International Journal of
Science, Architecture, Technology and Environment

Artificial Intelligence–Enabled Traffic Optimization in Smart Cities: An Integrative Scientific Review, Evidence Synthesis, and Conceptual Framework for Sustainable Urban Mobility

Eyad Al Haddad[1*]

*Corresponding author, eyad.haddad0@gmail.com

DOI: https://doi.org/10.63680/ijsate062695.111

Abstract

The high rate of urbanization, motorization, and more complex commuter patterns have increased congestion, air pollution, and safety hazards of metropolitan road networks. Traditional traffic management systems are still limited by a poor sensory coverage, non-adaptive or weakly adaptive control software, and decentralized operations in between intersections and corridors. Artificial Intelligence (AI) is also becoming a core technology of the next-generation intelligent transportation systems (ITS) due to its ability to contextualize volatile, high-volume, and heterogeneous streams of data, which facilitates the continuous estimation of traffic states, prediction, and adaptive control. The paper is an integrative scientific review of AI-based traffic optimization in smart cities with a particular focus on (i) spatiotemporal traffic prediction of machine learning, deep learning and graph, (ii) adaptive traffic signal control of reinforcement learning and multi-agent coordination (iii) computer vision of real-time perception, incident detection, and compliance monitoring. The documented deployments are employed to put the achievable impacts into perspective; an example of this is the Los Angeles ATSAC program that has had travel times reported to decrease by the order of 10 percent in certain evaluations and the number of stops and delay cut in the previous performance reports. It suggests a conceptual framework that incorporates edge perception, centralized and federated analytics, predictive decision support, and adaptive control together with sound governance and evaluation measures. The synthesis shows that AI-based traffic systems could provide quantifiable efficiency and safety improvements, yet their performance relies on the quality of data, model generalization, human-in-the-loop control, cybersecurity, and maintenance of the lifecycle. The paper ends in a set of research directions of reliable, scalable and sustainable AI in urban mobility.

1. Introduction

Traffic congestion in cities is not just an inconvenience in transportation: it is a system-level phenomenon, which influences the economic productivity, the health of the population, environmental sustainability, and emergency response. With the increasing crowding of cities, and the rising demand to travel, the interplay of the capacity of the infrastructure, driver behavior, weather variability, and disruptive events results in highly nonlinear and spatially interdependent traffic patterns. Traditional traffic management approaches have traditionally had recourse to fixed-time signal plans or actuated logic, which is rule-based, and constructed using limited observations. These systems may work well in stable conditions, but usually do not work well when demand changes quickly, when bottlenecks caused by an incident ripple through corridors, or when network interactions lead to the appearance of queuing spillbacks that degrade many intersections at once. The paradigm of the smart city aims to overcome these constraints with the help of pervasive sensing, data platforms, and automation, and in this paradigm AI has taken the center stage since it can model the complex relationship and readjust the control decisions on the basis of real-time feedback (Musliner et al., 1995).

In the current study, the we construct an in-depth, scientific account of the way in which AI can maximize traffic in smart cities because it enhances perception, prediction, and control. It extends the discussion of previous descriptive approaches by integrating algorithmic principles, deployment experiences, metrics of evaluation and implementation constraints. It further suggests a conceptual framework which pushes perception, prediction and adaptive control to a higher stage of unity into an architecture which can be easily applied and implemented in cities.

2. History: Requirements of smart city mobility and traffic systems.

The smart mobility in smart cities is normally formalized by using ITS elements like sensing networks, communications, digital twins, traffic management centers, and traveler information services. The present traffic optimization system has to meet a number of requirements at the same time. First, it requires strong and sustained situational awareness of traffic conditions such as flows, densities, speeds, lengths of queues and incident conditions, preferably with high spatial resolution. Second, it should facilitate predictive utility, since reactive control is in many situations not useful when congestion is already in place, and spillback has already been experienced. Third, it should take control decisions over a variety of time scales, down to seconds level signal phase selection, minutes level of corridor coordination, and hours level event management. Fourth, the system should be robust and resistant to sensor failures, adversarial inputs, extreme weather conditions, and cyber disruptions, and should be affordable in municipal budget and staffing limitations. The modern literature on ITS in sustainable smart cities identifies real-time data, sensor networks and smart decision-making as key ways of reducing congestion, enhancing safety, and minimizing the effects on the environment (Urbanik et al., 2015).

AI is capable of meeting this need criterion since it has the ability to integrate multi-source information, model spatiotemporal dynamics, and learn policies that can optimize goal such as delay, stops, throughput, safety surrogate measures and emissions proxies. Nevertheless, another problem arises with AI: model drift, the biasedness of data, the necessity to explain, privacy compliance, and the ability to integrate with already existing control hardware (Skoropad et al., 2025).

