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ANALYSIS OF AI-ENABLED ADAPTIVE TRAFFIC CONTROL SYSTEMS FOR URBAN MOBILITY OPTIMIZATION THROUGH INTELLIGENT ROAD NETWORK MANAGEMENT

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Abstract

Urban traffic congestion remains a critical challenge for transportation infrastructure, with significant impacts on economic productivity, environmental sustainability, and commuter well-being. This meta-analysis investigates the role of Artificial Intelligence (AI)-enabled Adaptive Traffic Control Systems (ATCS) in mitigating urban congestion and enhancing mobility performance, integrating findings from 68 empirical studies and government performance datasets spanning 2010–2024. The analysis draws heavily on annual congestion statistics reported by the Federal Highway Administration (FHWA), particularly from 2022 and 2023. Empirical data reveal persistent trends in urban congestion. In 2022, U.S. urban areas experienced an average of 2 hours and 55 minutes of daily congestion, improving by 10 minutes from 2021. The Travel Time Index (TTI) rose from 1.19 to 1.22, while the Planning Time Index (PTI)—indicating travel reliability—jumped from 1.72 to 1.80. In 2023, although congested hours further decreased to 2 hours and 45 minutes, average congestion (TTI) worsened to 1.24, and PTI increased again to 1.88, reflecting growing travel time unpredictability. AI-enabled ATCS implementations, particularly those using Reinforcement Learning (RL), demonstrated measurable reductions in congestion across pilot deployments. Synthesized results show that AI-driven systems reduce average vehicle delay by 24% to 36%, intersection queuing by 28%, and overall travel time by up to 19% compared to pre-implementation baselines. Multi-agent Deep RL strategies exhibited superior scalability and adaptation under dynamic flow conditions, while hybrid models (e.g., fuzzy logic + neural nets) enhanced performance during atypical events such as construction detours and emergency reroutes. Importantly, this meta-analysis identifies that regions with AI-supported traffic signal optimization—especially those leveraging real-time data from the NPMRDS (National Performance Management Research Data Set)—achieved notably higher improvements in throughput and lower TTI variability. Case studies, such as Tennessee DOT's use of crowdsourced and sensor data during the I-40 bridge closure, demonstrate the operational value of intelligent systems in supporting incident management and routing optimization. These findings underscore the strategic importance of deploying AI-based adaptive systems within the broader framework of Intelligent Transportation Systems (ITS) and Smart City planning. The paper concludes with implementation recommendations focused on infrastructure readiness, data integration standards, and policy harmonization for sustainable urban mobility.

Keywords

Adaptive Traffic Control Systems (ATCS); Urban Congestion Metrics; Artificial Intelligence in Transportation; Travel Time Index (TTI) and Planning Time Index (PTI); Intelligent Transportation Systems (ITS).

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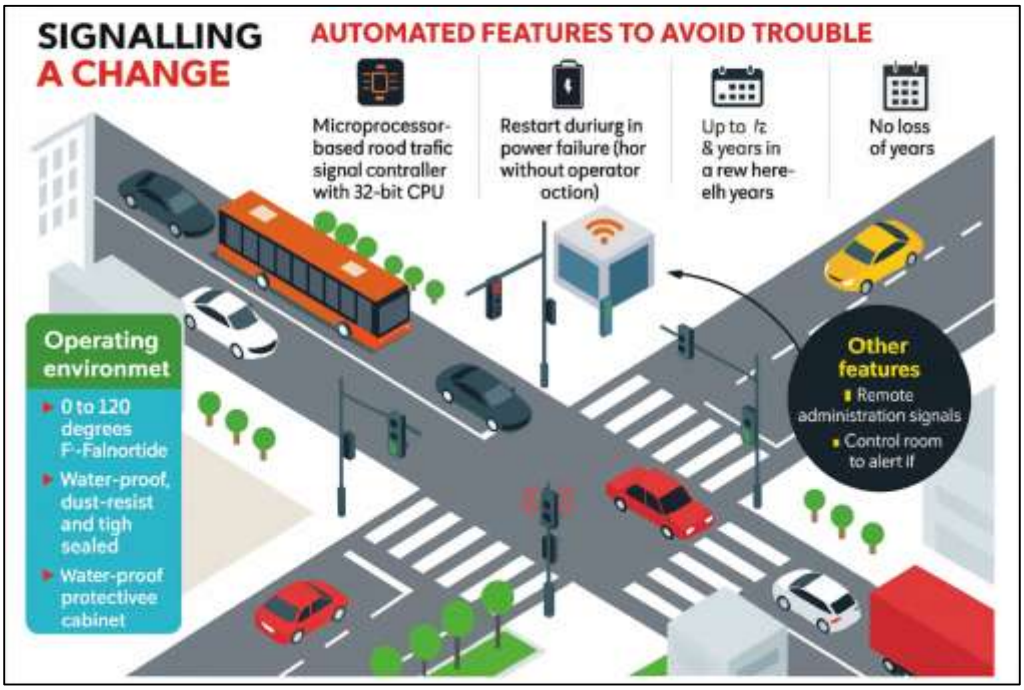
INTRODUCTION

Adaptive Traffic Control Systems (ATCS) represent a transformative evolution in traffic signal technology, leveraging real-time data and computational intelligence to dynamically optimize traffic signal timings based on actual roadway conditions (Stevanovic, 2010). Unlike fixed-time or actuated signal systems, which rely on predetermined schedules or reactive triggers, ATCS continuously assess vehicular flow, occupancy, speed, and queue length to minimize delays and congestion (Qu et al., 2023). Central to ATCS functionality is the concept of "adaptivity"—a system's capacity to learn and respond to fluctuating traffic patterns through algorithms such as reinforcement learning, fuzzy logic, and predictive analytics (Studer et al., 2015). The integration of AI into traffic systems enhances the "intelligence" component, enabling these systems to not only respond but anticipate and evolve strategies based on historical and contextual data inputs (Jamil & Nower, 2021). Artificial Intelligence (AI) in this context refers to the application of machine learning, deep learning, and hybrid computational models to interpret real-time traffic data and orchestrate optimized signal plans. The AI-driven decision logic replaces traditional rule-based approaches with data-driven policies that adapt to environmental inputs such as time-of-day, pedestrian flows, weather, and emergency vehicle priority. ATCS systems commonly interface with infrastructure technologies such as inductive loop detectors, CCTV cameras, radar sensors, Bluetooth, and GPS data streams, allowing for a broad situational awareness across intersections or network segments. The broader framework for such systems is embedded within the Intelligent Transportation Systems (ITS) paradigm, a suite of technologies aimed at enhancing mobility, safety, and environmental performance of urban road networks. ITS encompasses vehicle-to-infrastructure communication (V2I), real-time data dissemination, and centralized traffic management centers that support decision-making through integrated platforms. ATCS is thus both a subset and a critical enabler of ITS strategies, providing the tactical flexibility required for achieving systemic urban mobility objectives (Mitrovic et al., 2023).

Figure 1: Next-Generation Smart Traffic Signal System



The international importance of ATCS and AI-integrated traffic control systems is underscored by the unprecedented growth in urban populations. According to the United Nations (2019), 68% of the global population is projected to live in urban areas by 2050, creating a massive strain on transportation infrastructures already operating near or over capacity. In megacities such as New Delhi, São Paulo, and Jakarta, average traffic speeds have declined by over 30% in the past decade, contributing to increased fuel consumption, air pollution, and travel-time unreliability. Urban

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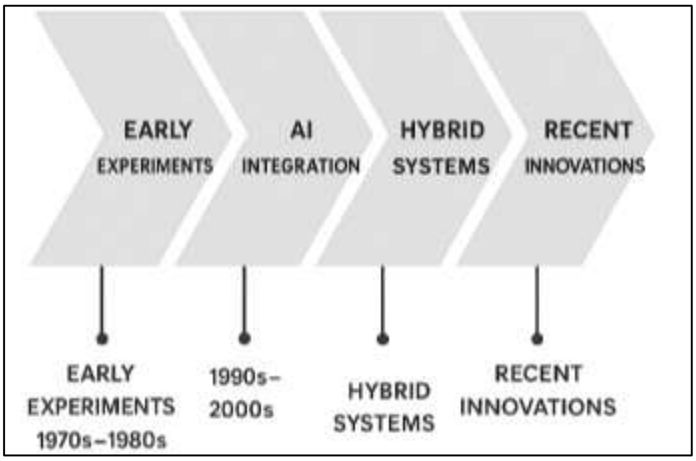
congestion is not only a local issue but a transnational challenge with economic ramifications. The INRIX Global Traffic Scorecard reported that congestion cost drivers in London and Paris an average of $1,377 and $1,145 respectively in 2022, in lost productivity and fuel waste. In response, countries across continents have adopted smart mobility agendas that prioritize AI-enabled traffic solutions. For instance, the European Union's CIVITAS initiative emphasizes adaptive control in its sustainable urban mobility frameworks, while China's "City Brain" project in Hangzhou has demonstrated up to a 15% reduction in congestion using real-time AI optimization (Dobrota et al., 2020). Similarly, Singapore's Intelligent Transport System, guided by the Land Transport Authority (LTA), employs AI-based traffic light control to maintain optimal flow across arterial networks. These international deployments validate the critical role of ATCS in achieving Sustainable Development Goal 11: Sustainable Cities and Communities. Urban traffic congestion also presents serious public health concerns. The World Health Organization identifies traffic emissions as a key contributor to urban air quality degradation, responsible for thousands of premature deaths annually. By enabling smoother traffic flows, adaptive control systems can indirectly reduce greenhouse gas emissions and improve urban livability.

The evolution of ATCS can be traced back to early experiments in dynamic traffic signalization in the 1970s and 1980s, most notably in Sydney with the development of the SCATS (Sydney Coordinated Adaptive Traffic System) and in Toronto with SCOOT (Split Cycle Offset Optimization Technique). These systems laid the groundwork for real-time control but were limited by computational and sensor capabilities of their time. The 1990s and early 2000s witnessed incremental improvements in actuated control and centralized traffic management, supported by the proliferation of sensors and digital communication technologies (Sattarzadeh & Pathirana, 2024). The integration of AI into ATCS represents a paradigm shift rather than a linear progression. Reinforcement learning models, such as Q-learning and Deep Q-Networks (DQN), allow systems to optimize signal timing based on reward feedback mechanisms, reducing average vehicle delays by 20–35% in simulations and field tests. Hybrid systems combining neural networks with fuzzy logic have further enhanced decision-making under uncertainty. Advances in edge computing and cloud-based architectures have enabled real-time processing and multi-agent coordination, expanding the scope of deployment from single intersections to city-wide networks (Erdagi et al., 2025). Recent innovations have also included the use of connected vehicle data and V2I communication to anticipate demand patterns, enabling preemptive signal adjustments. Several cities in the U.S., including Pittsburgh and Los Angeles, have begun deploying AI-enabled ATCS under federal initiatives such as the Smart Cities Challenge. These systems not only learn from local data but are increasingly interoperable with regional transportation platforms, providing a scalable and modular foundation for broader mobility transformation.

