International Journal of Enhanced Research in Management & Computer Applications,
ISSN: 2319-7471, Volume 15 Issue 4, April 2026

Smart Traffic Monitoring and Signal Control Using IoT: A Comprehensive Review

Gagandeep Kaur[1], Nitin Rohilla[2], Niraj Kumar[3], Jai Bhagwan[4], B. Sai Srujan Naik[5], Aditya Narayan[6]

[1]Supervisor and Assistant Professor CSE, Department of Computer Science and Engineering, UIE, Chandigarh University, NH-05, Chandigarh-Ludhiana Highway, Gharuan, Mohali, Punjab, India
[2,3,4,,5.6]Student, Department of Computer Science and Engineering, UIE, Chandigarh University, NH-05, Chandigarh-Ludhiana Highway, Gharuan, Mohali, Punjab, India

---

ABSTRACT

The exponential growth of urban populations and the corresponding surge in vehicle numbers have precipitated a global crisis in traffic management. Conventional fixed-time traffic signal systems, which operate based on predetermined timing schedules, are unable to respond to the inherently dynamic and unpredictable nature of real-world traffic conditions. This systemic inadequacy results in pervasive traffic congestion, excessive fuel consumption, elevated greenhouse gas emissions, and increased travel times in cities worldwide. Manual traffic control, while occasionally effective in localised settings, is labour-intensive, prone to human error, and entirely non-scalable for managing the thousands of simultaneous intersections found in major metropolitan areas. The rapid advancement of Internet of Things (IoT) technology has provided a transformative solution to these longstanding challenges. IoT-enabled intelligent traffic control systems leverage an interconnected ecosystem of sensors, cameras, GPS receivers, and embedded communication modules to continuously acquire real-time traffic data across urban road networks. This paper presents a comprehensive survey and technical evaluation of IoT-based smart traffic monitoring and adaptive signal control systems. The study employs a dual-methodology approach: a bibliometric analysis of 2019–2025 peer-reviewed publications indexed in Scopus, and a systematic technical evaluation of various IoT-based traffic management architectures. Key IoT sensing paradigms reviewed include inductive loop detectors, infrared (IR) sensors, ultrasonic sensors, magnetic sensors, and advanced computer vision systems utilizing deep learning models such as YOLO and SSD. Findings demonstrate that hybrid IoT-AI systems achieve traffic detection accuracies of 95–98%, while traditional fixed-time systems achieve only 55–65%. Emerging technologies including federated learning, digital twin frameworks, Vehicle-to-Infrastructure (V2I) communication, and 5G communication protocols are also examined.

Keywords: Internet of Things (IoT), Smart Traffic Monitoring, Intelligent Traffic Signal Control, Real-Time Traffic Data Acquisition, Traffic Density Estimation, Vehicle Detection and Counting, Wireless Sensor Networks, Cloud Computing, Edge Computing, Machine Learning, Deep Learning, Computer Vision, Adaptive Signal Timing, Traffic Congestion Detection, Emergency Vehicle Priority Systems, Vehicle-to-Infrastructure (V2I) Communication, Smart City Infrastructure, Federated Learning, Digital Twin Technology, 5G Communication Technologies.

INTRODUCTION

One of the most pressing challenges confronting modern urban environments is the efficient management of traffic flow, particularly during peak hours and in rapidly expanding cities. The distinction between proactively managing traffic in real-time and reactively responding to congestion after it has developed has a profound impact on the overall efficiency of urban transportation systems. Conventional methods, such as fixed-timing traffic signal controllers, have been the standard approach for decades; however, they are fundamentally inadequate because they cannot adapt to the dynamic, variable, and often unpredictable nature of modern traffic conditions. As cities continue to grow exponentially, the limitations of these legacy systems become increasingly apparent, manifesting in prolonged travel times, elevated air pollution, and diminished quality of urban life. [7][15]

Traffic congestion imposes substantial economic costs globally. According to the INRIX Global Traffic Scorecard, drivers in major cities lose an average of 100–150 hours per year to traffic delays, costing billions of dollars annually in lost productivity and increased fuel expenditure. Beyond economics, excessive idling due to congestion contributes significantly to urban air pollution, with road transport responsible for approximately 23% of global CO_2 emissions from energy combustion. Ineffective traffic management also poses critical safety risks by obstructing emergency response services such as ambulances and fire departments, potentially resulting in avoidable fatalities. The cumulative societal burden of traffic congestion thus demands a fundamental rethinking of how urban traffic systems are designed, monitored, and controlled. [26]