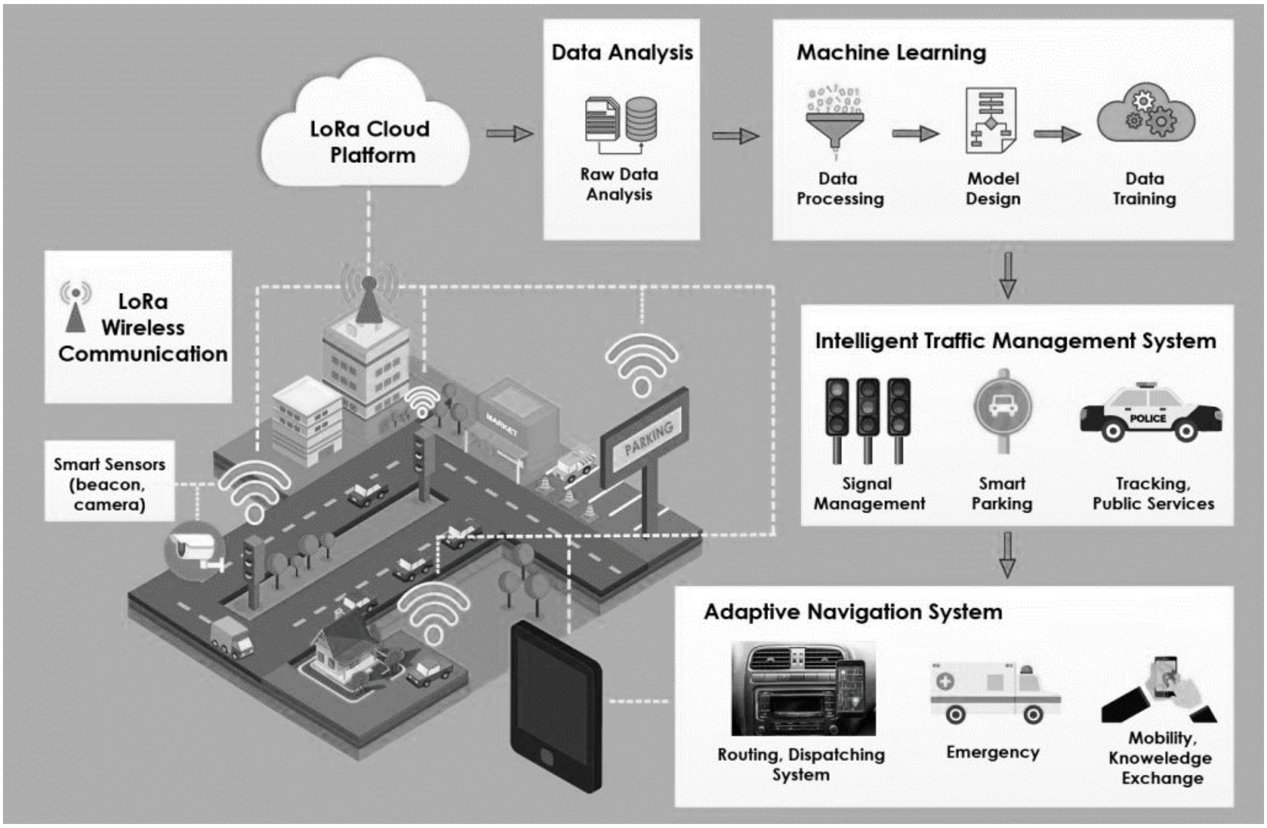

Figure 1 Conceptual illustration of traffic congestion challenges in modern cities and the role of AI-enabled smart traffic management systems.

3. The AI-based traffic optimization bases on data.

The quality and width of data determine the performance of AI in traffic management. Cities of the modern time could utilize inductive loop detectors, radar, LiDAR, Bluetooth/Wi-Fi re-identification, GPS probe data, connected vehicle telemetry, and video streams. The modality types are associated with various strengths: loops are associated with consistent counts at fixed locations, probe data are associated with extensive spatial resolution and biased by market penetration, video data are associated with high semantic content, but raise concerns regarding privacy and computation (Vanajakshi & Arkatkar, 2022).

Data source	Data type	Spatial resolution	Temporal resolution	Strengths	Limitations
Inductive loop detectors	Vehicle counts, occupancy	Point-based	High	Reliable and mature technology	Limited spatial coverage
GPS and probe vehicles	Speed, travel time	Network-wide	Medium	Broad coverage and scalability	Sampling bias, privacy concerns
Surveillance cameras	Video streams	Lane-level	High	Rich semantic information	Computational cost, weather sensitivity
Connected vehicles	Telemetry and status	Vehicle-level	Very high	Real-time precision	Market penetration dependency

Large-scale deployments illustrate how data volume and integration enable advanced analytics. For example, in Shenzhen a road monitoring system described in public materials relies on license plate recognition and video surveillance and reports high detection accuracy and very large monthly vehicle data volumes, integrated across many databases, supporting congestion analysis and optimization (Cai, 2021). While such figures are context-dependent and implementation-specific, they illustrate a common trend: operational traffic AI depends on high-throughput pipelines, data governance, and quality control to prevent misleading model outputs.