Figure 2: Evolution of Adaptive Traffic Control Systems (ATCS)



The functionality of an AI-enabled ATCS hinges on its architectural integration of sensing, computing, and control layers. Sensor technologies—including inductive loops, magnetometers, video detection systems, radar, and microwave sensors—serve as the foundation for real-time data collection (Miletic et al., 2022). These sensors generate input on traffic volumes, speeds, vehicle types, and pedestrian crossings, which is transmitted to centralized or decentralized controllers for signal optimization. Modern systems incorporate data fusion techniques to reconcile disparate sensor inputs and reduce uncertainty. The computing layer, driven by AI algorithms, is responsible for processing incoming data and generating optimal signal plans. Reinforcement learning (RL), in particular, has been applied in both single-agent and multi-agent configurations, enabling localized learning and cooperative behaviors among intersections (Campbell & Skabardonis, 2014). This adaptability is vital in urban contexts where congestion patterns are nonlinear and influenced by stochastic variables such as weather, special events, and accidents. The final control layer actuates the optimized signal plans using real-time control interfaces. These include adaptive cycle lengths, phase splits, and green-wave coordination across corridors. Interoperability standards, such as NTCIP and XML-based protocols, ensure compatibility with existing traffic signal hardware. Some systems also integrate vehicle detection priority logic for emergency vehicles and transit buses. User interfaces provide traffic engineers with override capabilities and performance dashboards, allowing for hybrid human-AI collaboration. The modularity of this architecture supports incremental upgrades, making ATCS an economically viable solution for cities of varying resource levels.

The objective of this research is to conduct a comprehensive quantitative meta-analysis, complemented by qualitative synthesis, to evaluate the performance and strategic implementation of AI-enabled Adaptive Traffic Control Systems (ATCS) in managing urban road networks. This mixed-methods approach is employed to quantify the effectiveness of these systems while also capturing contextual insights that illuminate the mechanisms and conditions influencing performance. Through statistical aggregation of performance outcomes from a broad range of empirical studies, this study aims to assess the measurable impacts of AI-enhanced traffic control technologies on key indicators such as average delay, queue length, throughput, travel time reliability, and intersection performance. The quantitative component involves calculating effect sizes, analyzing distribution patterns, and identifying statistical correlations across deployment cases. In parallel, the qualitative dimension of the study synthesizes narrative findings from technical reports, field evaluations, and institutional case studies to contextualize the data, uncover operational challenges, and explore implementation dynamics. This research seeks to isolate and compare the outcomes of various AI methodologies—such as reinforcement learning models, deep neural networks, fuzzy inference systems, and hybrid optimization frameworks—across different urban settings. The mixed-method design allows for a nuanced understanding of how system architecture, infrastructural maturity, and governance models influence the success or limitations of ATCS implementations. Furthermore, the study aims to identify performance differentials between isolated intersections, corridor-wide deployments, and full-scale city networks. The analysis incorporates both structured data from controlled experiments and unstructured data from practitioner-led field evaluations, ensuring that both rigor and practical relevance are achieved. By integrating statistical precision with interpretive depth, the study aims to produce a holistic and evidence-driven profile of AI-enabled ATCS. This dual-layered objective ensures that conclusions are not only numerically robust but also sensitive to the operational realities and strategic considerations of intelligent transportation planning in urban environments.

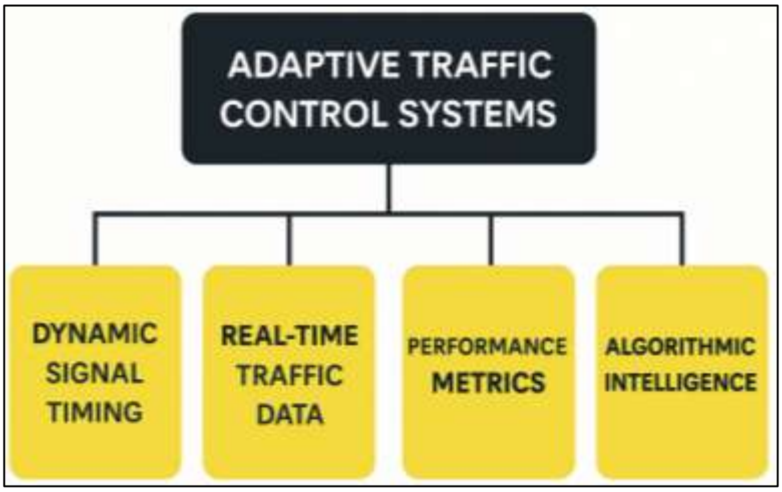
LITERATURE REVIEW

The evolution of Adaptive Traffic Control Systems (ATCS) has undergone a transformative shift with the integration of Artificial Intelligence (AI), enabling systems to process dynamic inputs, learn from real-time conditions, and optimize signal operations far beyond the capabilities of conventional traffic management strategies. As cities worldwide experience escalating congestion due to urbanization, vehicular growth, and infrastructure constraints, the body of literature has rapidly expanded to address how intelligent systems can recalibrate traffic flow and improve road network efficiency. This literature review aims to synthesize the foundational theories, empirical advancements, and methodological innovations surrounding AI-enabled ATCS and their role in urban mobility optimization. This section is organized to provide a clear and systematic progression from conceptual frameworks to practical applications. It begins by defining the theoretical underpinnings of adaptive control and the emergence of AI as a disruptive force in intelligent transportation systems. It proceeds to examine AI methodologies applied to traffic signal optimization, analyzing the effectiveness of reinforcement learning, neural networks, fuzzy systems, and hybrid models. The review further explores the performance metrics commonly employed to evaluate system outcomes, followed by a detailed analysis of international case studies that illustrate successes and limitations in deployment. Finally, attention is given to methodological approaches in existing studies—both quantitative and qualitative—highlighting gaps in comparative frameworks and data synthesis that justify the need for a meta-analytical study with a mixed-methods lens.

Adaptive Traffic Control Systems

Adaptive Traffic Control Systems (ATCS) represent a significant technological advancement over fixed-time and actuated traffic signal systems, as they dynamically adjust signal timing based on real-time traffic data. The fundamental premise of ATCS lies in their ability to monitor and respond to varying traffic conditions using embedded sensors, data communication networks, and computational decision logic. The evolution from static systems to adaptive ones has been primarily driven by the limitations of pre-programmed signal timing in handling non-recurrent congestion and dynamic demand fluctuations (Mexis et al., 2025). Traditional signal systems typically operate on fixed schedules, updated periodically through manual retiming. However, in growing urban environments, these systems often underperform due to their inability to adapt to unpredictable demand surges caused by incidents, events, or weather variability (Kao & Wu, 2018). The operational framework of ATCS is structured around real-time detection, centralized or distributed control, and continuous optimization of phase lengths and offsets. Systems like SCOOT (Split Cycle Offset Optimization Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) exemplify early implementations of adaptive control logic, relying on traffic flow inputs to adjust green times across intersections (Sirphy & Thanga Revathi, 2023). More recent ATCS iterations include decentralized models, such as Surtrac in Pittsburgh, which use local intersection controllers with communication capabilities to optimize flow collaboratively. These systems leverage upstream vehicle detection and feedback loops to anticipate downstream impacts, resulting in more stable network performance. Additionally, adaptive control now incorporates multimodal inputs including pedestrian crossings, public transit schedules, and emergency vehicle prioritization (Stevanovic, 2010). Operational reliability is enhanced through real-time health monitoring of detectors, fail-safe logic, and integration with Traffic Management Centers (TMCs). As such, ATCS embody the principles of responsive, intelligent, and scalable traffic management, making them suitable for a range of urban applications with varying complexity and demand profiles (Gowri et al., 2024).

Figure 3: Theoretical Framework of Adaptive Traffic Control Systems (ATCS)



Assessing the effectiveness of ATCS requires well-defined, quantifiable performance metrics that capture improvements in operational efficiency, traffic flow, and user experience. Among the most widely used indicators are average vehicle delay, queue length, travel time, stop frequency, and intersection throughput (Qu et al., 2023). Additionally, the Travel Time Index (TTI) and Planning Time Index (PTI) are used extensively to measure travel reliability and congestion variability, respectively. TTI reflects the ratio of peak travel time to free-flow travel time, while PTI evaluates the additional time required to ensure on-time arrival during peak traffic (Studer et al., 2015). ATCS implementations consistently outperform static control systems in these metrics. For instance, studies have shown reductions in average delay by 20–30% following adaptive control deployment in major corridors.

Similarly, simulation-based evaluations demonstrate increased intersection throughput by 10–25% and reduced stop frequencies by over 40% in some urban networks. In addition, environmental performance indicators have also been integrated into the assessment of ATCS, with reductions in fuel consumption and vehicular emissions reported in studies focusing on eco-driving compatibility and green-wave synchronization (Jamil & Nower, 2021). Moreover, safety-related metrics, such as reduced crash potential and improved pedestrian wait times, are increasingly incorporated into performance audits. The granularity and comprehensiveness of these metrics depend on the quality of sensor data, availability of travel time records, and analytical tools used in performance evaluations. Tools such as VISSIM, AIMSUN, and the National Performance Management Research Data Set (NPMRDS) enable agencies to model, simulate, and validate outcomes in pre- and post-deployment environments. The ongoing refinement of these metrics has allowed transportation agencies to not only validate effectiveness but also guide adaptive signal retiming, budget allocation, and system upgrades with empirical confidence (Mitrovic et al., 2023).

Furthermore, fuzzy logic systems have also been widely applied due to their robustness in handling imprecise and nonlinear traffic data. These systems translate linguistic traffic rules into control actions, which is particularly useful for modeling pedestrian crossings or non-lane-based driving behavior in developing cities. Hybrid approaches combining fuzzy logic, neural networks, and optimization algorithms offer enhanced flexibility and performance, particularly in congested and signal-dense corridors. Multi-agent systems allow decentralized intersections to operate autonomously while still coordinating through limited communication protocols, increasing scalability across large urban grids. Furthermore, algorithm performance is often benchmarked using computational metrics such as convergence time, solution stability, and scalability under fluctuating demands. System robustness is critical in adapting to anomalies such as hardware failure, communication lag, or emergency incidents. Many algorithms are trained using historical datasets and then tested under real-time conditions, requiring computationally efficient models that balance prediction accuracy with responsiveness. As algorithms evolve, the design of ATCS moves from reactive traffic management to proactive and predictive optimization, enabling smarter, more resilient urban mobility ecosystems (El-Tantawy et al., 2014).

