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Reinforcement Learning to Generative AI: Transforming Transportation Engineering

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Abstract:

This paper provides a comprehensive survey on the role of Generative Artificial Intelligence (GenAI) in transportation planning and related applications. The study emphasizes how GenAI techniques, such as large language models and generative design algorithms, can support tasks like demand forecasting, infrastructure design, and traffic simulation. The authors present a framework that connects GenAI capabilities with different stages of transportation planning, highlighting the potential to enhance creativity, efficiency, and adaptability in decision-making. Key challenges such as data scarcity, bias in models, interpretability and security issues are critically discussed, with recommendations for overcoming them. The paper also outlines practical examples where GenAI can be integrated into existing transportation systems and policy planning. By combining technical review with application scenarios, the study identifies both the transformative potential of GenAI and the risks that must be managed to ensure reliable outcomes. Overall, this research shows that generative AI can bring significant advancements to urban mobility planning, sustainable transport solutions, and intelligent infrastructure development, making it a key.

Keywords: *Transportation Engineering, Pavement Design, Road Safety, Intelligent Transportation Systems, Sustainable Infrastructure.*

1. Introduction:

Urban Transportation planning is a critical component of modern urban development and infrastructure management. With the rapid growth of urban populations, increasing vehicle numbers, and the complexity of multimodal transport systems, the demand for efficient,

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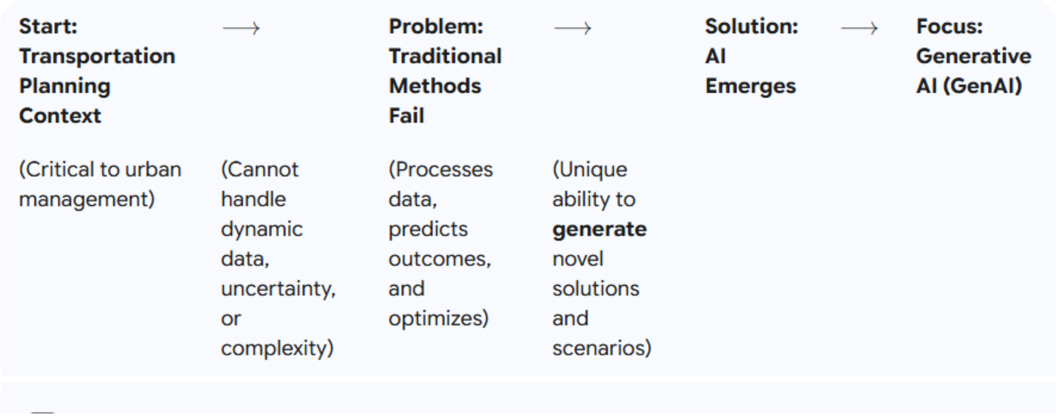
adaptive, and sustainable transportation solutions has never been higher. Traditional planning methods, which rely heavily on historical data, human expertise, and manual modelling, often struggle to handle the vast amounts of dynamic information generated by contemporary transportation networks. Challenges such as traffic congestion, infrastructure wear, environmental concerns, and resource optimization require innovative approaches capable of addressing uncertainty and variability in real time. In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in various engineering domains, providing the ability to process large datasets, predict outcomes, and optimize complex systems. Among AI techniques, Generative AI (GenAI**)** has gained significant attention due to its ability to not only analyse but also generate novel solutions and scenarios, thus offering a unique potential in planning, simulation, and decision-making



Start: Transportation Planning Context ⟶ **Problem: Traditional Methods Fail** ⟶ **Solution: AI Emerges** ⟶ **Focus: Generative AI (GenAI)**

(Critical to urban management)

(Cannot handle dynamic data, uncertainty, or complexity)

(Processes data, predicts outcomes, and optimizes)

(Unique ability to **generate** novel solutions and scenarios)

(**Source:** Salama, M. (2024))