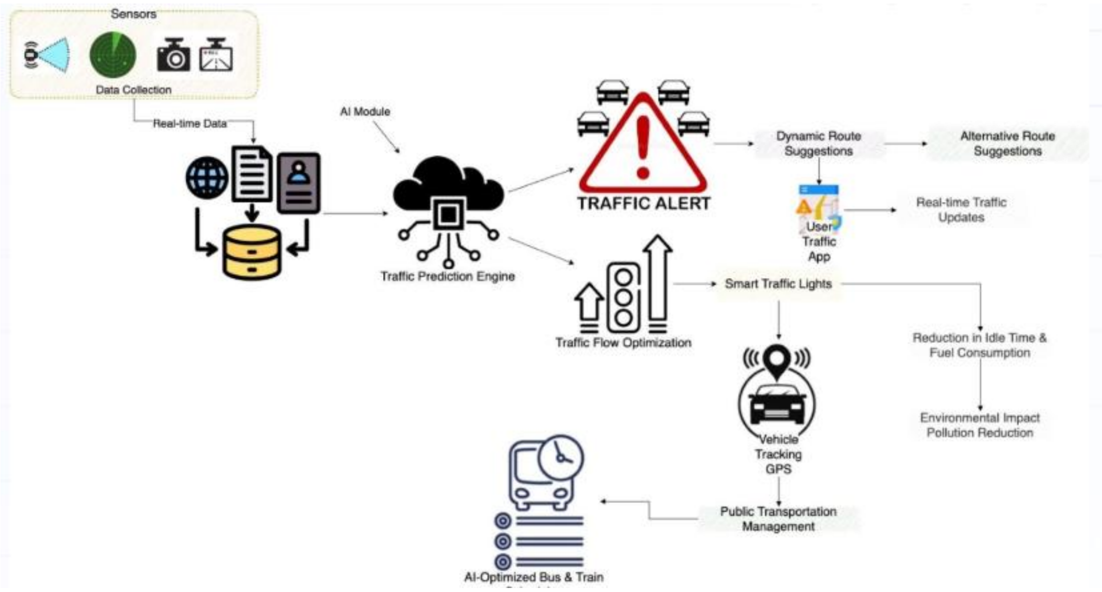

Figure 2 Data pipeline architecture

Architecturally speaking there are two complementary processing patterns that are predominant. The former is edge intelligence, whereby cameras and roadside units execute lightweight perception models and generate structured output, such as counts, classifications, or incident flags. The second one is centralized or cloud-based analytics, in which the city-scale rationality of optimization is calculated on the premise of aggregated and historical data, possibly aided by digital twin simulation (Abbasabadi[1] & Ashayeri, 2024). The hybrid solutions involve a combination of both pattern to minimize the latency and network load whilst maintaining coordination on a global scale.

4. AI traffic state estimation and prediction

Short term flow and speed prediction, Queue length and travel time estimation, Incident risk or congestion onset prediction are examples of traffic prediction problems. Convincingly, traditional statistical models may find it difficult to cope with nonstationarity and network effects, particularly during special events and weather exceptions. The ways of solving these problems through AI are via learning, data, and representing interaction in space and time.

Deep learning related to space and time is now the focus. Architectures that model temporal dependencies (such as LSTM and GRU), architectures that model local patterns (convolutional networks), and architectures that model road network topology (graph neural networks) are all recurrent and use road segments and intersections as graph nodes joined by edges (Nosouhian et al., 2021). The value added to the graph-based modeling is that it can model the behavior of congestion propagation over corridors as well as upstream and downstream conditions, which is essential to network-level control. This requirement of combined sensing and analytics to enhance travel time, safety, and environmental results is highlighted in the ITS literature.