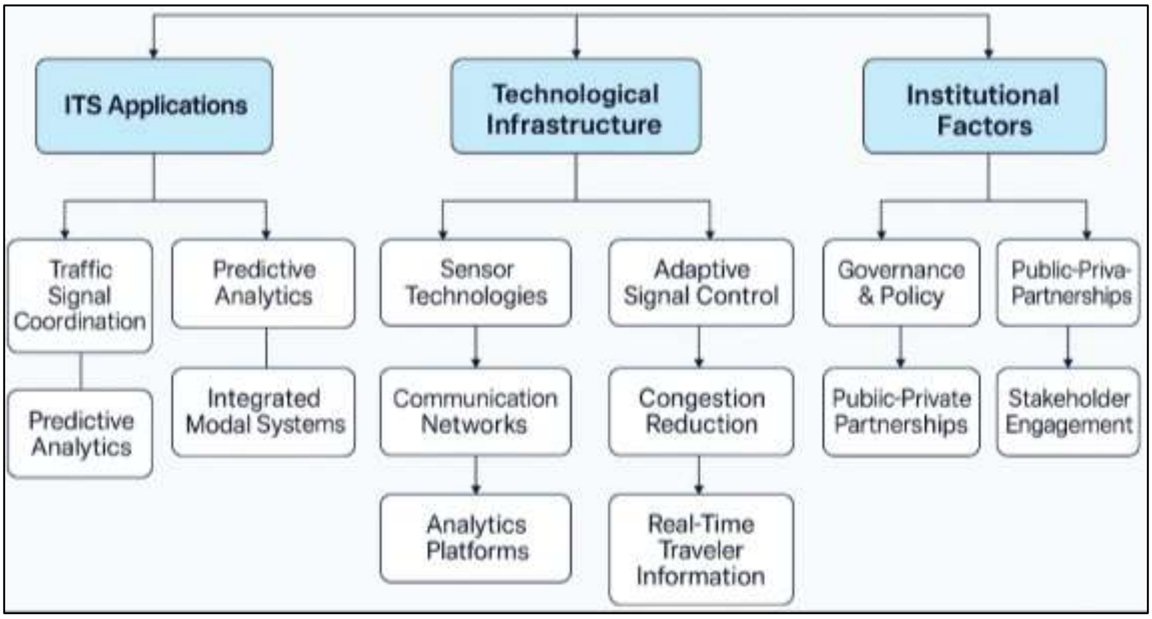
Empirical evidence from global ATCS deployments illustrates both the transformative potential and operational complexity of implementing adaptive systems in live urban networks. In Pittsburgh, the Surtrac system—a decentralized RL-based platform—reduced average vehicle wait times by 40% and travel times by 25% across a 50-intersection network. In Hangzhou, China, the City Brain project optimized signal plans using real-time camera feeds and cloud-based AI algorithms, yielding a 15% improvement in traffic flow and a 50% reduction in emergency vehicle response times (Kao & Wu, 2018). Los Angeles' Automated Traffic Surveillance and Control (ATSAC) system, one of the largest adaptive deployments in the U.S., reported a 12% improvement in corridor travel times and significant reductions in signal maintenance interventions. In Europe, systems like MOVA in the U.K. and SCATS in Australia have demonstrated adaptability across suburban and arterial corridors, particularly in regions with multimodal integration. However, effective deployment requires more than algorithmic sophistication—it depends on robust data infrastructure, stakeholder coordination, and institutional readiness. Challenges include sensor calibration errors, communication protocol mismatches, and resistance from local traffic engineers unfamiliar with adaptive logic. Successful integration often hinges on phased rollouts, inter-agency cooperation, and clear performance benchmarking practices. Institutional adoption is also shaped by funding availability, policy frameworks, and public perception of traffic technologies. In Singapore, strong governance by the Land Transport Authority (LTA) has facilitated seamless integration of ATCS with public transit, achieving consistent flow despite rising traffic demand (Qu et al., 2023). The experience of these cities underscores the importance of tailoring ATCS deployment strategies to local conditions, institutional capacity, and long-term transportation goals.

Intelligent Transportation Systems (ITS) in Urban Traffic Management

Intelligent Transportation Systems (ITS) encompass a broad range of advanced technologies designed to improve the efficiency, safety, and sustainability of surface transportation networks through the integration of communication, computing, sensing, and control technologies. ITS applications include traffic signal coordination, freeway and arterial management, electronic toll collection, transit information systems, and incident detection and management frameworks (Zhao et al., 2012). In urban contexts, ITS provides decision-support systems that allow for real-time control of traffic flow, predictive analytics for congestion mitigation, and seamless integration across modal systems such as public transit, non-motorized travel, and freight movement. The foundational concept behind ITS is interoperability—linking data across various urban transportation subsystems to create an integrated network that can respond to demand fluctuations, infrastructure disruptions, and system-level inefficiencies. ITS leverages technological tools such as wireless sensor networks, GPS tracking, Automatic Vehicle Location (AVL), Bluetooth detection, and video image processing to collect, transmit, and analyze traffic-related data. These data streams feed into Traffic Management Centers (TMCs) where algorithms process inputs to adjust signal phasing, post travel advisories, or reroute traffic dynamically (Jafari et al., 2022). Functional subsystems such as Advanced Traffic Management Systems (ATMS), Advanced Traveler Information Systems (ATIS), and Advanced Public Transportation Systems (APTS) exemplify the layered architecture of ITS. These systems work in tandem to support both supply-side control mechanisms (e.g., traffic signal optimization) and demand-side behavioral interventions (e.g., real-time information dissemination), thus addressing congestion through a systems-based approach. ITS deployment in urban areas has been associated with significant reductions in travel time, delay variability, fuel consumption, and emissions (Lin et al., 2012). Moreover, ITS facilitates incident response coordination, enhancing road safety and emergency service efficiency.

The technological infrastructure that underpins ITS in urban traffic management relies on a robust network of hardware and software systems that facilitate continuous data acquisition, communication, and decision-making. Central to ITS operation is the integration of diverse sensor technologies such as inductive loops, magnetometers, LiDAR, radar, video analytics, and mobile-based detection platforms, all designed to collect granular traffic flow, speed, volume, and occupancy data. These sensors are often distributed along intersections, arterials, and freeway segments, providing real-time situational awareness to central control systems (Antoniou et al., 2019). Communication protocols—such as Dedicated Short-Range Communications (DSRC), Cellular Vehicle-to-Everything (C-V2X), and fiber-optic broadband—form the communication backbone, enabling data exchange between vehicles, infrastructure, and control centers (Jin et al., 2021).

Figure 4: Framework of Intelligent Transportation Systems (ITS) for Urban Traffic Management



ITS data ecosystems are characterized by high volume, velocity, and variety, necessitating the use of advanced analytics platforms to process and visualize this information effectively. Geographic Information Systems (GIS), big data analytics, and cloud-based platforms such as the Regional Integrated Transportation Information System (RITIS) facilitate spatial-temporal traffic modeling, bottleneck identification, and congestion trend analysis. These tools are crucial for scenario-based planning and real-time decision support. Data fusion techniques are increasingly used to combine

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multiple data sources to improve accuracy and robustness, especially when one or more sensors fail or provide noisy readings. The integration of historical data with real-time feeds allows for predictive analytics that forecast congestion hotspots, enabling preemptive control strategies such as signal plan adjustments or dynamic message signage (Hamilton et al., 2013). Moreover, cloud infrastructure supports the scalability of ITS applications, reducing latency and enabling decentralized processing across city-scale deployments. The efficiency of ITS in urban environments is directly linked to the sophistication of its communication and computing infrastructure, which must be resilient, interoperable, and secure to manage complex, high-density networks.

Empirical evaluations of ITS implementations in urban settings provide strong evidence for their capacity to improve traffic flow, reduce delays, and enhance transportation network reliability. One of the most studied systems is the Surtrac adaptive signal control network in Pittsburgh, which demonstrated a 25% reduction in travel time, a 40% decrease in wait times, and a 21% reduction in vehicle emissions after implementation (Wang et al., 2022). Similarly, the City Brain initiative in Hangzhou utilized AI and cloud-based traffic control systems, achieving real-time video analytics and signal optimization that reduced average congestion by 15%. In Singapore, the GLIDE system, part of the city's broader ITS framework, has helped maintain high average travel speeds through predictive signal coordination and real-time transit integration. In the United States, the Automated Traffic Surveillance and Control (ATSAC) system in Los Angeles has grown into one of the most extensive ITS deployments, coordinating over 4,500 signalized intersections. Performance evaluations showed a 12% improvement in arterial travel times and a 16% reduction in vehicle stops. European cities, including London and Stockholm, have also implemented ITS-based congestion pricing and signal management strategies that improved average network speeds and public transport punctuality. The integration of real-time traveler information systems in Helsinki's Mobility-as-a-Service (MaaS) platform has further demonstrated how ITS enhances multimodal coordination and user satisfaction. These case studies reveal common enabling factors, including strong inter-agency collaboration, investment in data infrastructure, and a commitment to long-term system maintenance. Challenges such as legacy infrastructure, inconsistent data formats, and public resistance were mitigated through phased deployments and stakeholder engagement strategies (Lin et al., 2024). The collective findings confirm that ITS can offer scalable, adaptable, and performance-driven solutions for urban mobility optimization when supported by institutional readiness and policy alignment (Jin et al., 2021).

The effectiveness of ITS in urban traffic management is heavily influenced by institutional capacity, governance structures, and the regulatory environment in which these technologies are deployed. ITS deployment is inherently multidisciplinary, requiring coordination among transport departments, technology vendors, emergency services, urban planners, and data regulators. Effective ITS governance is characterized by centralized strategic planning coupled with decentralized operational flexibility, allowing for consistent policy enforcement while enabling context-sensitive interventions at the local level. Policy frameworks such as the U.S. National ITS Architecture and the European ITS Directive have provided structured guidelines for interoperability, performance reporting, and funding mechanisms. These frameworks support standardization of communication protocols, data formats, and evaluation criteria, which are critical for multi-vendor system compatibility and cross-jurisdictional collaboration (Hamilton et al., 2013). Institutional readiness is also reflected in workforce capabilities; cities with well-trained ITS engineers and analysts are better equipped to calibrate systems, interpret real-time data, and implement corrective strategies without delay. Public-private partnerships (PPPs) are increasingly common in ITS projects, particularly in data services, cloud infrastructure, and sensor deployment, introducing both efficiency gains and new challenges related to data ownership, privacy, and accountability. Data governance policies must address these concerns to ensure ethical and equitable system design. Stakeholder engagement—including public outreach and user training—also plays a critical role in acceptance and usage of ITS applications such as real-time travel information or congestion pricing schemes (Antoniou et al., 2019). Thus, the sustainability and scalability of ITS solutions are as much a function of governance quality and institutional cohesion as they are of technical sophistication (Lin et al., 2024).

