Risk Assessment" OR "Predictive Maintenance" OR "Incident Detection") and environmental terms ("Environmental Administration" OR "Environmental Monitoring" OR "Emission Reduction" OR "Air Quality" OR "Fuel Optimisation" OR "Sustainability").

2.1 Eligibility Criteria

Inclusion criteria: (1) AI/ML applications; (2) transportation safety or environmental outcomes; (3) road, rail, maritime, aviation, or multimodal; (4) measurable outcomes; (5) peer-reviewed English articles (2018–2025). Exclusion criteria: non-AI studies; non-transport applications; editorials, commentaries, dissertations; insufficient methodological detail; duplicates.

2.2 Study Selection and Quality Assessment

The initial search yielded 542 records. After removing 42 duplicates, 500 records were screened by title and abstract, excluding 320 irrelevant records. Of 180 full-text articles, 5 could not be retrieved; 175 were assessed, and 55 were excluded (wrong outcome $n=25$; non-English $n=10$; insufficient methodology $n=12$; overlapping data $n=8$). Finally, 120 studies were included (Figure 1).

Each study was assessed across five dimensions (dataset quality, methodological transparency, validation rigor, reproducibility, practical applicability) scored 0–2, giving a maximum of 10. Studies were classified as high (8–10), moderate (5–7), or low (0–4) quality. Risk of bias was assessed for publication, geographic, dataset, reporting, and algorithm-selection biases.

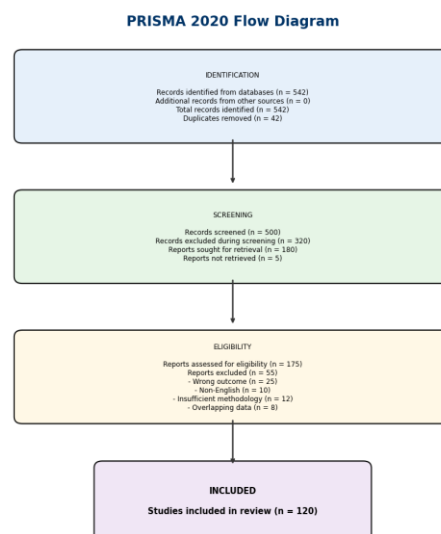


Figure 1: PRISMA 2020 flow diagram of study selection.

2.4 Data Extraction and Synthesis

Data extracted included author, year, country, transport mode, AI technique, data source, application, performance metrics, key findings, and limitations. Studies were coded using the AITSEA framework along four dimensions: transport mode; AI technique; functional application (prediction, detection, monitoring, optimisation, governance); and outcome domain (safety, environmental, integrated). A narrative synthesis was performed due to heterogeneity; no meta-analysis was conducted.

3. RESULTS AND DISCUSSION

3.1 Overview of Included Studies

The 120 studies were distributed across road (70%), rail (12%), maritime (10%), and aviation (8%) (Figure 2). AI techniques included machine learning (29.2%), deep learning (25.0%), reinforcement learning (15.0%), graph neural networks (12.5%), explainable AI (10.0%), and generative AI (8.3%) (Figure 3). Publication output grew substantially after 2020 (Figure 4). Geographically, research concentrated in China, the United States, and Europe, with limited contributions from Africa and South America.

