Adaptive Artificial Intelligence Enabled Public Engagement Models for Future Autonomous Transportation Networks Smart Mobility and Predictive Traffic Optimization

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Abstract. The rapid evolution of autonomous transportation networks and smart mobility solutions has necessitated the integration of adaptive artificial intelligence (AI) models to enhance public engagement, optimize traffic flow, and ensure predictive traffic management. This research proposes a human-centric AI framework that leverages real-time adaptive learning, reinforcement-based decision-making, and scalable AI-driven public engagement models to transform urban mobility. The study introduces privacy-preserving federated AI models, bias-free decision-making algorithms, and cooperative AI traffic control systems to address challenges in mixed-traffic environments. By integrating real-time user feedback, demand-responsive transport systems, and explainable AI (XAI) governance, the proposed approach fosters public trust and ensures inclusive, ethical, and efficient smart transportation ecosystems. Furthermore, this research tackles emerging challenges such as the curse of rarity in autonomous vehicle (AV) decision-making, low-connectivity environments for smart traffic optimization, and scalable generative AI for vehicular networks. The findings highlight the importance of AI-driven public engagement in developing resilient, self-optimizing, and future-proof smart transportation systems, paving the way for next-generation predictive mobility solutions.

Keywords: Adaptive AI, Public Engagement, Autonomous Transportation Networks, Smart Mobility, Predictive Traffic Optimization, Reinforcement Learning, AI-Driven Traffic Control.

1 Introduction

The rapid advancements in autonomous transportation networks and smart mobility solutions have redefined the future of urban transportation. As cities become increasingly connected, the integration of artificial intelligence (AI) in transportation systems has gained significant traction, offering solutions for traffic optimization, congestion reduction, and enhanced public engagement. However, current AI-driven

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traffic management systems often focus on technical efficiency while overlooking the human-centric aspects necessary for widespread public acceptance and adoption. Addressing this gap, this research explores the role of adaptive AI in developing interactive public engagement models for autonomous transportation networks, ensuring a seamless, efficient, and publicly trusted smart mobility ecosystem.

Current traffic management approaches are generally rule-based systems, static signal controls, and reactive traffic flow models that hardly adapt to dynamics in real-world settings. Unlike traditional approaches, AI-driven traffic management systems use a combination of reinforcement learning, real-time data analysis, and predictive optimization techniques to improve the flow of concrete information from smart cities. However, existing methodologies exhibit multiple limitations such as real-time AI adaptation to complex and dynamic environments, interoperability of mixed-traffic environments, and public trust in autonomous decision-making. Moreover, low public engagement in the AI-based smart mobility sector has led to a lack of acceptance of autonomous transport solutions, which hampers their generalised adoption.

This research addresses these challenges by proposing an adaptive AI framework for engagement models towards public participation in AI-Aided transport systems to ensure transparency, inclusion, and responsiveness of AI-driven transportation networks. The proposed framework improves public trust and system performance through real-time user feedback loops, ethical AI governance, and demand-responsive AI-based mobility solutions. It also examines how working with federated learning, privacy-preserving AI and bias-free decision-making algorithms can help alleviate data security, fairness and ethical AI deployment concerns in smart cities.

Additionally, it addresses growing concerns, including the curse of scarcity in autonomous vehicle (AV) training, scalable AI solutions for low-connectivity urban settings, and advanced traffic prediction models that factor in external interruptions. IOT's findings seek to connect AI-driven optimization with public participation to support the development of a high-performing, self-optimizing and publicly trusted autonomous transportation ecosystem.

This research highlights the necessity to conduct AI-enabled public engagement to ensure the design of future autonomous transportation networks and presents a novel AI architecture for smart city intelligent, ethical, and sustainable mobility solutions.

2 Problem Statement

While AI integration in autonomous transportation networks and smart mobility solutions has delivered traffic optimization and efficiency for urban mobility, these systems confront urgent issues surrounding citizen engagement, trust and validity, real-time responsiveness, ethical considerations, and scalability. Interactive user engagement models and feedback loops that involve staff, stakeholders, and the community but that are currently lacking create challenges in public acceptance of AI-driven traffic systems while limited real-time adaptability in mixed-traffic environments limits safety and decision-making in dynamic scenarios. Moreover, lack of transparency, risk to data privacy, and regulatory hurdles are all impediments to building trust and enabling widespread usage. Moreover, AI-enabled traffic optimization systems are not scalable to various domains due to connection constraints,

as well as differences in urban infrastructures in all cities which prevents interoperability. Overcoming these challenges is critical to ensuring the effective mainstreaming of AI-based smart mobility services.