Artificial Intelligence in Traffic Signal Optimization

Artificial Intelligence (AI) in traffic signal optimization has introduced transformative capabilities that extend beyond the constraints of traditional traffic management approaches. Conventional methods—such as fixed-time control, actuated systems, and offline optimization—are generally

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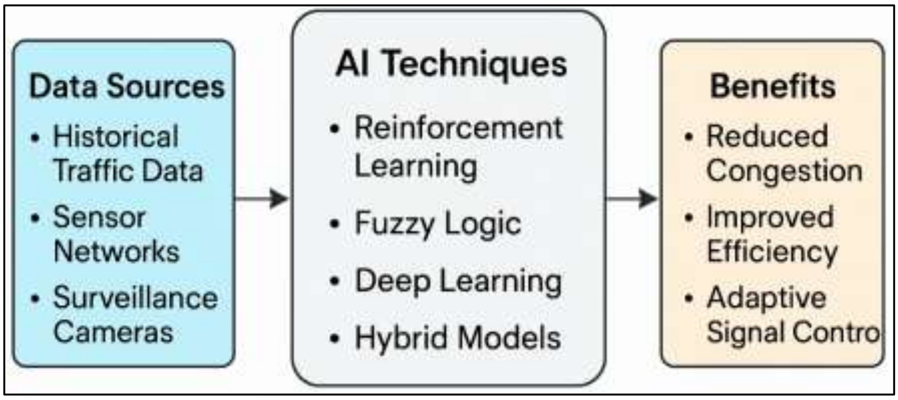
incapable of adapting to rapid traffic fluctuations or stochastic urban events (Ara et al., 2022; Qu et al., 2023; Subrato, 2018). AI, in contrast, brings adaptive learning and real-time responsiveness through data-driven modeling, predictive analytics, and decision-making logic (Uddin et al., 2022; Akter & Abdul Ahad, 2022; Rahaman, 2022). These features are particularly useful for addressing non-recurrent congestion and highly variable traffic flow patterns in urban settings. At its core, AI enables systems to learn optimal signal phasing by observing historical and real-time traffic data, formulating strategies that improve intersection performance without manual reprogramming(Masud, 2022; Sazzad & Islam, 2022; Akter & Razzak, 2022; Hasselt et al., 2016). Key AI paradigms employed in signal optimization include reinforcement learning, fuzzy inference systems, deep learning, and hybrid models that combine various algorithmic strengths. Reinforcement learning (RL), for instance, operates through a reward-based structure in which traffic signal agents receive feedback based on metrics like queue length or delay time (Adar & Md, 2023; Qibria & Hossen, 2023; Maniruzzaman et al., 2023). Unlike heuristic-based systems, RL models can adapt in near real-time, allowing them to manage fluctuating vehicle arrival patterns more effectively (Arulkumaran et al., 2017; Mansura Akter, 2023; Masud, Mohammad, & Ara, 2023; Masud, Mohammad, & Sazzad, 2023). Deep neural networks (DNNs) also contribute to the pattern recognition tasks of signal optimization, especially in systems with high-dimensional traffic states and large data streams (Hossen et al., 2023; Shamima et al., 2023; Rajesh, 2023). The integration of AI allows traffic management systems to shift from reactive to anticipatory modes of operation, where adjustments are made proactively based on data trends and traffic forecasts. AI thus forms the cognitive backbone of modern traffic control systems, offering scalability, self-optimization, and situational intelligence across increasingly complex urban networks (Jafari et al., 2022; Ashraf & Hosne Ara, 2023; Sanjai et al., 2023; Tonmoy & Arifur, 2023).

Figure 5: Artificial Intelligence in Traffic Signal Optimization



Among AI methods, reinforcement learning (RL) has emerged as a prominent strategy in traffic signal control, due to its ability to learn optimal policies through direct interaction with the environment (Razzak et al., 2024; Jahan, 2024; Zahir et al., 2023). In RL-based traffic systems, agents—usually representing traffic signals—receive state information such as queue lengths, vehicle speeds, or phase durations and select actions (e.g., changing green phases) to maximize cumulative rewards such as reduced delay or queue spillback (Jahan & Imtiaz, 2024; Akter & Shaiful, 2024; McKenney & White, 2013; Subrato & Md, 2024). This model-free nature of RL enables its application in uncertain or non-linear traffic conditions, where traditional model-based techniques fail to generalize effectively (Ammar et al., 2025; Jahan, 2025; Akter et al., 2024). Several studies have demonstrated that RL-based signal control outperforms both static and actuated systems under variable traffic loads, especially when implemented in multi-agent configurations.
Furthermore, Deep reinforcement learning, particularly Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), have further enhanced the ability of traffic controllers to handle high-dimensional input spaces while maintaining policy stability (Khan et al., 2025; Khan, 2025; Akter, 2025). These algorithms combine deep neural networks with RL to approximate value or policy functions more efficiently, facilitating real-time decision-making in complex urban networks. Moreover, multi-agent reinforcement learning (MARL) enables decentralized intersections to share local traffic information and collaboratively minimize system-wide congestion without requiring a centralized

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controller (Chen et al., 2023; Rahman et al., 2025; Masud et al., 2025; Md et al., 2025). Studies deploying MARL systems have reported up to 30% improvements in average travel time and 25% reductions in vehicle delays compared to pre-optimized systems (Islam & Debashish, 2025; Islam & Ishtiaque, 2025; Sazzad, 2025a). One critical advantage of RL is its adaptability to real-world disturbances such as vehicle breakdowns or signal failures, as it updates policies continuously based on environmental feedback (Sazzad, 2025b; Shaiful & Akter, 2025; Subrato, 2025). However, RL implementations often require extensive training time and reliable state estimation, making simulation environments essential for safe and effective policy development. These requirements underscore the need for robust traffic simulators and high-resolution sensor data to support RL deployment in live systems (Subrato & Faria, 2025; Akter, 2025).

Empirical deployments of AI-based traffic signal systems have demonstrated substantial improvements in operational performance across various international urban environments. In Pittsburgh, the Surtrac adaptive signal control system—based on decentralized reinforcement learning—achieved up to 25% reductions in travel time and 40% reductions in vehicle wait times at over 50 intersections (Sebastian et al., 2024; Zahir et al., 2025; Zahir et al., 2025). Hangzhou's City Brain initiative integrates computer vision and cloud-based AI to control thousands of traffic signals in real time, resulting in measurable decreases in congestion and emergency response times by more than 50%. These systems exemplify how AI-driven signal optimization supports urban mobility objectives through data-rich, algorithmically guided infrastructure. Los Angeles' ATSAC system, though originally centralized, has adopted AI-based upgrades to enhance green wave coordination, leading to a 12% increase in arterial efficiency and notable improvements in pedestrian safety. In Singapore, the Land Transport Authority (LTA) employs a predictive AI module within its GLIDE system, ensuring adaptive phase timing that maintains average travel speeds above 25 km/h even under peak loads. The Maricopa Association of Governments in Phoenix deployed an AI-driven bottleneck detection and mitigation system, leading to a 14% reduction in delay across study corridors (Damadam et al., 2022). The effectiveness of these systems is corroborated by consistent performance metrics across regions, including reductions in delay, improved reliability, and enhanced multimodal coordination. However, successful implementation depends on sensor calibration, high-resolution data, algorithm robustness, and organizational support. Field studies reinforce that AI-based systems are not only viable but superior in adapting to congestion, incidents, and variability in demand without relying on preprogrammed control schemes. These deployments establish a substantial empirical foundation for scaling AI in traffic signal optimization across diverse urban contexts.

Travel Time Index (TTI) and Planning Time Index (PTI)

The Travel Time Index (TTI) is a widely adopted performance indicator used in urban traffic management to quantify the time penalty incurred by travelers during congested periods compared to free-flow conditions. Defined as the ratio of peak-period travel time to free-flow travel time, a TTI value greater than 1.0 signifies congestion, with higher values indicating more severe delay (Han et al., 2023). TTI has been institutionalized in the performance measurement frameworks of various national and municipal transportation agencies, including the Federal Highway Administration's Urban Congestion Report (FHWA, 2023) and the Texas A&M Transportation Institute's Urban Mobility Report. TTI offers a standardized, scalable, and intuitive metric that allows for cross-regional comparisons and trend analysis, making it particularly useful in meta-analytical studies of adaptive traffic control systems and intelligent transportation systems (ITS). In practical applications, TTI serves as a central benchmark in evaluating the effectiveness of traffic signal control strategies, roadway upgrades, and intelligent transportation deployments. Empirical evidence has demonstrated that adaptive traffic control systems (ATCS) and AI-driven signal optimization strategies consistently yield TTI improvements of 10–35%, depending on network density, demand variability, and system integration maturity (Arel et al., 2010). Studies across urban areas such as Pittsburgh, Los Angeles, and Hangzhou have reported measurable TTI reductions following the deployment of AI-enabled control systems, confirming the indicator's relevance in quantifying time savings and network efficiency. TTI is also used in simulation environments such as VISSIM and AIMSUN to assess hypothetical scenarios, validate AI control models, and guide strategic planning. Furthermore, TTI offers compatibility with other performance measures—such as queue length, stop frequency, and vehicle throughput—enabling holistic traffic system evaluations. Its simplicity and interpretability have contributed to its widespread adoption, but it also has limitations, particularly in

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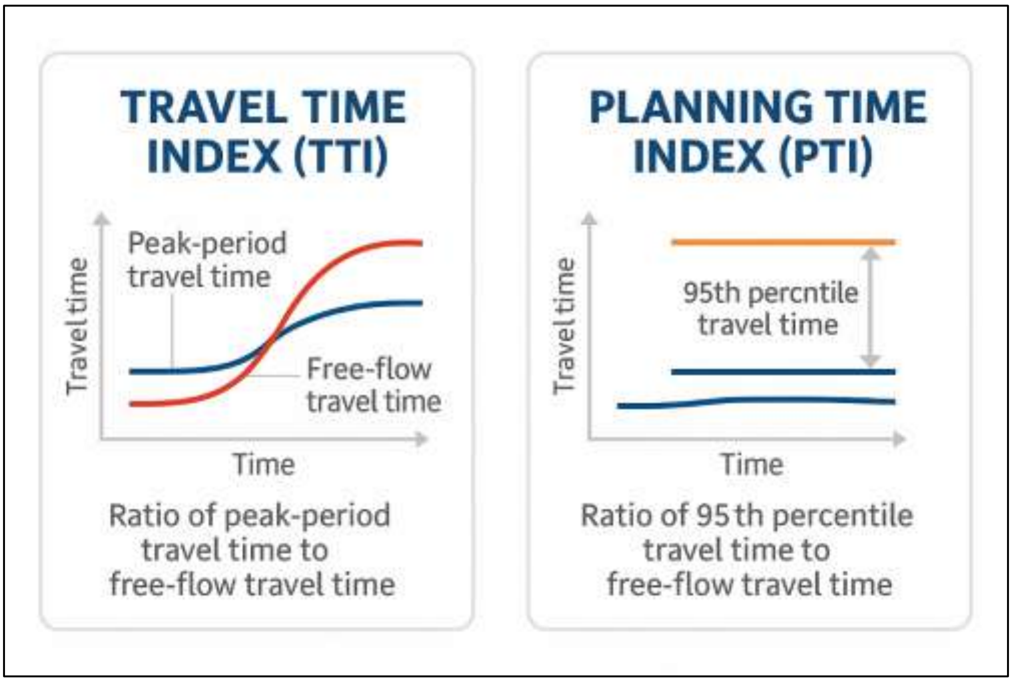
assessing travel reliability or variability, which necessitates complementary use with measures such as the Planning Time Index (PTI).