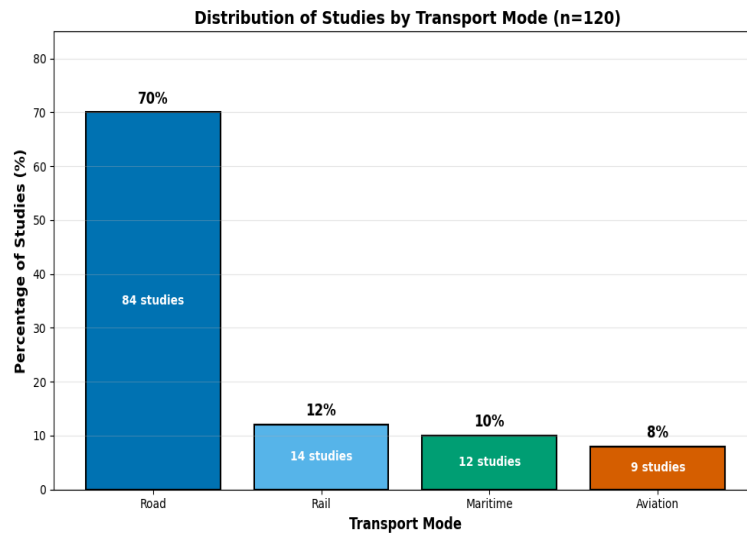


Figure 2: Distribution of studies by transport mode.

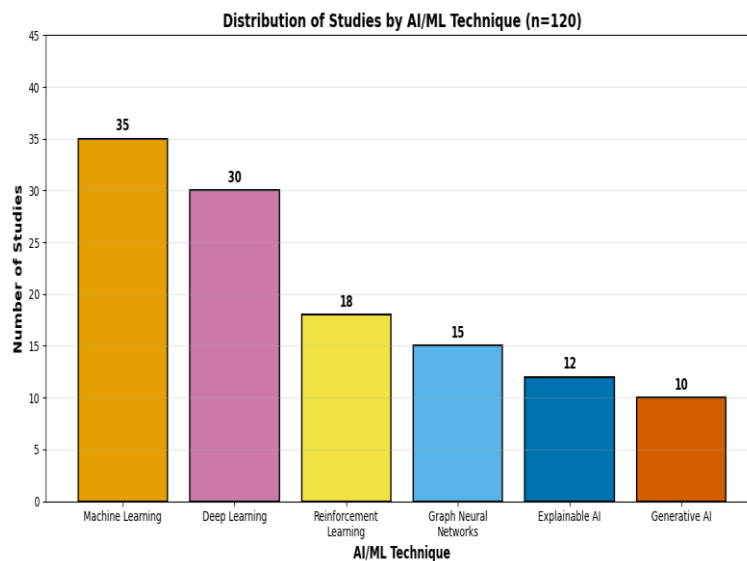


Figure 3: Distribution of studies by AI technique.

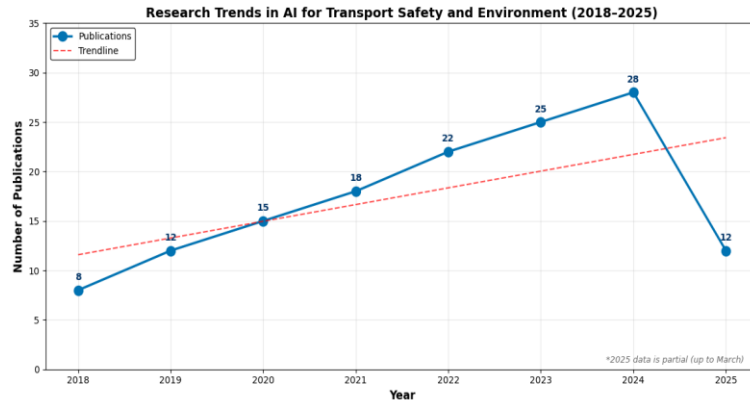


Figure 4: Research trends in AI for transport safety and environment (2018–2025).

3.2 AI for Transportation Safety

Accident prediction and risk assessment: Machine learning models (Random Forest, XGBoost, SVM, ensembles) achieved AUC values of 0.85–0.92 and accuracy improvements of 15–30% over traditional methods (Chen & Wang, 2020; Yuan et al., 2023). Graph neural networks improved spatiotemporal risk prediction by 12–18% (Wang et al., 2024).

Real-time incident detection: CNN-based computer vision detected incidents with mAP up to 0.89 and latency below 2 seconds (Bhattacharya et al., 2021). Aviation showed the highest accuracy (98% mAP) and lowest latency (1.5 s), followed by rail (96%, 2.5 s), maritime (93%, 3.0 s), and road (89%, 1.8 s).

