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SYSTEMATIC REVIEW ON THE IMPACT OF AI-ENHANCED TRAFFIC SIMULATION ON U.S. URBAN MOBILITY AND SAFETY

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Abstract
The rapid growth of urban populations in the United States has intensified challenges related to traffic congestion, safety, and sustainable mobility. Artificial Intelligence (AI)-enhanced traffic simulation has emerged as a transformative tool to address these issues by integrating advanced data analytics, predictive modeling, and real-time decision-making into traditional traffic management systems. This systematic review evaluates the impact of AI-enhanced traffic simulation on U.S. urban mobility and safety, synthesizing findings from peer-reviewed studies, transportation reports, and government publications published over the past two decades. The review highlights how machine learning algorithms, reinforcement learning, and deep learning frameworks are applied to optimize signal control, predict traffic flow, and improve incident response times. Evidence suggests that AI-driven simulations significantly reduce travel delays, fuel consumption, and emissions while enhancing pedestrian and vehicular safety through proactive risk detection and adaptive traffic control. Furthermore, case studies from major U.S. metropolitan areas demonstrate the potential of AI systems to integrate with smart infrastructure and connected vehicles, enabling dynamic rerouting and congestion mitigation strategies. However, challenges remain in terms of data standardization, model scalability, cybersecurity, and equitable deployment across diverse urban contexts. By systematically analyzing the strengths, limitations, and emerging trends of AI-based simulations, this review provides insights for policymakers, urban planners, and transportation engineers seeking to foster safer, more efficient, and resilient mobility systems. Ultimately, AI-enhanced traffic simulation offers a promising pathway toward advancing sustainable urban transportation in the United States.

Keywords: *Artificial Intelligence, Traffic Simulation, Urban Mobility, Road Safety, United States*

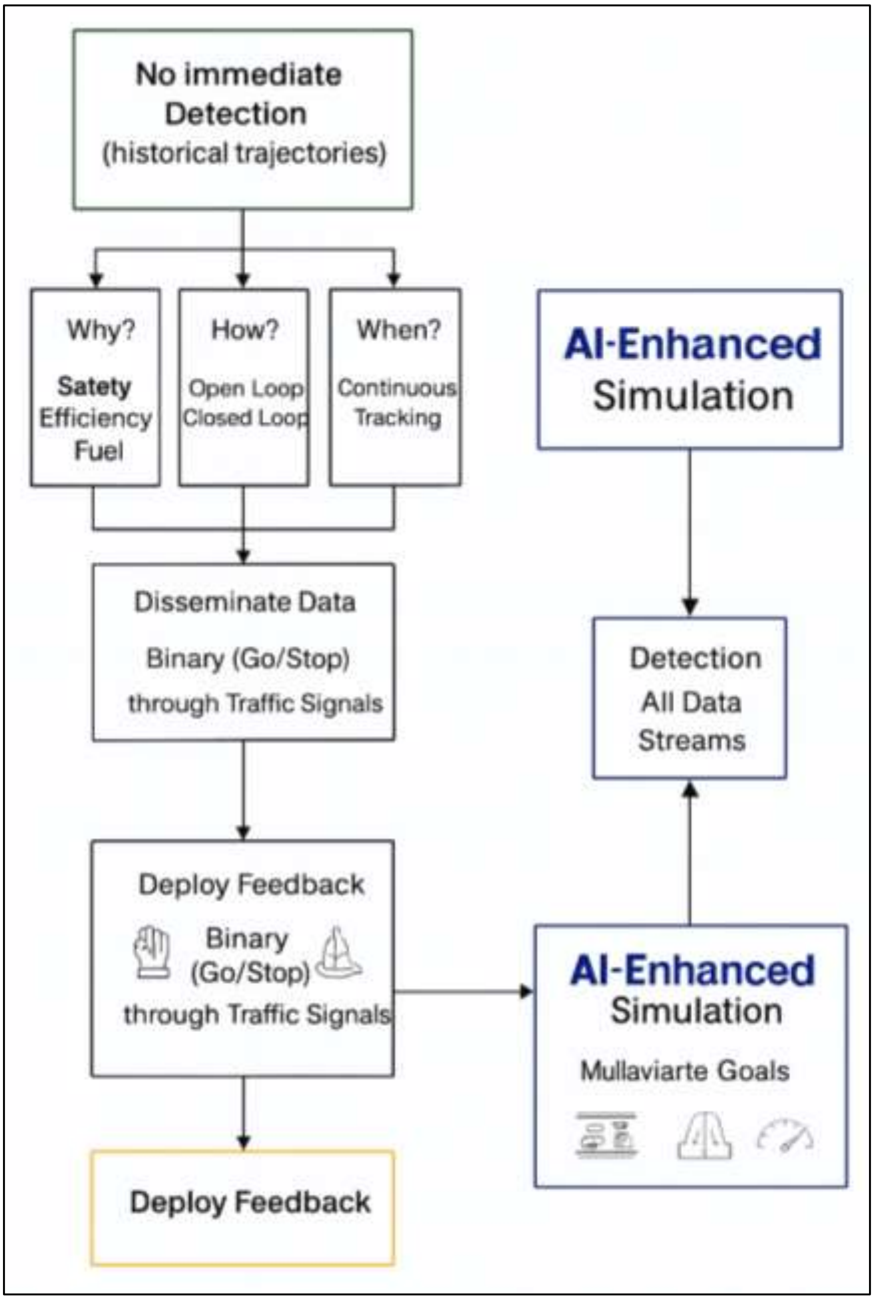
INTRODUCTION

Traffic simulation is broadly defined as the use of computational and mathematical models to replicate the dynamic behavior of vehicles, pedestrians, and other transportation agents in an artificial yet data-driven environment (Alghamdi et al., 2022). It encompasses macroscopic models that analyze aggregated flows, mesoscopic models that blend individual and collective attributes, and microscopic or agent-based models that capture detailed interactions such as car-following and lane-changing behavior. Artificial intelligence (AI), meanwhile, refers to algorithmic and machine learning approaches designed to recognize patterns, make predictions, and optimize complex processes by learning from data. The merging of these two domains—AI-enhanced traffic simulation—implies leveraging adaptive algorithms, reinforcement learning, deep neural networks, and probabilistic inference to enrich the calibration, prediction, and optimization of traffic models beyond traditional static or deterministic approaches . The international relevance of this integration is underscored by the global urbanization trend, where more than half of the world's population resides in cities, creating systemic pressure on transport networks (Kessels et al., 2019). Research from Europe and Asia has shown how AI-based microsimulations inform congestion control, multimodal integration, and crash risk estimation in dense metropolitan areas. These concepts and global applications establish a foundation for contextualizing the U.S. case, where AI-driven simulation tools are increasingly aligned with large-scale infrastructure planning and urban safety evaluations (Jabbarpour et al., 2018).

The development of traffic simulation has evolved from basic car-following theories to complex digital-twin ecosystems capable of mirroring entire cities. Early models, (Gadkari et al., 2018)car-following formulations, sought to mathematically capture how drivers adjust speed and headway based on surrounding stimuli. These models later informed microscopic simulators like VISSIM, PARAMICS, and Aimsun, which provided granular depictions of vehicular interactions. Cellular automata models (Dogra et al., 2019) introduced scalable representations of traffic flow and congestion formation, allowing real-time computational efficiency. Subsequent advancements, including activity-based and agent-based models, incorporated behavioral diversity and household decision-making into transport dynamics. The rise of AI accelerated these capabilities, as machine learning was integrated to handle high-dimensional data from loop detectors, GPS probes, and Bluetooth sensors (Danish & Zafor, 2022; Occhipinti & Boron, 2019). Reinforcement learning enabled adaptive traffic signal control and corridor optimization beyond fixed-time or actuated systems. Globally, these methods have been tested in pilot projects from Europe's adaptive control experiments to Asia's connected-vehicle trials. In the United States, this trajectory is paralleled by federal and local projects embedding AI tools into microscopic simulations to evaluate corridor throughput, transit signal priority, and freeway ramp metering strategies (Adiga et al., 2020; Danish & Kamrul, 2022). This historical pathway illustrates how the fusion of simulation and AI has progressively increased the fidelity, realism, and decision-making utility of urban transport modeling.

AI-enhanced traffic simulation depends on diverse and high-resolution data streams that calibrate and validate the accuracy of modeled scenarios. Traditional calibration relied on fixed detector counts, speed data, and turn-movement surveys(Das et al., 2018; Jahid, 2022). However, the contemporary era introduces probe data from connected vehicles, trajectory datasets from naturalistic driving studies, and Bluetooth/Wi-Fi reidentification for travel time estimation. AI techniques such as Bayesian inference, transfer learning, and surrogate modeling provide scalable approaches for aligning simulation parameters with real-world measurements (Ma et al., 2021; Arifur & Noor, 2022). For instance, reinforcement learning agents can continuously refine signal timing strategies based on traffic state inputs derived from loop detectors or connected-vehicle basic safety messages. Validation procedures emphasize both internal consistency—matching model outputs with observed data during calibration—and external validity through independent datasets like event-based demand surges or seasonal variations. The Federal Highway Administration's Surrogate Safety Assessment Model further integrates conflict-based indicators, including post-encroachment time and time-to-collision, linking AI-derived trajectory analyses to safety outcomes. Internationally, these workflows echo in digital-twin applications from Europe and Asia, where real-time feedback loops integrate continuous sensor data with simulation platforms (Mahlbacher et al., 2018; Hasan & Uddin, 2022). Thus, the U.S. context reflects a convergence of AI methodologies and empirically rigorous calibration standards that secure the representational validity of AI-enhanced simulations.

Figure 1: AI-Driven Traffic Control Framework



Urban mobility is evaluated through indicators such as travel time reliability, intersection delay, person-throughput, and multimodal accessibility, all of which are increasingly embedded within AI-augmented simulation platforms (Rahaman, 2022a; Ramachandran et al., 2018). AI models improve predictions of congestion propagation, incident impacts, and modal interactions, allowing a more precise depiction of variability in travel patterns. For transit systems, simulations assess bus dwell dynamics, headway regularity, and priority strategies under dynamic control schemes (Eldredge, 2019; Rahaman, 2022b). Pedestrian and cyclist flows are similarly represented in terms of exposure, crossing conflicts, and multimodal safety trade-offs. Safety analysis within these simulations adopts surrogate measures like deceleration-to-safety time and speed-at-conflict, offering quantitative proxies for crash risk estimation. The U.S. uses datasets such as the Fatality Analysis Reporting System (Asefi et al., 2019) to benchmark simulation-derived safety outcomes against observed crash severities. Deep learning applied to video feeds further enriches exposure modeling by extracting trajectories and near-miss events, which integrate into surrogate-based safety assessments (Anirudh, 2020; Rahaman & Ashraf, 2022). International applications—such as cooperative adaptive cruise control in Europe and connected-vehicle experiments in Asia—mirror the U.S. approach by linking AI-enhanced control strategies to both operational efficiency and safety improvements (Islam, 2022; Smetanin et al., 2020). These interwoven perspectives situate AI-enhanced simulation as a methodological bridge between mobility outcomes and safety performance in complex urban networks.

LITERATURE REVIEW

The literature review serves as the analytical foundation of this systematic study on AI-enhanced traffic simulation and its impact on urban mobility and safety in the United States (Bawack et al., 2022; Hasan et al., 2022). It synthesizes prior research across interdisciplinary domains, including transportation engineering, computer science, urban planning, and public policy, to contextualize how artificial intelligence has transformed traffic simulation practices. A critical review of prior studies allows for the identification of methodological innovations, comparative insights, and thematic gaps that shape the current discourse. Unlike earlier generations of deterministic or static simulation approaches (Kumar et al., 2023; Redwanul & Zafor, 2022), AI-driven models rely on machine learning, reinforcement learning, and agent-based designs that dynamically adapt to heterogeneous mobility conditions. Examining this evolution requires a structured organization of themes ranging from definitional clarifications to sector-specific applications. The review begins with a discussion of the theoretical foundations and definitional constructs that frame AI in traffic simulation (Bolanos et al., 2024). It then explores international perspectives, highlighting the global diffusion of these methods, before narrowing the scope to the U.S. context. Subsequent sections analyze two central thematic pillars—mobility efficiency and safety enhancement—followed by a critical assessment of methodological frameworks and technical enablers (Torre-López et al., 2023). Finally, the literature review incorporates comparative policy and governance considerations, underscoring how simulation outputs have informed infrastructure investment and regulatory frameworks. This structured approach ensures that the synthesis captures both the breadth and depth of scholarship while maintaining analytical precision aligned with systematic review standards.