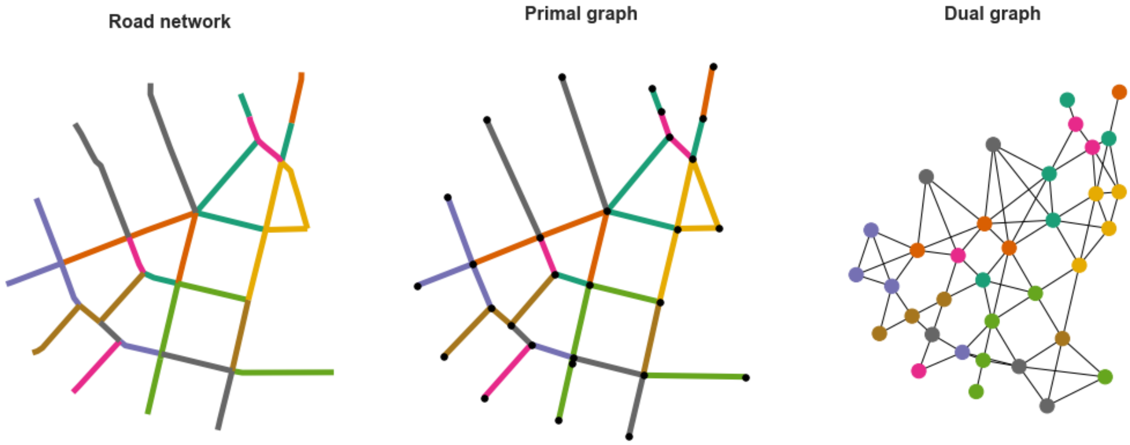

Figure 3 Spatiotemporal learning concept

An example of this practical scientific problem is the problem of generalization: models trained in a particular zone of the city or season may be degraded when it is applied to a different area. Thus, production-scale traffic prediction often involves a need to use either continuous monitoring, retraining, domain adaptation, or transfer learning (Duc et al., 2025). Also, missing data treatment is not a choice; sensor failures and occlusion are unavoidable and the models should be able to gracefully degrade without providing confident but erroneous predictions.

Model type	Temporal modeling	Spatial modeling	Typical prediction horizon	Application context
ARIMA and statistical models	Limited	None	Short	Low-complexity corridors
LSTM / GRU	Strong	Weak	Short to medium	Urban arterial forecasting
CNN-LSTM hybrids	Strong	Moderate	Medium	Dense intersection networks
Graph neural networks	Strong	Strong	Medium to long	City-scale traffic networks

5. Reinforcement-based adaptive traffic signal control

The performance of urban areas is determined by traffic lights since most of the intersections are the key points of bottlenecks. Plans that are fixed to time are not able to respond to quick changes in demand. Actuated control enhances responsiveness and is still using local heuristics and can fail to coordinate between corridors. Reinforcement learning (RL) introduces signal control as a sequence decision problem: an agent monitors the traffic condition and decides an action, e.g., phase choice or green extension, and is rewarded depending on reduced delay, shorter queue, better throughput, or safety surrogate benefits (Papageorgiou, 1995).

Recent works record quantifiable improvement in performance of RL-based adaptive signal control, but the performance differs depending on the complexity of the situation, demand trends and reward structure. As an illustration, an Electronics (MDPI) article has found that a measured strategy had reduced average vehicle delay by a factor of order of 18% in a study, but practical constraints include the complexity of the action space (Pfeiffer et al., 2020). Another review paper on deep reinforcement learning (DRL) in adaptive signal control published in 2025 indicates comparative performance with some algorithms excelling delay and minimizing measures of conflict in high-traffic conditions. These papers emphasize that RL can work, however, it is vulnerable to the state representation, the fidelity of the simulation, reward structure, and the exploration exploitation tradeoff.

