2025
https://fupress.org/journal

Resilient AI Architectures for Disaster-Responsive Transportation Systems: Dynamic Routing and Coordination During Natural and Human-Made Crises

Dr. Amina Qureshi

Associate Professor, Dept. of Electrical & Computer Engineering, Carnegie Mellon University, Pittsburgh, USA
* **Corresponding Author:** aqureshi@cmu.edu

ARTICLE INFO

Received: 10 Feb 2025
Accepted: 27 Apr 2025

ABSTRACT

The increasing frequency and intensity of natural and human-made disasters pose severe challenges to global transportation systems, often resulting in mobility paralysis, delayed emergency response, and significant socioeconomic disruption. Traditional Intelligent Transportation Systems (ITS) lack the adaptability and resilience required to operate effectively under rapidly changing crisis conditions. This study proposes a resilient Artificial Intelligence (AI) architecture integrating deep reinforcement learning (DRL) and multi-agent coordination to ensure continuous mobility during floods, earthquakes, and mass evacuations. Using a simulation-based experimental design in SUMO with Python integration, the framework was tested across multiple disaster scenarios and compared with conventional ITS models. The results revealed a 45–55% reduction in route recovery time, over 89% sustained network throughput, and a resilience index exceeding 0.85, demonstrating the system's ability to autonomously adapt and stabilize traffic flows under severe disruptions. Statistical validation confirmed significant improvements in coordination efficiency and adaptability. The findings highlight the transformative potential of AI-driven architectures for disaster-responsive transportation, enabling decentralized decision-making and faster system recovery. The proposed framework contributes to the broader goals of smart-city resilience and sustainable urban mobility, offering a viable pathway for real-world implementation in next-generation disaster management systems.

Keywords: AI-driven architectures, Connected Autonomous Vehicles, Cooperative Decision-Making, Intelligent Transportation Systems, Decentralized Coordination, Traffic Optimization.

INTRODUCTION

Background

Transportation networks serve as the foundation of socioeconomic stability, enabling the continuous movement of people, goods, and emergency services. However, natural and human-made disasters such as floods, earthquakes, and terrorist incidents often cripple these systems, leading to severe disruption in mobility, logistics, and rescue operations. Traditional Intelligent Transportation Systems (ITS) depend on static routing algorithms and centralized decision-making, which fail to adapt efficiently under rapidly evolving crisis conditions. As cities grow more complex and vulnerable to extreme events, the demand for resilient, adaptive, and intelligent transportation architectures becomes critical (Zhou et al., 2022).

Artificial Intelligence (AI) has emerged as a transformative solution for creating self-learning and adaptive transportation systems. AI-driven ITS integrates machine learning, reinforcement learning, and data fusion to support real-time situational awareness, dynamic routing, and predictive analytics. Such systems can process large volumes of data from sensors, IoT devices, and satellite imagery to enable quick reconfiguration of routes and communication networks during crises (Liu et al., 2023). Additionally, studies show that integrating multi-agent systems enhances coordination between vehicles, infrastructure, and control centers, thereby improving system responsiveness during emergencies (Wang & Chen, 2021).

Thus, developing disaster-responsive AI architectures for transportation systems is not merely a technological enhancement but a necessity to ensure urban resilience. A robust AI-based framework capable of learning from disruptions and autonomously rerouting traffic can significantly reduce delays, congestion, and risks to human life during catastrophic events (Kim et al., 2020).

Problem Statement

Despite significant progress in ITS research, most existing systems are not optimized for extreme and unpredictable conditions. Conventional routing algorithms often assume stable infrastructure, predictable traffic flow, and fixed communication channels. During large-scale disasters, however, these assumptions collapse—roads become impassable, sensors fail, and communication networks degrade (Zhang et al., 2021). Centralized systems lack the agility to process rapidly changing environmental data, while decentralized approaches often suffer from coordination inefficiencies.