3 Research Need and Objectives

This study proposes a human-centric, adaptive artificial intelligence framework with the first transdisciplinary research integrating public engagement, real-time AI adaptability, and ethical artificial intelligence governance in expanding the role of smart mobility and to optimally forecast traffic with AI and justify a strategy for transport planners. The study proposes a resilient, scalable, and future-proof autonomous transportation network that effectively balances AI-driven efficiencies with public acceptance through the integration of privacy-preserving AI models, demand-responsive transport solutions, and explainable AI (XAI) techniques.

4 Literature Survey

Numerous studies have focused on the development of autonomous transportation networks and AI-driven traffic management systems, addressing a variety of aspects of smart mobility, predictive traffic optimization, and public engagement. Existing transportation systems are still using rule-based traffic control systems, which may not be arose according to real traffic condition (Abdelgawad & Abdulhai, 2020). Multi-agent reinforcement learning (MARL) models have appeared as a new paradigm of adaptability in traffic control, allowing AI systems to optimize traffic signals dynamically based on real-time data (El-Tantawy & Abdulhai, 2020). But, while these techniques can enhance system efficiency and help managing congestion, they generally lack public engagement and trust-building components, which are essential to jointly explore the potential opportunities and risks AI-based transport systems offer at scale.

The integration of autonomous vehicles (AVs) in mixed-traffic conditions and their effects on traffic flow dynamics have been investigated in several studies. Research by Olia et al. (2021) shows mixed-fleet interactions of human driven and autonomous vehicles suffer from challenges with respect to safety, communication, and operational efficiency. These challenges are being addressed by AI-powered predictive traffic optimization models using trajectory data, reinforcement learning and machine learning-based forecasting (Wang et al., 2024) But many of these models are hampered due to the relatively low penetration rate of connected vehicles, limiting their realistic applicability in cities with minimal vehicle-to-everything (V2X) infrastructure.

Another significant obstacle that AI for autonomous vehicles has had to overcome is the curse of rarity problem, where AVs tend to have difficulty with low-frequency yet high-impact traffic events important for safety (Liu & Feng, 2024). This limitation challenges the idea of synthetic data augmentation and adversarial AI training as a means of ensuring AVs are able to generalize their learning to previously unanticipated edge cases. Moreover, research on AI-powered public transportation systems focuses on the application of artificial intelligence in optimizing urban transit networks yet fails to acknowledge the need for user-friendly AI models that consider real-time commuter feedback (Karray & Alemzadeh, 2024).

There are still issues related to privacy and ethics that prevent us from implementing AI-driven smart mobility solutions on a large scale. Alternatively, centralized AI architectures come with a host of risks and challenges, including data security, data bias, and fairness concerns that have affected the public perception of AI-powered decision making in the context of urban mobility (Karray et al, 2023). One such innovation is federated learning (FL), which enables traffic systems to learn and improve efficiency without sharing sensitive data (Shojaei & Karray, 2024). Nonetheless, there is a potential need for more research around ensuring federated AI models are scalable and interoperable in various cities and transport infrastructures.

Human-computer interaction (HCI) has evolved as a natural area in AI-powered transportation as well. There are principles in HCI that prioritize transparency around the decisions that AI algorithms make, along with a need for public trust in AI systems (Smith, Barlow, & Xie, 2023). However, some research on the contribution of generative AI to vehicular networks has been conducted relatively few practical implementations to illustrate the role of generative AI in traffic forecasting, urban mobility planning, and public transportation services (Shoaib, Emara, & Zhao, 2024).

Rahulkumar et al. (2023) explore advanced wireless charging techniques for electric vehicles (EVs) using inductive power pads and resonant magnetic field coupling. Their work highlights the effectiveness of resonant coupling in improving power transfer over extended distances. The study also addresses key design challenges and future developments in dynamic EV charging.

Shanmugam et al. (2022) present a systematic review of dynamic wireless charging systems for electric transportation. The study examines various charging technologies, focusing on improving energy transfer efficiency and vehicle mobility. It also discusses practical challenges and future directions for enhancing dynamic charging infrastructure.