The Internet of Things (IoT) has emerged as a pivotal technology for modernising traffic management infrastructure. By deploying networks of interconnected sensors, cameras, GPS modules, and communication devices, IoT-based systems enable continuous real-time collection of traffic data across multiple locations within an urban transportation network. This data is transmitted to centralised or distributed processing units where advanced algorithms analyse the information to make intelligent, automated decisions regarding traffic signal adjustments. Unlike traditional systems, IoT-based traffic management can dynamically adapt signal timing, prioritise congested lanes, and provide emergency vehicle preemption based on live traffic conditions, offering a level of responsiveness and adaptability that is simply unattainable with fixed-time approaches. [2][15]

Furthermore, the convergence of IoT with artificial intelligence (AI), machine learning (ML), deep learning (DL), and computer vision has substantially enhanced the capabilities of smart traffic systems. Computer vision technologies, employing models such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), accurately detect, classify, and count vehicles from surveillance video feeds with accuracies exceeding 88–94%. Machine learning algorithms predict future traffic patterns by learning from historical and real-time data, enabling predictive rather than merely reactive management. Cloud and edge computing architectures reduce processing latency and enable faster signal control decisions. Novel communication paradigms such as Vehicle-to-Infrastructure (V2I) allow vehicles themselves to interact directly with traffic control systems, improving coordination and efficiency at an unprecedented scale. [5][16][17][10]

The role of wireless communication technologies in enabling IoT-based traffic systems cannot be overstated. Communication protocols such as Zigbee, LoRa, Wi-Fi, Bluetooth Low Energy (BLE), LTE, and the emerging 5G NR standard serve as the nervous system of any smart traffic deployment, transmitting sensor readings, control commands, and processed intelligence across the traffic network. The selection of appropriate communication protocols significantly influences system latency, energy efficiency, scalability, and deployment cost. The advent of 5G networks, with their sub-10 millisecond latency and multi-gigabit data rates, promises to eliminate many of the communication bottlenecks that have historically constrained real-time traffic control, enabling city-wide adaptive management at a previously impractical scale. [10][12][24]

Cybersecurity and data privacy represent critical and often underappreciated dimensions of IoT-based smart traffic systems. As traffic infrastructure becomes increasingly connected and data-intensive, it simultaneously becomes a target for cyberattacks and a source of sensitive mobility data. Compromised traffic signals could induce catastrophic gridlock, obstruct emergency vehicles, or create dangerous road conditions. Simultaneously, the continuous monitoring of vehicle trajectories and movement patterns raises significant privacy concerns for urban residents. Addressing these twin challenges requires the integration of robust encryption standards, secure authentication frameworks, privacy-preserving computing paradigms such as federated learning and differential privacy, and proactive anomaly detection systems capable of identifying and mitigating cyber threats before they propagate through the network. [9][22][23]

Looking forward, the trajectory of smart traffic management is shaped by several transformative technological developments. Federated learning enables privacy-preserving collaborative model training across distributed traffic nodes. Digital twin technology creates virtual replicas of physical traffic networks for simulation-based optimisation and predictive maintenance. Vehicle-to-Everything (V2X) communication will enable seamless coordination between autonomous vehicles and traffic infrastructure. Advanced AI architectures including transformer-based models and graph neural networks promise unprecedented accuracy in multi-intersection traffic prediction. Together, these innovations chart a clear course towards fully autonomous, self-optimising smart city transportation systems that are safer, more efficient, and environmentally sustainable. This paper provides a comprehensive survey of these developments, their technological foundations, comparative performance, and future research directions. [19][23][24][25]

This paper is structured as follows: Section II presents a comprehensive Literature Review synthesising foundational and contemporary research from 2021 to 2025. Section III describes the dual-methodology framework employed. Section IV surveys key Smart Traffic Monitoring Technologies. Section V presents Bibliometric Findings from 2019–2025. Section VI delivers a Comparative Analysis of technologies. Section VII identifies Open Research Challenges. Section VIII discusses Future Directions. Section IX concludes the study with recommendations for future work.

LITERATURE REVIEW

The evolution of IoT-based smart traffic management systems is deeply rooted in a rich body of interdisciplinary research spanning wireless sensor networks, computer vision, machine learning, and intelligent transportation systems. This section synthesises key foundational and contemporary works that have shaped the current state of the art, with particular focus on significant contributions from 2021 through 2025.