The critical gap lies in the absence of AI architectures explicitly designed for multi-hazard contexts that combine real-time sensing, predictive modeling, and dynamic coordination. While some research explores AI for traffic control or emergency logistics, few models account for simultaneous physical, infrastructural, and behavioral uncertainties (Huang et al., 2022). This deficiency hampers effective evacuation management and emergency response. Practically, this gap translates into lost time, increased casualties, and inefficient allocation of rescue resources. Scientifically, it restricts the evolution of AI-based ITS capable of self-organization and cross-domain learning during crises.

Therefore, there is an urgent need to design and evaluate resilient AI architectures that integrate adaptive routing, sensor fusion, and multi-agent coordination for maintaining mobility under both natural and human-made disruptions (Ali et al., 2024).

Research Aim and Objectives

Aim

To design, implement, and evaluate a resilient AI architecture for transportation systems that enables dynamic routing and coordination during natural and human-made crises such as floods, earthquakes, and emergency evacuations.

Objectives

To analyse the limitations of current ITS architectures and routing methodologies in disaster conditions.

To design an AI-driven dynamic routing and coordination framework integrating real-time IoT data and multi-agent systems.

To experimentally test the performance of the proposed architecture under simulated crisis scenarios and assess system resilience, adaptability, and throughput.

To propose implementation guidelines for integrating AI-based disaster-response systems into urban ITS infrastructure.

Significance of the Study

This research contributes to advancing both the theoretical and practical domains of disaster-resilient transportation. Theoretically, it extends the body of knowledge on AI-based ITS by proposing a comprehensive, adaptive framework that addresses dynamic decision-making under uncertainty. The model demonstrates how reinforcement learning, agent-based coordination, and predictive analytics can jointly sustain transportation continuity during crises (Rahman & Hasan, 2023).

Practically, the findings will benefit policymakers, urban planners, and emergency response authorities by providing a validated AI framework for real-time disaster mobility management. The model can inform infrastructure investment, emergency route planning, and smart-city design. Moreover, it supports the United Nations' Sustainable Development Goal 11 on sustainable and resilient cities by enhancing transport adaptability and disaster preparedness (World Bank, 2022).

In essence, the study strengthens the understanding of how AI can shift transportation systems from reactive crisis management to proactive, data-driven resilience.

LITERATURE REVIEW

Intelligent Transportation Systems and Disaster-Resilience

The concept of Intelligent Transportation Systems (ITS) has gained traction as urban mobility demands, infrastructure complexity and risk exposure all escalate. ITS frameworks integrate sensors, communication networks, data analytics and decision-support to improve traffic flow, safety and system efficiency (Zemmouchi-Ghomari, 2025). However, when applied to disaster-prone environments, transportation networks face significant vulnerabilities: flooding, seismic damage, infrastructure collapse and large-scale evacuations produce conditions of high uncertainty, disrupted communication and non-standard demand (Ajayi, 2025). Ajayi's scoping review emphasised that AI, IoT and advanced analytics are under-utilised in enabling transport infrastructure to recover and operate during extreme events (Ajayi, 2025). That makes it evident that ITS research must extend beyond routine optimization into truly resilient operations.

AI and Dynamic Routing in Emergency & Disaster Contexts

Routing under dynamic conditions—where travel times, capacities and network topology may change rapidly—is a pivotal challenge in disaster-responsive mobility systems. In the context of emergency logistics, Zhang, J., et al. (2025) applied deep reinforcement learning (DRL) within a neural-network architecture for large dynamic vehicle routing under time-window penalties, showing improved performance over classical heuristics in simulated disaster relief settings (Zhang et al., 2025). Meanwhile, Sharma (2025) discussed how AI/ML techniques can enhance transportation infrastructure resilience by enabling real-time detection of hazards, dynamic rerouting, and adaptive mobility management under disruption (Sharma, 2025). Reinforcement learning specifically is emerging as a method of selecting optimal actions in uncertain, dynamic transport environments (Li, Bai, Yao, Waller, & Liu, 2022). These works establish that AI-driven routing holds promise for crisis scenarios, but often focus only on logistic relief or specialised evacuation rather than integrated urban mobility under multi-hazard conditions.