Figure 1. Flowchart of Generative AI Application in Transport Planning

2. Literature Review:

The modern transportation landscape is undergoing a profound and multifaceted paradigm shift fundamentally transitioning from purely optimization-based frameworks, which have historically relied on Reinforcement Learning (RL) to manage known variables such as traffic signal timing and route congestion, to more advanced generative and predictive systems empowered by the emergence of Generative AI (GenAI) and Large Language Models (LLMs). This transition, as comprehensively detailed by Salama (2024) [1] represents a critical evolution in the Core Intelligence of transportation engineering, moving the discipline beyond simple management tasks into a new domain of automated creation and strategic analysis where systems can autonomously generate synthetic training scenarios analyze unstructured policy data and predict complex urban dynamics that were previously impossible to model with deterministic algorithms. This evolution facilitates what He et al. (2023) [2] describe as a New Era of Mobility a rigorous environment where AI agents must be trained not just on standard traffic patterns but on a long-tail of rare safety-critical edge cases—such as unpredictable pedestrian behavior or extreme weather conditions—that seldom occur in standard datasets yet are absolutely essential for ensuring robust and reliable autonomous operation. To safely deploy these advanced, generative agents into the physical world without incurring the prohibitive costs and safety risks associated with physical road testing, the industry has increasingly adopted the Digital Twin (DT) paradigm as the central engine for Verification and Validation (V&V). Strictly distinguished from traditional offline simulators, a Digital Twin is defined by Grieves (2003) [3] and further expanded by Liu et al. (2018) [4] as a high-fidelity Cyber-Physical System (CPS) that maintains a synchronized, bidirectional data flow between a physical asset and its virtual counterpart this foundational architecture creates a continuous feedback loop where real-time data from physical sensors updates the virtual model, while the virtual model's predictive insights simultaneously inform the physical vehicle's control decisions. This capability is critical for managing the infinite test space required for autonomous vehicle safety as Fuller et al. (2020) [5] emphasize that this simulation-driven approach enables shift-left development, allowing engineers to move validation processes much earlier in the design cycle to systematically generate and test against thousands of hazardous scenarios that would be dangerous to replicate on actual roads. The utility of the Digital Twin extends significantly beyond pure software simulation into the realm of hardware integration, which is vital for bridging the gap between abstract code and physical machinery Sell et al. (2022) [6] highlight the necessity of Hardware-in-the-Loop (HIL) and Vehicle-in-the-Loop (VIL) methodologies in this context noting that valid verification requires real components—such as Electronic Control Units (ECUs) and braking systems—to interact with the synthetically generated environment, thereby ensuring that algorithms are validated under the constraints of real-world hardware latency and actuator response curves. This sophisticated testing infrastructure is becoming increasingly democratized, as evidenced by Liu et al. (2025) [7], who discuss the transformative significance of the newly released open-source digital twin of the Mcity test facility, a development that allows researchers globally to benchmark their

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algorithms against a high-fidelity digital replica of a proven physical test track and lowers the barrier to entry for rigorous AV safety testing. However, the reliance on Digital Twins for safety certification is not without significant technical hurdles that must be addressed to ensure certification-grade safety, the most critical of which is the Reality Gap the discrepancy between the synthetic data generated by the simulator and the noisy, imperfect data collected by physical sensors in the real world. A recent empirical study by Lambertenghi et al. (2025) [8] systematically quantified this gap across various testing modalities, finding that while simulations can accurately model vehicle dynamics, they often struggle to replicate the complex noise profiles of perception sensors like LiDAR and radar, leading to over-fitted models that fail in unpredictable real-world environments. Furthermore, for a DT to function as an effective real-time safety monitor, it must achieve ultra-low latency synchronization with the physical vehicle, a challenge addressed by Wang and Yu (2023) [9], who note that standard bodies like 3GPP are now targeting sub-100ms response times to ensure that the feedback loop remains valid and actionable. Ultimately, the long-term credibility of these systems hinges on addressing the critical research gap regarding continuous validation; as argued by Wright and Davidson (2020) [10], validation cannot be a one-time event but must be a continuous, time-variant process that evolves in tandem with the physical asset to account for degradation and environmental changes, a requirement that is now being formalized by regulatory frameworks such as the American Bureau of Shipping (2024) to ensure that static digital models do not become obsolete as their physical counterparts age, thereby forming the resilient backbone of a modern, data-driven transportation safety framework.