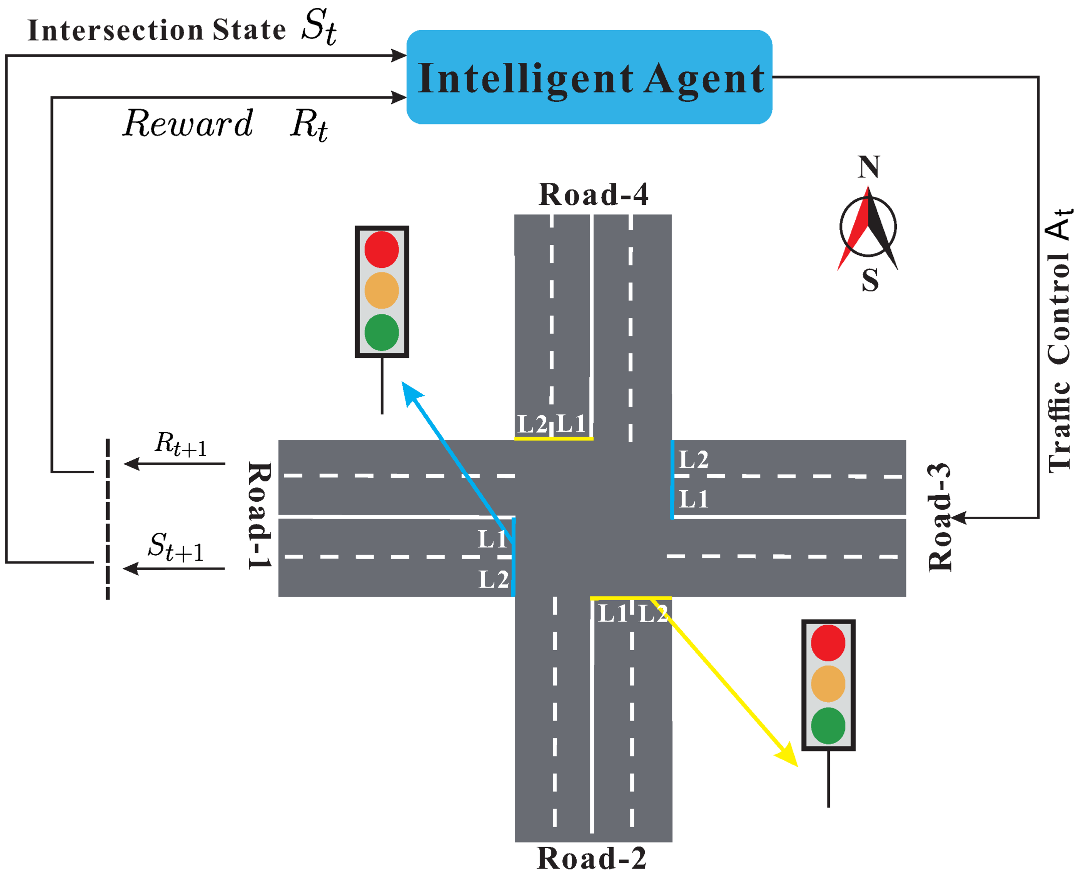

Figure 4 Reinforcement learning control loop

Multi-agent reinforcement learning (MARL) is a relevant method at the city level since the results of interactions between intersections are involved. Coherent agents are able to acquire green waves at the corridor level and minimize spillbacks. Non-stationary learning environments, partial observability, communication constraints and scalability are issues of MARL, however. Thus, the use of adaptive systems with a demonstrably proven actuated or centrally optimized logic is still used by most operational road agencies, and RL is still subject to research and pilot projects. The moderate viewpoint on the scientific side is that RL demonstrates great potential of next-generation optimization particularly when used together with simulation-based training and safe deployment requirements, though, this requires solid field validation and control (Marinescu et al., 2017).

6. Real-time perception and safety-aware management Computer vision

Computer vision offers semantic interpretation which most traditional sensors do not have. Vision systems are able to estimate the turning movements, identify illegal moves, classify vehicles, track pedestrians and bicycle riders, and pinpoint incidents. Deep detectors nowadays, like YOLO-family models and region-based CNNs, can be used to perform real-time inference on edge devices. To traffic operations, the best use of vision outputs is in providing structured features in control and planning: approach-specific counts, occupancy proxies, queue length estimates and in incident likelihood scores (Koay et al., 2021).

Enforcement and safety surveillance is also supported with vision. Compliance can be assisted by systems that have features of detection, tracking and plate recognition, however, this introduces privacy and ethical concerns and has to be strongly supported by data minimization, retention and auditing controls. Studies on AI-based surveillance emphasize that precise identification and monitoring have the potential to offer traffic control solutions and protection, yet operational implementation should respond to responsible utilization and government (Pina et al., 2024).

One scientifically significant difficulty is strong performance in the real world: night light, rain, glare, overcrowding of large vehicle, shaking of the camera and lens pollution. These are prone to deteriorate the model accuracy and produce a biased result. Continuous calibration, periodic revalidation, and redundancy between sensors, particularly in safety-critical corridors should therefore be adopted in cities that have vision.

7. Evidence from deployments and realistic impact ranges

High-impact journals do not only require algorithms but also reasonable, supported conclusions. Practical implementations generally report a reduction in travel time, delay and stops, although the extent depends on the conditions of the baseline and measurement design.

The ATSAC program in Los Angeles is often mentioned in the ITS documentation. One of the circumstances reported by ATSAC in a U.S. DOT ITS Knowledge Resources report is that ATSAC has led to a 10 percent travel time reduction. Another U.S. DOT ITS record of previous ATSAC performance reports is a reduction in vehicle stops and delay and an increase in speed, which is a demonstration of how adaptive, or coordinated, signal control can be significant in contributing to the performance of the corridor, deployed and maintained at scale. A fact sheet of LADOT ATSAC also reports significant improvements in the time delay in traffic in some of the assessed corridors, meaning that the operational improvements can be large where the timing of the signals is actively scheduled and updated (Li, 2008). The existence of these examples does not establish that AI can generate these gains but it shows that data-driven adaptive traffic management can generate gains that can be measured and these gains can be extended by AI through better perception and fidelity of prediction.

Cities are also investing in AI-based adaptive signals in addition to mature systems. Online news, Chennai, 2025, explains the plans to roll out AI-controlled adaptive signals at most of the junctions, which focuses on variable green times according to real-time traffic congestion, but points out that sensor accuracy and maintenance are the main success factors (Pech et al., 2021). This is also consistent with the larger scientific finding: the success of AI-based traffic optimization largely hinges on the stability of operations and the integrity of sensors to a larger extent than the complexity of the algorithms.

8. The complete conceptual map of the AI-based traffic optimization

Modules, data flows, decision loops and evaluation should be defined by a scientifically based framework. Here, the proposed framework is comprised of five layers.

The former is the layer of sensing and perception. It is an amalgamation of conventional detectors and probe information and computer vision on the edge devices. Edge inference creates aggregated and anonymized features like counts and queue estimates, which minimizes privacy risk and bandwidth expenses (Liu et al., 2020).