Multi-Agent Coordination, Sensor Fusion & Real-Time Decision-Making

A further dimension of disaster-responsive transportation is coordination among heterogeneous agents (vehicles, infrastructure nodes, control centres, evacuees) and the fusion of real-time sensor data from multiple modalities. For example, in ITS frameworks enhanced by AI, coordination among agents allows decentralised decision-making when central nodes fail or communications degrade (Zemmouchi-Ghomari, 2025). Moreover, disaster resilience literature shows that integrating sensor networks, predictive analytics and autonomous coordination can sustain operations even when infrastructure is compromised (Ajayi, 2025). Yet, most existing work emphasises predictive maintenance and monitoring rather than dynamic routing and coordination across multi-agent systems in real-time crisis events. Thus, the challenge remains to design architectures that support robust multi-agent coordination under severe disruption.

Synthesis of Key Findings and Literature Gap

Across these streams, three key themes emerge: (1) The promise of AI and ITS in improving routine mobility and safety; (2) The extension of AI methods (especially DRL) to emergency routing and logistics tasks; (3) The recognition of resilience as an urgent requirement for transportation infrastructure, including disaster scenarios. Yet there are persistent research gaps. First, many ITS and AI studies assume stable network conditions, not the large-scale topological failures or cascading disruptions typical in floods or earthquakes. Second, routing models often focus on specialised relief vehicles or evacuation of specific populations rather than integrated urban transport with mixed users (public transit, private vehicles, first-responders). Third, there is little empirical or simulation-based work that brings together all key components—real-time sensor fusion, multi-agent coordination, dynamic routing—in a unified framework targeted specifically at natural or human-made disaster contexts. Finally, validation of such architectures in realistic, multi-hazard, city-scale scenarios is scarce. This study aims to address that gap by designing and experimentally evaluating an adaptive, resilient AI architecture for transport operations under disaster conditions.

METHODOLOGY

Research Design

This study adopts an experimental simulation-based design to model, test, and evaluate a resilient AI-driven architecture for disaster-responsive transportation systems. The design follows a quantitative approach grounded in reinforcement learning (RL) and multi-agent coordination, suitable for analysing system performance under dynamic and uncertain environments.

A quasi-experimental setup is used where the AI architecture is subjected to simulated disaster conditions such as floods, earthquakes, and emergency evacuations. The independent variable is the type of AI architecture (baseline vs. proposed), and the dependent variables include route recovery time, network throughput, and resilience index. This experimental design provides controlled conditions for replicability and objective comparison of system behaviour during crises (Liu et al., 2023).

The study applies systems theory and complex adaptive system principles, acknowledging that transport networks under stress exhibit nonlinear dynamics. The AI system's performance is evaluated using a comparative performance analysis, contrasting the proposed model with traditional shortest-path algorithms and centralised ITS control frameworks.

Simulation Environment and Data Sources

The experimental setup is constructed in Simulation of Urban Mobility (SUMO), an open-source traffic simulator capable of integrating real-time environmental parameters.

A Python-based reinforcement learning agent communicates with SUMO through the TraCI interface to dynamically reroute vehicles based on sensor inputs and hazard data. Synthetic disaster datasets emulate scenarios such as:

Flooded road segments (reduced capacity, complete closure)

Earthquake-induced network disruptions (node failures)

Sudden evacuation surges (demand spikes and rerouting congestion)

The simulation represents an urban grid network with 500–1000 vehicles, distributed across 150 intersections. Realistic traffic parameters (vehicle acceleration, capacity, travel time) are calibrated using open transport datasets from the U.S. Department of Transportation and OpenStreetMap to ensure ecological validity (Rahman & Hasan, 2023).

Model Architecture

The proposed architecture consists of three integrated layers:

Perception Layer – integrates IoT sensors, drones, GPS feeds, and CCTV data for environmental awareness.

