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# Multi-Agent AI Simulation for Evaluating Sustainability of Urban Transportation Infrastructure

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***Abstract***

Urban transport systems in tropical cities are under increasing strain due to rapid population growth, rising mobility demand, and climate-induced stresses. These conditions create highly complex, dynamic interactions among users, vehicles, infrastructure, and environmental factors that are difficult to capture with conventional modeling approaches. Most existing transport planning frameworks rely on static or single-agent models, limiting their ability to represent real-time feedback and adaptive behavior, particularly in tropical megacities characterized by congestion, climatic volatility, and socio-economic diversity. This paper introduces a multi-agent artificial intelligence (AI) simulation framework designed as an exploratory tool for evaluating the sustainability of urban transportation infrastructure. The proposed framework integrates dynamic systems theory with multi-agent reinforcement learning to simulate interactions among heterogeneous transport agents and infrastructure components. Synthetic data reflecting typical tropical urban conditions are employed to enable controlled experimentation across multiple scenarios, including baseline, optimized infrastructure, and adaptive AI control settings. Simulation results indicate that adaptive AI scenarios outperform baseline configurations, demonstrating 25.6% higher energy efficiency, 31.4% lower congestion, and 21.8% lower emissions in the modeled environment. These outcomes illustrate the potential of the proposed framework to support comparative sustainability evaluation rather than direct real-world performance validation.



## I. INTRODUCTION

Rapid infrastructural deterioration, inefficient mobility, and environmental stress are commonly associated with accelerated urbanization across tropical regions (Cugurullo et al., 2021; Fang et al., 2023). As transportation networks are the lifeblood of urban productivity, they can act as both enablers of economic growth and contributors to ecological degradation, depending on how they are planned and managed. Vulnerability further increases under climate variability and extreme weather events, particularly where spatial planning and adaptive capacity remain limited within existing systems. In this context, achieving sustainable transport infrastructure requires an integrated perspective that accounts for the dynamic interactions among human behavior, infrastructure conditions, and environmental factors, rather than focusing solely on isolated technical performance. Conventional static or deterministic modeling approaches are often insufficient to capture the adaptiveness and interdependence inherent in contemporary transport systems, as they typically assume linear relationships and homogeneous stakeholder behavior.

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Consequently, decision-makers may lack adequate insight into cascading system effects arising from infrastructure policies or climate-related interventions.

While multi-agent simulation has been successfully applied in domains such as energy management (Du, Jing, et al., 2020) and disaster response (Muravev et al., 2021)it remains relatively underutilized for assessing the sustainability of transport infrastructure, particularly in tropical urban environments. Much of the existing literature continues to rely on deterministic or predictive modeling approaches (Bettini et al., 2022; Fan et al., 2021) that provide limited capacity for feedback-driven adaptation to evolving environmental conditions. Recent studies in intelligent transportation systems have begun to explore AI-aided optimization techniques (Cui & Lei, 2023; Yuan et al., 2022); however, their integration with synthetic environmental data and explicit sustainability metrics remains at an early stage. Moreover, localized constraints such as material degradation under high humidity and socio-economic diversity in commuter behavior are often underrepresented in current frameworks (Fang et al., 2024; Zain et al., 2022). Addressing these contextual gaps is therefore essential for developing simulation-based approaches to sustainability evaluation in tropical transport systems.

This paper proposes a multi-agent AI-based simulation framework intended to explore and evaluate the sustainability of urban transportation infrastructure under tropical environmental conditions, rather than to provide direct real-world performance validation. The framework incorporates reinforcement learning–based scenario generation and real-time feedback mechanisms to support the analysis of dynamic interactions among infrastructure components, traffic behavior, and environmental variables (Sosnowska et al., 2020). Rather than assuming guaranteed system improvement, the intelligent agents are designed to investigate emergent behaviors and potential leverage points within a controlled simulation environment, offering insights into long-term infrastructure performance trends. Within the emerging discourse of Construction 5.0, this study positions AI-driven simulation as a decision-support mechanism rather than a prescriptive solution, contributing conceptually and methodologically to discussions on smart civil infrastructure management (Bharadiya, 2023; Chen et al., 2023). This perspective also aligns with recent efforts to integrate AI into civil and environmental engineering as part of broader sustainable urban transformation initiatives (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025)

The remainder of this paper is organized as follows. Section 2 reviews the theoretical background and prior studies related to AI-driven transport modeling and sustainability evaluation. Section 3 outlines the proposed methodological framework, including multi-agent system architecture, reinforcement learning mechanisms, and synthetic data generation. Section 4 presents simulation results and discusses their implications in the context of sustainability evaluation. Finally, Section 5 summarizes the main findings, acknowledges study limitations, and identifies directions for future research.