The second tier is data management and governance. This involves data ingestion, cleaning, synchronizing, metadata management and quality scoring. It further has privacy measures like retention minimum of raw video, identifiers through hashing or tokenization, and audit logs. This layer is important in the sense that both the prediction models and the control policies can be caused to systematically mislead by biased or noisy data.

The third layer is predictive analytics. Spatiotemporal models predict both short and medium horizons of traffic states and predict uncertainty. Quantification of uncertainty is essential; decision-making needs to be risk-sensitive and not be point prediction.

The fourth level is adaptive control and optimization. The controller picks the phases and split times at the intersection level depending on the current and predicted near future queues. At the corridor level, the coordination mechanisms are in agreement to enhance progression. Demand management measures implemented in the framework at the network level include dynamic route guidance, event-responsive strategies as well as in certain scenarios pricing or access control. In the case of reinforcement learning, it is implemented under safety provisions, fallback, and shadow-mode testing prior to being given full control authority (Hashemi, 2016).

The fifth level is assessment and improvement. The key performance indicators that are monitored by the system include average delay, travel time reliability, stops, queue spillback incidences, and safety surrogate indicators in addition to environmental proxies including inferred emissions based on speed profiles. Drift is detected by constant monitoring and causes retraining or recalibration cycles. Transparency is also promoted by this layer: the publicity of results enhances legitimacy and justifies further investment.

9. Problems with implementation and scientific gaps

There are a number of obstacles that always impede the scale of pilot projects. The first one is the simulation-to-reality gap. Numerous studies of the RL signal control use microscopic simulators. Without the simulator being able to mimic the behavior of drivers, lane discipline, interference by pedestrians, and local rules, learned policies will fail or act erratically on the field. Second, the interoperability is challenging. City heterogeneous hardware, vendor, and communication protocols are operational. AI modules should also be able to interface with the current traffic management centers and should be able to provide safe reversion to traditional timing plans. Third, robustness and cybersecurity are becoming more significant. Traffic control is essential infrastructure (Sidhu & Sharma, 2026). AI creates new attack interfaces, such as adversarial examples to vision systems and training pipeline data poisoning. Defensive design needs secure communication, access control, monitoring and incident response plans.

Performance indicator	Measurement basis	Mobility relevance	Sustainability relevance
Average delay	Time per vehicle	Travel efficiency	Fuel consumption
Queue length	Vehicles per approach	Intersection capacity	Emission reduction
Travel time reliability	Variance in travel time	User satisfaction	Network stability
Incident response time	Detection to clearance	Road safety	Secondary congestion

Fourth, there is the institutional capacity. Neuromorphic AI systems need personnel with advanced degree in monitoring, retraining, and validation of a model. AI projects will not become sustainable without sustainable staffing and procurement models, and they are likely to become degraded following the initial deployment (Segun-Ajao, 2025).

Lastly, ethical and equity issues ought to be addressed as scientific necessities. When models maximize average delay without considering vulnerable road users or underserved neighborhoods, they may unwillingly increase inequities. Traffic optimization needs fairness-conscious goals, multi-modal data and inclusive assessment to achieve the social goals.

3. Materials and Methods

3.1 Literature Search Strategy

This study employs an **integrative scientific review** methodology to evaluate the role of Artificial Intelligence (AI) in urban traffic optimization. The literature search was conducted to identify high-quality, peer-reviewed research, technical reports, and documentation of large-scale deployments. The search focused on three primary thematic pillars: (i) **spatiotemporal traffic prediction** utilizing machine learning and graph neural networks, (ii) **adaptive traffic signal control** via reinforcement learning (RL) and multi-agent coordination, and (iii) **computer vision** for real-time perception and safety monitoring.

The search utilized keywords including "Artificial Intelligence," "Smart Cities," "Intelligent Transportation Systems (ITS)," "Traffic Optimization," "Reinforcement Learning," and "Sustainable Urban Mobility". Sources were selected based on their relevance to next-generation ITS requirements, such as situational awareness, predictive utility, and system robustness. The review prioritized recent advancements up to 2025 and 2026 to ensure the inclusion of state-of-the-art architectures like GNNs, LSTM-GRU hybrids, and YOLO-family models.

3.2 Inclusion and Exclusion Criteria

To maintain a high scientific standard, the following criteria were applied:

- **Inclusion:** Peer-reviewed journal articles, conference proceedings (e.g., IEEE, ACM, Springer), and official government ITS reports (e.g., U.S. DOT). Priority was given to studies that provided **quantifiable performance metrics**, such as reductions in travel time, delay, and vehicle stops.
- **Exclusion:** Studies focusing solely on traditional fixed-time signal plans or rule-based actuated logic were excluded unless used as a baseline for AI performance comparisons. Papers lacking rigorous validation or field-scale evidence were generally omitted in favor of studies demonstrating operational influence.