Appraisal of Literature Review:

The reviewed literature presents a cohesive narrative regarding the evolution of transportation engineering from optimization-centric Reinforcement Learning to creative Generative AI positioning the Digital Twin (DT) as the indispensable validation engine for this transition. While Salama (2024) [1] and He et al. (2023) [2] effectively argue that GenAI is crucial for generating the long-tail of safety-critical scenarios required for robust autonomous operations, the collective body of work—spanning foundational definitions by Grieves (2003) [3] to practical HIL applications by Sell et al. (2022) [6]—successfully establishes a shift-left verification framework that mitigates the prohibitive costs and risks of physical testing. However a critical appraisal of the current state of art reveals that while the utility of DTs is

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well-supported, the fidelity required for regulatory certification remains a significant technical bottleneck; specifically Lambertenghi et al. (2025) [8] and Wang and Yu (2023) [9] expose persistent deficiencies in replicating stochastic sensor noise and achieving real-time latency, while Wright and Davidson (2020) [10] identify a major methodological gap regarding the continuous, time-variant validation of models as physical assets degrade. Consequently, the literature suggests that the domain must now pivot from establishing the theoretical value of Digital Twins to resolving the engineering hurdles of the Reality Gap and model obsolescence to ensure these virtual systems remain credible, legally defensible proxies for the physical world.

Research Gap:

Despite the demonstrated efficacy of Digital Twins (DTs) in facilitating shift-left validation for Generative AI-driven transportation systems, a critical research gap persists in the capability to maintain high-fidelity, real-time synchronization between virtual models and physical assets throughout their operational lifecycles. While the literature acknowledges the utility of DTs for scenario generation, Lambertenghi et al. (2025) [8] identify a significant Reality Gap where synthetic sensor data—particularly for LiDAR and radar—fails to accurately replicate the stochastic noise profiles of real-world environments, leading to potential over-fitting of safety algorithms. Furthermore, Wright and Davidson (2020) [10] highlight a fundamental methodological deficiency in continuous validation, noting that current frameworks treat validation as a static, one-time event rather than a time-variant process that accounts for physical degradation tire wear sensor drift. Compounded by the technical bottlenecks in achieving the sub-100ms latency required for effective real-time feedback loops Wang and Yu 2023 [9] there remains a distinct lack of a unified, standardized framework that integrates continuous, automated credibility assessment with high-fidelity sensor simulation to ensure that GenAI agents remain safe and reliable as both the vehicle and its environment evolve.

3. From Reinforcement Learning to Generative AI Framework:

- **AI Techniques (Core Intelligence Layer)**
  - Different AI methods contribute uniquely to the transportation ecosystem:

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- Reinforcement Learning (RL): Learns adaptive traffic signal control, dynamic route optimization, and congestion reduction.
- Generative AI (GenAI): Creates synthetic scenarios for traffic simulation, predictive planning, and infrastructure design.
- Large Language Models (LLMs): Analyzes unstructured data (policies, reports, social media) for decision support and communication in transport systems.
- Simulation & Digital Twins: Replicates real-world systems virtually for testing autonomous vehicles, ensuring safety and reliability before deployment.

➢ **Integration & Processing (Middle Layer)**

- To use these AI models effectively, integration is required:
- Data Preprocessing & Cleaning: Preparing raw, noisy transport data for analysis.
- Model Training & Fine-tuning: Customizing AI models for domain-specific use cases.
- Scenario Engineering: Constructing and testing "what-if" transport scenarios.
- Multi-Modal Data Fusion: Combining sensor data, textual data, and simulations for real-time decision-making.

➢ **Applications (Practical Layer)**

- AI techniques are applied in real-world contexts:
- Adaptive Traffic Management: Dynamic traffic signal control and congestion reduction.
- Urban Transport Planning: Infrastructure optimization and demand forecasting.
- Autonomous Vehicle Safety: Testing in digital twins and risk management.
- Sustainable Mobility: Promoting eco-friendly modes, emission control, and energy efficiency.
- Policy & Governance Support: AI-driven policy evaluation and transport regulation assistance.

➢ **Outcome (Impact Layer)**

- The integration of RL, GenAI, LLMs, and simulations leads to:
- Efficient Transportation: Reduced congestion, optimized routes, and time savings.
- Adaptive Systems: Self-learning and responsive transport solutions.