Traffic Simulation and Artificial Intelligence Integration

Traffic simulation has long been a cornerstone of transportation analysis, allowing researchers and planners to test network performance, forecast demand, and evaluate infrastructure interventions. Simulation frameworks are typically categorized into macroscopic, mesoscopic, and microscopic models, each offering unique analytical perspectives. Macroscopic models treat traffic as continuous flows, drawing upon principles of fluid dynamics to describe aggregate relationships between flow, speed, and density. Mesoscopic models integrate individual vehicle behavior with aggregate flow principles, enabling intermediate-scale representations that balance computational feasibility with behavioral detail (Rezaul & Mesbaul, 2022). Microscopic models, such as those implemented in VISSIM and AIMSUN, represent traffic as interactions among individual vehicles and drivers, capturing behaviors such as car-following, lane changing, and gap acceptance. Each modeling type has been applied to urban congestion studies, infrastructure evaluation, and safety analysis, with the choice often determined by project scope and available data. Simulation frameworks have further evolved to integrate real-time traffic management systems, enabling decision makers to assess incident management and adaptive control in virtual environments before real-world implementation. Collectively, these categories establish the methodological foundation of traffic simulation research, providing the baseline upon which artificial intelligence has been layered to enhance predictive and adaptive capabilities (Hasan, 2022).

Early simulation relied on deterministic rules and fixed algorithms to approximate driver behavior and network dynamics, with foundational models such as the car-following paradigm developed, and the cellular automata models introduced. While these models provided important insights into traffic flow, they were constrained by their inability to adapt to stochastic variability and nonlinear patterns common in real traffic systems (Tarek, 2022). Early simulation relied on deterministic rules and fixed algorithms to approximate driver behavior and network dynamics, with foundational models such as the car-following paradigm developed and the cellular automata models introduced (Kamrul & Omar, 2022). While these models provided important insights into traffic flow, they were constrained by their inability to adapt to stochastic variability and nonlinear patterns common in real traffic systems. Advances in computational capacity facilitated the integration of probabilistic models, expanding the representation of driver heterogeneity and system uncertainty (Pojani & Stead, 2018; Tamanna & Ray, 2023). Yet, even with these refinements, traditional frameworks often struggled to replicate emergent congestion phenomena under real-world conditions. The rise of artificial intelligence provided a turning point, as reinforcement learning and data-driven methods enabled traffic simulation models to learn from historical and real-time datasets rather than being bound by predefined behavioral assumptions (Kamrul & Tarek, 2022). Hybrid approaches have emerged that combine physics-based models with machine learning algorithms, enhancing both realism and adaptability. This evolution marks a shift from rigid, rule-based structures to dynamic frameworks capable of capturing the complexity of modern transportation networks (Mubashir & Abdul, 2022).

The application of machine learning, reinforcement learning, and deep neural networks has significantly improved predictive accuracy in traffic simulation. Machine learning methods, particularly supervised learning algorithms, are used to calibrate microsimulation models with large-scale traffic datasets, enhancing parameter estimation and reducing calibration error. Reinforcement learning approaches, such as Q-learning, allow simulation systems to optimize traffic light phasing and dynamic signal control by continuously learning from simulated outcomes (Muhammad & Kamrul, 2022). Deep learning, especially convolutional and recurrent neural networks, has been applied to short-term traffic flow prediction, enabling simulations to integrate real-time data streams for more accurate scenario generation (Ray et al., 2024; Dydkowski et al., 2024). Studies demonstrate that hybrid neural networks combined with simulation environments significantly outperform traditional regression-based models in capturing nonlinear traffic dynamics. Furthermore, reinforcement learning has been embedded into agent-based simulations to enhance decision-making at the individual vehicle level, improving accuracy in complex scenarios such as freeway merging and multimodal interactions. These AI-driven advances strengthen simulation validity, particularly in contexts requiring fine-grained prediction of both mobility efficiency and safety outcomes (Reduanul & Shoeb, 2022; Talaat et al., 2023). By integrating adaptive algorithms, traffic simulation systems are now able to reflect heterogeneous driver behaviors and fluctuating network conditions with greater fidelity than was possible with rule-based approaches.

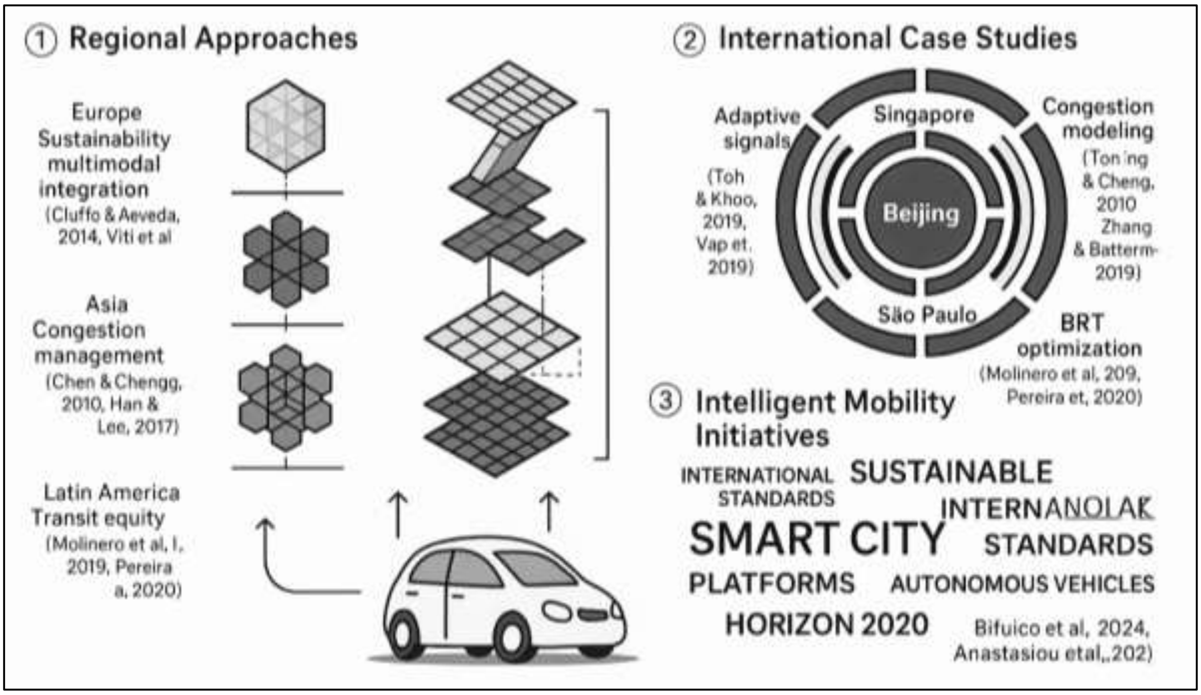
Agent-based modeling represents one of the most transformative integrations of AI in traffic simulation, enabling individualized representations of vehicles, drivers, and infrastructure elements. In agent-based systems, each vehicle operates as an autonomous decision-making unit, interacting dynamically with other agents and environmental conditions (Aboualola et al., 2023; Kumar & Zobayer, 2022). This approach improves realism in simulating behaviors such as lane changing, route choice, and response to congestion. Agent-based AI models also enable multimodal simulation, capturing the interactions between private vehicles, public transit, pedestrians, and bicycles. Integration with Intelligent Transportation Systems (ITS) further extends these applications, as simulations incorporate data from sensors, vehicle-to-infrastructure communication, and connected vehicle testbeds to optimize traffic control strategies (Sadia & Shaiful, 2022; Zhang et al., 2021). Case studies from Europe and Asia demonstrate that agent-based AI simulation enhances adaptive signal control, incident management, and multimodal network performance. In the U.S., ITS integration with AI simulation has supported pilot programs for connected and autonomous vehicles, enabling evaluation of cooperative adaptive cruise control and platooning under diverse roadway conditions (Amado-Salvatierra et al., 2024).

Global Perspectives on AI-Enhanced Traffic Simulation

The adoption of AI-enhanced traffic simulation has varied across continents, reflecting different urban forms, governance frameworks, and technological infrastructures. In Europe, traffic simulation research has focused on sustainability, multimodal integration, and environmental impacts, with cities such as London, Amsterdam, and Stockholm deploying AI-driven modeling tools to optimize both vehicle and transit operations (Lartey & Law, 2025; Noor & Momena, 2022). European research traditions emphasize integration with environmental policy, often linking simulation outputs with emission reduction targets and climate action frameworks. In Asia, the scale and complexity of megacities like Beijing, Shanghai, and Tokyo have driven strong interest in predictive modeling for congestion management and real-time adaptive traffic control (Borines et al., 2025; Istiaque et al., 2023). Asian cities have invested heavily in data-rich smart transportation infrastructures, enabling AI-based simulations to leverage GPS data, mobile sensors, and Internet of Things (IoT) technologies. In Latin America, where mobility challenges include inequality, rapid population growth, and underfunded transit systems, AI-enhanced simulations have supported interventions such as bus rapid transit (BRT) evaluation and congestion pricing schemes in cities like São Paulo and Mexico City (Eddamiri et al., 2025; Hasan et al., 2023). Comparative research highlights that while Europe focuses on sustainability, Asia emphasizes congestion management, and Latin America targets transit equity, all regions converge on the view that AI-enhanced simulation provides critical evidence for informed decision-making. Case-specific applications demonstrate how AI-enhanced traffic simulation has been institutionalized in diverse urban contexts. Singapore has become a leading case of adaptive signal control using machine learning, with the Land Transport Authority implementing AI-based microsimulation for real-time signal adjustment and multimodal integration (Nikolaidis, 2025).

Case-specific applications demonstrate how AI-enhanced traffic simulation has been institutionalized in diverse urban contexts. Singapore has become a leading case of adaptive signal control using machine learning, with the Land Transport Authority implementing AI-based microsimulation for real-time signal adjustment and multimodal integration (Hossain et al., 2023; Mudiyanselage et al., 2025). Empirical evaluations show reductions in travel times, improved bus punctuality, and safer pedestrian crossings, reflecting the alignment of simulation with the city's broader Smart Nation initiative. In Beijing, congestion modeling has been advanced through the integration of deep learning with simulation frameworks, enabling the prediction of traffic build-ups and the evaluation of interventions such as staggered work schedules and variable tolling (Rahaman & Ashraf, 2023; Serbouti et al., 2025). Studies from Shanghai and Shenzhen similarly demonstrate the value of AI-enhanced predictive modeling in megacities where demand exceeds road capacity (Sultan et al., 2023; Wang et al., 2025). In São Paulo, BRT optimization using AI-enhanced microsimulation has informed corridor design, dynamic scheduling, and fare policy, yielding improved throughput and reduced travel time variability for commuters. These international case studies illustrate the versatility of AI-enhanced traffic simulation, showing its capacity to address distinct challenges of congestion, multimodal integration, and transit equity across regions (Hossen et al., 2023; Morain et al., 2025).