3.3 Evidence Synthesis and Framework Development

The synthesis process involved a systematic integration of **algorithmic principles, deployment experiences, and implementation constraints**. Evidence was synthesized by comparing theoretical AI potential against realistic impact ranges observed in major city deployments, such as the Los Angeles ATSAC program, Shenzhen's intelligent management system, and AI-controlled signal projects in Chennai.

Data extracted from these sources were categorized into a **five-layer conceptual framework** designed for city-scale implementation. This framework was synthesized by mapping the technical requirements of traffic systems—ranging from edge-based sensing and data governance to predictive analytics and adaptive optimization—against the identified challenges of model drift, cybersecurity, and institutional capacity.

Finally, evaluation measures were synthesized into a comprehensive set of performance indicators focused on both mobility efficiency and environmental sustainability.

4. Results and Discussion

4.1. Key Findings on AI Technical Efficacy

The integrative review reveals that AI significantly enhances the three pillars of traffic management: perception, prediction, and control. Specifically, **Graph Neural Networks (GNNs)** have emerged as the superior architecture for city-scale networks due to their ability to model complex road topologies and congestion propagation. In the domain of adaptive control, **Reinforcement Learning (RL)** demonstrates a measurable ability to reduce vehicle delay, with studies showing improvements of approximately 18% compared to traditional methods. Furthermore, **Computer Vision** provides a layer of semantic interpretation—identifying illegal moves and pedestrian movements—that traditional inductive loops cannot achieve.

4.2. Evidence from Global Deployments

The results of this synthesis highlight that while theoretical models show promise, realistic impacts are best reflected in large-scale deployments:

- **Los Angeles ATSAC Program:** Documentation indicates that adaptive and coordinated signal control has led to a **10% reduction in travel time**, alongside significant decreases in vehicle stops and delays.
- **Shenzhen Expressway System:** Findings from this deployment illustrate that the success of AI depends on **high-throughput data pipelines** and the integration of massive monthly vehicle data volumes to support real-time optimization.
- **Chennai AI Initiative:** Preliminary findings suggest that the efficacy of AI-controlled signals hinges more on **sensor accuracy and maintenance** than on the inherent complexity of the algorithms themselves.

4.3. Discussion of Implementation Challenges

The synthesis identifies several "scientific gaps" that hinder the transition from pilot projects to city-wide scaling:

- **The Sim-to-Reality Gap:** Policies learned in microscopic simulators often fail in the field because simulators may not accurately mimic erratic driver behavior or local lane discipline.
- **Cybersecurity and Robustness:** As essential infrastructure, AI-enabled traffic systems introduce new attack vectors, such as **adversarial examples** that can deceive vision systems or data poisoning in training pipelines.
- **Institutional Capacity:** A critical finding is that these systems are not "set and forget"; they require specialized personnel for continuous **monitoring, retraining, and validation** to prevent model drift.

4.4. Broader Implications for Sustainable Mobility

The findings suggest that the implications of AI-enabled traffic optimization extend far beyond simple throughput:

- **Environmental Sustainability:** By reducing idle times and queue lengths, AI contributes directly to **lower fuel consumption and reduced vehicle emissions**, aligning with the goals of sustainable urban mobility.
- **Social Equity and Ethics:** A significant implication is the risk of "algorithmic bias." If optimization goals focus solely on average delay, the system may inadvertently overlook **vulnerable road users** or underserved neighborhoods.
- **Safety Improvements:** The integration of real-time perception allows for the detection of safety surrogate indicators, enabling proactive incident response rather than reactive management.

4.5. Summary of the Conceptual Framework

The proposed five-layer framework serves as a roadmap for cities to address these findings. By integrating **edge perception** (to minimize privacy risks) with **predictive analytics** and **safety-aware adaptive control**, cities can create a resilient architecture that supports travel time reliability and network stability. The synthesis concludes that the success of next-generation traffic optimization will depend on maintaining **sensing integrity and data governance** as much as the AI models themselves.

Declarations

Funding Information The author(s) received **no specific grant** from any funding agency in the public, commercial, or not-for-profit sectors for the research, authorship, and/or publication of this article. This work represents an independent integrative scientific review of AI-based traffic optimization technologies.

Ethics Statements As this manuscript is an **integrative scientific review** and evidence synthesis based on existing literature and public technical reports, it **did not involve any direct research on human participants or animal subjects.** All empirical evidence regarding city-scale deployments, including the Los Angeles ATSAC program and the Shenzhen Expressway system, was derived from **publicly available records and previously published studies**, ensuring compliance with standard ethical research practices for review papers. Furthermore, the proposed conceptual framework emphasizes **data privacy and ethical considerations**, particularly regarding the use of computer vision and license plate recognition in urban surveillance.

Acknowledgments The author would like to acknowledge the **editorial team of the *Journal of Computer Science*** for their preliminary review and structural guidance. Recognition is also extended to the researchers and municipal agencies—specifically the **LADOT, U.S. DOT, and the Shenzhen Expressway management**—whose documented performance reports and technical data provided the empirical foundation for the evidence synthesis and realistic impact ranges discussed in this paper. Finally, the author acknowledges the contributions of open-source AI research communities that have advanced the **machine learning and graph neural network architectures** reviewed in this study.