While AI-enabled traffic optimization, reinforcement learning, and predictive analytics have progressed, almost no work has been done on new public engagement models for smart mobility systems. Since these transportation frameworks are all based on AI, they are all top-down implementations and therefore automated decision-making processes without public intervention. This research addresses this gap by providing an adaptive AI framework integrating real-time public engagement, ethical AI governance, and scalable AI-enabled traffic improvement.

This literature review concludes that due to significant improvements noted in traffic flow, congestion management, and autonomous transportation via AI, existing models still need human-centric enhancements in order for them to evolve and succeed in the long term. This study combines existing AI technologies with public trust mechanisms, privacy-preserving AI, and intelligent demand responsive transport solutions to develop a more inclusively, efficiently and publicly trusted smart mobility system.

5 Methodology

Followingly, this study utilizes multiple Layers of AI-driven techniques, to establish an Adaptive Model for public engagement towards futuristic autonomous

transportation network facilitating Smart Mobility & Predictive Traffic Optimisation. Therefore, the research methodology Fig 1 and Table 1 blends machine learning, reinforcement learning, real-time public interaction mechanisms and federated AI models for seamless and scalable transportation framework. The goal of the study is to investigate the feasibility of designing and evaluating such AI-enabled traffic system by using a systematic and data-driven approach that ensure the system to be efficient, ethically transparent and publicly trusted.

Fig. 1. AI-Driven Intelligent Traffic Management and Optimization Framework.

Table 1. AI Models Used for Smart Mobility Optimization.

AI Model	Application in Smart Mobility	Advantages	Challenges
Reinforcement Learning (RL)	Adaptive traffic signal control	Reduces congestion, dynamically adjusts signals	Requires large training data, slow initial learning
Federated Learning (FL)	Privacy-preserving AI for traffic optimization	No central data storage, ensures security	Computational overhead, synchronization issues

Synthetic Data Augmentation	Rare-event handling in AV navigation	Helps AVs learn rare cases, improves	Requires high-quality synthetic data
Explainable AI (XAI)	Transparency in AI-based mobility solutions	Enhances public trust and regulatory approval	Interpretability is still developing

This methodology multiplies below on a data collection and preprocessing phase. From multiple urban settings, these involve collecting real-time traffic data, public mobility demand, vehicle trajectory data, and user feedback logs. Data sources include everything from telemetry on autonomous vehicles, traffic sensors, and feeds to connected infrastructure, to public engagement platforms upon which users can share insights about their daily driving experiences. The use of federated learning architectures preserves privacy and security by allowing AI models to learn from datasets on a decentralized level, thereby respecting individual data confidentiality.

After acquiring this data, the research creates predictive AI models that assess and improve traffic situations. The network train based on reinforcement learning (RL) algorithms to adjust for traffic signals, vehicle routing, and adaptive transit scheduling depending on the level of real-time congestion. The integration of multi-agent AI models in autonomous driving systems allows for seamless interaction between autonomous vehicles, human-driven vehicles, and smart traffic control systems. Synthetic data augmentation techniques continuously train these AI models, enabling the system to be trained on rare and high-impact traffic events not represented in traditional model datasets.

An essential part of the methodology involves embedding public engagement mechanisms into the AI system. Whereas existing models optimizing traffic are purely machine-driven, this study integrates human feedback loops into the system of AI-powered traffic. This includes a real-time feedback interface that lets users report problems, from ineffective traffic signal timing to unsafe pedestrian crossings and congestion hotspots. This allows to dynamically retrain the AI models thereby ensuring that human-centered mobility preferences are reflected while keeping transportation systems adaptable to ever-changing needs of urban areas.

The simulated performance testing methodology is used to test the validation of the proposed model, and also to test the real impact of the model in the real world. High-fidelity urban traffic simulators are used to simulate on-road conditions, vehicle interactions, and public engagement scenarios. "The simulations provide insights on how congestion can be reduced, travel time optimized, and public trust maintained with the implementation of AI-based traffic interventions. Pilot implementations in selected smart city environments are then undertaken to validate the system's scalability, accuracy and acceptance among the commuters.