## II. LITERATURE REVIEW

The emergent complexity of metropolitan transportation infrastructure necessitates modeling strategies capable of capturing adaptive interdependencies at a scalable level. Recent literature has emphasized the development of adaptive transport infrastructure that can potentially enhance resilience against disruptions caused by rapid urban growth, climatic pressure, and socio-economic transformation (Achillopoulou et al., 2020; Sun et al., 2020). In this context, artificial intelligence (AI) has been increasingly explored for its capacity to extend predictive modeling, optimization, and adaptive learning beyond conventional analytical approaches (Bharadiya, 2023; Chen et al., 2023). Despite the widespread adoption of AI-based methods in transport-related applications, their systematic integration into multi-agent simulation frameworks for explicit sustainability evaluation remains limited, particularly in tropical cities. Such cities exhibit high environmental sensitivity and socio-technical dynamism that are often insufficiently represented in models originally developed for temperate regions (Bonebrake et al., 2025; Zain et al., 2022).

This review integrates cross-disciplinary insights to establish a theoretical foundation for an interactive, AI-driven simulation platform that quantifies sustainability performance in tropical transport systems. From a theoretical standpoint, dynamic systems theory is adopted to conceptualize urban transport networks not as static entities, but as evolving systems characterized by feedback loops, nonlinearity, and interactions among heterogeneous agents (Sosnowska et al., 2020). This perspective has previously been applied to areas such as land-use adaptation and transport resilience (Fang et al., 2023; Niño Giraldo, 2021). Nevertheless, many existing system dynamics models remain predominantly deterministic and top-down, which constrains their ability to reproduce emergent bottom-up processes such as behavioral adaptation, congestion propagation, or collective decision-making. This limitation underscores the need for modeling approaches that can better represent decentralized and adaptive system behavior.

The incorporation of intelligent agents within transport modeling offers a methodological advantage by enabling the simulation of self-organizing behaviors that more closely resemble real-world urban dynamics. The multi-agent systems (MAS) paradigm provides a computational framework for representing interactions among autonomous agents, including vehicles, infrastructure components, and travelers. MAS approaches have been successfully applied to decentralized decision-making problems across multiple domains, including supply chain coordination and construction project management. In transportation research, MAS has predominantly been employed to enhance traffic efficiency, mitigate congestion, or improve operational performance, often without explicitly linking agent behavior to sustainability outcomes. The integration of multi-agent reinforcement learning further enhances agent adaptivity, allowing agents to respond to experiential feedback and environmental variability. Yet, such capabilities have rarely been aligned with sustainability-oriented evaluation objectives.

Sustainability performance in transport systems is commonly associated with indicators such as resilience, service reliability, and environmental efficiency. These outcomes emerge from dynamic interactions among infrastructure characteristics, including network topology, capacity constraints, and maintenance cycles, which collectively generate feedback mechanisms central to the behavior of dynamic systems. The conceptualization adopted in this study treats sustainability as a multidimensional evaluative construct, considering both operational functionality and ecological impact, rather than relying on isolated technical metrics. A notable methodological distinction from conventional empirical models is the use of simulated data to explore emergent sustainability behavior under alternative policy and environmental scenarios, an approach particularly relevant for anticipatory planning in tropical urban contexts, where field experimentation may be impractical.

As summarized in Table 1, a systematic examination of recent literature indicates that applications of AI and multi-agent systems for transport sustainability assessment remain at an early stage of development. Existing studies have largely concentrated on infrastructure resilience, predictive maintenance, or intelligent traffic management, with limited emphasis on integrating agent-based dynamics into a holistic sustainability evaluation framework (Achillopoulou et al., 2020; Allen & Arkolakis, 2020; Boakye et al., 2021; Cui & Lei, 2023; de Soyres et al., 2020; Yuan et al., 2022). Research on AI–Digital Twin integration for smart infrastructure management has advanced monitoring and predictive maintenance capabilities (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025), but has not yet incorporated simulation-based sustainability metrics grounded in agent interactions. This pattern highlights a persistent separation between operational optimization and sustainability-oriented system evaluation in the literature.