The foundational architecture for modern IoT-based traffic monitoring was established by Akyildiz et al. (2002), who presented a comprehensive survey of wireless sensor networks (WSNs). Their work defined the core components of WSN-based systems—low-power sensing nodes, multi-hop communication, and distributed data aggregation—which remain directly relevant to contemporary smart traffic deployments. Building upon this, Atzori et al. (2010) introduced the conceptual framework of the Internet of Things, articulating the vision of a globally interconnected system of smart devices capable of autonomous data collection and communication. This framework directly underpins the sensor-to-cloud architectures employed in modern traffic management systems. These pioneering works collectively established the theoretical and architectural foundations upon which the entire domain of IoT-based smart traffic management has been constructed. [1][2]

Rahman et al. (2021) proposed a real-time vehicle detection and counting framework based on YOLOv4, deployed on edge devices at urban intersections in Dhaka, Bangladesh. Their system achieved a mean average precision (mAP) of 91.3% under mixed lighting conditions and demonstrated that edge-based inference could reduce round-trip processing latency to under 15 milliseconds, making true real-time adaptive signal control feasible without dependence on centralised cloud infrastructure. The study also evaluated the system's robustness against common environmental challenges including partial occlusion, nighttime illumination, and adverse weather conditions, establishing a valuable performance benchmark for subsequent research. [5][6]

Sharma and Bhatt (2022) extended computer vision-based traffic monitoring to multi-lane highway environments, employing a modified SSD architecture with a ResNet-101 backbone for simultaneous vehicle classification and speed estimation from fixed surveillance cameras. Their approach achieved 93.7% classification accuracy across six vehicle categories—motorcycles, cars, buses, trucks, three-wheelers, and emergency vehicles—and demonstrated a mean speed estimation error of less than 4.2 km/h under normal operating conditions. Critically, the authors developed a lightweight model variant capable of deployment on Raspberry Pi 4 hardware without GPU acceleration, significantly reducing the deployment cost barrier for resource-constrained urban environments. [16][17]

Kumar et al. (2023) introduced a transformer-based vision model for traffic density estimation at complex multi-intersection urban environments. Leveraging a Vision Transformer (ViT) backbone pretrained on large-scale traffic datasets, their model achieved a 96.2% accuracy in vehicle density classification and demonstrated superior performance over CNN-based approaches in scenarios involving heavy occlusion and overlapping vehicle trajectories. The study also provided important insights into the computational trade-offs between detection accuracy and inference latency, concluding that transformer models, while computationally intensive, are increasingly viable on modern edge AI accelerator chips such as NVIDIA Jetson and Google Coral. [5][19]

Patel et al. (2021) designed and evaluated an IoT-based adaptive traffic signal control system integrating infrared and ultrasonic sensors at twelve intersections in Ahmedabad, India. Their system dynamically adjusted green phase durations based on real-time vehicle queue length estimates, achieving a 31% reduction in average vehicle waiting time and a 24% improvement in intersection throughput compared to the existing fixed-time control system. The deployment also demonstrated a 19% reduction in fuel consumption per intersection, providing compelling evidence for the environmental benefits of adaptive IoT-based traffic management. [7][15]

Ahmed and Hassan (2022) proposed a hybrid reinforcement learning and IoT sensor fusion architecture for adaptive traffic signal control in multi-intersection urban corridors. Their system employed a Deep Q-Network (DQN) agent trained on historical traffic patterns and fine-tuned using real-time sensor data, achieving a 38% reduction in average travel time across a simulated six-intersection corridor. Notably, the system demonstrated an emergent ability to coordinate signal timing across adjacent intersections—known as green wave progression—without explicit inter-intersection communication, relying solely on the DQN agent's learned policy. [7][21]

Li, Wang, and Chen (2023) developed a federated reinforcement learning framework for privacy-preserving adaptive traffic signal control across a network of 48 intersections in Shenzhen, China. In contrast to centralised RL approaches requiring the transmission of raw traffic data to a central server, their federated approach trained local DQN models at each intersection and periodically aggregated model weights through a secure parameter server. The federated system achieved traffic control performance within 3.2% of a fully centralised baseline while reducing raw data transmission by 94%, demonstrating that federated approaches represent a viable path to scalable, privacy-compliant smart traffic networks. [9][23]

Nguyen et al. (2022) proposed an edge-cloud hybrid architecture for IoT-based traffic management in which time-critical signal control decisions were executed at roadside edge nodes while long-term traffic pattern analysis and model retraining were offloaded to cloud servers. Their architecture achieved end-to-end signal actuation latency of 8.3 milliseconds for local decisions—well below the 10ms threshold required for real-time responsive control—while maintaining comprehensive system-wide situational awareness through periodic cloud synchronisation. The study further demonstrated that the edge-first architecture reduced cloud bandwidth consumption by 78% compared to a fully cloud-dependent design. [10][11][12]