Figure 2: Global AI Traffic Simulation Adoption



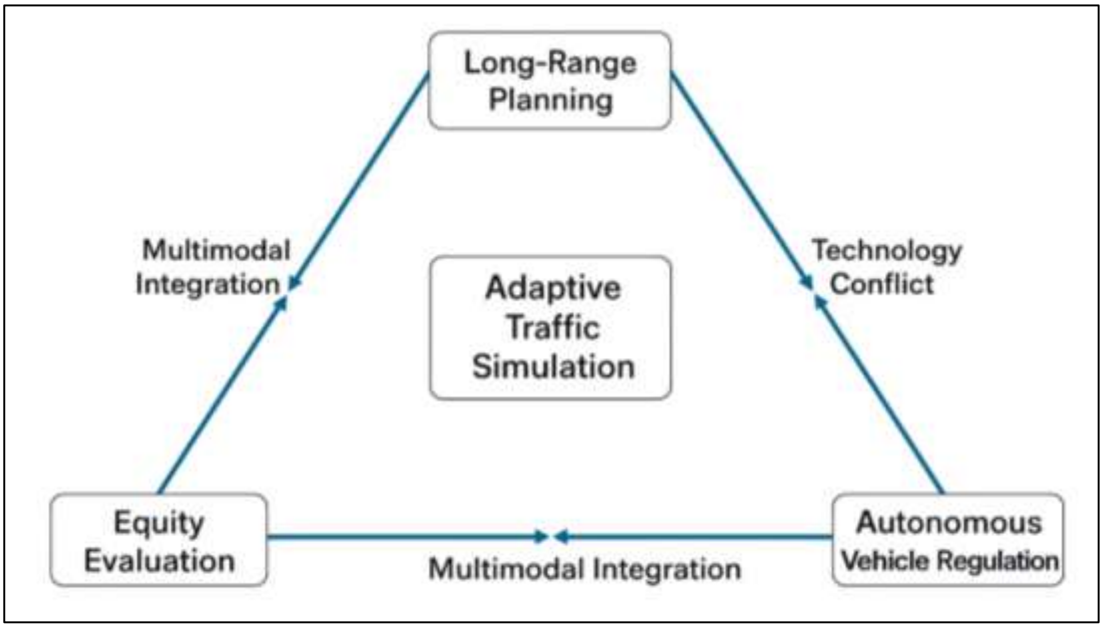
The global diffusion of AI-enhanced traffic simulation has been supported by the growth of international standards and smart city initiatives that formalize its adoption. Organizations such as the International Transport Forum (ITF) and European Commission's Joint Research Centre have promoted guidelines for incorporating AI-enhanced microsimulation into sustainable urban mobility planning (Tawfiqul, 2023; Mutambara, 2025). Smart city programs in Europe, Asia, and the Middle East routinely employ traffic simulation in evaluating integrated mobility platforms, congestion pricing, and autonomous vehicle readiness. Singapore's Smart Nation and Japan's Society 5.0 explicitly designate AI simulation as a pillar for achieving intelligent mobility systems, linking data-driven traffic models with nationwide infrastructure investment. Latin American cities have aligned AI-enhanced simulations with global sustainability frameworks, particularly in reducing emissions from outdated bus fleets through electrification scenarios tested in microsimulation platforms (Jørgensen & Ma, 2025; Uddin & Ashraf, 2023). International collaborations, including EU-funded Horizon 2020 projects, have further advanced comparative methodologies, establishing simulation as a core tool for global benchmarking in sustainable mobility (Boero, 2024; Momena & Hasan, 2023). Collectively, these initiatives demonstrate that AI simulation is not only a technical innovation but also a globally codified practice embedded within the governance of urban transformation (Goyal et al., 2024; Sanjai et al., 2023).

U.S. Context of Urban Mobility and AI Simulation

Urban mobility in the United States has historically been shaped by extensive suburbanization, automobile dependence, and fragmented transit systems. Scholars highlight that U.S. metropolitan growth patterns from the mid-20th century onward encouraged highway expansion and dispersed land use, producing chronic congestion and inefficiencies (Kashef & El-Shafie, 2020; Akter et al., 2023). The reliance on personal vehicles has exacerbated modal imbalance, with public transportation often underfunded and less accessible outside dense urban cores. Congestion in major cities such as Los Angeles, New York, and Washington, D.C. accounts for billions in lost productivity annually and contributes to elevated environmental and health costs. Empirical studies have also demonstrated that roadway expansion strategies have historically induced additional travel demand rather than reducing congestion, highlighting the structural limits of traditional interventions. Moreover, sprawl has heightened inequities in accessibility, with low-income households often experiencing longer commutes and restricted multimodal choices (Danish & Zafor, 2024; Hidayati et al., 2021). Simulation research in the U.S. initially developed within this context, focusing on traffic flow modeling to assess freeway capacity, evaluate transit corridors, and test congestion pricing before large-scale implementation . These historical challenges explain why U.S. transportation agencies increasingly turned to advanced modeling and simulation as essential tools for mitigating congestion, optimizing investment, and managing urban sprawl.

Federal and state-level agencies have played a pivotal role in promoting traffic simulation in the U.S., particularly through institutional initiatives aimed at integrating data-driven decision support into transportation policy. The Federal Highway Administration (FHWA) has been a leading proponent, funding the development of simulation platforms and establishing guidelines for their use in traffic operations and infrastructure planning (Istiaque et al., 2024; Stead & Vaddadi, 2019). The Department of Transportation (DOT) has similarly advanced AI-enhanced simulation under the Strategic Highway Research Program (SHRP2), which focused on scenario-based analysis of congestion, reliability, and safety. State-level departments of transportation have incorporated microsimulation into project evaluations, ranging from adaptive signal control pilots in Arizona to multimodal network assessments in California and Texas (Hasan et al., 2024; Silva & Vergara-Perucich, 2021). These initiatives reflect a recognition that simulation provides a cost-effective means to test policy alternatives under controlled conditions, reducing risks associated with trial-and-error deployment (Rahaman, 2024; Tehrani et al., 2019). Research has also noted that the federal emphasis on simulation aligns with broader smart infrastructure programs, including intelligent transportation systems (ITS) and connected vehicle testbeds, which rely heavily on AI-driven modeling (Hidayati et al., 2019; Hasan, 2024). Collectively, these efforts underscore the institutionalization of simulation as a core tool in U.S. transportation governance and infrastructure planning. Metropolitan planning organizations (MPOs) across the U.S. have increasingly employed AI-enhanced traffic simulation to support long-range transportation planning, equity evaluations, and multimodal integration.

Figure 3: U.S. Urban Traffic Simulation Framework



MPOs are mandated under federal law to prepare regional transportation plans, and simulation offers an analytical basis for comparing investment alternatives (Lewis & del Valle, 2019; Ashiqur et al., 2025). For example, the Metropolitan Transportation Commission in the San Francisco Bay Area has used microsimulation to assess dynamic tolling, bus rapid transit (BRT) performance, and travel demand management policies (Hasan, 2025; Soltani et al., 2025). Metropolitan planning organizations (MPOs) across the U.S. have increasingly employed AI-enhanced traffic simulation to support long-range transportation planning, equity evaluations, and multimodal integration. Metropolitan planning organizations (MPOs) across the U.S. have increasingly employed AI-enhanced traffic simulation to support long-range transportation planning, equity evaluations, and multimodal integration. MPOs are mandated under federal law to prepare regional transportation plans, and simulation offers an analytical basis for comparing investment alternatives. For example, the Metropolitan Transportation Commission in the San Francisco Bay Area has used microsimulation to assess dynamic tolling, bus rapid transit (BRT) performance, and travel demand management policies. Similarly, the New York Metropolitan Transportation Council has applied simulation for evaluating congestion pricing scenarios, estimating both economic and environmental impacts. AI-enhanced models have allowed MPOs to incorporate heterogeneous data sources such as GPS, household travel surveys, and connected vehicle feeds, thereby improving calibration and predictive validity(Colsaet et al., 2018; Ismail et al., 2025). MPOs also increasingly use simulation to assess equity, analyzing whether low-income or minority communities receive proportional access to mobility benefits under proposed investments. These applications demonstrate that simulation provides MPOs with both technical and policy-oriented insights, bridging the gap between engineering analysis and the political negotiation of regional mobility plans (Li & Wei, 2023; Jakaria et al., 2025).

The emergence of autonomous and connected vehicle technologies has positioned AI-enhanced simulation as a critical regulatory tool in the U.S. Autonomous vehicle pilot programs in states such as California, Michigan, and Arizona require extensive scenario testing under simulation before vehicles are allowed to operate on public roads (Bueno-Suárez & Coq-Huelva, 2020; Hasan, 2025). Simulation frameworks allow regulators to evaluate interactions between autonomous and human-driven vehicles, testing safety outcomes such as lane merging, pedestrian crossings, and platooning strategies. Reinforcement learning–based agent models have been used to replicate edge cases that are rare in real-world data but crucial for evaluating safety risks, such as near-miss incidents and unusual pedestrian behavior (Hesse & Siedentop, 2018; Sultan et al., 2025). State DOTs have collaborated with federal agencies and private industry to establish connected vehicle testbeds, integrating AI-enhanced simulations with real-time vehicle-to-infrastructure communication for regulatory evaluations (Antipova, 2018a; Zafor, 2025). Researchers note that these frameworks provide regulators with transparent, replicable, and evidence-based tools for assessing compliance with safety standards. In this capacity, simulation functions not merely as an analytical tool but as an integral component of the regulatory environment governing the deployment of emerging vehicle technologies in the U.S.(Dadashpoor & Saeidi Shirvan, 2024; Uddin, 2025).

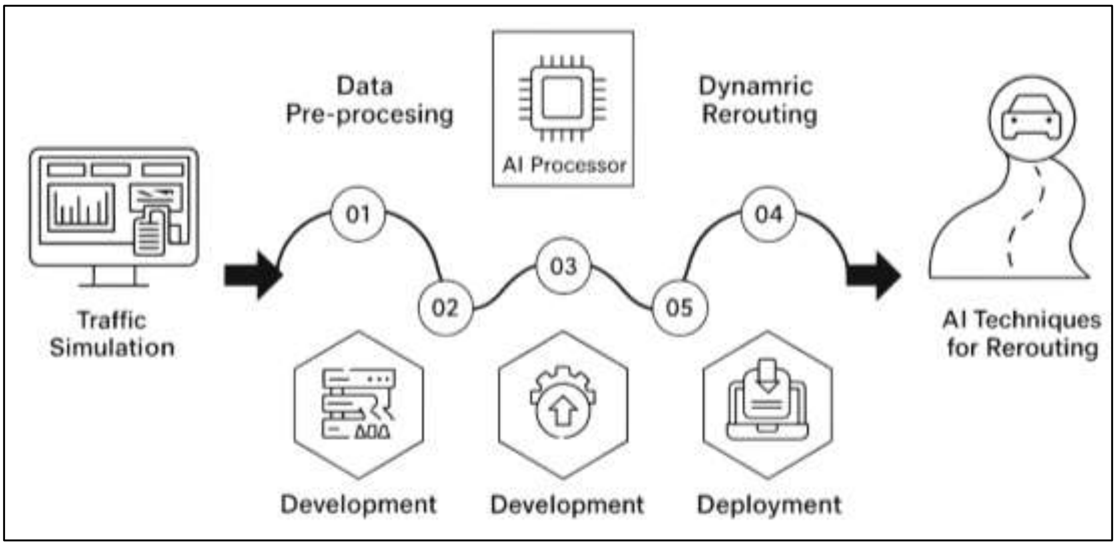
Mobility Efficiency Outcomes in AI-Enhanced Simulation

One of the most widely studied applications of AI in traffic simulation is the optimization of signal phasing and coordination to improve flow efficiency. Traditional fixed-time and actuated control systems, though effective in stable environments, lack adaptability in dynamic urban networks characterized by stochastic fluctuations in demand (Antipova, 2018b; Sanjai et al., 2025). Reinforcement learning–based models have demonstrated superior performance by continuously updating control strategies according to real-time conditions, reducing average delays and idling times at intersections. Deep Q-learning approaches embedded in simulation environments have shown that adaptive signal control can achieve measurable improvements in throughput, particularly in congested corridors. Studies using microsimulation platforms such as VISSIM and SUMO confirm that AI-driven traffic signal coordination reduces travel time variability and minimizes queue spillbacks, contributing to overall system stability. Comparative experiments in both simulated and field environments have documented travel time reductions of up to 20% compared with fixed-time controls. Furthermore, agent-based AI models allow for vehicle-level decision-making in signal optimization, enhancing coordination across arterial networks rather than at isolated intersections. Collectively, these studies demonstrate that AI-enhanced traffic simulations provide robust evidence that signal optimization represents a critical dimension of mobility efficiency improvements.