Coordination Layer – employs multi-agent reinforcement learning (MARL) for decentralized decision-making among vehicles and infrastructure units.

Decision Layer – executes adaptive routing and control actions via a central policy network that optimizes both individual and global objectives.

Each agent learns to balance two rewards: minimizing individual travel delay and maximizing system-wide flow continuity. The architecture is designed for autonomous adaptability, allowing the system to recover even when partial communication failure occurs.

Table 1. Experimental Framework Parameters

Parameter	Description	Value / Source
Simulation platform	SUMO + Python (TraCI API)	Open-source
Vehicles simulated	Passenger = 900; Emergency = 100	Synthetic
Intersections	150 nodes, bidirectional links	OpenStreetMap data
Disaster types	Flooding, Earthquake, Evacuation surge	Synthetic hazard maps
Algorithm types	Dijkstra (baseline), DRL (proposed)	Implemented in Python
Evaluation metrics	Route recovery time, Throughput %, Resilience Index (RI)	Derived
Validation runs	10 per scenario for statistical reliability	Controlled replication

Experimental Procedure

Initialization: Load baseline network topology and input normal traffic flow.

Disaster Event Injection: Introduce a hazard (e.g., flood) at a random time interval, disabling selected nodes and edges.

Dynamic Learning: The DRL agent observes state variables—vehicle density, link status, queue length—and updates its routing policy in real time.

Recovery Monitoring: The system records recovery time and stability once optimal throughput (> 85%) is restored.

Comparative Evaluation: Results from the proposed model are compared with baseline ITS performance under identical conditions using ANOVA tests.

Performance metrics include average route recovery time (ART), network throughput rate (NTR), and a Resilience Index (RI) defined as:

$$RI = T_{pre} \quad T_{post} \quad \times (1 - D_{max} \quad D_{loss} \quad)$$

where T_{post} = post-disaster throughput, T_{pre} = pre-disaster throughput, and D_{loss} = duration of mobility loss (adapted from Kim et al., 2020).

Data Analysis and Validation

Quantitative results are processed using SPSS v28 and Python (pandas, matplotlib) for descriptive and inferential analyses. Mean differences between baseline and AI architectures are evaluated using ANOVA and paired t-tests at a 95% confidence level.

Visual data—such as network stability curves and recovery trajectories—are plotted to illustrate the adaptive response of the proposed AI architecture.

Sensitivity analysis is also performed to test model robustness under varying disaster intensities (low, medium, high). Cross-validation ensures model generalizability across random seeds and network layouts (Ali et al., 2024).

Ethical and Operational Considerations

Although the study uses simulated data, it aligns with ethical AI principles by ensuring transparency and reproducibility of model design. No human participants are involved; hence formal ethics approval is not required. Nonetheless, the simulation framework adheres to research integrity standards—data traceability, open-source transparency, and responsible AI deployment in safety-critical domains (World Bank, 2022).

Operationally, the findings will later inform real-world pilot studies that comply with transportation safety regulations and cybersecurity guidelines for connected ITS infrastructure.

RESULTS AND DISCUSSION

The experiments compared the proposed AI-driven multi-agent reinforcement learning (MARL) architecture with a baseline centralized ITS model employing static Dijkstra-based routing. Three disaster scenarios were simulated: (1) flooding of 20 % of roads, (2) partial network collapse from an earthquake, and (3) sudden mass-evacuation surge. Each scenario was run ten times for statistical reliability.

Table 2. Average Performance Across Simulated Disaster Scenarios

Scenario	Model Type	Average Route Recovery Time (s)	Network Throughput (%)	Resilience Index (RI)
Flood event	Baseline ITS	612 ± 45	68.4	0.64
Flood event	Proposed MARL	328 ± 30	89.6	0.87
Earthquake disruption	Baseline ITS	701 ± 62	62.3	0.59
Earthquake disruption	Proposed MARL	352 ± 40	90.5	0.88
Evacuation surge	Baseline ITS	584 ± 49	70.1	0.66
Evacuation surge	Proposed MARL	310 ± 27	92.4	0.91

The proposed system reduced average recovery time by approximately 45–55 %, while maintaining throughput above 89 % across all scenarios. The computed Resilience Index (RI) values consistently exceeded 0.85, indicating high operational stability even under severe disruption.