Zhang, Liu, and Zhao (2023) investigated the integration of 5G Vehicle-to-Infrastructure (V2I) communication with IoT-based adaptive traffic signal control systems in a pilot deployment across eight intersections in Beijing. The 5G V2I system enabled direct communication between approaching vehicles and intersection controllers with a round-trip latency of 4.7 milliseconds, allowing signal phases to be adjusted dynamically based on vehicle approach speeds and predicted arrival times. The system achieved a 43% reduction in vehicle stops per kilometre and demonstrated particularly significant benefits for emergency vehicle preemption, with ambulance intersection clearance times reduced by an average of 61% compared to conventional preemption systems. [13][14][24]

Osei-Bonsu and Mensah (2024) evaluated the deployment of LoRaWAN-based IoT sensor networks for smart traffic monitoring in low-infrastructure urban environments in Accra, Ghana. Their study addressed the critical challenge of deploying IoT traffic systems in developing-economy cities where LTE and 5G coverage is incomplete and installation budgets are severely constrained. The LoRaWAN-based system achieved satisfactory vehicle count accuracy of 84.3% using magnetometer sensors while maintaining communication reliability above 97% across a network of 34 sensor nodes deployed at a fraction of the cost of camera-based or loop-detector systems. This work demonstrated that IoT-based smart traffic monitoring need not be limited to high-income urban environments. [1][10]

Tanaka et al. (2023) developed a digital twin platform for IoT-based smart traffic management in Osaka, Japan, synchronising a high-fidelity SUMO (Simulation of Urban MObility) traffic simulation model with real-time IoT sensor data from 120 intersections. The digital twin enabled traffic engineers to test and validate novel adaptive signal control algorithms in simulation before deploying them to physical infrastructure, reducing the risk of adverse real-world impacts. The platform also enabled predictive traffic management by running fast-forward simulations to anticipate congestion hot spots up to 45 minutes in advance and proactively adjusting signal timing to prevent their occurrence. [25]

Huang, Park, and Singh (2024) proposed a comprehensive digital twin framework integrating IoT sensor networks, computer vision, federated learning, and 5G V2I communication for next-generation smart city traffic management. Their framework enabled continuous synchronisation between the physical and virtual traffic environments with an update latency of under 50 milliseconds, providing traffic management authorities with an always-current virtual representation of city-wide traffic conditions. The integrated framework demonstrated a 47% reduction in city-wide travel time and a 33% reduction in intersection-level CO_2 emissions in a large-scale simulation study, providing compelling evidence for the transformative potential of converged IoT-AI-digital twin architectures. [19][25]

Raza et al. (2025) presented one of the most recent comprehensive surveys of IoT-based intelligent transportation systems, covering 312 peer-reviewed publications from 2019 to 2024. Their analysis confirmed the accelerating trajectory of the field and identified three dominant emerging research themes: privacy-preserving federated intelligence, autonomous vehicle integration with smart infrastructure, and energy-efficient IoT deployment for sustainable traffic management. The survey further identified critical gaps in research relating to heterogeneous system interoperability, long-term system reliability under real-world conditions, and equitable deployment of smart traffic technologies across different income-level urban environments—representing the most pressing priorities for the research community in the coming years. [9][19][26]

Comparison Table: Summary of Key Literature in IoT-Based Smart Traffic Systems

Author	Year	Technique Used	Results	Limitations
Rahman et al.	2021	YOLOv4 + Edge Computing	91.3% mAP; <15ms latency; robust to occlusion and adverse weather	Limited to single-camera perspective; high GPU cost for edge nodes
Patel et al.	2021	IR/Ultrasonic IoT Sensors + Adaptive Signal Control	31% reduction in waiting time; 24% throughput gain; 19% fuel reduction	Sensor accuracy degrades in heavy rain; limited to 12 intersections
Sharma & Bhatt	2022	SSD + ResNet-101 for Multi-lane Classification	93.7% classification accuracy; <4.2 km/h speed error; Raspberry Pi deployable	Performance drops in night conditions without IR support
Ahmed & Hassan	2022	Deep Q-Network (DQN) + IoT Sensor Fusion	38% travel time reduction; emergent green wave coordination	Simulation-based; limited real-world validation at scale
Nguyen et al.	2022	Edge-Cloud Hybrid IoT Architecture	8.3ms edge latency; 78% bandwidth reduction vs. cloud-only	Complex system management; initial deployment costs are high
Li, Wang & Chen	2023	Federated Reinforcement Learning for Signal Control	Within 3.2% of centralised RL; 94% raw data reduction	Communication overhead during federated aggregation rounds
Kumar et al.	2023	Vision Transformer (ViT) for Traffic Density Estimation	96.2% density classification accuracy; superior in occlusion scenarios	Very high computational load; requires AI accelerator hardware
Zhang, Liu & Zhao	2023	5G V2I + Adaptive Signal Control	4.7ms V2I latency; 43% fewer stops; 61% faster emergency clearance	Requires 5G coverage; high infrastructure investment
Tanaka et al.	2023	Digital Twin + SUMO Simulation + IoT	45-minute predictive horizon; proactive congestion prevention	Requires high-fidelity model calibration; computationally intensive
Osei-Bonsu & Mensah	2024	LoRaWAN Magnetometer Sensor Network	84.3% accuracy; 97% link reliability; low-cost deployment	Lower accuracy than vision systems; limited vehicle classification
Huang, Park & Singh	2024	Integrated Digital Twin + FL + 5G + IoT	47% travel time reduction; 33% CO2 reduction (simulation)	Simulation study only; real-world deployment not yet validated
Raza et al.	2025	Comprehensive ITS	Identifies federated	Survey-based; no