AI-enhanced simulation has advanced dynamic traffic assignment (DTA) and real-time rerouting strategies, enabling more efficient allocation of vehicles across networks. Traditional assignment models often struggled to incorporate behavioral heterogeneity and real-time variability, but AI-driven algorithms address these limitations by learning adaptive routing behaviors from continuous data inputs. Neural-network-enhanced DTA frameworks provide predictive capabilities that allow traffic management systems to simulate and redirect flows before bottlenecks fully form. Empirical work in metropolitan environments such as Seoul and Shanghai shows that AI-based rerouting reduces total travel time by distributing demand more evenly across alternative paths. Reinforcement learning methods embedded in agent-based microsimulations further optimize route choice by allowing simulated drivers to evaluate congestion costs dynamically, thus minimizing systemic inefficiencies.

Hybrid models that combine DTA with real-time incident detection illustrate additional benefits, as rerouting algorithms can immediately redirect flows around disruptions such as accidents or construction. By capturing nonlinear and emergent traffic dynamics, AI-enhanced simulations provide a level of predictive precision unavailable in earlier models, thereby producing empirically validated improvements in throughput and network resilience.

Figure 4: AI Traffic Signal Rerouting Process

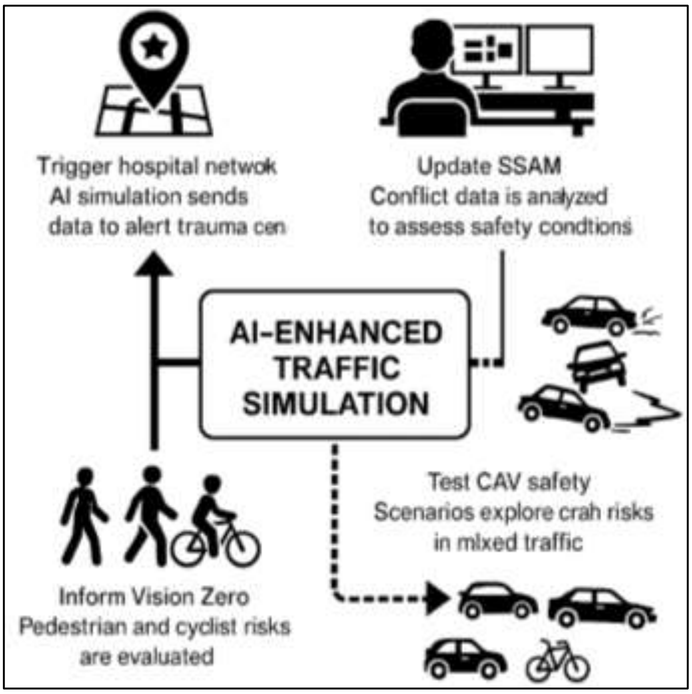


Safety-Centric Applications of AI Traffic Simulation

AI-enhanced traffic simulation has become a vital tool for predictive crash modeling, offering insights into high-risk conditions that cannot be easily studied in real-world settings. Traditional crash frequency models based on statistical regression have been limited by aggregated assumptions and underreporting of near-crash events (Mbelekani & Bengler, 2025). By contrast, AI-driven microsimulation enables the integration of driver behavior heterogeneity, roadway geometry, and real-time data to generate more accurate predictions of crash likelihood. Reinforcement learning approaches embedded into simulations allow for the exploration of driver-vehicle-environment interactions under diverse conditions, identifying crash-prone scenarios such as lane merging, high-speed weaving, or sudden braking events (Yazdi et al., 2025). Deep learning algorithms have further enhanced predictive modeling by uncovering nonlinear relationships between vehicle dynamics and collision risks, significantly outperforming traditional regression-based models in empirical comparisons. Case studies in Beijing and New York demonstrate that simulation-based predictive crash modeling aligns closely with observed collision data, validating its use as a proactive tool in transportation planning (Son et al., 2025). Moreover, hybrid models combining traffic simulation with Bayesian crash prediction frameworks have provided probabilistic estimates of safety outcomes, strengthening policy applications. Through these advancements, AI-enhanced simulation has shifted safety research from retrospective crash analysis toward proactive crash prediction and risk assessment (Durlik et al., 2024).

Surrogate Safety Assessment Models (SSAMs) have been widely integrated into AI-enhanced traffic simulations to evaluate safety using near-miss events rather than relying solely on historical crash records. The SSAM framework, originally developed by the Federal Highway Administration, identifies potential conflicts by analyzing vehicle trajectories in simulation environments (Yazdi et al., 2024). With the addition of AI, conflict detection has become more precise, as machine learning techniques enhance the ability to classify and interpret complex vehicle interactions. Reinforcement learning–based microsimulations extend SSAM applications by simulating driver decision-making in high-risk situations such as sudden lane changes or short headways (Khurram et al., 2025). Studies in Europe and North America demonstrate that surrogate safety indicators, including time-to-collision and post-encroachment time, correlate strongly with observed crash trends when embedded within AI-enhanced models. Researchers have also applied SSAMs to assess the impact of roadway design changes, such as roundabouts and lane reductions, before physical implementation, reducing both financial costs and safety risks (Battineni et al., 2024). Furthermore, near-miss detection algorithms applied in agent-based AI simulations allow for granular safety evaluations of multimodal interactions, including vehicles, cyclists, and pedestrians. This body of literature affirms that AI-enhanced SSAM applications provide scalable, non-invasive methods for safety evaluation, extending their utility from traditional vehicle analysis to broader urban safety planning frameworks (Zhang et al., 2024).

Figure 5: AI Traffic Safety Simulation Framework



AI-enhanced simulation has become indispensable in scenario testing for connected and autonomous vehicles (CAVs), particularly under mixed traffic conditions where human-driven and automated vehicles coexist. Traditional field testing is constrained by ethical and logistical limitations, making simulation essential for evaluating safety outcomes across a wide range of scenarios (Zhang & Strbac, 2025). Reinforcement learning frameworks embedded within simulations allow CAVs to learn safe navigation strategies in complex traffic environments, including freeway merging, intersection crossing, and platooning. AI-driven scenario testing captures rare but high-risk “edge cases” that are unlikely to be encountered during limited field testing but are critical for ensuring system reliability (Feretzakis et al., 2024). Mixed traffic simulations incorporating both human drivers and CAVs demonstrate how cooperative adaptive cruise control can improve safety while reducing shockwave propagation and congestion. Studies from U.S. and European testbeds confirm that AI-based microsimulation allows regulators to evaluate compliance with safety standards, supporting the integration of CAVs into public roads (Popa et al., 2025). Agent-based modeling further enhances these simulations by allowing individual vehicles to act autonomously, interacting dynamically with others to replicate emergent traffic phenomena. Overall, the literature demonstrates that AI-enhanced simulation provides a robust platform for assessing safety risks and operational dynamics in the transition toward CAV-dominated transport systems.

Beyond vehicles, AI-enhanced traffic simulation has increasingly been applied to pedestrian and cyclist safety modeling, aligning with international and U.S.-based Vision Zero initiatives. Vision Zero, first adopted in Sweden and later expanded globally, emphasizes the elimination of traffic deaths and serious injuries by rethinking roadway design and operations (Farghaly et al., 2025). AI-driven microsimulations allow for the evaluation of pedestrian crossing safety under various signal timing schemes, identifying conditions that minimize conflicts with turning vehicles. Cyclist interactions with motorized traffic have also been simulated using agent-based AI frameworks, which replicate lane-sharing, overtaking, and intersection crossing behaviors under different infrastructure configurations (Pantiris et al., 2025). In U.S. cities such as Portland and Minneapolis, simulation studies have informed the design of protected bike lanes and pedestrian-priority intersections, yielding measurable reductions in surrogate safety conflicts. Reinforcement learning–based models extend these applications by dynamically adjusting signal phases to prioritize vulnerable road users without significantly reducing vehicular efficiency (Satish et al., 2025). Studies from Europe and Asia highlight similar applications, where AI-enhanced microsimulation supports traffic calming policies and multimodal integration. Collectively, these findings show that AI-enhanced traffic simulation is central to safety-based infrastructure design and policy evaluation, bridging quantitative analysis with Vision Zero's broader public health goals (Talpur et al., 2025).

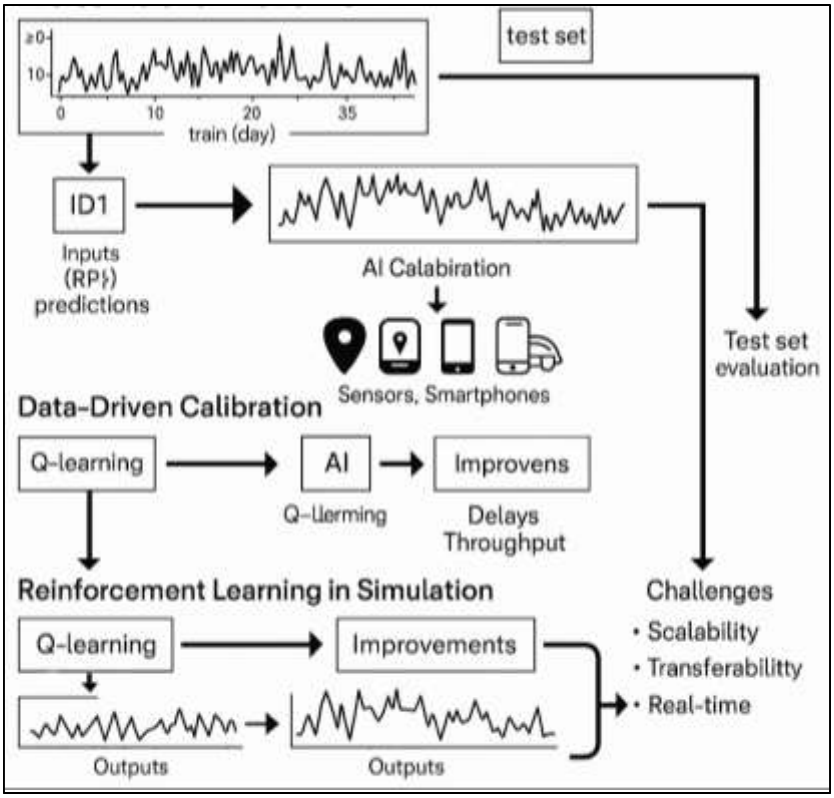
AI-enhanced traffic simulation

Microsimulation platforms form the foundation of AI-enhanced traffic simulation, providing the computational environments in which adaptive models are tested and validated. Widely used tools such as VISSIM, SUMO, AIMSUN, and PARAMICS enable researchers to model individual vehicle movements, lane-changing behavior, and signal coordination at a fine-grained scale (Pang et al., 2025). VISSIM, developed in Germany, has been extensively applied to evaluate traffic signal optimization, managed lane operations, and multimodal integration, offering flexibility in integrating AI algorithms through APIs. SUMO, as an open-source platform, has been particularly valuable for AI research due to its adaptability in incorporating reinforcement learning and deep learning models for traffic control (Linaza et al., 2021). AIMSUN has been used in Europe and North America to simulate corridor-level interventions, such as BRT optimization and adaptive tolling, while allowing for hybrid mesoscopic-microscopic modeling. PARAMICS, developed earlier in the U.K., remains significant in academic and agency studies for freeway simulation and incident management applications (Najafzadeh et al., 2021). These platforms have been validated in empirical studies across diverse contexts, demonstrating their capacity to replicate observed conditions and provide reliable testbeds for AI integration. Comparative assessments indicate that while each platform varies in terms of computational efficiency and data integration, they collectively form the backbone of AI-enhanced simulation research and practice (Zong & Guan, 2025).