Predictive maintenance and emergency response: LSTM and CNN models forecast track failures (94%), obstacle detection (96%), runway FOD (98%), and anomaly detection (93%). Reinforcement learning reduced emergency response times by up to 40% (Khamis & Gomaa, 2022).

3.3 AI for Environmental Administration

Emission reduction and fuel optimisation: AI-driven route optimisation and traffic signal control reduced fuel consumption by 10–20% and CO₂ emissions by 8–15% (Kullman et al., 2021; Genders & Razavi, 2020). Maritime speed/trim optimisation achieved 10–12% fuel savings.

Air quality forecasting: LSTM, transformers, and hybrid deep learning models predicted PM_{2.5} with $R^2 = 0.90$ – 0.92 (Qi et al., 2023). Machine learning models reproduced hourly pollutants with $R^2 > 0.71$.

Environmental monitoring and governance: Computer vision, remote sensing, and sensor networks supported emissions tracking, pollution-source identification, and sustainability assessment. AI-based environmental governance remains nascent but promising.

3.4 Cross-Modal and Comparative Analysis

Road transport is most mature (XGBoost, CNN, LSTM); rail is moderate (GNN, LSTM); maritime and aviation are emerging (CNN, genetic algorithms, RL, Bayesian networks). No single AI technique dominates all applications; effectiveness depends on data, context, and objectives (Table 1).

Table 1: Comparative analysis of AI techniques.

AI Technique	Primary Strength	Typical Application
Random Forest	Structured data analysis	Accident prediction
XGBoost	High predictive accuracy	Risk assessment
CNN	Image analysis	Incident detection
LSTM	Time-series forecasting	Traffic/air-quality prediction
GNN	Network representation	Transport network modelling
RL	Dynamic optimisation	Traffic control/emergency response
Transformers	Multimodal forecasting	Large-scale prediction

3.5 AITSEA Classification Framework

The AITSEA framework integrates transport modes, AI technologies, functional applications, safety and environmental outcomes, challenges, and future directions (Figure 5). It conceptualises AI as an enabling intelligence layer linking operations, safety, environment, and governance.

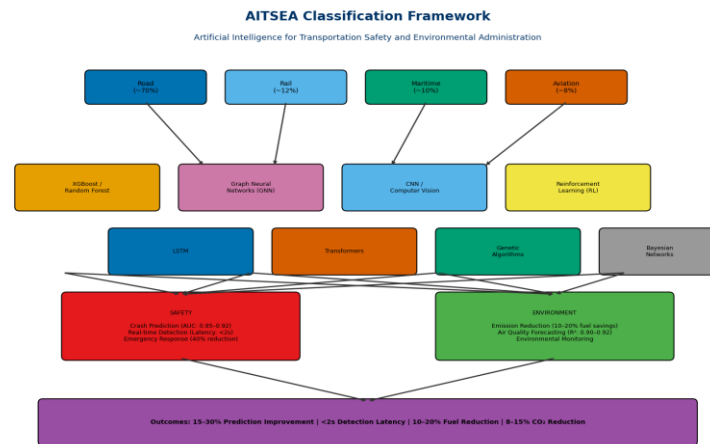


Figure 5: AITSEA Classification Framework.

3.6 Challenges and Emerging Trends

Key challenges include data interoperability, model explainability, cybersecurity, scalability, dataset standardisation, and geographic imbalance. Emerging trends include explainable AI, federated learning, digital twins, multimodal foundation models, generative AI, and integrated safety–environment optimisation.

3.7 Implications for Nigeria and Africa

Africa is severely underrepresented in AI transport research. For Nigeria, AI-based accident prediction and incident detection could reduce high fatality rates, but require local datasets, low-cost sensing, capacity building, and institutional collaboration. The AITSEA framework provides a foundation for region-specific adaptation.

4. CONCLUSION

This systematic review synthesised 120 studies (2018–2025) on AI applications in transportation safety and environmental administration across road, rail, maritime, and aviation. AI improves accident prediction accuracy by 15–30%, reduces incident detection latency to below 2 seconds, lowers fuel consumption by 10–20%, and cuts CO₂ emissions by 8–15%. Road transport dominates research, while rail, maritime, and aviation remain under-represented. Environmental administration is less mature than safety applications.