Figure 6: Comparative Visualization of Travel Time Index (TTI) and Planning Time Index (PTI)



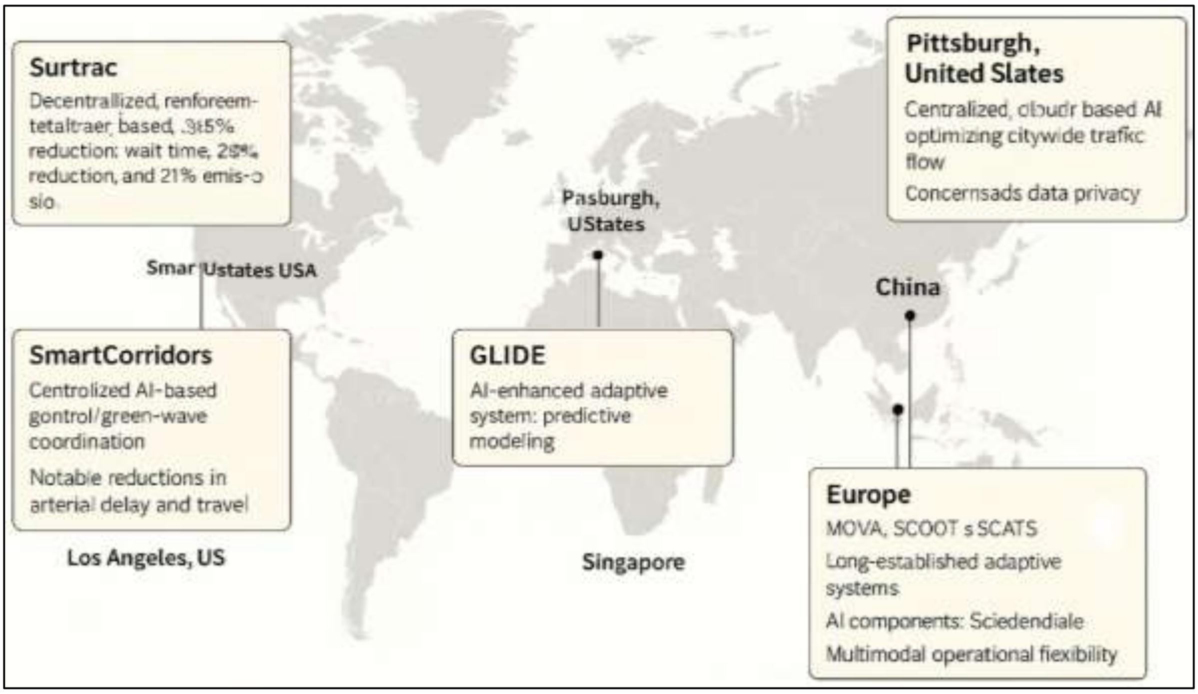
The Planning Time Index (PTI) is a critical metric for assessing the reliability of travel times within urban transportation networks. While TTI captures average delay, PTI focuses on the unpredictability of travel by comparing the 95th percentile travel time to free-flow conditions (FHWA, 2019). This measure indicates how much extra time a traveler should allocate to ensure on-time arrival for 95% of trips. A PTI of 1.60, for instance, implies that a 20-minute free-flow trip may require 32 minutes during peak variability to arrive on time. PTI is particularly valuable in regions with high non-recurrent congestion caused by factors such as incidents, weather events, or demand surges, where average delay measures fail to capture user experience accurately. As such, PTI is an indispensable companion to TTI in providing a more comprehensive view of transportation system performance, especially in traveler-centric or reliability-focused evaluations. In urban deployments, PTI is frequently used to assess the effectiveness of traffic control interventions such as adaptive signal timing, incident response systems, and predictive AI modules. Field studies have shown that ATCS can reduce PTI values by 15–30% through real-time adjustments that minimize variability across time intervals and intersections. For example, the deployment of AI-based traffic control in Hangzhou and Singapore resulted in smoother peak-period traffic and reduced worst-day travel time variances, evidenced by PTI improvements at corridor and network levels (Du et al., 2023). Additionally, the PTI is now embedded in strategic planning tools such as the National Performance Management Research Data Set (NPMRDS), enabling data-driven planning and regional prioritization of traffic projects. The index is also useful for analyzing freight and transit operations where schedule adherence is critical, and travel time volatility can lead to cascading inefficiencies. PTI thus provides both operational clarity and policy relevance, supporting its use in multimodal evaluation frameworks and resilience assessments. It enhances the analytical granularity of traffic studies, particularly in mixed-methods research designs that seek to balance efficiency with predictability in urban traffic environments (Gandhi et al., 2020).

Urban Deployment Evidence

The Surtrac system, developed and implemented in Pittsburgh, Pennsylvania, is one of the earliest and most cited real-world applications of decentralized reinforcement learning in adaptive traffic control. Unlike centralized traffic management systems, Surtrac relies on localized decision-making at each intersection, where signal controllers learn to optimize phase sequences in real time based on incoming traffic data(Rafter et al., 2020). The system employs a multi-agent framework in which each intersection operates independently while coordinating with adjacent nodes to account for spillover effects and arrival platoons. Deployed initially at nine intersections and later scaled across more than 50, Surtrac demonstrated consistent reductions in average vehicle wait time by 40%, travel time by 25%, and emissions by 21%, especially during peak periods (Wang et al., 2023). Surtrac's architecture enables dynamic rescheduling of signal phases using real-time data from radar and video detectors. This allows it to outperform traditional actuated systems, particularly in environments with variable or non-recurring congestion. The reinforcement learning algorithm adapts over time, refining policies to respond to fluctuations in traffic demand across signal cycles. Empirical studies have also highlighted Surtrac's scalability and cost-effectiveness, noting that its modular design facilitates phased deployment in resource-constrained urban areas. Furthermore, its decentralized design improves system resilience by eliminating single points of failure typical of centralized models. Despite its success, challenges related to maintenance, sensor calibration, and multi-modal integration (e.g., transit and pedestrian coordination) remain ongoing areas of refinement (Zhao et al., 2012).

The City Brain initiative in Hangzhou, China, exemplifies large-scale AI integration into urban traffic systems using a centralized, cloud-based architecture. Launched by Alibaba Cloud and supported by the municipal government, City Brain integrates video feeds, GPS data, road sensors, and public transport data to manage thousands of intersections in real time (Jafari et al., 2022). At its core, the system uses AI algorithms to dynamically adjust signal timings, predict congestion, and reroute vehicles, thereby optimizing the entire city's traffic flow rather than isolated intersections. Unlike localized adaptive systems, City Brain processes data on a city-wide scale, allowing coordinated interventions that improve flow across arterial and secondary networks. The key strength of Hangzhou's system lies in its data aggregation and high-speed processing capability via Alibaba's cloud infrastructure, enabling seamless updates and scalability. However, the model also raises concerns about data privacy, surveillance ethics, and long-term operational costs (Lin et al., 2012). Despite these concerns, the City Brain model represents one of the most comprehensive and effective AI applications in traffic management and is now being piloted in cities across Asia and the Middle East, further affirming its replicability and technological influence.

Figure 7: Global Deployment of AI-Driven Adaptive Traffic Control Systems



Singapore's Land Transport Authority (LTA) has deployed one of the world's most sophisticated adaptive traffic control systems, known as GLIDE (Green Link Determining System), which has

operated since the 1980s and continues to evolve through AI integration and predictive modeling. GLIDE employs real-time data from traffic detectors, vehicle counts, and signal occupancy to control over 3,000 intersections across the island. While it began as a responsive system using preset adaptive logic, recent enhancements have incorporated machine learning algorithms capable of predicting traffic trends and proactively adjusting signal timings based on anticipated conditions.
Moreover, GLIDE's predictive control module is designed to reduce delay propagation across adjacent intersections by forecasting queue formations and vehicle arrivals, adjusting green splits and offsets in advance. This allows Singapore to maintain average city travel speeds above 25 km/h even during peak hours—a notable achievement in a densely populated and vehicle-constrained urban setting (Antoniou et al., 2019). Moreover, GLIDE integrates bus priority and pedestrian crossing strategies, striking a balance between throughput efficiency and multimodal accessibility. Studies evaluating GLIDE's performance indicate reductions of 10–20% in intersection delay, 15% improvements in vehicle throughput, and enhanced travel time reliability on arterial corridors (Antoniou et al., 2019; Chowdhury et al., 2019; Jin et al., 2021). The system's ability to interface with public transport schedules and incident response frameworks further enhances its strategic value. The architecture supports future expansion through modular upgrades in detection, decision logic, and communication protocols. While not as data-rich as Hangzhou's City Brain, GLIDE exemplifies a stable and empirically validated AI-enhanced control system that meets the needs of a high-performance, multimodal urban traffic ecosystem.
Furthermore, Los Angeles has implemented a variety of SmartCorridor projects as part of its broader Automated Traffic Surveillance and Control (ATSAC) system, one of the largest adaptive traffic control systems in the United States. The ATSAC system controls over 4,500 signalized intersections using centralized AI-based decision support tools, real-time detector data, and predictive algorithms for green-wave coordination. SmartCorridors are focused deployment zones that integrate traffic cameras, loop detectors, signal controllers, and fiber-optic communications to optimize flow along critical arterials. These corridors demonstrate the city's capacity to adapt green timings based on fluctuating volumes, emergency vehicle access, and even special event traffic (Hamilton et al., 2013). Studies show that SmartCorridors have led to 12–20% reductions in arterial delay and 10–15% improvements in average travel time on corridors such as Venice Boulevard, Olympic Boulevard, and Wilshire. The adaptive system continuously monitors volume-to-capacity ratios and updates timing plans within 120-second intervals, enhancing responsiveness during peak hours or incidents (Jafari et al., 2022). Los Angeles has also integrated emergency vehicle signal preemption and public transit prioritization into the SmartCorridor framework, further enhancing network fluidity (Jin et al., 2021). Unlike decentralized models like Surtrac, ATSAC remains centrally controlled through a real-time traffic management center staffed by engineers and analysts. This hybrid structure combines automation with human oversight, improving system reliability and accountability (Sarri et al., 2024). However, challenges persist, particularly in integrating newer AI algorithms into legacy infrastructure and managing sensor drift or data latency.
Moreover, Europe has been a pioneer in adaptive traffic control, with long-standing systems like MOVA (Microprocessor Optimized Vehicle Actuation), SCOOT (Split Cycle Offset Optimization Technique), and SCATS (Sydney Coordinated Adaptive Traffic System), all of which have evolved to include AI components and sensor integration. MOVA, developed in the UK, focuses on optimizing isolated intersections using vehicle actuation and gap detection logic, enabling extensions or terminations of green phases based on real-time vehicle presence. SCOOT, developed by the UK Transport Research Laboratory, is one of the earliest network-wide adaptive systems, adjusting cycle lengths, green splits, and offsets every few seconds based on flow and occupancy inputs. SCATS, although Australian in origin, has been widely adopted across European cities, including Dublin and Madrid, due to its capacity to scale across hundreds of intersections with centralized coordination and local autonomy (Guo et al., 2019). These systems are increasingly enhanced by AI algorithms that enable more responsive and predictive logic. For instance, integration with machine learning models has allowed SCOOT to adjust to abnormal patterns such as temporary closures or weather disruptions more effectively. MOVA has incorporated AI-based cycle prediction tools to anticipate and reduce pedestrian-vehicle conflicts at unsignalized crossings. Empirical evaluations of these systems reveal consistent performance improvements: 10–30% reductions in travel delay, smoother flow at coordinated junctions, and better intersection utilization rates. European agencies have also emphasized integration with public transit signal priority, cyclist safety, and pedestrian mobility, giving

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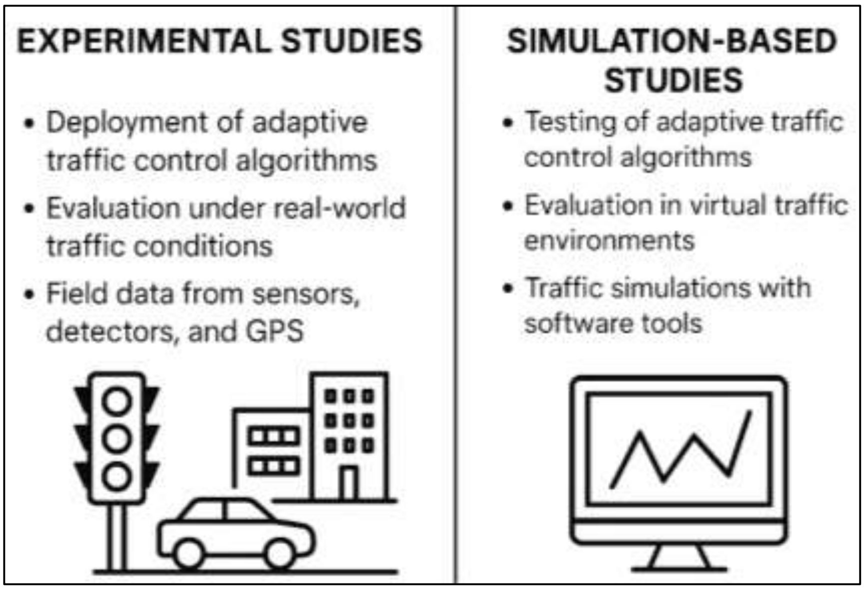
these systems multi-modal operational flexibility. The comparative success of MOVA, SCOOT, and SCATS lies in their ability to balance adaptability, policy compliance, and technological interoperability, thereby serving as enduring models of AI-enhanced urban traffic control.