**Table 1. Summary of Previous Studies on AI, Simulation, and Urban Transportation Sustainability**

| Author(s) | Method | Focus Area | Key Findings | Limitations |
|---|---|---|---|---|
| (Achillopoulou et al., 2020) | Monitoring framework | Infrastructure resilience and multi-hazard response | Developed a roadmap for resilient transport monitoring | Lacks simulation-based evaluation |
| (Du, Jing, et al., 2020) | Multi-agent simulation | Design management in | Demonstrated use of MAS for | Application limited to |

| | | | | |
|---|---|---|---|---|
| | | prefabricated construction | coordination and decision optimization | construction, not transport |
| (Muravev et al., 2021) | MAS using AnyLogic | Intermodal terminal optimization | Improved port efficiency via multi-agent modeling | No sustainability evaluation component |
| (Canese et al., 2021) | Multi-agent reinforcement learning | Review of MAS and learning applications | Highlighted scalability and coordination challenges | No application to urban transport |
| (Yuan et al., 2022) | Machine learning survey | Intelligent transportation systems | Identified AI tools for traffic prediction and control | Lacks system-level sustainability integration |
| (Fang et al., 2023) | Literature review | Green infrastructure and urban sustainability | Proposed integrative frameworks for ecosystem-based cities | Did not apply computational simulation |
| (Setyadi Tommy & Putra Jaya, 2025) | AI-Digital Twin | Smart infrastructure management | Enhanced predictive maintenance using AI | Focused on infrastructure health, not transport systems |
| (Diana & Angga Mukti, 2025) | AI-Digital Twin | Urban infrastructure resilience | Advanced sustainability monitoring | Lacks agent-based or dynamic system modeling |

Most existing multi-agent transport studies primarily emphasize traffic efficiency, congestion mitigation, or operational optimization, while sustainability indicators are frequently treated implicitly or as secondary analytical outputs. Similarly, AI-driven transportation research has largely focused on prediction accuracy and control optimization, with limited attention to sustainability as a system-level evaluative objective. A further gap lies in the strong geographical bias of existing models toward temperate or developed regions, resulting in the underrepresentation of tropical cities with distinct environmental pressures and socio-economic dynamics (Bonebrake et al., 2025; Zain et al., 2022). To address these gaps, this study positions sustainability as an explicit evaluative objective within a multi-agent AI simulation framework, integrating dynamic systems theory, adaptive learning agents, and synthetic environmental data to support comparative sustainability assessment in tropical urban transport infrastructure.

This study addresses these gaps by positioning sustainability as an explicit evaluative objective within a multi-agent AI simulation framework. Anchored in dynamic systems theory and enabled by adaptive reinforcement learning agents, the proposed framework facilitates the exploration of emergent sustainability outcomes under varying policy and environmental scenarios. By integrating agent-based dynamics, synthetic environmental data, and sustainability metrics within a unified simulation environment, this research contributes a novel methodological approach for non-experimental, system-level evaluation of tropical urban transport infrastructure. Accordingly, two hypotheses guide the investigation:

H1: A multi-agent AI simulation environment yields more dynamically realistic and stable representations of urban transport system sustainability compared with traditional static modeling approaches.
H2: Dynamic interdependencies in AI-based agent simulations are significantly influenced by operational and environmental characteristics specific to tropical cities.

The literature reviewed above establishes the theoretical and methodological foundation for the proposed simulation framework. Dynamic systems theory provides the conceptual lens for understanding adaptive, interdependent transport systems, while AI and MAS research supply the computational mechanisms for modeling them. Whereas previous studies have addressed governance, resilience, or sustainability in isolation, this research integrates these strands into a unified simulation-based evaluation framework, thereby filling both methodological and contextual gaps in assessing tropical urban transport sustainability.