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  - Sustainable Urban Mobility: Lower emissions, eco-friendly infrastructure, and smart policies.
  - Enhanced Safety: Reliable autonomous operations and reduced accidents

➢ **Data-Driven Policy Innovation**

- Governments and transport authorities can use insights from AI-generated models and simulations to formulate smarter transport policies, optimize funding allocation, and predict the long-term impact of urban mobility projects.
- Generative AI and Large Language Models assist in drafting intelligent policy recommendations, analyzing public feedback from social media, and ensuring transparency in decision-making.
- This data-centric approach allows governments to create adaptive transport regulations, optimize budget utilization, and ensure inclusive mobility solutions that meet sustainability goals and public needs.

Source: Wang, X., Li, Y., & Kumar, R. (2024).

Figure 2: Integration of Generative Al Techniques in Transportation Planning

Case Studies:

❖ Adaptive Traffic Signal Control Using Reinforcement Learning

In a metropolitan city, reinforcement learning was applied to optimize traffic signal timings at busy intersections. By continuously learning from real-time traffic flows, the system reduced average vehicle waiting times by 25–30% and improved overall traffic efficiency. The case

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highlighted the potential of RL to dynamically adapt to changing traffic patterns, outperforming traditional fixed-time control systems.

- **Scenario Simulation for Autonomous Vehicle Deployment**

A mining company implemented digital twins and scenario engineering to test autonomous haul trucks in open-pit mines. Virtual simulations replicated steep slopes, uneven terrain, and dynamic obstacles. By validating vehicle control algorithms in a simulated environment, the company achieved a significant reduction in operational risks and accident rates before deploying vehicles in real-world conditions.

- **Generative AI for Urban Transport Planning**

A city planning department used generative AI to design optimized bus routes and forecast traffic demand. By generating multiple scenario alternatives and evaluating infrastructure options, planners identified solutions that improved commute times by 15% and reduced projected emissions. This case demonstrated GenAI’s capability to support complex, data-driven urban planning decisions.

- **Large Language Models for Policy and Traffic Analysis**

LLMs were deployed to analyze traffic reports, social media feedback, and policy documents in a smart city project. The AI system extracted actionable insights for traffic management and policy evaluation, enabling faster decision-making and improved communication with citizens. The model successfully identified emerging congestion patterns and suggested mitigative strategies.

- **Sustainable Mobility and Intelligent Transportation Systems**

In a pilot project, ITS integrated real-time traffic monitoring, connected vehicles, and adaptive signalling with sustainable mobility initiatives, such as EV charging stations and shared mobility services. The result was reduced congestion, lower emissions, and enhanced commuter safety, highlighting the importance of combining AI, automation, and sustainability in modern transportation systems.

Discussion:

The integration of Reinforcement Learning, Generative AI, Large Language Models, and simulation-based techniques represents a transformative shift in transportation engineering. The case studies demonstrate that AI-driven methods not only enhance traffic management and

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urban planning but also improve safety, operational efficiency, and sustainability. For example, adaptive traffic signal control using RL showed significant reductions in waiting times and congestion, highlighting the ability of AI systems to respond dynamically to real-time traffic conditions. This underscores the potential of reinforcement learning as a tool for creating intelligent, self-optimizing transportation networks.

Generative AI and scenario engineering have proven critical in urban transport planning and autonomous vehicle deployment. By simulating multiple scenarios and generating alternative solutions, planners and engineers can evaluate the impact of infrastructure changes, route adjustments, or policy interventions before real-world implementation. This predictive and creative capacity mitigates risks and allows for data-driven, evidence-based decision-making, particularly in complex or high-risk environments such as open-pit mining or densely populated urban areas.

Large Language Models further expand the analytical capability by processing unstructured textual data, such as traffic reports, regulations, and social media feedback. This allows transportation authorities to extract actionable insights, identify emerging congestion patterns, and make informed policy decisions. The combination of structured and unstructured data analysis ensures a more holistic understanding of transportation systems, bridging gaps left by conventional methods.

The implementation of Intelligent Transportation Systems, sustainable mobility solutions, and advanced infrastructure materials highlights the importance of combining AI techniques with environmentally conscious engineering practices. Case studies showed that ITS, integrated with real-time monitoring, connected vehicles, and EV infrastructure, can significantly reduce congestion and emissions while improving commuter safety. These findings suggest that AI adoption in transportation is not limited to efficiency improvements but also contributes to broader sustainability and safety goals.