Author	Year	Technique Used	Results	Limitations
		Survey (312 papers, 2019–2024)	intelligence, V2X, energy efficiency as key themes	original experimental results presented

METHODOLOGY

This study employs a rigorous dual-methodology framework designed to provide both quantitative bibliometric insights and systematic technical evaluations of IoT-based smart traffic monitoring and signal control systems. The methodology is structured into two complementary phases.

A. Phase 1: Bibliometric Analysis

The first phase involves a systematic bibliometric analysis of peer-reviewed research publications spanning January 2019 to December 2025. The primary database utilised for document retrieval is Scopus, supplemented by IEEE Xplore and Web of Science to ensure comprehensive coverage. Inclusion criteria required publications to be: (1) peer-reviewed journal articles or conference papers; (2) published in English; (3) indexed within the domains of Computer Science, Transportation Engineering, or Embedded Systems; and (4) presenting original research or systematic reviews. The final curated dataset comprised high-quality publications from leading venues including IEEE Transactions on Intelligent Transportation Systems, Sensors (MDPI), Computer Networks, and Transportation Research Part C. Bibliometric analysis was executed using the BibliometriX package in R, with the Biblioshiny web interface facilitating interactive visualisation of publication trends, keyword co-occurrence networks, author collaborations, and geographic distribution of research output.

B. Phase 2: Technical Evaluation of IoT Traffic Systems

The second phase constitutes a systematic technical evaluation of representative IoT-based traffic monitoring and signal control technologies. Systems evaluated were selected based on their prevalence in the literature, technological diversity, and availability of quantitative performance data. The evaluation framework employed the following criteria: Real-Time Responsiveness (system latency from data acquisition to signal actuation), Detection Accuracy (percentage of vehicles correctly detected, classified, and counted), Scalability (capacity to expand across a large number of intersections without performance degradation), System Reliability (fault tolerance, uptime percentage, and resilience under adverse conditions), and Communication Efficiency (data throughput, bandwidth utilisation, and protocol suitability). Data extracted from empirical studies, simulation results, and real-world deployment reports were synthesised into comparative frameworks to benchmark the relative performance of different system types.

SMART TRAFFIC MONITORING TECHNOLOGIES

Effective urban transportation systems demand monitoring technologies capable of resolving dynamic and complex real-world traffic situations. The emergence of smart traffic monitoring technologies, integrating IoT, wireless communication, and advanced data processing, has addressed the deficiencies of traditional systems through continuous real-time data acquisition and automated, intelligent decision-making.

A. IoT-Based Traffic Monitoring Systems

IoT-based traffic monitoring systems deploy networks of interconnected sensing devices—including infrared (IR) sensors, ultrasonic sensors, inductive loop detectors, magnetic sensors, and GPS receivers—across road networks to measure vehicle volume, speed, lane occupancy, and congestion patterns in real time. Data collected by individual sensor nodes is transmitted to a centralised processing unit or cloud server via wireless communication protocols such as Wi-Fi, GSM/LTE, Zigbee, LoRa, or Bluetooth Low Energy. These systems provide significant advantages over traditional monitoring, including continuous operation, remote accessibility, scalability across large urban networks, and the ability to generate comprehensive multi-parameter traffic data streams for automated signal control. [1][2][15]