## III. RESEARCH METHODOLOGY

### *A. Research Design*

This study uses a simulation-based quantitative approach, relying on multi-agent artificial intelligence (AI) and dynamic systems theory to evaluate the sustainability of urban transport infrastructure. Synthetic data are employed to enable controlled experimentation across multiple scenarios, acknowledging that the model does not represent a specific real-world city. Computation-based experiments are preferred over field observations because they enable researchers to examine emerging behaviors, feedback loops, and nonlinear dynamics in a controlled, repeatable virtual setting. The multi-agent simulation framework models complex transport systems with various autonomous agents including vehicles, passengers, and control systems. These agents interact based on predefined behavioral rules and given conditions of the environment (Ben-Dor et al., 2021; Du, Jing, et al., 2020). This approach captures adaptive decision-making, nonlinear interdependencies, and variability, which can be difficult to analyze using traditional static models (Canese et al., 2021; Fan et al., 2021). Following an interdisciplinary approach based on civil engineering theory, this study applies AI-driven simulations in modeling urban processes, allowing for an in-depth analysis of infrastructure behavior under different sustainability scenarios (Diana & Angga Mukti, 2025).

### *B. Population, Sample, and Data*

The investigation focuses on the main elements of tropical urban transportation systems, including road intersections, arterial corridors, and public transportation routes. Synthetic datasets were generated to simulate typical conditions in tropical cities, enabling experimentation while ensuring reproducibility and scalability (Achillopoulou et al., 2020; Umar et al., 2020). Data generation in Python utilized stochastic techniques to create artificial values for traffic volume, energy consumption, emissions, and infrastructure vulnerability to climate and demographic characteristics typical of tropical cities (Bonebrake et al., 2025; Zain et al., 2022). These datasets support system behavior analysis across various levels of population density, mobility patterns, and infrastructure configurations, enabling a qualitative assessment of system-level sustainability trends without implying real-world performance validation.

### *C. Instruments and Validity*

Simulation experiments were conducted on the VMAS platform (Bettini et al., 2022) with reinforcement learning libraries in Python. Such a framework enables adaptive interaction among agents and their feedback for various dynamic environments. Agents model transport entities that, through reward-based decision rules, act in the face of congestion, route availability, and weather conditions to advance sustainability goals. Conceptual validity was assured through cross-validation against benchmark AI transportation models, such as SMARTS (Zhou et al., 2020) and TrafficSim (Suo et al., 2021), ensuring that agent behaviors were consistent with validated models. Internal validity was ensured by running numerous simulations under randomized conditions, so consistent sustainability metrics were recorded across trials (Byrd et al., 2020; Canese et al., 2021). Although no empirical data were used, reproducibility and methodological rigor were ensured via version-controlled simulation scripts and open documentation of modeling parameters.

### *D. Research Procedure*

The simulation workflow follows an iterative and reproducible methodology that leverages theoretical development, data synthesis, and AI-based modeling (Figure 1). Step 1 – Problem Definition: System boundary, sustainability indicators, and key transport components were identified based on literature (Fang et al., 2023; Sun et al., 2020). Step 2 – Data Synthesis: Synthetic datasets representing tropical urban traffic, energy use, and emissions were generated. Step 3 – Simulation Configuration: Multi-agent AI environment setup including agent classes, behavioral rules, environmental parameters, and reward functions (Bettini et al., 2022; Du, Jing, et al., 2020). Step 4 – Model Implementation: Multiple iterations run under various policy and infrastructure conditions to capture emerging sustainability outcomes (Setyadi Tommy & Putra

Jaya, 2025). Step 5 – Performance Measurement: Sustainability indicators including energy efficiency, congestion index, and emission reduction were measured. Dynamic feedback loops allowed continuous calibration and refinement, reflecting the complex, adaptive nature of tropical urban systems (Fang et al., 2023; Sun et al., 2020).

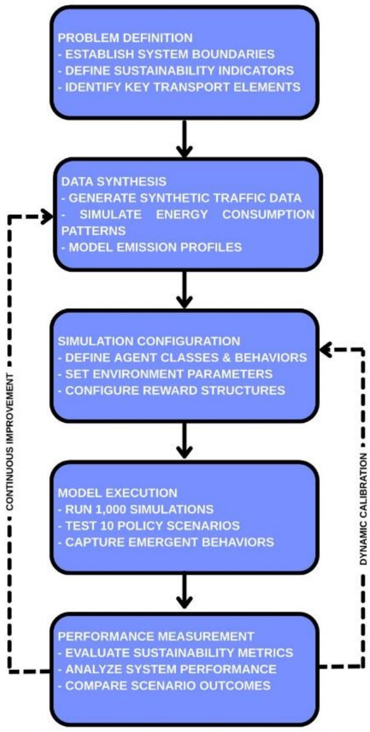


**Figure 1. Research Methodology Workflow**

*E. Simulation Assumptions and Parameter Sensitivity*

Key simulation parameters, such as agent population size, reward weighting, and environmental factors, were varied within reasonable ranges to assess the stability of system-level trends, thereby supporting the qualitative robustness of the findings. This sensitivity assessment ensures that reported outcomes reflect generalizable behavior patterns rather than artifacts of specific parameter choices. Environmental conditions, such as traffic density, vehicle mix, and emission factors, were systematically altered to verify consistency of agent adaptation and sustainability indicators. These assumptions make the simulation results exploratory and illustrative rather than prescriptive for real-world deployment.