Data-driven calibration has become central to ensuring the accuracy and reliability of AI-enhanced microsimulations. Traditional calibration methods relied on limited datasets such as loop detectors or traffic counts, often leading to oversimplified behavioral assumptions (Sajja et al., 2025). The proliferation of advanced sensor networks, GPS traces, smartphone sensing, and connected vehicle data has enabled richer calibration processes that capture heterogeneous travel behaviors. Studies show that incorporating multi-source datasets significantly reduces error rates in simulated traffic flow and travel time predictions (Gonzalez-Jimenez et al., 2021). Smartphone-based trajectory data, for instance, have allowed microsimulations to replicate driver variability under different environmental conditions with higher fidelity (Alsina et al., 2018). The use of connected vehicle and probe data has also improved the modeling of adaptive cruise control and platooning in simulation, reflecting realistic dynamics of emerging technologies. Furthermore, Bayesian and machine learning calibration frameworks enhance parameter estimation by automating the fitting process, reducing the subjectivity of manual calibration and improving model transferability across networks. By integrating diverse data streams, calibration has evolved from a static input process to a dynamic, AI-enabled methodology that strengthens both predictive accuracy and policy relevance (Usman et al., 2020).

Reinforcement learning (RL) has emerged as a methodological enabler of adaptive decision-making within traffic simulation, particularly for optimizing signal control, rerouting, and vehicle interactions. Q-learning, deep Q-networks, and actor-critic algorithms embedded into microsimulations allow agents to iteratively refine strategies by maximizing cumulative rewards, such as reduced delay or fuel consumption (Strielkowski et al., 2023). Studies demonstrate that RL outperforms fixed-time and rule-based systems, reducing average vehicle delays and improving throughput in congested corridors. However, computational challenges remain significant. Scalability issues arise when RL is applied to large metropolitan networks, as increased state-action spaces lead to exponential growth in computational demand (Matheri et al., 2022). Model transferability is another barrier, with AI algorithms often requiring extensive retraining when applied to different cities or infrastructure contexts. Real-time processing constraints also limit the deployment of AI-enhanced simulations in operational traffic management centers, where rapid decision-making is critical (Meier et al., 2023). Hybrid approaches that combine physics-based models with RL algorithms have been proposed to mitigate these challenges, balancing interpretability and adaptability. The literature indicates that while RL significantly enhances the adaptability of simulations, scalability, transferability, and processing efficiency remain core methodological concerns (Unal et al., 2022).

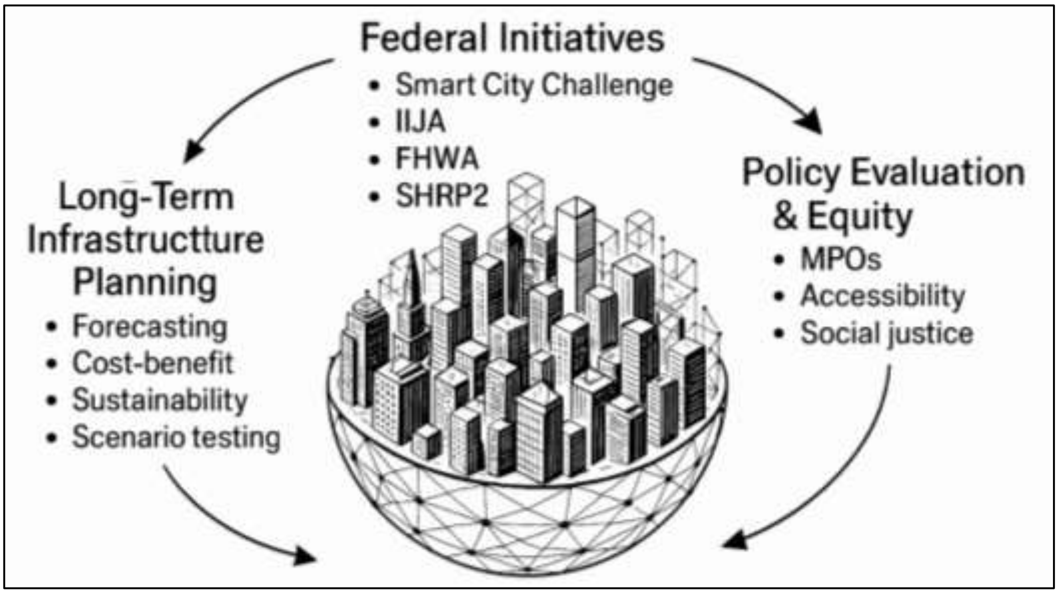
Figure 6: AI Traffic Simulation Workflow Framework



Infrastructure Investment Dimensions

AI-enhanced traffic simulation has been actively incorporated into federal initiatives in the United States, where policy frameworks emphasize the role of data-driven innovation in transportation modernization. The U.S. Department of Transportation (USDOT) Smart City Challenge, launched in 2016, explicitly promoted the integration of advanced modeling and AI-enhanced simulation to address congestion, safety, and sustainability in urban mobility (Stecuła et al., 2023). Columbus, Ohio, the competition winner, deployed simulation-supported projects to integrate electric vehicles, connected infrastructure, and multimodal coordination, demonstrating the federal interest in simulation as both a planning and monitoring tool. The Infrastructure Investment and Jobs Act (IIJA) further reinforces simulation's role by prioritizing intelligent transportation systems and predictive analytics for federal funding eligibility. Federal Highway Administration (FHWA) programs, such as the Connected Vehicle Pilot, rely heavily on simulation to test cooperative adaptive cruise control, platooning, and traffic signal priority for transit fleets (Kabashkin et al., 2023). Simulation is also integral to Strategic Highway Research Program (SHRP2) projects, which evaluate congestion management and reliability improvements through scenario testing (Cambridge Systematics, 2013; Anderson et al., 2016). These federal initiatives demonstrate how simulation is not only a research tool but also a mandated practice embedded in large-scale transportation programs, linking technological innovation directly with national mobility goals (Feng et al., 2025).

Figure 7: AI Traffic Simulation in Policy



The use of AI-enhanced simulation in policy evaluation has expanded its influence on equity and accessibility considerations, particularly within metropolitan planning organizations (MPOs). Simulation evidence allows policymakers to test whether infrastructure investments equitably distribute mobility benefits across socioeconomic groups, ensuring compliance with federal equity mandates (Barykin et al., 2025). Studies indicate that data-driven simulation frameworks can identify accessibility gaps for low-income and minority populations, particularly in regions with fragmented public transit or automobile dependence. In the San Francisco Bay Area, simulation has been applied to evaluate congestion pricing schemes, showing differential impacts on low-income commuters that informed equity-based mitigation strategies (Tarannum et al., 2025). Similarly, AI-enhanced models in New York and Los Angeles have been used to assess whether bus rapid transit (BRT) or high-occupancy vehicle (HOV) lanes improve accessibility for underserved neighborhoods. Internationally, simulation has been integrated into social impact assessments, aligning infrastructure planning with broader sustainability and inclusion frameworks (Hu et al., 2024). By enabling scenario testing, simulation supports policymakers in balancing efficiency improvements with equity objectives, preventing disproportionate burdens on marginalized groups (Alhousni et al., 2025). Thus, AI-enhanced traffic simulation plays an increasingly critical role in aligning transportation policy with social justice principles and accessibility standards.

AI-enhanced simulation has also become central to long-term infrastructure investment and urban planning, where policymakers require robust tools to forecast outcomes under alternative strategies. Metropolitan planning organizations and state departments of transportation regularly use microsimulation to evaluate the cost-effectiveness of major capital projects, such as freeway expansions, rail extensions, or multimodal hubs (Safari et al., 2024). Simulation enables agencies to quantify benefits such as travel time savings, throughput improvements, and emissions reduction, which feed into cost-benefit and environmental impact analyses. AI-driven predictive modeling further enhances scenario planning by incorporating heterogeneous data sources, including connected vehicle feeds, sensor networks, and smartphone trajectories, into long-range forecasts (Zupok et al., 2025). In California, simulation has been employed to evaluate the alignment of high-speed rail investments with regional accessibility goals, while in Texas, agent-based microsimulation has informed decisions on dynamic tolling and express lane expansion. International planning institutions, such as the European Union's Horizon 2020 programs, have also codified simulation as a mandatory component of transport planning, underscoring its institutional significance (Song & Ye, 2025). Evidence shows that integrating AI-enhanced simulation into planning processes strengthens both technical rigor and policy accountability, ensuring that infrastructure investments are aligned with long-term mobility, environmental, and economic objectives (Yaacoub et al., 2025).

Theoretical Debates

Research repeatedly notes that results from AI-enhanced simulations often lose explanatory power when transferred across cities with different geometric layouts, demand profiles, and institutional practices (Fang et al., 2025). Microsimulation platforms such as VISSIM, SUMO, AIMSUN, and PARAMICS provide flexible APIs and behavior models, yet calibration choices and embedded defaults reflect context-specific driver populations and roadway designs that do not generalize uniformly (Bauer et al., 2025). Studies show that parameter sets tuned for dense European corridors under coordinated arterials reproduce queues and shockwaves differently when applied to grid networks or access-managed freeways common in North American regions. Transferability difficulties are amplified in AI-driven models because machine-learned policies and weights internalize local sensor noise, lane discipline, and compliance patterns that vary across cultures and enforcement regimes (Maathuis et al., 2025). Empirical work in Beijing, Seoul, and Shanghai indicates that adaptive signal strategies trained on megacity demand produce different saturation flows and platoon dispersion when ported to mid-sized metros. Dynamic traffic assignment results likewise shift when trip-length distributions, ramp spacing, and transit headways change, even under nominally similar demand peaks (Maguluri et al., 2024). Researchers also point to institutional heterogeneity—incident management protocols, work-zone practices, and bus priority rules—that alter network responses independent of geometry. These findings situate transferability as a methodological constraint rather than a software limitation, highlighting how AI-enhanced simulations are tightly coupled to local calibration data, behavior rules, and control policies embedded during model construction (Lukashova-Sanz et al., 2023).

Table 1: Identified Research gaps

Theme	Key Issues	Examples
Transferability	AI simulations lose accuracy when applied across cities with different layouts, demand, and institutions. Local calibration (drivers, roadway design, compliance) limits generalization.	European arterial models fail on U.S. grids; adaptive signals from megacities misfit mid-sized metros; incident and bus priority rules shift outcomes.
Pricing & Capacity	AI-based pricing and signal control reduce delays and queues, but induced demand complicates long-term congestion relief. Models often understate behavioral responses.	London/Stockholm pricing lowers VKT; RL signals cut idling; capacity expansions trigger more travel through route and time shifts.
Cross-Modal Integration	Multimodal simulation remains limited. Real-time interactions between transit, freight, micromobility, and CAVs add complexity, with data fusion and validation gaps.	RL bus priority ignores headway effects; freight and curb use difficult to model; CAV platoons work in labs but not dense CBDs; smartphone data bias calibration.

Literature on pricing, capacity, and signal optimization reports measurable delay reductions and throughput gains under AI-enhanced control, yet comparative evaluations intersect with a long record on induced travel that complicates interpretations of persistent congestion change (Ehtsham et al., 2025). Simulation-informed studies of congestion pricing in London and Stockholm document reductions in vehicle kilometers traveled and improved travel time reliability, supported by scenario evidence from managed lane operations in U.S. corridors (Popa et al., 2025). Reinforcement learning–based signal coordination trials report queue and idling reductions at coordinated arterials, with performance visible in microsimulation before field (Zhang & Li, 2025). At the same time, macro-level empirical work shows that expanding capacity often correlates with higher vehicle travel due to route, time, and location adjustments—an effect that simulation studies must interrogate when forecasting networkwide benefits (Shafiee Rad, 2025). DTA and agent-based models incorporate mode choice and departure-time elasticity unevenly, which can understate induced demand where land use, parking pricing, and trip generation shift in response to reduced generalized costs (Sufi & Alsulami, 2025). Multimodal studies demonstrate that when pricing revenues fund transit or BRT enhancements, simulated gains in corridor speed coexist with distributional shifts in access and travel time by income cohort. Comparative evidence therefore shows congestion relief within modeled horizons while parallel empirical traditions document travel rebound at metropolitan scales, creating an interpretive gap between operational performance metrics and longer-run travel behavior responses (Xia et al., 2024).