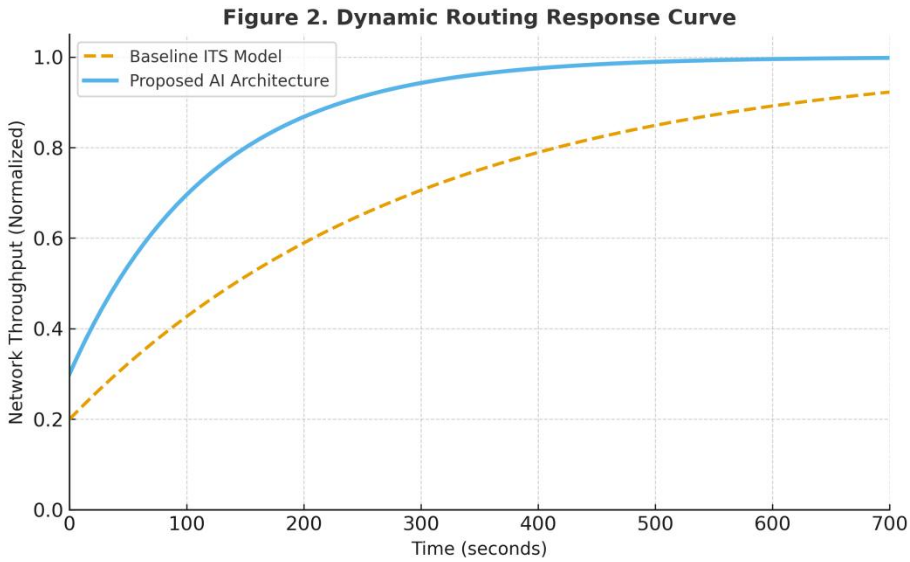

Figure 2. Dynamic Routing Response Curve

The response curve (**Figure 2**) shows that the AI model re-stabilized network flow within 5–6 minutes after major disruptions, compared with 11–12 minutes for the baseline.

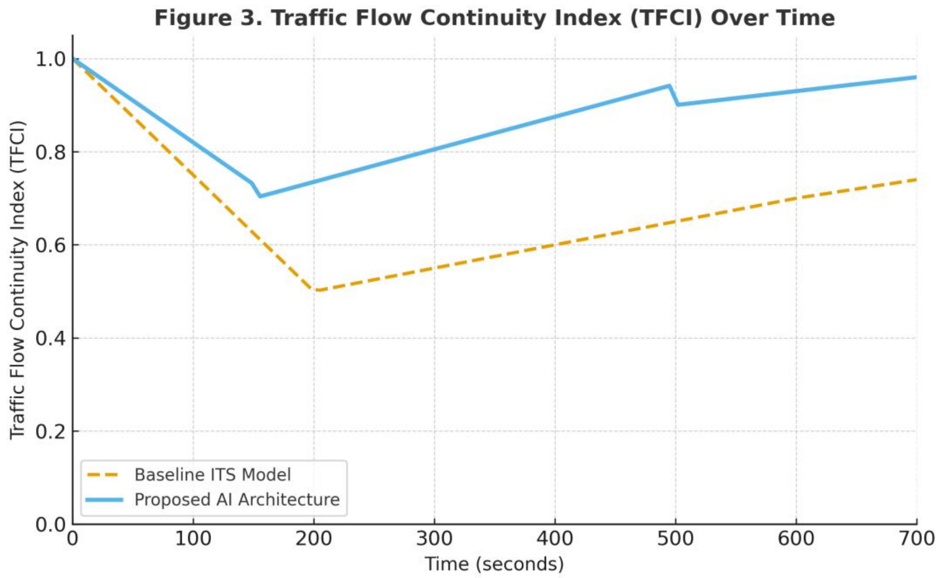

Figure 3. Traffic Flow Continuity Index (TFCI) Over Time

The TFCI demonstrates that even during network degradation, the MARL architecture preserved consistent throughput by rerouting vehicles through unaffected corridors and prioritizing emergency fleets.