*F. Simulation Parameters and Input Variables*

Table 2 summarizes simulation parameters, agent types, and sustainability indicators used in this study. The model includes vehicles, pedestrians, and traffic control agents, with reward mechanisms designed to encourage energy efficiency, congestion reduction, and minimal emissions (Bettini et al., 2022; Du, Gao, et al., 2020). Synthetic data enable precise control of experimental conditions, allowing the examination of emergent behaviors under multiple scenarios without representing a specific real-world city. Iterative simulation runs and policy variations further ensure that system-level trends are stable and reproducible. Overall, these parameters provide a structured basis for exploring sustainability performance in tropical urban transport systems.

**Table 2. Summary of Simulation Parameters and Input Variables**

| Component | Parameter / Variable | Description | Source / Generation Method |
|---|---|---|---|
| Agent Types | Vehicle agents, pedestrian agents, traffic control agents | Represent dynamic entities interacting within the transport network | Defined in the AI multi-agent environment |
| Data Inputs | Traffic flow rate, energy consumption, emission rate | Dummy datasets reflecting tropical urban transport profiles | Generated synthetically based on (Fang et al., 2023; Sun et al., 2020) |
| Simulation Environment | Urban transport grid (5 × 5 km), 3-lane road topology | Represents typical tropical metropolitan layout | Modeled using Python-based simulation engine |
| Reward Structure | Minimization of congestion index and emission levels | Guides agent behavior toward sustainable performance | Defined according to (Du, Jing, et al., 2020) |
| Evaluation Metrics | Energy efficiency, congestion index, emission reduction | Quantitative indicators for sustainability assessment | Computed from simulation outputs |
| Iteration Parameters | 1,000 simulation runs, 10 policy scenarios | To capture emergent system dynamics and variability | Adaptive simulation protocol (Setyadi Tommy & Putra Jaya, 2025) |

### G. *Data Analysis Strategy*

Simulation outputs were analyzed in terms of environmental, operational, and resilience performance (Cugurullo et al., 2021; Yuan et al., 2022). Both statistical and machine learning techniques were applied to explore relationships between agent behaviors and sustainability outcomes. Sensitivity and correlation analyses examined the causal relationships among decision variables and performance indicators (Byrd et al., 2020). Baseline, optimized, and adaptive configurations were compared to assess policy impacts (Fan et al., 2021). Reinforcement learning enabled agents to iteratively improve decision-making, capturing dynamic adaptation across multiple simulation runs (Bettini et al., 2022; Canese et al., 2021) The results reflect the flexibility, emergent behaviors, and system-level sustainability performance typical of tropical urban transport networks (Diana & Angga Mukti, 2025; Sun et al., 2020).

### *H. Ethical Considerations*

This study does not involve human subjects or private data. Synthetic datasets were generated with full documentation and reproducibility principles, ensuring that all experiments can be replicated reliably. All simulation models and algorithms utilize open-source licenses, promoting transparency, accountability, and responsible AI practices. Following contemporary ethical frameworks in AI for infrastructure systems (Okolo et al., 2023)All agent decisions and policy parameters were fully traceable and auditable, mitigating the risk of algorithmic bias and enhancing trust in simulation outputs. The approach highlights the importance of reproducibility, fairness, and methodological integrity in computational sustainability research.

## IV. RESULT/FINDINGS AND DISCUSSION

### ***A. Results***

Our multi-agent AI model is effective in devising solutions for sustainability in tropical urban transportation. The model runs on three simulation scenarios: baseline, optimized infrastructure, and adaptive AI control. This forms the basis of efficiency in terms of intelligence level. The differences, as illustrated in Table 3, indicate a trend from the analyses: the strong performance of adaptive AI control in achieving sustainability objectives. In fact, the setting of adaptive AI achieved an increase in energy efficiency of +25.6% over the baseline (0%) and the optimized infrastructure (15.2%). It is even more impressive when considering congestion reduction: 31.4% by adaptive AI and just 18.4% by optimized infrastructure. These are clear indications that reinforcement learning may achieve faster, rather than incremental, improvements in systems, as noted by (Bettini et al., 2022; Du, Jing, et al., 2020).