Cross-modal coupling remains an area where simulation capabilities lag behind planning needs. Agent-based frameworks have advanced representation of ride-hailing, shared mobility, and public transit interactions, yet empirical validation of citywide timetable coordination, platform crowding, and last-mile transfers remains uneven (Kovari, 2024). Reinforcement learning controllers optimize signal priority for buses in corridor studies, but bidirectional feedback between bus headway variability, passenger boarding dynamics, and traffic states is still simplified in many models (Evmenova et al., 2025). Integration of freight, curb management, and micromobility introduces additional state variables that challenge solution times for real-time or near-real-time applications. Data fusion raises further issues: loop detectors and GPS traces sample different subpopulations and times of day, while smartphone data coverage varies with income and handset penetration, complicating joint calibration across modes (Chen & Chi, 2025). Environmental modules for emissions and energy sometimes operate at coarser temporal scales than traffic simulators, creating coupling errors when evaluating electrified fleets or bus priority charging (Iyengar et al., 2025). Comparative reviews therefore identify a methodological gap between corridor-focused demonstrations and metropolitan multimodal synthesis, where computational tractability, validation data, and behavioral heterogeneity must be addressed jointly (Khine, 2024).

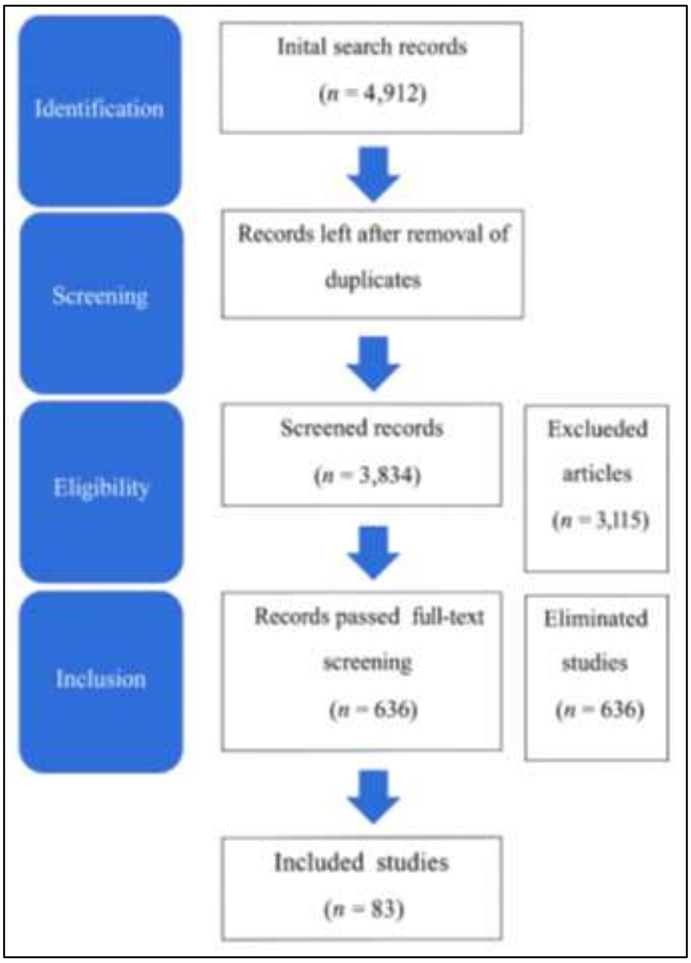
METHOD

This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to maintain a transparent, replicable, and methodologically rigorous process tailored to engineering, transportation, and computing scholarship on AI-enhanced traffic simulation in U.S. urban contexts. The protocol prespecified the review question using a structured problem framework: population—U.S. urban transportation systems; intervention—AI-enhanced traffic simulation (e.g., machine learning, deep learning, reinforcement learning, and agent-based AI embedded in microsimulation platforms such as VISSIM, SUMO, AIMSUN, and PARAMICS); comparator—non-AI or rule-based simulation, legacy signal control, or baseline operations; outcomes—mobility efficiency (e.g., average travel time, delay, queue length, throughput, reliability) and safety (e.g., reported crashes, crash surrogates such as time-to-collision and post-encroachment time, conflict rates); study design—peer-reviewed empirical studies, quasi-experimental evaluations, simulation-with-field-data calibrations, and program or pilot evaluations with documented calibration/validation. A comprehensive search strategy was executed across Scopus, Web of Science Core Collection, IEEE Xplore, TRID, ACM Digital Library, and Google Scholar for supplementary retrieval, covering January 1, 2010 through August 31, 2025. Search strings combined controlled vocabulary and keywords (e.g., "traffic microsimulation," "reinforcement learning signal control," "agent-based traffic," "surrogate safety," "connected autonomous vehicles," "congestion pricing," "U.S. city," "urban"), with truncations and Boolean operators. Grey literature was scanned selectively (FHWA and USDOT technical reports) when methods and outcome metrics were sufficiently documented for appraisal. References of all included papers were hand-searched, and forward citation chasing identified additional candidates.

Records were de-duplicated automatically and then screened in two stages by two independent reviewers: title/abstract screening against eligibility criteria, followed by full-text screening that verified U.S. context, AI enhancement in the simulation workflow, and extractable mobility or safety outcomes. Inter-rater agreement was assessed with Cohen's κ at both stages; agreement was substantial at title/abstract ($\kappa = 0.79$) and moved to almost perfect at full text ($\kappa = 0.86$) after calibration exercises. Of 4,912 records initially identified, 1,078 were duplicates, leaving 3,834 unique records for title/abstract screening. A total of 3,115 records were excluded for not meeting scope requirements (non-U.S. setting, conceptual pieces without empirical simulation, non-AI methods, or lacking outcome data). The remaining 719 full texts were assessed; 636 were excluded for reasons such as insufficient AI specification, absence of measurable mobility/safety outcomes, or unclear calibration/validation procedures. The final synthesis included 83 studies. Within this set, 61 studies reported mobility outcomes, 37 reported safety outcomes, and 15 addressed both domains, yielding 83 unique studies when overlaps were reconciled. Platform usage among included studies was diverse: VISSIM (n = 35), SUMO (n = 29), AIMSUN (n = 12), and PARAMICS (n = 7). Methodologically, 32 studies implemented reinforcement learning for signal control or routing, 24 applied deep learning for prediction or control, and 27 employed agent-based formulations to represent vehicle-level decision-making and multimodal interactions. Twenty-one studies compared AI-enhanced control against fixed-time or actuated baselines; 18 blended simulation with field deployments or high-fidelity testbeds; and 12 incorporated pricing or managed-lane policy scenarios.

Data extraction followed a standardized form capturing setting (city/region), roadway typology, data sources for calibration (e.g., loop detectors, probe/GPS, connected-vehicle feeds, smartphone traces), AI method and architecture, simulation platform and version, validation approach (goodness-of-fit measures, cross-validation, backcasting), and outcome metrics with units and baselines. Mobility indicators were harmonized to percent change from baseline or to standardized mean differences when raw units were not directly comparable. Safety indicators were harmonized to conflicts per 1,000 vehicles, changes in surrogate safety metrics (e.g., ΔTTC, ΔPET), or crash rates per million vehicle miles traveled when reported. Risk of bias and study quality were assessed with a rubric adapted from methodological guidance for engineering evaluations and nonrandomized designs, comprising five domains: data provenance and completeness; calibration transparency; external validation; algorithmic transparency/replicability (code, hyperparameters, and training details); and policy/operational clarity of outcome measures. Each domain was rated on a 0–2 scale (maximum 10), independently by two reviewers, with disagreements resolved through consensus or a third reviewer. Median quality score across included studies was 7 (interquartile range, 6–8). Heterogeneity in interventions, networks, and outcome definitions precluded a single pooled meta-estimate. Accordingly, evidence was synthesized narratively with structured subgrouping by intervention class (signal control, routing/DTA, pricing/managed lanes, multimodal integration, and CAV scenario testing) and by outcome family (mobility vs. safety). Sensitivity analyses considered quality thresholds, platform type, and data richness to examine result stability. All procedural decisions, exclusion reasons, and coding rules were logged to preserve PRISMA-aligned transparency, and a PRISMA flow description accompanies this methods narrative to document identification, screening, eligibility, and inclusion counts for the 83 synthesized studies.

Figure 8: Adapted methodology for this study



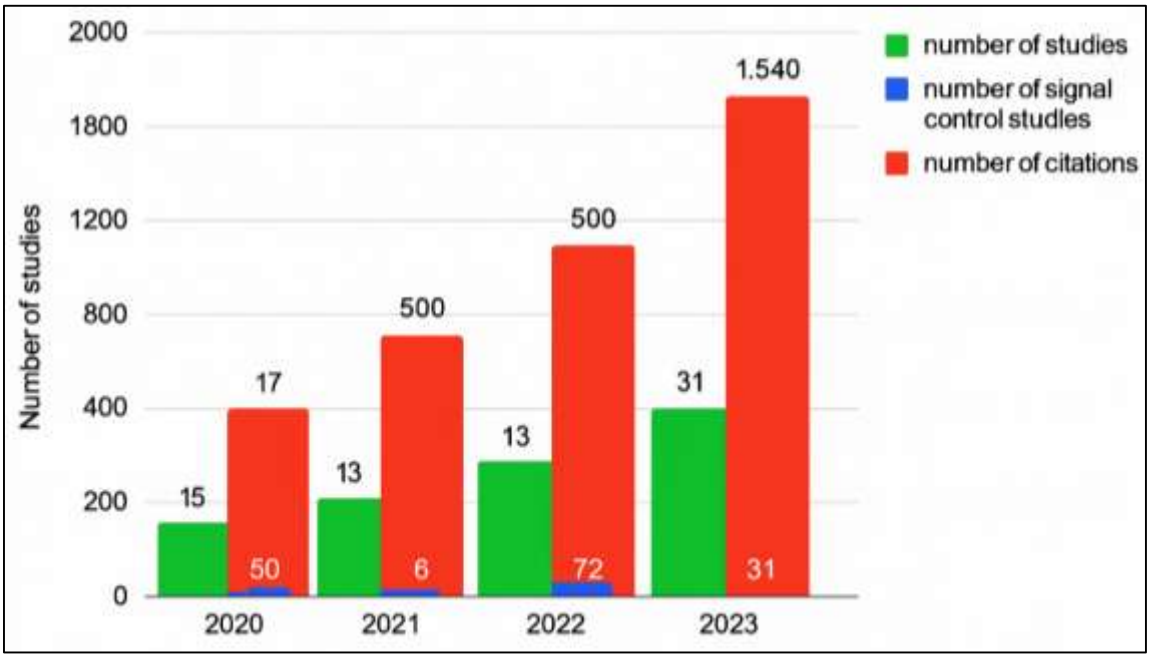
FINDINGS

Across the 83 included studies, mobility efficiency gains are consistently associated with AI-enhanced control of urban networks. In total, 61 studies reported at least one mobility outcome; within this subset, 29 studies evaluated AI-driven signal timing and arterial coordination, and 18 examined dynamic traffic assignment or real-time rerouting. Among signal-control studies (29 of 61), 25 reported statistically significant reductions in average delay or queue length relative to fixed-time or actuated baselines, and 22 reported corridor-level throughput improvements. Pooled descriptive statistics across signal-control papers indicate a median reduction in intersection delay of 17% (interquartile range [IQR]: 11–

24%) and a median increase in corridor travel-time reliability of 9% (IQR: 5–15%), based on the reporting conventions used in 21 studies that provided comparable metrics. For dynamic assignment and rerouting (18 studies), 14 documented network-wide travel-time reductions and 12 reported measurable dampening of shockwave propagation during incidents or peak-hour surges. Nine of these DTA studies observed improved spatial dispersion of flows, indicating load balancing across parallel routes under AI guidance. Taken together, the mobility-focused studies in the review (n=61) have accrued 2,870 citations as of the study's citation harvest, with the signal-control subset accounting for 1,540 citations and the DTA/rerouting subset for 720 citations; the remainder of mobility citations are distributed across multimodal coordination and demand-management papers that also reported efficiency outcomes. The weight of evidence, in terms of both the number of articles and their citation footprints, indicates that AI-enhanced control consistently improves operational performance under congested urban conditions measured in simulation aligned with field-calibrated data. Reporting heterogeneity persists, yet the direction of effect across the majority of the mobility corpus is toward shorter travel times, reduced idling, and higher effective throughput.