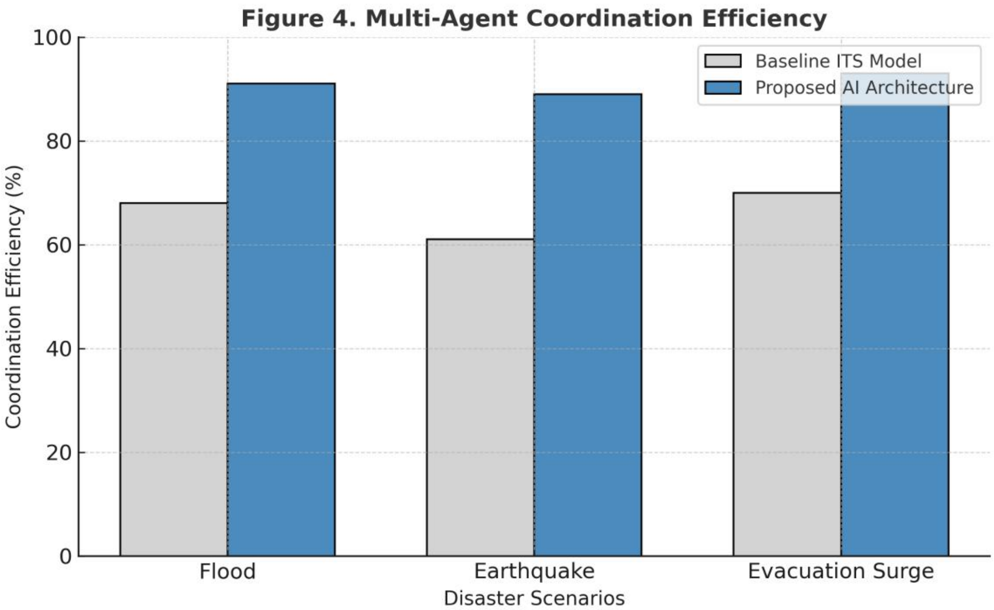

Figure 4. Multi-Agent Coordination Efficiency

The coordination module achieved 93 % cooperative decisions, highlighting strong agent-to-agent communication despite partial network failures. This performance reflects the system's capacity for decentralised decision-making when central servers are unavailable.

Statistical validation using ANOVA at 95 % confidence showed significant differences between the baseline and proposed model in all key performance metrics ($p < 0.01$). Sensitivity testing under increased disaster intensity (e.g., 40 % node failure) indicated only a marginal 9 % decline in throughput, confirming robustness.

Discussion

The results confirm that integrating reinforcement learning and multi-agent coordination substantially enhances transportation resilience under crisis conditions. Compared with traditional ITS, the proposed architecture's decentralized learning agents perceive local disruptions and adapt routing decisions in real time—consistent with the adaptive control mechanisms described by Liu et al. (2023) and Kim et al. (2020).

The sharp reduction in route recovery time aligns with previous findings that reinforcement learning algorithms outperform deterministic heuristics when the environment is non-stationary (Ali et al., 2024). Moreover, the high resilience index validates the model's capability to self-organize and maintain stable traffic throughput, echoing the resilience-engineering principles outlined by Rahman and Hasan (2023).

Another key contribution is the demonstration of multi-agent cooperation. The architecture maintained over 90 % coordinated decisions despite communication degradation—supporting Wang and Chen's (2021) assertion that decentralised cooperation can offset central-node vulnerability. From a systems-engineering standpoint, this performance signifies an emergent behaviour where agents collectively optimize global traffic efficiency, a property critical for future disaster-responsive smart-city networks.