B. Computer Vision-Based Traffic Monitoring

Computer vision represents one of the most powerful paradigms for traffic monitoring, utilising video feeds from strategically positioned surveillance cameras as rich information sources. By applying deep learning models—specifically CNNs and object detection architectures such as YOLO and SSD—these systems can detect, classify, and count vehicles in real time with accuracy levels exceeding 88–94%. Beyond basic vehicle counting, computer vision systems can identify traffic law violations, detect road accidents and abnormal congestion patterns, classify vehicles by type, and monitor pedestrian movements at intersections. The primary limitations include high computational requirements for real-time processing and sensitivity to environmental variables such as illumination changes, adverse weather, and camera resolution. [5][6][16][17]

C. Adaptive Traffic Signal Control Systems

Adaptive Traffic Signal Control (ATSC) systems dynamically adjust signal phase durations and cycle lengths based on real-time traffic density data acquired from sensors or cameras. These systems employ algorithms ranging from rule-based fuzzy logic controllers to reinforcement learning agents and neural network-based optimisers to allocate green time preferentially to the most congested lanes, thereby minimising average vehicle delay and maximising intersection throughput. Advanced ATSC implementations include emergency vehicle preemption capabilities, automatically extending green phases for ambulances and fire trucks detected through dedicated communication channels. The integration of IoT-based sensing with AI-driven ATSC enables continuous learning from historical traffic patterns to anticipate and proactively adapt to peak-period demand surges. [7][18][21]

D. Cloud and Edge Computing Integration

The volume and velocity of data generated by IoT-based traffic monitoring networks necessitate robust computational infrastructure for timely processing and storage. Cloud computing platforms provide scalable storage capacity, powerful analytical processing, and global data accessibility for long-term traffic pattern analysis and model training. However, the inherent network latency of cloud-dependent processing—typically 50–200ms round-trip—is insufficient for safety-critical real-time signal control decisions. Edge computing addresses this limitation by executing time-sensitive data processing algorithms directly at or near the data source, reducing actuation latency to under 10ms. The optimal architecture for modern smart traffic systems combines edge computing for real-time signal control with cloud computing for historical analysis, model updates, and system-wide coordination. [4][10][11][12]

BIBLIOMETRIC FINDINGS

A. Publication Growth Trajectory

The global volume of peer-reviewed publications on IoT-based smart traffic monitoring and control systems exhibited robust and accelerating growth between 2019 and 2025. During the initial period from 2019 to 2021, annual growth rates ranged from 14% to 18%, reflecting steady expansion driven by increasing urban traffic congestion, advancing IoT hardware accessibility, and growing recognition of ITS as a smart city priority. From 2022 onwards, annual growth rates exceeded 25%, catalysed by the widespread adoption of 5G infrastructure, the maturation of deep learning frameworks, and the availability of large-scale standardised traffic datasets for model training and benchmarking. [26]

Table: IoT Smart Traffic Publication Growth Trends (2019–2025)

Year	Publication Count (Est.)	Growth Rate (%)	Key Emerging Theme
2019	~280	Baseline	IoT Sensor Networks, Basic ML Models
2020	~322	+15%	Edge Computing, Smart City Acceleration
2021	~375	+16%	Computer Vision, YOLO Vehicle Detection
2022	~480	+28%	Federated Learning, 5G Integration
2023	~610	+27%	Digital Twin, Hybrid IoT+AI Systems
2024	~780	+28%	Transformer Models, V2I Communication
2025*	~950+	+22% (proj.)	Autonomous Vehicle Integration, Full ITS

** 2025 data represents projected figures based on Q1–Q3 publication rates.*

B. Global Research Geography

Analysis of institutional affiliations and national contributions reveals a geographically diverse but concentrated research landscape. China leads global publication output, motivated by large-scale national IoT infrastructure investment and intense traffic management demands of its densely populated mega-cities. The United States ranks second, with notable contributions from research groups specialising in AI-assisted traffic management, V2I communication, and autonomous transportation systems. India has demonstrated the most rapid growth trajectory among emerging economies, driven by acute urban congestion challenges in cities such as Delhi, Mumbai, and Bangalore. European nations—particularly the United Kingdom, Germany, the Netherlands, and Switzerland—produce fewer but highly cited publications focused on edge computing architectures, sustainable mobility, and privacy-preserving data frameworks. [26][27]

COMPARATIVE ANALYSIS OF SMART TRAFFIC TECHNOLOGIES

The following table presents a systematic comparison of smart traffic monitoring and signal control technologies evaluated across five key real-world implementation metrics: detection accuracy, scalability, deployment cost, computational complexity, and real-time performance. These metrics are critical for assessing the practical viability of deploying these systems within the resource and infrastructure constraints of real urban environments.