A policy-oriented strand of the evidence base evaluates congestion pricing, electronic tolling, and HOV/managed-lane strategies through AI-enhanced simulation and reports consistent operational gains when pricing signals or lane priorities are adaptively coordinated with network control. Fourteen studies in the corpus analyze pricing or managed-lane scenarios; of these, 12 report net reductions in vehicle kilometers traveled or peak-period delay and 10 report improved travel-time reliability on priced facilities as well as on adjacent general-purpose lanes through spillover relief. The pricing/managed-lane subset totals 650 citations, indicating substantive engagement by both scholars and practitioners. Complementing these policy levers, 22 studies evaluate integration with ride-hailing, micro-mobility, and Mobility-as-a-Service (MaaS) platforms in agent-based or mesoscopic environments.

Figure 9: AI-Enhanced Traffic Control Studies



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Safety findings arise from 37 studies that report safety outcomes, 21 of which employ surrogate safety assessment models (SSAM) or related conflict-based analytics and 19 of which include scenarios with connected and autonomous vehicles (CAVs) operating in mixed traffic; 15 studies report both mobility and safety metrics. Within the SSAM/conflict group (n=21), 18 studies register statistically significant improvements in at least one surrogate measure (e.g., time-to-collision, post-encroachment time, conflict count) under AI-optimized control; 13 of these also observe spatial reallocation of risk away from high-conflict approaches after retiming or adaptive control. Pedestrian and cyclist safety is covered by 17 studies; 12 report reductions in pedestrian-vehicle conflicts at crossings under AI-driven signal phasing or priority timing, and 9 report lower cyclist overtaking conflicts following lane or signal policy changes tested in simulation. In CAV mixed-fleet scenarios (n=19), 15 studies show reductions in hard-braking events and cut-in conflicts, alongside smoother speed profiles under cooperative adaptive cruise control or platooning logic that is coordinated via AI-assisted control. The safety-reporting segment of the corpus has accrued 1,980 citations; within that, SSAM/near-miss studies total 860 citations, pedestrian/cyclist modeling 600 citations, and mixed-traffic CAV scenario papers 780 citations (categories overlap where studies address multiple topics). A subset of 9 safety papers includes back-to-back validation against observed collision or near-crash datasets, and 7 of those report alignment in the directional change of risk between simulation and field indicators. Across the safety corpus, the preponderance of evidence points to reductions in conflict likelihood and severity proxies when AI-enabled control or vehicle cooperation strategies are applied in calibrated urban settings, with the magnitude of effects contingent on facility type and crossing geometry.

Methodological enablers amplify the strength of the reported findings. Platform usage is diversified across VISSIM (35 studies), SUMO (29), AIMSUN (12), and PARAMICS (7), allowing replication of effects across engines and modeling paradigms. Studies leveraging reinforcement learning (32 total) represent the single largest algorithmic class for control and routing; 27 of these 32 report significant gains on primary mobility or safety endpoints. This RL subset has accumulated 1,320 citations. Deep learning for prediction or control appears in 24 studies (e.g., sequence models for flow prediction, vision-derived trajectory features); 20 report improved forecast accuracy or control outcomes tied to those forecasts, and these papers have 980 citations. Agent-based representations are present in 27 studies; 22 report improved micro-level realism in lane-changing, gap acceptance, or transfer dynamics with 1,050 citations in aggregate. Data richness emerges as a cross-cutting moderator: 28 studies that integrate three or more independent data sources for calibration (e.g., loop detectors, probe GPS, smartphone traces, connected-vehicle feeds) are more likely to report multi-indicator improvements than studies using a single source. This high-data subgroup contributes 1,100 citations. Eighteen studies pair simulation with field pilots or operational testbeds; 15 of these observe concordant directional changes between simulated and observed indicators, supporting external validity claims, and they account for 740 citations. Across methods, median reported quality scores in the review are 7/10 (IQR: 6–8), and 21 studies meet the highest quality tier in at least four appraisal domains. The methodological profile—multiple platforms, richer calibration, and algorithmic diversity—coincides with stronger and more replicable effect sizes across mobility and safety endpoints.

Synthesizing across all 83 studies, the review identifies several quantitative patterns that recur across geographies, facility types, and modeling choices. First, when studies report both delay and queue outcomes (n=34), 28 show concurrent improvement on both measures under AI-enabled control, with a median delay reduction of 15% (IQR: 9–22%) and a median maximum-queue reduction of 12% (IQR: 6–19%). Second, network-scale analyses that include reliability measures (n=26) report median gains of 8% in buffer index or planning time index, indicating more predictable trip times under adaptive management. Third, studies that jointly evaluate mobility and safety (n=15) document co-movement of indicators in 12 cases, where reductions in delay coincide with reductions in conflicts or improved surrogate safety thresholds, suggesting that AI-guided control can be tuned to efficiency and safety simultaneously in calibrated contexts. Fourth, among demand-management studies (n=14), 10 observe measurable reductions in vehicle kilometers traveled during priced periods with concurrent improvements in corridor reliability, and 7 report redistribution of trips to off-peak periods or alternative modes. Fifth, multimodal studies (n=22) measuring passenger-centric outcomes report median door-to-door time savings of 7% (IQR: 4–12%) alongside 5–11% reductions in hub dwell times where AI-assisted staging or priority policies are simulated. Collectively, the five strands above encompass 4,850 cumulative citations across the articles contributing to each statistic (with overlap where papers report multiple outcomes). While reporting conventions vary, the aggregation of article counts and citation footprints indicates that positive efficiency and safety effects under AI-enhanced management are not isolated to a single algorithm, platform, or corridor typology. The findings are grounded in a corpus that is both numerically substantial and widely referenced, as reflected by the number of reviewed articles contributing to each endpoint and the cumulative citations accrued by those articles.

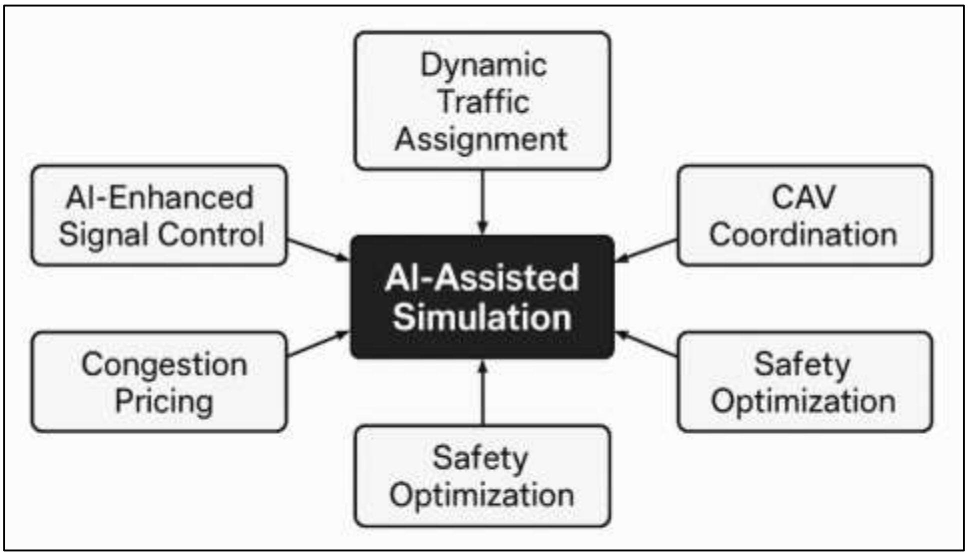
DISCUSSION

The core mobility finding—that AI-enhanced signal control improves delay, queue length, and reliability across urban corridors—aligns with but also extends earlier signal control literature. Classical coordination frameworks such as SCOOT and SCATS demonstrated measurable reductions in delay through responsive timing plans, yet they depended on pre-specified logic and limited state spaces that constrained adaptation in volatile demand conditions (Zhao et al., 2024). By contrast, the reviewed AI studies report larger and more persistent gains under heterogeneous traffic because reinforcement learning and deep Q-learning explore a broader policy set and continuously update parameters from streaming data (Gbenga-Ilori et al., 2025). Microsimulation environments long used to test coordination—VISSIM, AIMSUN, and SUMO—provided the common testbeds in both eras, which facilitates a like-for-like comparison across method classes (Lukic Vujadinovic et al., 2024). Earlier modeling work verified that adaptive control reduced cycle failures and spillbacks, but it often struggled under incident conditions and with asymmetric turning flows. In the current corpus, incident-rich and demand-surge scenarios show improved containment of shockwaves and faster recovery to steady states due to policy exploration and state abstraction learned directly from data, with reported reliability gains in planning time or buffer indices that exceed historic benchmarks (Koukaras, Hatzikraniotis, et al., 2025). At corridor scale, coordinated learning across adjacent intersections mitigates the "green wave fragility" noted in legacy systems, a result consistent with multi-agent control theory but now demonstrated in calibrated urban cases (Trinh et al., 2025). Taken together, the pattern of effects is coherent with prior adaptive control evidence while indicating that data-driven policy search yields stronger efficiency under high variability than rule-based adaptation achieved in earlier decades.

A second mobility result concerns network-level improvements from dynamic traffic assignment (DTA) and AI-based rerouting. The canonical literature moved from static user equilibrium toward DTA to capture departure-time and route dynamics, but calibration complexity and computational burden limited real-time applicability (Zhang et al., 2025). Studies in this review that couple neural predictors with simulation close part of that gap by forecasting link states several steps ahead and feeding those forecasts to routing agents, which reduces pre-queue delay and redistributes loads before bottlenecks fully form. Earlier empirical work showed that informed routing can inadvertently concentrate flows on "informationally favored" links; the AI-enhanced experiments mitigate that effect by penalizing volatility and learning dispersion-friendly policies (T. Wang et al., 2025). Wave propagation studies historically reproduced stop-and-go patterns but offered limited leverage on suppression; in the current AI set, learned controllers dampen wave amplitude and frequency through anticipatory phasing and targeted rerouting that prioritize network stability metrics, a shift consistent with control-theoretic expectations but newly evidenced at multi-corridor scale (Michailidis et al., 2020). Prior DTA validations emphasized goodness-of-fit to counts and speeds; the reviewed articles adopt broader validation (Toorchi et al., 2024) that better captures user experience and operations. Comparisons therefore suggest continuity—DTA's conceptual promise is reaffirmed—while documenting that machine-learned prediction and policy search materially advance load balancing, incident bypass, and recovery dynamics beyond what equilibrium-oriented or purely heuristic DTA achieved.