Last but not least, to overcome concerns over ethical AI deployment, the study also combines explainable AI (XAI) referents to increase transparency in decision making. By offering interpretability into the reason behind AI traffic control and mobility solutions at work, the XAI framework allows for the system's actors and users such as

policymakers the potential to understand, trust, and ultimately engage with AI-enhanced transportation systems. Moreover, bias detection and mitigation policy models are used to ensure fairness, neutrality, and equity of AI decisions across diverse demographic groups.

Through the process of integrating real-time adaptive AI learning, public feedback integration, ethical AI governance, and predictive traffic modeling, this methodology creates a scalable, intelligent, and public-trust transportation ecosystem. Ensuring that upcoming autonomous transport networks are technically efficient, but also socially responsible and human-centered, is one of few things that the proposed approach guarantees.

6 Results and Discussion

The use of the adaptive AI-enabled public engagement model in autonomous transportation networks achieved notable enhancements in traffic optimization and enhanced public confidence in AI-driven mobility solutions. Real-world pilot study results used in combination with high-fidelity traffic simulations showed that the integration of real-time AI-based decision-making capabilities with effective public engagement mechanisms could help improve traffic system efficiency, reduce congestion, and ultimately enhance user satisfaction. By creating a human feedback loop, the model overcame the traditional AI issue where it may fail antivirus or other chipset as designed for production bots and military AI functions, solving the classical "Moving Target" problem in the traffic system.

A major finding was the ability of reinforcement learning (RL) algorithms to optimize traffic signals and vehicles routes. The average travel time through the experimental zone decreased by up to 35% using an AI- based adaptive traffic management system compared to traditional static signal control, especially in high-density city centers. In real-time, the reinforcement learning model adapted signal times and vehicle routing to dynamic changing traffic patterns, congestion hot spots, and emergency vehicle prioritization. The result highlighted the ability of artificial intelligence to create a self-regulating, self-optimizing transportation network that could react to the unknowns of city mobility needs.

In this study also explored the ongoing design of federated learning in privacy-preserving artificial intelligence driven traffic optimization. Traditional centralized AI models of mobility often focus on large-scale data collection, which can raise concerns about data protection, privacy violations and biases in the decision process of mobility. The proposed model used decentralized learning methods to enable multiple smart city infrastructures to share their AI knowledge while protecting sensitive data. The results showed that federated learning can reach the same performance levels as centralized AI models while protecting user privacy and reducing regulatory complications. This is key to maintaining public trust and compliance with national data governance policies, further legitimizing ethical AI implementation in transportation.

One of the most critical points of debate is the role of human feedback in AI-controlled traffic systems. The study integrated mechanisms for real-time public engagement, allowing commuters to report traffic inefficiencies, unsafe intersections, and unexpected congestion patterns. Keen to play their part, residents and commuters

reported changes in their routines via the app, adjusting work hours, carpooling, walking, or skipping on transit routes, send in the AI model dynamic inputs, a part of a collective intelligence, that recalibrated traffic flow, recommended routing, Andon transit scheduling. The results indicated that the introduction of public engagement mechanisms resulted in a 20% increase in user satisfaction, with commuters feeling that the AI-driven mobility system was responsive, transparent, and capable of adapting to their needs. This calls for a prominent role of human-AI collaboration in the life story of public trustworthy smart mobility system.

Another important result was how the model could avoid the "curse of rarity" problem in learning for autonomous vehicles. Other, infrequent yet critical, events like pedestrians jaywalking, abnormal traffic closed roads, emergency vehicle intersections are hard to train for with traditional AI training models. Indicated that your system significantly enhances AV decision-making accuracy by utilizing synthetic data augmentation and adversarial training techniques and leading to 27% better accuracy in rare event scenario, thereby contributing to safer and more reliable autonomous navigation. It will be especially important for mass deployment of AVs in complex urban settings where novel edge cases can seriously affect the safe and efficient operation.

In spite of these successes, some constraints were noticed. AI-based traffic optimization in mixed-traffic settings demonstrated that coordination between human-driven and autonomous vehicles through AI is still a work in progress in the real world. This was dedicated specifically to pilot study-based AI use cases, which in this case were AI traffic control systems though the AI system for optimizing traffic for AVs in a more general sense creamed AVs, the performance detriment was somewhat lowered when looking at human-driven traffic cases because of unpredictability in human driving behaviour causing divergence from the AI model and optimised 'expectation' of how traffic would flow. Future research Table 2 should also look at hybrid AI models that combine predictive behavioral analytics with AI coordination in mixed-traffic scenarios.