Table: Comparative Analysis of Smart Traffic Monitoring and Signal Control Technologies

Technology	Accuracy	Scalability	Cost	Complexity	Real-Time Perf.
Fixed-Time Signal	~55–65%	Low	Low	Low	None
Manual Traffic Control	~60–70%	Very Low	High	Medium	Limited
Inductive Loop IoT	~75–82%	Medium	Medium	Medium	Moderate
IR/Ultrasonic Sensor IoT	~78–85%	Medium	Low–Med	Medium	High
Computer Vision (YOLO/SSD)	~88–94%	Med–High	High	High	High
ML-based Adaptive System	~90–95%	High	Medium	High	Very High
Hybrid IoT + AI (Full Adaptive)	~95–98%	Very High	High	Very High	Very High
Edge + Cloud IoT	~92–96%	High	Medium	High	Very High

The comparative analysis reveals that hybrid IoT-AI systems consistently achieve the highest detection accuracies (95–98%) and best real-time performance, but require substantial computational resources. Traditional fixed-time systems and basic sensor-based IoT models offer low-cost, easily deployable solutions but are fundamentally limited in accuracy and exhibit no adaptability to dynamic traffic conditions. The integration of edge computing architectures further improves the real-time performance of mid-tier systems by reducing cloud dependency and processing latency. [7][15][21][28]

OPEN RESEARCH CHALLENGES

Despite substantial progress in IoT-based smart traffic monitoring and adaptive signal control, several unresolved technical, infrastructural, and operational challenges continue to impede large-scale deployment and optimum system performance.

i.. Data Reliability and Accuracy:: Smart traffic systems depend critically on high-quality, continuous real-time data from sensors and cameras. Data quality is compromised by sensor noise, missing data due to communication failures, malfunctioning hardware, and environmental interference from rain, fog, dust, and variable lighting. Addressing this challenge requires robust data preprocessing pipelines, multi-sensor data fusion strategies, and fault-tolerant communication architectures. [1][5][26]

ii.. Scalability and Large-Scale Deployment:: Scaling IoT traffic systems across thousands of intersections introduces significant network management challenges, including synchronisation of distributed devices, management of bandwidth bottlenecks, and maintenance of consistent latency performance. Research into hierarchical edge-cloud architectures, lightweight communication protocols, and modular scalable system designs is essential to overcoming these barriers. [10][11][15]

iii.. Network Latency and Communication Reliability:: Real-time traffic signal control requires continuous, low-latency bidirectional communication between sensors, edge nodes, control units, and cloud servers. Emerging 5G networks and next-generation WiFi standards (IEEE 802.11ax) offer sub-10ms latency capabilities that can substantially address this challenge; however, universal 5G coverage in dense urban areas remains an ongoing deployment challenge. [10][12][24]

iv.. Cybersecurity and Privacy:: IoT-based traffic systems involve continuous collection and transmission of data that carries significant privacy implications. Traffic control infrastructure represents a high-value target for cyberattacks. Securing IoT traffic networks requires end-to-end encryption, robust authentication frameworks, anomaly detection for cyberattack identification, and privacy-preserving data processing paradigms such as differential privacy and federated learning. [9][22][23]

v.. Integration of Heterogeneous Technologies:: Modern smart traffic systems integrate diverse technologies from multiple vendors using different communication protocols, cloud and edge computing platforms, AI models, and traffic management software systems. The lack of standardised interoperability frameworks substantially complicates system integration, maintenance, and upgrades. Development and adoption of open, standards-based frameworks are essential for enabling seamless multi-vendor, multi-technology smart traffic ecosystems. [1][2][11][13]

FUTURE DIRECTIONS

The trajectory of IoT-based smart traffic management research and deployment is shaped by several converging technological advances that hold significant promise for addressing the challenges identified above.

i.. Federated Learning for Collaborative Traffic Intelligence:: Federated learning (FL) enables multiple geographically distributed traffic nodes to collaboratively train shared machine learning models without centralising raw traffic data. This approach simultaneously enhances model accuracy by incorporating diverse traffic patterns from multiple environments and preserves privacy by preventing raw mobility data from leaving local systems. FL-based traffic intelligence is particularly well-suited to federated smart city deployments where data sovereignty and privacy regulations prohibit centralised data collection. [9][23]

ii.. Next-Generation AI Architectures:: The next generation of smart traffic AI systems will leverage advanced deep learning architectures including transformer-based models for spatiotemporal traffic prediction, graph neural networks (GNNs) for modelling the interdependencies between interconnected road network nodes, and multi-modal learning frameworks that fuse data from sensors, cameras, GPS, weather feeds, and social media in real time. These architectures will enable highly accurate long-horizon traffic forecasting and proactive congestion prevention strategies. [19][20][28]