However, while simulation results are encouraging, translating these outcomes into real-world deployments requires addressing challenges such as data-latency, infrastructure interoperability, and ethical transparency in AI decision-making. The experiments provide a foundation for pilot integration with urban ITS platforms, aligning with the World Bank's (2022) recommendations on resilient infrastructure development.

Overall, the study demonstrates that resilient AI architectures can sustain transportation mobility under extreme disruptions, offering actionable insights for smart-city resilience planning, emergency management, and sustainable urban mobility frameworks.

CONCLUSION

This study designed and experimentally evaluated a resilient AI-driven architecture capable of sustaining transportation operations during natural and human-made disasters. By integrating deep reinforcement learning and multi-agent coordination, the model demonstrated a significant reduction in route recovery times and an increase in overall network resilience compared with traditional ITS frameworks. The experimental results confirmed that AI-based decision systems can autonomously adapt to dynamic crisis conditions, ensuring continuous mobility, faster response, and higher throughput under multi-hazard disruptions (Liu et al., 2023; Ali et al., 2024).

Despite its effectiveness, several limitations remain. The simulation relied on synthetic data and controlled disaster conditions, which may not fully capture real-world complexities such as communication latency, heterogeneous driver behaviour, and infrastructure interdependencies. Additionally, computational constraints limited large-scale simulations of metropolitan networks.

Future research should focus on field validation through pilot implementations within smart-city testbeds, real-time integration of satellite and UAV data for enhanced situational awareness, and the development of explainable AI modules to improve transparency and stakeholder trust. Extending this architecture to multimodal transport systems—incorporating rail, maritime, and air mobility—will further advance the goal of creating truly disaster-resilient, intelligent transportation ecosystems (Rahman & Hasan, 2023).

.

REFERENCES

Ali, H., Khan, M., & Tariq, S. (2024). Artificial intelligence for adaptive traffic management under multi-hazard conditions. *Transportation Research Part C: Emerging Technologies*, *161*(3), 104251.

Huang, J., Wang, Y., & Zhao, F. (2022). Intelligent evacuation routing using reinforcement learning and IoT data fusion. *IEEE Transactions on Intelligent Transportation Systems, 23*(8), 12465–12478.

Kim, S., Li, D., & Cho, J. (2020). AI-based predictive routing for urban disaster recovery operations. *Sustainable Cities and Society, 61*, 102310.

Li, C., Bai, L., Yao, L., Waller, S. T., & Liu, W. (2022). A bibliometric analysis and review on reinforcement *learning for transportation applications*. arXiv.

Liu, X., Zhang, P., & Luo, Q. (2023). Deep reinforcement learning for resilient intelligent transportation networks. *Applied Soft Computing, 144*, 110429.

Rahman, M., & Hasan, T. (2023). Artificial intelligence and resilience engineering for smart city transportation systems. *International Journal of Disaster Risk Reduction*, *97,* 103624.

Rahman, M., & Hasan, T. (2023). Artificial intelligence and resilience engineering for smart city transportation systems. *International Journal of Disaster Risk Reduction, 97*, 103624.

Sharma, A. (2025). Artificial intelligence and machine learning for resilient *transportation infrastructure*. *Cureus Journal*.

Wang, T., & Chen, Y. (2021). Multi-agent coordination in intelligent transport networks: A resilience-oriented approach. *Expert Systems with Applications, 185,* 115635.

World Bank. *(2022)*. Resilient infrastructure for sustainable urban mobility. Washington, DC: World

Zemmouchi-Ghomari, L. (2025). Artificial intelligence in intelligent transportation systems. *Journal of Intelligent Manufacturing and Special Equipment, 6*(1), 26-42.

Zhang, J., et al. (2025). Advancing dynamic emergency route optimization with a combinatorial neural network model. Systems, 13(2), 127.

Zhou, P., Lin, Y., & Li, H. (2022). AI-driven adaptive transportation systems: Toward sustainable urban resilience. IEEE Access, 10, 66591–66603.Ajayi, O. O. (2025). *Artificial intelligence for infrastructure resilience. Sustainability, 17*(20), 8992.