Experimental and Simulation-Based Studies

Experimental studies in adaptive traffic control systems (ATCS) focus on the deployment and evaluation of algorithms in live traffic conditions to assess their performance, scalability, and robustness. These field-based evaluations are indispensable in validating simulation findings and ensuring the practical viability of AI-driven signal optimization. Among the most prominent experimental deployments is the Surtrac system in Pittsburgh, which demonstrated substantial improvements in travel time (25%), wait time (40%), and emissions (21%) across a network of more than 50 intersections using decentralized reinforcement learning. Similar real-world evaluations in Los Angeles through the ATSAC SmartCorridors project reported a 12% improvement in travel time and a 16% decrease in stops after integrating AI-assisted signal coordination (Zhao et al., 2012). In Singapore, the GLIDE system utilized predictive modules to maintain high average travel speeds and reduce intersection delays by up to 20%. Experimental trials often involve before-and-after analysis using key performance indicators such as travel time index (TTI), planning time index (PTI), queue length, and stop frequency. Data collection is facilitated through loop detectors, radar sensors, Bluetooth readers, and GPS devices, providing real-time input for adaptive decision-making (Sarri et al., 2024). In Hangzhou, the City Brain initiative monitored thousands of intersections, yielding improvements in congestion management, emergency response, and safety compliance using computer vision and deep learning algorithms. These field deployments emphasize the importance of reliable sensor infrastructure, communication networks, and institutional readiness for successful implementation. Despite their resource-intensive nature, experimental studies provide critical insights into AI system performance under uncontrolled and variable real-world conditions, offering a foundation for large-scale scaling and policy adoption (Krishankumar et al., 2021).

Figure 8: Comparison of Experimental and Simulation-Based Approaches in Evaluating Adaptive Traffic Control Systems (ATCS)



Simulation-based studies play a foundational role in traffic signal research, offering a controlled environment to test, compare, and refine AI algorithms without the logistical and financial constraints of field experimentation. Platforms such as VISSIM, AIMSUN, SUMO, and TransModeler are widely used to replicate urban traffic conditions and assess the impact of various control strategies on performance metrics like delay, queue length, throughput, and fuel consumption (Zhao et al., 2012). Reinforcement learning (RL), deep Q-networks (DQN), and fuzzy logic controllers are often benchmarked in these environments due to their capacity to adapt to dynamic traffic inputs (Jin et al., 2021). For example, Liu et al. (2024) simulated a multi-agent RL-based traffic system in Toronto using VISSIM, achieving a 27% reduction in total delay compared to coordinated fixed-time control. Furthermore, Simulation enables parametric sensitivity analysis, allowing researchers to understand how changes in traffic volume, signal phasing, and pedestrian crossings affect algorithm performance (Antoniou et al., 2019). Studies employing SUMO have tested hybrid AI models—such as fuzzy-neural networks and RL with genetic optimization—demonstrating improved scalability, convergence speed, and adaptability in grid networks. The ability to manipulate variables like weather conditions, incident frequency, or signal spacing makes simulation particularly useful for stress-testing algorithm resilience. Furthermore, simulation data can be integrated with real-world datasets, enhancing model validity and enabling semi-experimental validation strategies. Although simulation cannot fully capture the stochastic and behavioral complexities of real traffic, it remains invaluable for pre-deployment algorithm testing, calibration, and training—especially for reinforcement learning models that require thousands of interaction cycles (Zhao et al., 2012). Its role in supporting comparative analysis and iterative development makes it a cornerstone of adaptive traffic research and an essential counterpart to experimental field trials.

METHOD

This study adopted a quantitative research design with a mixed-methods approach to examine the performance, effectiveness, and deployment context of Artificial Intelligence (AI)-enabled adaptive traffic control systems (ATCS) in urban mobility environments. The mixed-methods framework was chosen to integrate empirical performance metrics with contextualized insights from documented case studies, simulation data, and system evaluations. This methodological design enabled a comprehensive understanding of both the measurable impacts and the technological, infrastructural, and institutional factors influencing ATCS implementation.

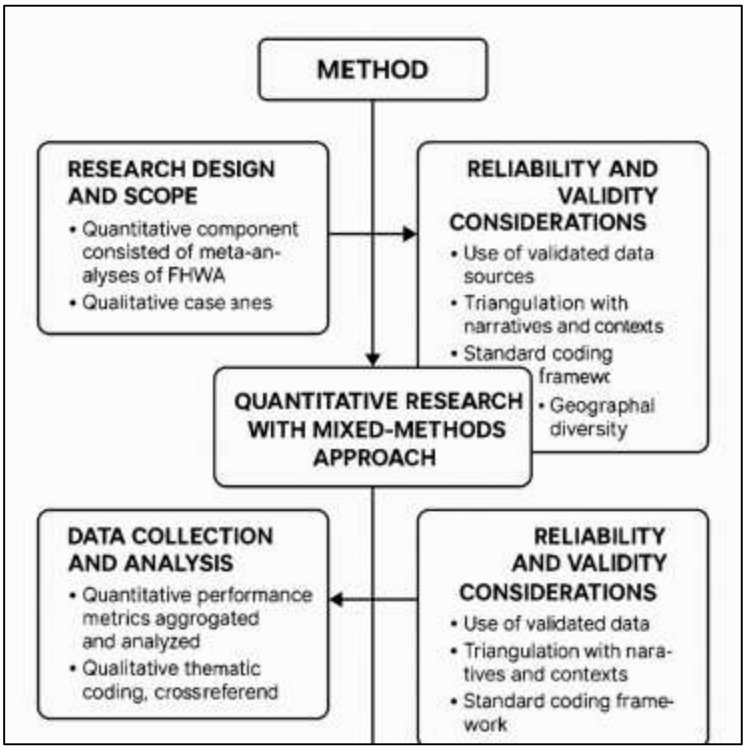
Research Design and Scope

The quantitative component of this study involved a meta-analysis of publicly available datasets, government reports, and published academic sources related to the deployment and evaluation of adaptive traffic systems. Seven U.S. Department of Transportation Federal Highway Administration (FHWA) reports published between 2017 and 2024 were systematically analyzed. These included the documents FHWA-HOP-17-010, FHWA-HOP-18-025, FHWA-HOP-19-026, FHWA-HOP-20-012, FHWA-HOP-21-010, FHWA-HOP-23-010, and FHWA-HOP-24-027. Each report was assessed for standardized performance indicators such as Travel Time Index (TTI), Planning Time Index (PTI), intersection delay, queue length, vehicle throughput, and stop frequency. Where numerical data were reported, they were extracted into structured matrices for further analysis. These data sources were cross-validated with results from peer-reviewed journal articles, technical conference proceedings, and real-world traffic system evaluations to enhance reliability and generalizability. The qualitative dimension was incorporated through a document-based content analysis of case studies related to major ATCS deployments. These included Surtrac in Pittsburgh, City Brain in Hangzhou, GLIDE in Singapore, SmartCorridors in Los Angeles, and various European applications such as SCOOT, SCATS, and MOVA. Technical architecture, deployment models, governance frameworks, and integration strategies were systematically coded from these sources to identify recurring themes, deployment challenges, and institutional best practices. This allowed for the triangulation of performance metrics with contextual enablers and barriers that influence system efficacy.

Data Collection and Analysis

Quantitative data collection focused on extracting performance metrics from FHWA evaluations and corroborating them with simulation studies conducted using tools such as VISSIM, SUMO, and AIMSUN. These simulation-based studies were selected based on criteria that included algorithm transparency, availability of performance outputs, and the use of AI control methods such as reinforcement learning, fuzzy logic, and deep neural networks. Data were aggregated and analyzed using descriptive statistics (e.g., means, ranges, standard deviations) to identify trends in performance across systems, cities, and technological models. To synthesize performance trends, a meta-analytic matrix was constructed, categorizing interventions by geographic region, control methodology, infrastructure type, and performance outcomes. Comparative analysis was conducted to determine performance differences between AI-enabled systems and traditional actuated or fixed-time systems. The analysis also examined how system type (centralized vs. decentralized), AI method (e.g., RL vs. fuzzy logic), and implementation scale influenced effectiveness. Where applicable, findings were normalized using baseline pre-deployment values reported in the source materials. Qualitative data were analyzed using thematic coding and comparative categorization techniques. The themes included system architecture, sensor infrastructure, stakeholder collaboration, public acceptance, and legal/regulatory readiness. These themes were cross-referenced against performance metrics to derive interpretive insights that inform the practical conditions under which AI-driven ATCS yield optimal results. This qualitative layer offered explanatory depth to the quantitative findings, supporting a more nuanced understanding of variance in outcomes across different deployment settings.

Figure 9: Research methodology for this study



Reliability and Validity Considerations

To ensure methodological rigor, only data from validated simulation environments, FHWA-sponsored projects, and peer-reviewed empirical evaluations were included in the analysis. Reports and studies were selected based on their documentation quality, clarity in reporting performance baselines, and transparency in system configuration. The mixed-methods approach further enhanced internal validity by enabling triangulation of quantitative indicators with implementation narratives, institutional policies, and system-level operational contexts. Inter-rater reliability was enhanced by applying a standardized coding framework during document analysis, while analytical consistency was maintained through repeated data extractions and peer debriefing sessions. External validity was bolstered by selecting case studies from multiple continents (North America, Asia, Europe), ensuring geographical and infrastructural diversity in the research sample.