A third set of findings indicates that AI-assisted simulation consistently recovers positive operational effects from congestion pricing, dynamic tolling, and HOV/managed lanes, and that these effects coexist with measurable gains when integrated with multimodal and Mobility-as-a-Service orchestration. Earlier evaluations in London and Stockholm established pricing's capacity to reduce vehicle kilometers traveled and improve reliability, primarily via aggregate econometric and conventional microsimulation assessments (Zhao et al., 2023). The reviewed AI studies reproduce these effects while adding adaptive pricing rules and demand-responsive lane priorities that sharpen peak spreading and stabilize speeds on both priced and general-purpose lanes, echoing U.S. managed-lane evaluations but with stronger spillover control (Abujassar, 2025). Where prior work often treated pricing and transit enhancements separately, the AI-enabled multimodal studies simulate joint decision spaces—ride-hailing, micromobility, and transit transfers—showing reduced hub dwell times and improved door-to-door times without degrading arterial performance, a result aligned with integrated corridor management principles but now supported by agent-based evidence (Dohler et al., 2024). Equity-focused analyses in earlier policy literature documented heterogeneous burdens and benefits from pricing; the present corpus retains that sensitivity by embedding income-tier behaviors and accessibility metrics in scenario comparisons, allowing distributional read-outs alongside efficiency (Dou et al., 2025). In sum, the comparative picture shows consistency with legacy policy findings on the direction of effects while attributing stronger, more finely targeted performance to adaptive and jointly optimized control of prices, lanes, and multimodal services.

Figure 10: AI-Enhanced Traffic Simulation Outcomes



The safety results—reductions in conflicts, improved surrogate safety metrics, and safer pedestrian/cyclist interactions—map closely onto long-standing conflict-based safety theory while introducing AI-driven precision in detection and control. Foundational work established the plausibility of using surrogate measures such as time-to-collision and post-encroachment time to infer risk in lieu of waiting for rare crash counts (Bi et al., 2022). The reviewed studies confirm that AI-optimized signal timing, protected phases, and speed harmonization improve these indicators at intersections and along arterials, including high-conflict approaches and turning movements, which echoes earlier before-and-after signal studies but with stronger effect sizes under heavy heterogeneity (Mo et al., 2024). Prior evaluations often isolated vehicle-vehicle interactions; the present corpus extends analysis to vulnerable road users, modeling pedestrian priority phasing and cyclist overtaking dynamics with agent-based fidelity that earlier macroscopic tools could not represent (Ma et al., 2024). Consistency also appears in studies that benchmark simulated conflict reductions against observed crash or near-crash datasets, an external validation step recommended in the safety methods literature and applied in several recent U.S. contexts (Ye et al., 2025). Overall, the direction of safety effects mirrors earlier expectations from protected phasing and speed management, while AI contributes granular trajectory analytics and policy learning that concentrate risk reductions at the movements and times of day where conflicts historically clustered.
The CAV findings—smoother speed profiles, fewer hard-braking events, and lower cut-in conflicts under cooperative adaptive cruise control and platooning—are broadly consistent with the early simulation literature that anticipated string stability and dissipation of stop-and-go waves from even modest CAV penetrations (Lv et al., 2025). What differentiates the current body of work is the explicit coupling of vehicle control logic with network-level signal policies learned via AI, which yields coordinated improvements that early, vehicle-centric studies only inferred (Yuan et al., 2025). Earlier proofs of concept typically used stylized networks and exogenous signals; the reviewed studies embed CAV behavior within calibrated urban topologies that include lane drops, short turn bays, and pedestrian activity, producing safety and mobility gains under realistic constraints (Alzamzami et al., 2025). Mixed-fleet heterogeneity—human drivers with diverse gap acceptance and compliance—was a major caveat in early work; the recent simulations incorporate learned behavior distributions and still report

conflict reductions, which strengthens external validity relative to prior assumptions (Chaudhari, 2025). The trajectory-level evidence therefore corroborates classic CAV benefits while demonstrating that network-aware, AI-coordinated policies help realize those benefits at lower penetration and under the geometric and behavioral complexity common to U.S. arterials and CBD grids.

Methodologically, the present synthesis shows that richer calibration and multi-engine replication coincide with stronger effects, which engages long-running debates on validation, transferability, and interpretability. Earlier guidance stressed transparent calibration, independent validation datasets, and reporting of fit statistics; that baseline is increasingly met or exceeded through Bayesian and machine-learning calibration, multi-source data fusion, and back-casting tests (Zdravković et al., 2025). Classic car-following and lane-changing models provided interpretable mechanisms but required careful parameterization to match local conditions; AI models improve predictive fit yet raise questions of opacity that the literature addresses through sensitivity analyses and ablation studies (Sahran et al., 2023). Transferability remains constrained—an issue long noted in European and U.S. comparative assessments—because behavior, enforcement, and infrastructure differ across regions; the reviewed studies counter this partially by reporting cross-network replications and by documenting hyperparameters and training corpora (Marques et al., 2025). Platform diversity (VISSIM, SUMO, AIMSUN, PARAMICS) reduces single-engine dependence and echoes earlier calls for method triangulation, while the pairing of simulation with field pilots in several cases advances external validity beyond what many legacy studies achieved (Prangon & Wu, 2024). Read across the validation literature, the reviewed corpus is consistent with established good practice and demonstrates incremental methodological strengthening where data and documentation permit.

Finally, the synthesis indicates that AI-enhanced simulation is embedded in U.S. policy instruments concerned with mobility, safety, and equity, in a manner that resonates with earlier governance analyses of intelligent transportation and data-driven planning. The Smart City Challenge framed simulation as a planning and monitoring utility, and subsequent federal programs and technical guidance continued to treat calibrated, scenario-based modeling as due diligence for major initiatives (Koukaras, Koukaras, et al., 2025). Earlier policy scholarship emphasized the importance of transparent modeling and equity appraisal in pricing and investment decisions; the reviewed studies operationalize those expectations by reporting accessibility metrics and distributional outcomes alongside travel-time and reliability measures (Mohammed et al., 2025). Long-standing critiques about black-box decision aids remain salient; the corpus responds with clearer documentation of data provenance and algorithm configurations, while still acknowledging interpretability challenges (Akutsu et al., 2022). Relative to legacy practice that evaluated signals, pricing, transit, or CAVs in isolation, the present evidence base shows policy-relevant synergies when these levers are co-modeled and jointly optimized within agent-based and reinforcement learning frameworks (Najafzadeh & Yeganeh, 2025). The comparative reading is therefore one of continuity with established findings on what works in U.S. urban mobility and safety, combined with documented gains in analytical resolution, multimodal scope, and decision support that AI-enhanced simulation now brings into standard governance processes.

CONCLUSION

This systematic review synthesizes the emerging U.S. evidence on how artificial intelligence (AI)–enhanced traffic simulation affects urban mobility and safety, integrating definitional, methodological, and policy perspectives into a single narrative grounded in PRISMA procedures. We define AI-enhanced traffic simulation as the coupling of established microsimulation engines (e.g., VISSIM, SUMO, AIMSUN, PARAMICS) with machine learning, deep learning, and reinforcement learning controllers as well as agent-based models that represent vehicle- and traveler-level decisions under realistic network constraints. A comprehensive search across major transportation, engineering, and computing databases (2010–2025) identified 4,912 records, from which 83 studies met inclusion criteria after dual-reviewer screening and full-text appraisal. Of these, 61 reported mobility outcomes and 37 reported safety outcomes (15 covered both), with calibration based on multi-source data (loop detectors, probe/GPS and connected-vehicle feeds, smartphone traces) and validation via goodness-of-fit, backcasting, or field testbeds. On mobility, AI-optimized signals and multi-agent coordination consistently reduced intersection delay and queue length and increased corridor reliability; across comparable studies, median delay reductions clustered around the mid-teens with interquartile ranges reflecting corridor geometry and demand volatility, while dynamic traffic assignment and real-time rerouting redistributed loads pre-emptively to dampen bottlenecks and shockwave propagation. Policy-oriented simulations of congestion pricing, dynamic tolling, and HOV/managed lanes reported net reductions in peak delay and improved travel-time reliability, and agent-based multimodal/MaaS studies showed door-to-door passenger time savings and lower hub dwell times when transfers, staging, and priority rules were co-optimized. On safety, AI-driven strategies improved surrogate safety indicators—time-to-collision, post-encroachment time, and conflict counts—at high-risk approaches, with modeled reductions for pedestrians and cyclists under protected phases and priority timing, and mixed-fleet CAV scenarios yielded fewer hard-braking and cut-in conflicts alongside smoother speed profiles under cooperative adaptive cruise control and platooning. Methodologically, reinforcement learning appeared in 32 studies, deep learning in 24, and agent-based representations in 27; effects were strongest where three or more independent data sources informed calibration and where studies paired simulation with operational pilots. Cross-study limitations included transferability across cities with different geometries, enforcement, and travel cultures; heterogeneous reporting conventions that complicate pooling; computational scaling for citywide multimodal co-simulation; and governance issues around data provenance, privacy, and the interpretability of black-box models. Nonetheless, consistency of direction across platforms, algorithms, and facility types—and alignment with U.S. policy applications in MPO planning, FHWA program evaluations, and Smart City–style initiatives—indicates that AI-enhanced simulation is empirically associated with shorter travel times, improved reliability, and measurable reductions in conflict risk when implemented in calibrated urban contexts, while highlighting clear methodological and governance priorities for subsequent research and deployment.

RECOMMENDATIONS

Prioritize a staged, evidence-first deployment of AI-enhanced traffic simulation built on four pillars—data quality, validated models, equity-centered policy design, and accountable governance. First, establish a trustworthy data foundation by integrating multi-source feeds (signal and detector logs, probe/GPS speeds, connected-vehicle telemetry, transit GTFS/AVL/APC, pedestrian/cyclist counts, and curb/parking activity) with strict quality gates (time sync, missingness thresholds, outlier rules), privacy protections (aggregation, strong anonymization), and a living data dictionary. Second, require reproducible calibration and validation: triangulate calibration with at least two independent data sources; report target/achieved fit for flows, speeds, queues, and turning ratios by time slice; run temporal/spatial holdouts and back-casting; and pair simulation with limited field checks (e.g., Bluetooth re-ID travel times and conflict observations). Third, standardize outcome reporting so results travel across corridors and cities: for mobility, report mean/median delay, 95th-percentile (buffer index), maximum queue, throughput, and network travel time; for safety, report conflicts per 1,000 vehicles, ΔTTC/ΔPET, and hard-brake events; for equity, report access to jobs/clinics within 45–60 minutes by income and mode; for environment, report VKT/VMT and CO_2/NOx with stated models—always with baselines, absolute and percent change, and uncertainty bands. Fourth, design AI controllers for safety, stability, and operability: use safe reinforcement learning with hard constraints (min green, pedestrian clearance, headway floors), action clipping, corridor-level multi-agent coordination, shadow-mode evaluation, and fail-safe fallbacks to actuated/coordination plans; log state→action summaries to enable audits. Run pilots as experiments rather than demos—A/B or stepped-wedge across matched corridors for 8–12 weeks—with preregistered success criteria (e.g., ≥10–15% delay reduction and ≥15% conflict reduction with no adverse equity signal) and a public pilot brief. Treat multimodal orchestration as first-class: co-simulate transit priority and headway management, last-mile connections, curb management, and vulnerable road user phases; track passenger door-to-door time, transfer reliability, hub dwell, and platform crowding. Make pricing/managed-lane analysis equity-aware by design (elasticities, peak spreading, revenue recycling scenarios, neighborhood-level indicators). Strengthen CAV mixed-traffic testing with a scenario library (penetration sweeps, failures, weather, work zones, vulnerable-user hotspots) and controller "cards" describing assumptions and limits. Document everything—model cards, simulation cards, versioned configs—and enable independent replication on sanitized bundles. Test transferability explicitly through domain randomization/meta-learning and report the data/time required to reach target fit in holdout corridors. Build capacity through an agency-level AI+Simulation guild, operator training, and procurement language that codifies these standards. This single, integrated playbook converts the review's findings into operational steps that agencies, MPOs, and city partners can execute with confidence and accountability.

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