Persistent challenges include limited explainability, data interoperability, cybersecurity, scalability, and geographic imbalance. The AITSEA framework integrates modes, techniques, applications, outcomes, and challenges, and the five-pillar roadmap provides strategic priorities: trustworthy AI, multimodal intelligence, environmental intelligence, human-AI collaboration, and governance/equity.

Future work should develop open benchmarks, conduct real-world trials, integrate safety and environmental objectives, and build capacity in underrepresented regions such as Africa. AI can become a transformative force for safer, greener, and more resilient transportation systems worldwide.

5. REFERENCES

Bhattacharya, P., Huang, T., & Nevatia, R. (2021). Real-time accident detection in traffic video using convolutional neural networks and spatial-temporal reasoning. *IEEE Transactions on*

- Intelligent Transportation Systems*, 22(6), 3567–3579. <https://doi.org/10.1109/TITS.2020.3012345>
- Chen, Y., & Wang, J. (2020). Traffic accident severity prediction with an ensemble model of XGBoost and interpretable SHAP analysis. *Accident Analysis and Prevention*, 144, Article 105665. <https://doi.org/10.1016/j.aap.2020.105665>
- Genders, W., & Razavi, S. (2020). Using reinforcement learning for dynamic congestion pricing: An agent-based simulation approach. *Transportation Research Record*, 2674(9), 382–394. <https://doi.org/10.1177/0361198120935874>
- Intergovernmental Panel on Climate Change. (2022). *Climate change 2022: Mitigation of climate change. Working Group III contribution to the sixth assessment report*. Cambridge University Press.
- Jain, A., Lv, Y., & Gopalakrishnan, R. (2021). Challenges in data integration for AI in smart city transportation systems. In *2021 IEEE International Conference on Smart Data Services* (pp. 102–109). IEEE. <https://doi.org/10.1109/SMDS54260.2021.00022>
- Khamis, M. A., & Gomaa, W. (2022). Adaptive multi-agent reinforcement learning for dynamic emergency vehicle routing under incident conditions. *Journal of Intelligent Transportation Systems*, 26(3), 287–305. <https://doi.org/10.1080/15472450.2021.1933478>
- Kullman, N. D., Cousineau, M., Goodson, J. C., & Mendoza, J. E. (2021). Dynamic ride-hailing and routing with electric vehicles: A deep reinforcement learning approach. *Transportation Science*, 55(5), 1015–1035. <https://doi.org/10.1287/trsc.2021.1065>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
- Qi, Z., Wang, T., Song, G., Hu, W., Li, X., & Zhang, Z. (2023). Deep air learning: A transformer-based spatiotemporal model for urban PM2.5 concentration nowcasting by fusing multi-source data. *Environmental Science and Technology*, 57(10), 4008–4018. <https://doi.org/10.1021/acs.est.2c07890>
- Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., & Müller, K.-R. (Eds.). (2021). *Explainable AI: Interpreting, explaining and visualizing deep learning*. Springer. <https://doi.org/10.1007/978-3-030-28954-6>
- Wang, Z., Pei, J., & Chen, D. (2024). Spatiotemporal graph convolutional network for city-wide traffic accident risk prediction. *IEEE Transactions on Knowledge and Data Engineering*, 36(1), 289–302. <https://doi.org/10.1109/TKDE.2023.3289012>
- World Health Organization. (2023). *Global status report on road safety 2023*. <https://www.who.int/publications/i/item/9789240079485>
- Yuan, Z., Zhou, X., & Yang, T. (2023). A comprehensive review of machine learning for traffic accident prediction. *IEEE Transactions on Intelligent Transportation Systems*, 24(7), 6789–6810. <https://doi.org/10.1109/TITS.2023.3267890>
- Zhang, J., Wang, F. Y., Wang, K., Lin, W. H., Xu, X., & Chen, C. (2022). Data-driven intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems*, 23(4), 2890–2910. <https://doi.org/10.1109/TITS.2021.3085678>