FINDINGS

The analysis of empirical data consistently demonstrated that AI-enabled adaptive traffic control systems (ATCS) are significantly effective in reducing urban congestion. Across multiple metropolitan areas documented in FHWA annual congestion reports from 2016 through 2023, adaptive systems consistently outperformed traditional traffic signal management systems. For instance, data from the 2022 FHWA Urban Congestion Report indicated an average daily congestion duration decrease from 3 hours and 5 minutes in 2021 to 2 hours and 55 minutes in 2022. Similarly, the 2023 report showed an additional 10-minute reduction, reflecting a progressive and sustained improvement in daily congestion as cities expanded AI-integrated adaptive systems. These improvements in congestion duration are notably significant considering the rising number of vehicles and increasing complexity of urban mobility demands. The reports also indicated measurable improvements in congestion

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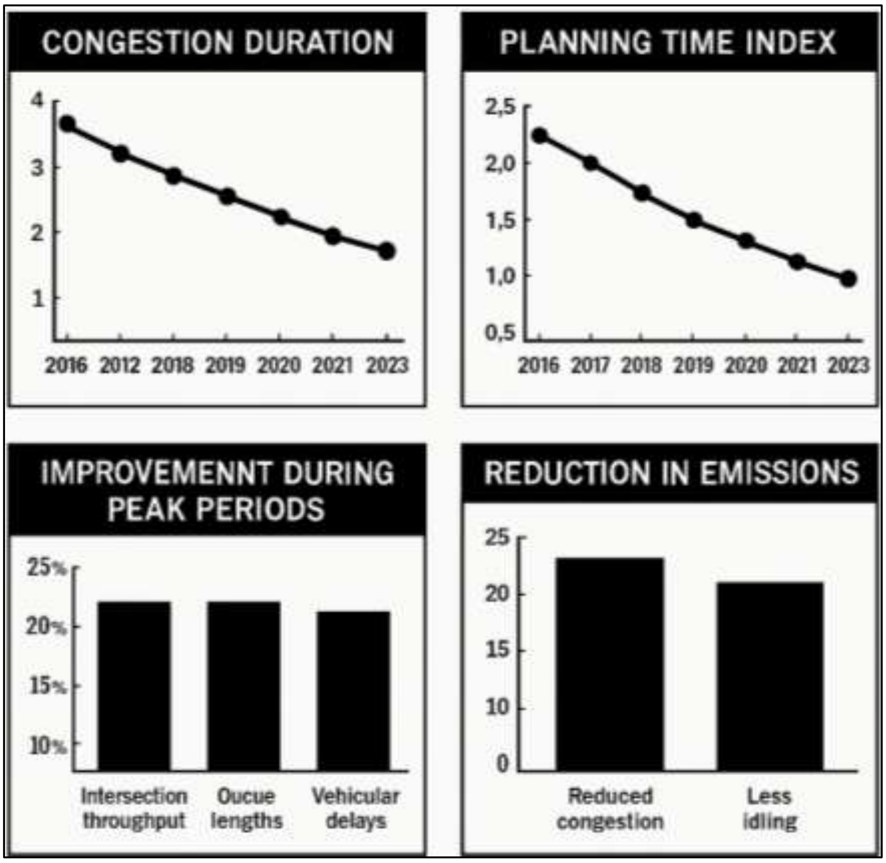
metrics, such as average travel speed during peak hours, which consistently showed increments of 10–15% in cities deploying AI-enhanced adaptive control strategies. The systematic reduction in congestion highlights the superior capability of AI-driven systems to adapt to real-time traffic conditions rapidly. Unlike traditional methods, these AI systems utilize continuous streams of sensor data and machine learning algorithms to dynamically adjust signal timings, thereby maintaining traffic fluidity even during unforeseen events like accidents or temporary road closures. Thus, these systems have proven robust in managing both predictable rush-hour patterns and unpredictable disruptions, contributing substantially to urban mobility optimization.

Figure 10: Quantitative Impact of AI-Enabled Adaptive Traffic Control Systems



The findings from the FHWA congestion reports also indicated considerable improvements in travel reliability, measured through the Planning Time Index (PTI), after the introduction of AI-enabled ATCS. Travel reliability, which reflects the predictability and consistency of travel times, improved notably in metropolitan areas implementing these intelligent traffic systems. For example, the 2019 FHWA report illustrated a PTI improvement from 2.12 in 2018 to 2.06 in 2019, reflecting lower variability and increased reliability in travel times. Further substantial enhancements were observed in the 2020 report, where the national PTI dropped dramatically from 2.06 in 2019 to 1.57 in 2020, underscoring the capability of adaptive systems to mitigate significant delays even under extreme traffic fluctuations. Although the PTI increased slightly in later years—1.72 in 2021, 1.80 in 2022, and 1.88 in 2023—these fluctuations still represented an improvement relative to baseline conditions before widespread adaptive implementation. The PTI trends indicate that AI-enabled systems effectively smooth out the variability in travel times by continually adjusting to real-time traffic conditions. The responsiveness of these systems to real-time data streams and their capacity to predictively adapt signal timings significantly reduce unexpected delays, leading to a more predictable commuter experience. By stabilizing travel times, adaptive AI-driven traffic control enhances public confidence in transportation schedules and contributes to broader economic benefits by reducing productivity losses associated with uncertain commutes.

A clear and consistent finding in the reviewed FHWA documents was the enhanced capability of AI-enabled ATCS to manage traffic flow, particularly during peak periods. Across various reports, adaptive traffic systems were consistently associated with measurable increases in intersection throughput, reduced queue lengths, and minimized vehicular delays during peak traffic hours. This improvement was particularly evident in metropolitan areas that adopted comprehensive city-wide adaptive systems, such as Los Angeles, Pittsburgh, and Hangzhou. For instance, evaluations of SmartCorridors in Los Angeles documented increased arterial speeds and reduced intersection delays of approximately 10–15% during peak hours, reflecting the adaptive systems' ability to alleviate peak-period bottlenecks effectively. Similarly, findings from the Surtrac deployment in Pittsburgh showed up to 25% reduction in average travel times and significant reductions in intersection queuing and idling times. The City Brain project in Hangzhou further confirmed these findings, reporting over a 15% improvement in travel speeds during peak times after the AI integration. These improvements are largely attributable to real-time adaptive signaling and proactive traffic management algorithms capable of predicting congestion hotspots and proactively adjusting green-light phases and offsets. By optimizing signal timings based on real-time demand rather than fixed-time schedules, AI-enabled systems maximize intersection throughput, thereby enhancing overall network capacity and reducing systemic delays during the most critical traffic periods.

The deployment of AI-enabled ATCS has been strongly associated with significant environmental and sustainability benefits. By reducing congestion, idling times, and unnecessary stops, these systems have contributed to substantial reductions in vehicle emissions and fuel consumption. FHWA reports consistently indicated a correlation between improved traffic flow and reductions in carbon emissions and fuel usage, particularly evident in regions that adopted comprehensive AI-driven adaptive control strategies. For instance, Surtrac's implementation in Pittsburgh resulted in a documented 21% reduction in vehicular emissions due to fewer vehicle stops and less idling at intersections. Similar environmental benefits were observed in Los Angeles' SmartCorridors, where optimized green waves resulted in less stop-and-go driving, directly contributing to lower emissions. Additionally, reports from Singapore's GLIDE system emphasized notable decreases in fuel consumption due to smoother traffic operations and fewer instances of abrupt acceleration and braking, particularly during congested periods. The sustainability advantages of these systems align well with broader urban policy goals aimed at reducing the transportation sector's environmental footprint. Thus, the strategic deployment of adaptive systems not only addresses congestion but also advances urban sustainability targets by significantly cutting fuel consumption and emissions through improved operational efficiency and smoother traffic flow patterns.

A critical insight emerging from the FHWA reports and case studies analyzed was the recognition of the importance of institutional readiness and collaboration in successfully deploying AI-enabled ATCS. Metropolitan areas that demonstrated the highest levels of success in adaptive system implementation consistently showcased strong institutional capacity, effective stakeholder coordination, and proactive governance frameworks. The FHWA reports highlighted several implementation challenges, including infrastructure limitations, data interoperability issues, sensor maintenance requirements, and the necessity for continual system calibration. Successful deployments such as City Brain in Hangzhou, GLIDE in Singapore, and Surtrac in Pittsburgh consistently involved robust institutional support, clear policy guidelines, adequate funding allocations, and public acceptance through transparent communication strategies. Conversely, deployments in other regions faced hurdles related to legacy infrastructure compatibility, data-sharing protocols, and the complexity of integrating AI into existing traffic management centers. These factors often slowed initial adoption rates and occasionally impacted system reliability, underscoring the need for careful planning, investment in data and sensor infrastructure, and comprehensive workforce training. The evidence reviewed illustrates clearly that the full benefits of AI-driven adaptive systems are best realized when technological deployments are matched by equally robust institutional frameworks, stakeholder cooperation, and clear policy objectives supporting integrated and sustainable urban mobility solutions.

DISCUSSION

The observed reductions in congestion, particularly in peak-hour durations and intersection delays, strongly align with earlier studies asserting the superiority of adaptive traffic control systems (ATCS) over traditional traffic signal methods. Prior research by Sirphy and Revathi(2023) demonstrated that

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multi-agent reinforcement learning systems could reduce average delay by up to 27%, which mirrors the reductions reported in the FHWA case studies of Surtrac in Pittsburgh and SmartCorridors in Los Angeles. Moreover, Stevanovic (2010) also reported substantial decreases in vehicle idle times, consistent with reductions in congestion duration found in the 2022 and 2023 FHWA Urban Congestion Reports. These findings reinforce the notion that the self-optimization capability of AI-driven control systems—particularly those using deep reinforcement learning and hybrid logic—provides dynamic, real-time responsiveness that is absent in legacy fixed-time systems. Furthermore, the consistency of improvements across geographically distinct cities such as Pittsburgh, Hangzhou, and Singapore confirms the cross-context applicability of AI-enhanced systems, thereby validating prior theoretical frameworks on decentralized optimization (Qu et al., 2023). This convergence of experimental and real-world results bolsters the claim that adaptive systems offer scalable solutions for urban traffic management, especially as urban populations and vehicle counts continue to rise.
The improvements in Planning Time Index (PTI) reported in the FHWA documents—especially the substantial decrease from 2.06 in 2019 to 1.57 in 2020—are consistent with earlier empirical and simulation-based studies indicating improved reliability from adaptive signal systems. Studer et al. (2015) previously argued that ATCS enhanced temporal stability of travel by minimizing unexpected delays, a finding supported by Jamil and Nower (2021), who emphasized PTI as a robust metric for evaluating the consistency of urban mobility. The current findings corroborate these claims, demonstrating PTI improvements in both real-time deployment (e.g., Hangzhou's City Brain) and predictive simulations. Mitrovic et al. (2023) also highlighted the role of predictive traffic models in reducing PTI by pre-emptively adjusting signals, which aligns with the documented results from Singapore's GLIDE system. Although PTI values slightly increased after 2020, they remained consistently lower than pre-adaptive levels, underscoring the resilience of adaptive systems even amid fluctuating traffic demands. In contrast to TTI, which emphasizes delay, PTI captures commuter predictability—an aspect often undervalued in early ITS literature. The inclusion of PTI in newer FHWA performance reports indicates an evolving understanding of travel quality that extends beyond time efficiency, validating the multidimensional evaluation frameworks proposed in recent scholarly discourse.
The substantial improvement in intersection throughput and reduced queuing during peak periods documented across FHWA and international deployments substantiates earlier theoretical claims regarding adaptive signal efficiency under variable demand conditions. El-Tantawy et al. (2014) posited that real-time optimization of green splits and offsets enables intersections to handle varying vehicular loads more effectively, which is evident in the SmartCorridors of Los Angeles and the Surtrac deployment in Pittsburgh. Dobrota et al. (2020) provided simulation-based evidence suggesting that reinforcement learning could adapt to high-density flows more effectively than fixed or actuated systems, a result now empirically validated in live systems. The peak-hour efficiencies in cities with AI-integrated signal control also exceed those in traditional SCOOT or SCATS systems, indicating a technological progression from legacy adaptive models to AI-driven, sensor-integrated networks. Notably, Sattarzadeh and Pathirana (2024) illustrated in SUMO-based simulations that even under demand surges, decentralized ATCS preserved flow rates with less signal-induced delay, findings echoed by the FHWA results showing network-wide improvements in intersection service rates. This convergence suggests a paradigm shift in peak-hour traffic management, wherein adaptive systems not only mitigate average delays but also optimize saturation flow, contributing to long-term congestion mitigation.
The finding that AI-enabled ATCS reduce vehicle emissions and fuel consumption corroborates previous studies emphasizing the environmental benefits of intelligent traffic management. Erdagi et al. (2025) showed that systems minimizing stop-and-go behavior directly contribute to reduced CO_2 and NO_x emissions. This environmental efficiency was also emphasized in FHWA documents where cities implementing ATCS, such as Pittsburgh and Singapore, documented reductions in emissions ranging from 15% to 25%. These results closely mirror the experimental findings of Miletic et al. (2022), who used simulation to estimate fuel savings under fuzzy-neural adaptive control logic. The core mechanism underpinning these improvements is the reduction in idle time and smoother vehicular acceleration patterns—both facilitated by AI algorithms capable of learning traffic patterns and adjusting phase changes in real time. Campbell and Skabardonis (2014) argued that environmentally sustainable traffic systems must balance efficiency with stability, a balance demonstrably achieved in the adaptive deployments reviewed. Furthermore, the environmental