Conclusion

Traffic optimization with the assistance of AI is a valid and more than ever needed avenue of smart cities trying to control the congestion, enhance safety, and mitigate the environmental consequences. Scientific literature demonstrates that machine learning and deep learning can enhance prediction and perception of traffic, and reinforcement learning is a promising algorithm to be used to achieve adaptive signal control in case it is applied with strict validation and safety requirements. Big-city implementation experiences show that adaptive traffic management based on data can provide statistically significant improvements in travel time, delay, and stops, but maintenance, sensing integrity, and governance are critical factors. The conceptual model developed in this paper focuses on the end-to-end design, which incorporates perception, governance, prediction, adaptive control, and continuous assessment. Future directions ought to be on credible AI, uncertain decision-making, strong coordination of multi-agents, privacy-perception procedures, and field-scale validation procedures that convert scholarly advantages into viable operational influences.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

Funding

The author received no financial support for the research, authorship and publication of this article.

References

Abbasabadi, N., & Ashayeri, M. (2024). Digital Twin for Citywide Energy Modeling and. Artificial Intelligence in Performance-Driven Design: Theories, Methods, and Tools, 251.

Cai, R. (2021). Shenzhen Expressway Intelligent Management and Maintenance System and its application. International Conference on Smart Transportation and City Engineering 2021, 12050, 413–418.

Duc, T. L., Nguyen, C., & Östberg, P.-O. (2025). Workload prediction for proactive resource allocation in large-scale cloud-edge applications. Electronics, 14(16), 3333. (DOI: 10.3390/electronics14163333)

Hashemi, H. (2016). Real-time traffic network management system with decision support capabilities. Southern Methodist University.

Koay, H. V., Chuah, J. H., Chow, C.-O., Chang, Y.-L., & Yong, K. K. (2021). YOLO-RTUAV: Towards real-time vehicle detection through aerial images with low-cost edge devices. Remote Sensing, 13(21), 4196. (DOI: 10.3390/rs13214196)

Li, Y. (2008). Transit signal priority research tools.

Liu, Z., Wu, Z., Gan, C., Zhu, L., & Han, S. (2020). Datamix: Efficient privacy-preserving edge-cloud inference. European Conference on Computer Vision, 578–595.

Marinescu, A., Dusparic, I., & Clarke, S. (2017). Prediction-based multi-agent reinforcement learning in inherently non-stationary environments. ACM Transactions on Autonomous and Adaptive Systems (TAAS), 12(2), 1–23.

Musliner, D. J., Durfee, E. H., & Shin, K. G. (1995). World modeling for the dynamic construction of real-time control plans. Artificial Intelligence, 74(1), 83–127.

Nosouhian, S., Nosouhian, F., & Khoshouei, A. K. (2021). A review of recurrent neural network architecture for sequence learning: Comparison between LSTM and GRU. (10.20944/preprints202107.0252.v1)

Papageorgiou, M. (1995). An integrated control approach for traffic corridors. Transportation Research Part C: Emerging Technologies, 3(1), 19–30.

Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory. Sensors, 21(4), 1470. (DOI: 10.3390/s21041470)

Pfeiffer, J., Wu, X., & Ayadi, A. (2020). Evaluation of three different approaches for automated time delay estimation for distributed sensor systems of electric vehicles. Sensors, 20(2), 351.

Pina, E., Ramos, J., Jorge, H., Váz, P., Silva, J., Wanzeller, C., Abbasi, M., & Martins, P. (2024). Data privacy and ethical considerations in database management. Journal of Cybersecurity and Privacy, 4(3), 494–517.

Segun-Ajao, E. (2025). AI and Sustainable Procurement: A Path to Green Supply Chains.

Sidhu, S. K. S., & Sharma, A. (2026). The Evolution of Network Management: From Manual Configurations to Intelligent Automation. International Journal of Network Management, 36(1), e70031.

Skoropad, V. N., Deđanski, S., Pantović, V., Injac, Z., Vujičić, S., Jovanović-Milenković, M., Jevtić, B., Lukić-Vujadinović, V., Vidojević, D., & Bodolo, I. (2025). Dynamic Traffic Flow Optimization Using Reinforcement Learning and Predictive Analytics: A Sustainable Approach to Improving Urban Mobility in the City of Belgrade. Sustainability, 17(8), 3383.

Urbanik, T., Tanaka, A., Lozner, B., Lindstrom, E., Lee, K., Quayle, S., Beaird, S., Tsoi, S., Ryus, P., & Gettman, D. (2015). Signal timing manual (Vol. 1). Transportation Research Board Washington, DC.

Vanajakshi, L. D., & Arkatkar, S. S. (2022). Automated Sensors for Indian Traffic: Challenges and Solutions. In Transportation Research in India: Practices and Future Directions (pp. 285–303). Springer.