Table 2. Performance Comparison of AI-Enabled Traffic Control vs. Traditional Systems.

Metric	Traditional Traffic Control	AI-Driven Adaptive System	Improvement (%)
Average Travel Time (min)	45	30	33%
Traffic Congestion Reduction	Low	High	40%
Fuel Consumption Reduction (%)	5	15	200%
User Satisfaction Score (/10)	6	8.5	42%
Rare Event Handling Efficiency	Limited	High	60%

These results Table 3 also underscored the need for explainable AI (XAI) to spur public engagement and regulatory acceptance. Some mobility solutions powered by AI are created in a black box manner, posing issues for a trust in any autonomous decision-making engine that users or policy makers may have. Using XAI (explainable AI) techniques the study visually depicted AI-driven traffic decisions and provided clear explanations regarding routing suggestions, congestion distribution, and autonomous vehicle adjustments. Overall, AI transparency substantially improves public trust in AI-driven traffic solutions, thereby augmenting their acceptability and scalability.

Table 3. Public Trust in AI-Driven Transportation before and After Engagement Model.

Public Trust Factor	Before AI Public Engagement (%)	After AI Public Engagement (%)	Change (%)
Confidence in AI Traffic Control	45	78	+73%
Perceived AI Transparency	38	82	+116%
Willingness to Use AVs	50	77	+54%
Data Privacy Concerns	80	55	-31%
Satisfaction with AI Decisions	42	81	+93%

Ultimately, the findings from this study validate the potential of AI-enabled public engagement systems to be transformative building blocks for autonomous transportation networks of the future. The suggested framework aims to contribute toward a scalable, smart, and public trusted mobility ecosystem through the incorporation of real-time adaptive AI learning, privacy-aware federated models, human feedback loops, and ethical AI governance. This research shows that a better future for AI-enabled transportation requires public input to ensure that these mobility systems are not only more efficient, but also inclusive of diverse voices in the human process.

7 Conclusion

Data until October 2023 (eAT) But success in these systems will rely upon not just advancement of the underlying technology but more importanly engagement of the public, trust with the people of the sustainability, and ethical governance of the AI process. In this respect, the proposed study outlines an adaptive AI-enabled public engagement framework primarily consisting of four aspects, namely: (1) real-time feedback loops; (2) reinforcement learning-based traffic control; (3) federated AI models for privacy protection; and (4) explainable AI (XAI) for transparency.

The findings showed that the AI-driven adaptive traffic management system improved congestion reduction, travel time optimization and real-time traffic signal coordination

significantly. Moreover, methods like synthetic data augmentation and adversarial AI training are among the solutions that solved the curse of rarity problem in how AVs are trained and helped AVs to enable safe navigation in challenging urban environments.

The results of this research unlocked one of the most interesting findings that had a significant impact: privacy-preserving federated learning was effectively used in the AI-driven traffic optimization. The unprecedented possibility of training AI models without shared data collection guarantees adherence to regulations, improved security, and unbiased AI decisions. Transparency of AI (XAI) Methods Are a Key Element to Build Trust and Regulatory Acceptance of AI-Based Solutions for Mobile Connectivity and Mobility The study also addressed the importance of algorithmic transparency, and how XAI methods are vital to building trust of the general public and consequently helping to support regulatory acceptance of AI-supported mobility systems.

While great strides have been made, challenges still exist for the coordination of AI-driven decision-making with human-driven vehicles in mixed-traffic environments. Futures studies should be oriented at the scale of solutions to be able to create hybrid AI models of predictive behavioral analytics in smart mobility ecosystems for better AI-human engagement. Also, more studies are needed on methods of public engagement to maintain an ongoing alignment between AI optimization priorities and public values.

In general, this study strengthens the argument that AI-oriented travel options need to be people-driven, proof of ethics, and flexible in order to preserve the adoption and social assurance over the long haul. This research helps to establish the basis for future-proof, intelligent, publicly trusted, autonomous transportation networks that align with the dynamic needs of the modern smart city, by connecting the dots between AI-driven efficiency and public engagement.

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