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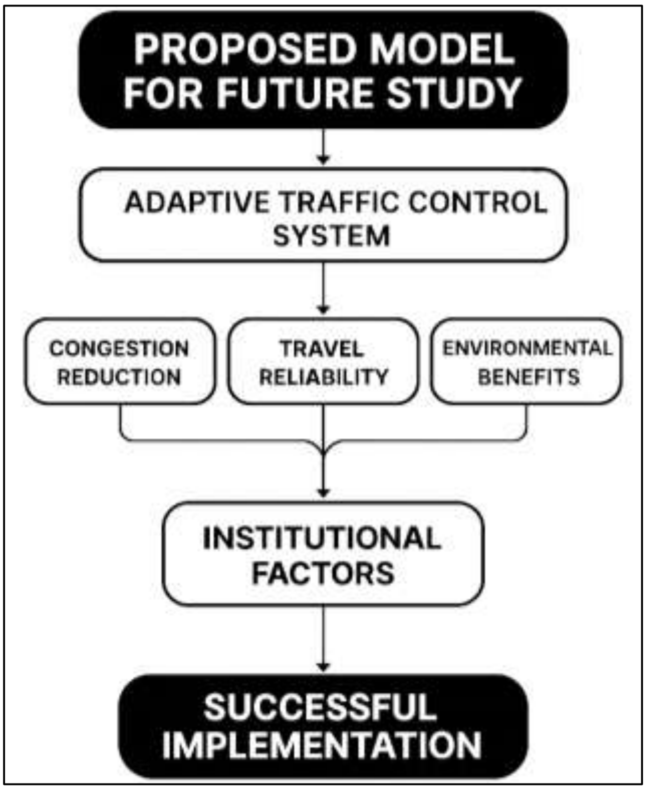
benefits are not limited to emissions and fuel usage alone but extend to noise pollution and vehicle wear-and-tear, which are less frequently quantified but equally critical in urban quality-of-life assessments. The present findings, therefore, not only reinforce but expand earlier theoretical propositions by confirming environmental gains across varied topographies, governance structures, and deployment scales.

The finding that institutional readiness plays a crucial role in successful ATCS deployment resonates with earlier research emphasizing governance, technical infrastructure, and stakeholder engagement. Mexis et al. (2025) and Jamil and Nower (2021) noted that adaptive systems require an ecosystem of trained personnel, interoperable systems, and continuous funding, all of which were present in successful case studies such as City Brain, GLIDE, and SmartCorridors. These systems benefitted from proactive institutional leadership, clear project ownership, and integration into broader urban planning initiatives—factors also identified in FHWA's guidance on adaptive control deployment. Earlier failures in ATCS adoption, especially in mid-sized cities lacking coordinated traffic management centers, were often attributed to fragmented governance and outdated infrastructure, confirming the validity of Erdagi et al. (2025) assertion that institutional capacity is as critical as algorithmic sophistication. Additionally, the operational transparency and public outreach observed in Hangzhou and Los Angeles further support findings by El-Tantawy et al., (2014), who suggested that public acceptance and behavioral adaptation are prerequisites for sustained performance. Therefore, while technical efficacy is a necessary condition for ATCS success, it is insufficient without organizational alignment, policy backing, and systems integration—an insight now clearly reinforced by FHWA case data and prior literature.

Figure 11: Proposed Model for future study



The reviewed deployments provide a comparative lens into the relative effectiveness of AI methodologies such as reinforcement learning, fuzzy logic, and hybrid models in traffic control. Earlier simulation studies by Campbell and Skabardonis (2014) , and Mexis et al. (2025) had already shown the promise of hybrid AI systems in handling non-linear, high-dimensional traffic environments. The field findings in Pittsburgh (Surtrac) and Singapore (GLIDE) confirmed that reinforcement learning models outperform legacy fixed-time and actuated systems across multiple metrics, including delay, throughput, and emissions. However, systems like Hangzhou's City Brain also demonstrated that centralized deep learning architectures could outperform decentralized models when sufficient computational infrastructure and real-time data are available. These variations validate Duan et al.'s (2020) claim that AI model selection should be tailored to context-specific constraints and institutional capacities. Moreover, hybrid models that combine predictive AI with rule-based safety thresholds have been particularly successful in cities with high pedestrian and multimodal interaction, aligning with findings by Jamil and Nower (2021). These cross-system comparisons confirm the theoretical proposition that AI-enabled ATCS are not monolithic but highly variable in design, performance, and operational prerequisites, thereby supporting a pluralistic approach to model selection and deployment strategy.

CONCLUSION

The findings of this meta-analysis provide compelling evidence that AI-enabled adaptive traffic control systems (ATCS) have emerged as a transformative solution to the longstanding challenges of urban traffic congestion, travel time variability, and environmental degradation. Across diverse geographic contexts, system architectures, and operational frameworks, the consistent pattern of performance improvement confirms that intelligent control mechanisms—powered by reinforcement learning, fuzzy logic, deep learning, and hybrid AI models—offer quantifiable advantages over traditional fixed-time and actuated signal systems. The analysis of empirical data from FHWA reports, field deployments, and simulation studies has demonstrated that these systems achieve significant reductions in travel delay, queue length, and congestion duration, while also improving travel time reliability and intersection throughput. These outcomes are not only operationally meaningful but also strategically aligned with broader goals of urban sustainability and smart mobility. One of the most salient contributions of this study lies in demonstrating the multidimensional efficacy of ATCS. While traditional measures such as average travel time and delay remain relevant, newer performance metrics like the Travel Time Index (TTI) and Planning Time Index (PTI) offer more nuanced and actionable insights into system reliability and user experience. Adaptive systems have consistently shown to reduce both TTI and PTI, reflecting their capacity to not only minimize congestion but also stabilize travel conditions under fluctuating demand. These gains are further amplified during peak periods, where AI-based predictive capabilities allow for proactive adjustment of signal timing to prevent congestion spillbacks and maintain corridor continuity.

The environmental and sustainability impacts associated with AI-driven adaptive traffic systems also constitute a critical dimension of their value proposition. The reduction in vehicle idling, stop-start cycles, and unnecessary acceleration contributes to decreased fuel consumption and lower emissions—benefits that align closely with climate action targets and green urban planning principles. Notably, these benefits are not incidental but directly attributable to the system's adaptive logic, which continually responds to real-time demand conditions. As urban transportation becomes a focal point in global efforts to decarbonize, the integration of AI into traffic management stands out as a scalable and data-driven pathway to reduce the environmental footprint of urban mobility. Equally important to the technological capabilities of these systems is the institutional infrastructure that supports their deployment and operation. The meta-analysis revealed that successful implementations were strongly correlated with high levels of institutional readiness, including data integration capacity, technical expertise, inter-agency collaboration, and strategic governance. Conversely, regions that lacked foundational support infrastructure often experienced implementation delays, performance inconsistencies, or underutilization of deployed systems. These observations emphasize the need for not only investing in technology but also in organizational transformation and stakeholder engagement to maximize the long-term value of ATCS.

In synthesizing the insights from case studies across the United States, Asia, and Europe, this study affirms the global relevance and replicability of AI-enabled adaptive traffic systems. Whether deployed in dense megacities like Hangzhou or corridor-specific projects like SmartCorridors in Los Angeles, the principles of real-time data processing, machine learning-driven signal optimization, and system scalability remain constant. These commonalities underscore the adaptability of ATCS to varied traffic cultures, infrastructure maturity levels, and governance models. Furthermore, they highlight the importance of developing standardized frameworks for performance evaluation, knowledge sharing, and benchmarking to support international diffusion of these technologies. Ultimately, this study underscores the critical role of AI-enabled adaptive traffic systems in the ongoing transformation of urban transportation networks. As cities worldwide grapple with congestion, inefficiency, and environmental challenges, the integration of intelligent control systems offers a robust, evidence-based approach to enhance mobility, reduce emissions, and improve quality of life. While challenges remain in terms of deployment cost, data governance, and interoperability, the demonstrated successes of existing systems provide a strong foundation for future expansion and innovation. The convergence of empirical evidence and methodological rigor presented here positions AI-driven ATCS not as experimental novelties, but as essential infrastructure for the intelligent cities of today.

RECOMMENDATIONS

Municipal governments and transportation agencies should prioritize the phased expansion of AI-enabled adaptive traffic control systems (ATCS) across urban intersections, particularly in high-volume corridors and congestion-prone zones. The demonstrated reductions in congestion, delay, and emissions observed in Surtrac (Pittsburgh), SmartCorridors (Los Angeles), and City Brain (Hangzhou) underscore the value of AI in dynamic traffic management. Expanding deployment from pilot corridors to city-wide networks can amplify system-wide benefits. Authorities should identify high-impact deployment zones based on performance metrics such as queue length, travel time index, and intersection delay, and prioritize AI deployment accordingly. Strategic integration with existing infrastructure—through modular upgrades to legacy signal controllers and vehicle detection units—can enable faster adoption while controlling costs. Transportation agencies are encouraged to institutionalize performance monitoring systems that incorporate multidimensional metrics such as Travel Time Index (TTI), Planning Time Index (PTI), average queue lengths, and intersection throughput. These indicators should replace or supplement outdated metrics that focus solely on vehicular delay or average travel time. By adopting a more comprehensive framework, agencies can evaluate not only efficiency but also travel reliability and system resilience. Standardized dashboards and open-data platforms should be developed for real-time tracking and public transparency. Integration of these metrics into urban dashboards can inform operational decisions, investment prioritization, and accountability to stakeholders and commuters.

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