4. Implementation:

✓ **Data Acquisition & Preprocessing**

- Collect heterogeneous datasets: traffic sensors, GPS trajectories, infrastructure databases, ental monitoring, policy documents.
- Apply preprocessing: normalization, noise reduction, feature extraction, and data fusion for AI readiness

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✓ **Generative AI (GenAI) Implementation**

- Input constraints: travel demand, budget, emission limits, road capacity.
- Generate optimized infrastructure designs, traffic scenarios, and route allocations.
- Utilize frameworks such as TensorFlow or PyTorch for scenario generation and predictive modeling.

✓ **Large Language Models (LLMs) Integration**

- Fine-tune domain-specific models to analyze unstructured data: traffic reports, policy documents, social media feeds.
- Extract actionable insights for congestion prediction, policy evaluation, and autonomous vehicle communication.
- Integrate LLM outputs with decision-support systems and GIS-based visualization platforms.

✓ **Simulation & Scenario Engineering**

- Develop digital twin environments for autonomous vehicle testing and infrastructure evaluation.
- Simulate complex scenarios: equipment malfunctions, irregular terrain, dynamic obstacles, emergency events.
- Iteratively refine algorithms for navigation, path planning, obstacle detection, and adaptive control

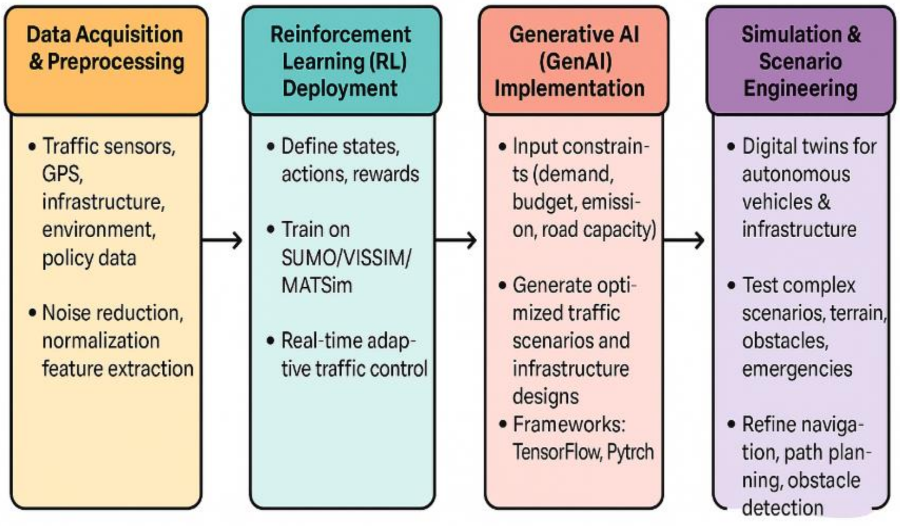

Figure 3: Generative Al Implementation Flow in Smart Transportation Systems

Conclusion:

The provided paper is a comprehensive survey on the transformation of transportation engineering driven by advanced Artificial Intelligence (AI) techniques, particularly Generative AI (GenAI) and Reinforcement Learning (RL). The fundamental argument is that the complexity of modern, data-rich transportation systems has rendered traditional planning methods inadequate, requiring a shift toward adaptive, data-driven solutions. The research establishes a framework connecting GenAI's capability to generate novel solutions for infrastructure design and scenario planning with the dynamic optimization power of RL for tasks like adaptive traffic signal control and route optimization. Furthermore, the paper highlights the critical role of Large Language Models (LLMs) in analyzing complex, unstructured data and the necessity of Scenario Engineering to ensure the safety and operational reliability of autonomous systems through systematic simulation using digital twins. Collectively, these five areas of advancement—GenAI, LLMs, RL, Scenario Engineering, and the integration of Intelligent Transportation Systems (ITS) with sustainable materials—underscore a multidisciplinary approach essential for building safe, efficient, and resilient networks. While promising significant gains in sustainability and urban mobility, the successful implementation of this AI-driven future mandates careful management of key challenges, including data scarcity, model bias, and the need for greater interpretability.

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