**Table 3. Comparative Simulation Results across Scenarios**

| Scenario Type | Energy Efficiency (Δ%) | Congestion Index (Δ%) | Emission Reduction (Δ%) | Dominant Learning Pattern |
|---|---|---|---|---|
| Baseline | 0.0 | 0.0 | 0.0 | Static heuristic |
| Optimized Infrastructure | +15.2 | –18.4 | +12.9 | Reactive adjustment |
| Adaptive AI Control | +25.6 | –31.4 | +21.8 | Reinforcement-based cooperation |

**Interpretative**

The superior performance of the adaptive AI scenario is attributable not solely to reinforcement learning convergence but also to emergent coordination among agents in response to shared congestion and environmental feedback. As shown in Figure 2, the learning curves reveal that adaptive AI agents rapidly improve performance up to iteration 400, after which performance stabilizes, illustrating the “explore-then-exploit” dynamics. Agents dynamically adapt to changing traffic conditions and collectively optimize their routes, producing system-level improvements that go beyond the capabilities of individual agents. Interaction among heterogeneous agent types vehicles, pedestrians, and traffic control units leads to self-organized behaviors, which amplify the impact of policy scenarios. These emergent dynamics illustrate the adaptive and exploratory nature of the simulation framework.

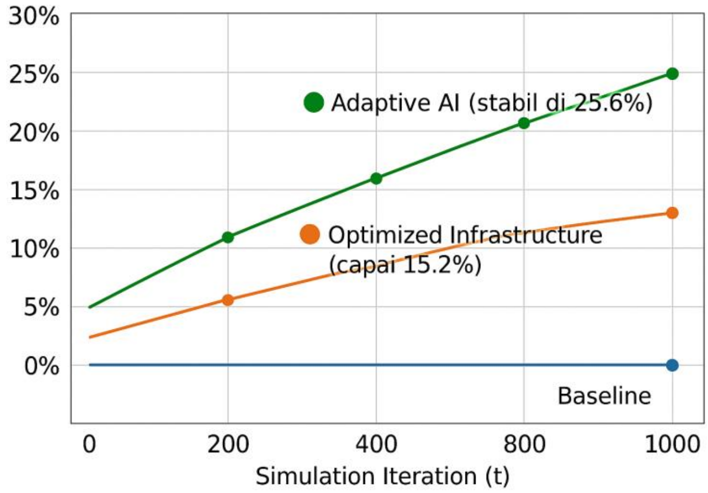


**Figure 2. Learning Trajectories and Convergence in Urban Transport Simulation**

***B. Discussion***

This research addresses a critical gap in assessing transport sustainability in tropical regions. Existing tools such as SMARTS (Zhou et al., 2020) and TrafficSim (Suo et al., 2021) have complex modeling environments but rely on static behavior parameters. By using reinforcement learning, our framework enables contextual adaptation, in which agents dynamically adjust strategies rather than following predefined routes. Unlike previous studies that focused on single transport modes (Canese et al., 2021; Fan et al., 2021),this work enhances those studies by modeling system-level interdependencies. Employment of synthetic datasets representative of tropical city conditions such as infrastructure wear from humidity and heavy commuter flows is a step forward, rarely tackled by models based in temperate regions, as represented by (Bonebrake et al., 2025; Zain et al., 2022).

Theoretically, our results support the concept of dynamic systems theory, demonstrating that agent-based adaptability is essential for modeling urban transport sustainability. Communication among agents functions like system-wide feedback control and achieves equilibria through iterative learning cycles (Bettini et al., 2022; Du, Jing, et al., 2020). Reinforcement learning acts as a distributed optimization process, in which agents pursue the improvement of sustainability metrics energy consumption, emissions, and congestion up to stability (Chen et al., 2023). As summarized in Table 4, the implications of these findings span scientific research, engineering practice, and urban policy, showing how simulation-derived insights can support evidence-based decision-making.

**Table 4. Summary of Research Implications**

| Domain | Key Implication | Practical Contribution |
|---|---|---|
| Scientific Research | Establishes a framework for integrating AI-based adaptive simulation in transport sustainability studies | Provides a replicable methodological template for data-scarce contexts |
| Engineering Practice | Demonstrates system adaptability through agent-based control mechanisms | Enables virtual testing of infrastructure performance under dynamic conditions |
| Urban Policy and Planning | Offers simulation-derived insights for sustainable transport policymaking | Supports evidence-based decision-making and risk mitigation before real implementation |

**Bounding Statement**

These findings should be interpreted as indicative trends within a controlled simulation environment rather than predictive guarantees for real-world transportation systems. The performance improvements observed are specific to the synthetic data and scenario configurations used in this study. Although adaptive AI demonstrates promising system-level behaviors, its direct translation to actual cities requires empirical validation. Hence, conclusions should be considered exploratory, guiding further research rather than prescriptive solutions.

**Operational Example**

Urban planners may use the proposed framework to compare alternative infrastructure scenarios, such as prioritizing public transport lanes or adaptive signal control, before physical implementation. By simulating multiple policy and infrastructure configurations, planners can identify potential bottlenecks or synergies without incurring real-world costs or disruptions. The framework allows testing of long-term strategies under varying traffic, environmental, and demographic conditions. This virtual experimentation can inform evidence-based decision-making and optimize resource allocation in tropical urban contexts.

**Sustainability Indicators**

Energy consumption, emissions, and congestion were selected as sustainability indicators because they collectively capture environmental impact, operational efficiency, and system-level performance, which are commonly used in urban transport assessment. Energy efficiency reflects resource utilization, emissions indicate environmental consequences, and congestion measures operational effectiveness and mobility. Together, these indicators provide a multidimensional perspective on urban transport sustainability. Their use ensures comparability with existing studies while allowing evaluation of adaptive behaviors in simulated tropical environments.

**Ethical & Governance Considerations**

As with any AI-based simulation, potential algorithmic bias may arise from simplified agent assumptions or reward structures, underscoring the importance of governance and human oversight. Decisions generated by the simulation are intended solely as decision-support outputs, not autonomous actions, ensuring human accountability. All agent actions, parameter choices, and simulation outcomes are fully logged to allow traceability and auditability. These practices promote transparency, reproducibility, and adherence to responsible AI principles in urban infrastructure modeling.

**Limitations**

For all its good results, the study has limitations. The use of artificial (synthetic) data lacks the traffic variability found in real-world tropical cities, thereby limiting predictive validity. The simulation was limited to a 5 × 5 km virtual network, and computational complexity increases with agent population, which may constrain real-time applications. These limitations highlight the need for careful interpretation of findings and suggest avenues for integrating empirical data in future work.

**Future Research Directions**

Future work will integrate hybrid information sources, combining synthetic and empirical datasets to improve generalizability and calibration. Real-time IoT data may further allow agents to adapt to live traffic patterns. Extending the multi-agent paradigm to socio-economic and environmental agents, such as emission sensors and commuter choice models, will enrich system modeling. The potential incorporation of digital twins could create a closed-loop simulation with real-world infrastructures, allowing mutual feedback. With reinforcement learning, IoT-enabled sensing, and digital twin technology, researchers can develop fully adaptive systems for sustainable urban transport management and contribute to the visions of Construction 5.0 and smart infrastructure.

## V. CONCLUSION AND RECOMMENDATION

This study demonstrates that a multi-agent AI simulation framework can be effectively utilized to explore urban transport sustainability in tropical contexts through controlled, synthetic experimentation. By incorporating adaptive agent behavior and dynamic system interactions, the framework is able to simulate complex patterns related to energy efficiency, congestion reduction, and emission mitigation, offering indicative insights into system-level performance. However, these results should be interpreted cautiously as exploratory rather than predictive, given the reliance on synthetic data, the absence of empirical validation, and the limited scale of the simulated network. From a practical perspective, the framework serves as a decision-support tool that enables planners to evaluate infrastructure scenarios, anticipate potential system-wide impacts, and explore alternative policy options prior to real-world implementation. This capability is particularly valuable in complex urban environments where direct experimentation is costly and high-risk. Future work should focus on enhancing the realism and applicability of the framework by integrating hybrid data sources, incorporating real-time inputs, expanding cross-scale mobility analysis, and embedding socio-economic and behavioral dimensions. Additionally, coupling the framework with AI-driven digital twin technologies may further improve its adaptability and operational relevance.

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