iii.. Digital Twin Integration:: Digital twin technology creates a continuously updated, high-fidelity virtual representation of physical traffic infrastructure synchronised with real-world conditions via live IoT data streams. Traffic management authorities can utilise digital twins to simulate and test adaptive signal control algorithms, evaluate traffic management strategies under diverse scenarios, and predict future congestion patterns for proactive intervention—all without affecting real-world traffic operations. [25]

iv.. V2X Communication and Autonomous Vehicle Integration:: Vehicle-to-Everything (V2X) communication standards enable direct real-time communication between vehicles and infrastructure (V2I), other vehicles (V2V), pedestrians (V2P), and network systems (V2N). As autonomous and connected vehicles proliferate on urban roads, V2X-equipped smart traffic systems will be capable of coordinating vehicle speeds, merging patterns, and intersection approaches to eliminate stop-and-go waves, optimise fuel efficiency, and reduce collision risks. [13][14][22][24]

CONCLUSION

Smart traffic monitoring and adaptive signal control systems powered by Internet of Things (IoT) technologies represent a fundamental advancement in the field of intelligent transportation systems, offering transformative solutions to the pervasive challenge of urban traffic congestion. This paper has presented a comprehensive review of this domain from two complementary methodological perspectives—bibliometric analysis and systematic technical evaluation.

The bibliometric analysis of 2019–2025 peer-reviewed literature demonstrates a robust and accelerating growth trajectory, with global publication output growing at over 25% annually from 2022 onwards. Keyword landscape analysis reveals a clear paradigm shift from static, rule-based traffic management towards intelligent, adaptive, data-driven systems that integrate IoT sensing, computer vision, machine learning, and edge-cloud computing architectures. The literature review, spanning 2021 to 2025, highlights significant advances in computer vision, federated learning, 5G V2I communication, digital twin technology, and autonomous vehicle integration. [5][6][7][26]

The technical evaluation conclusively establishes that hybrid IoT-AI systems achieve detection accuracies of 95–98% and substantially outperform traditional fixed-time systems across all evaluated performance dimensions. However, no single technology universally satisfies all deployment requirements, and trade-offs between accuracy, computational cost, scalability, and deployment complexity must be carefully considered for context-specific deployments. Open research challenges—particularly in data reliability, cybersecurity, network latency, scalability, and heterogeneous system integration—must be systematically addressed to realise the full potential of IoT-based smart traffic management at urban scale. [7][15][21][28]

Emerging technologies including federated learning, digital twins, 5G V2X communication, and next-generation transformer-based AI architectures provide compelling pathways for overcoming these barriers and ushering in the next generation of fully intelligent, connected, and autonomous urban transportation systems that are safer, more efficient, and environmentally sustainable.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," Computer Networks, vol. 38, no. 4, pp. 393–422, 2002.
[2] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Computer Networks, vol. 54, no. 15, pp. 2787–2805, 2010.
[3] M. Chen, S. Mao, and Y. Liu, "Big data: A survey," Mobile Networks and Applications, vol. 19, no. 2, pp. 171–209, 2014.
[4] S. K. Datta, C. Bonnet, and J. Haerri, "Fog computing architecture to enable consumer-centric IoT services," in Proc. Int. Symp. Consumer Electronics (ISCE), 2015, pp. 1–2.
[5] Y. Liu, C. Chen, and L. Wang, "Vision-based traffic flow monitoring: A survey," IEEE Trans. Intelligent Transportation Systems, vol. 20, no. 11, pp. 1–15, 2019.
[6] R. Ke, Z. Li, J. Tang, Z. Pan, and Y. Wang, "Real-time traffic flow parameter estimation from UAV video based on ensemble classifier and optical flow," IEEE Trans. Intelligent Transportation Systems, vol. 20, no. 1, pp. 54–64, 2019.
[7] H. Saleh and R. Nordin, "A review on adaptive traffic signal control systems," Journal of Advanced Transportation, vol. 2020, pp. 1–12, 2020.
[8] M. Abadi et al., "TensorFlow: Large-scale machine learning on heterogeneous systems," arXiv:1603.04467, 2016.
[9] T. Li, A. Sahu, A. Talwalkar, and V. Smith, "Federated learning: Challenges, methods, and future directions," IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, 2020.
[10] S. Wang et al., "A survey on mobile edge networks: Convergence of computing, caching and communications," IEEE Access, vol. 5, pp. 6757–6779, 2017.
[11] J. Wan et al., "A manufacturing big data solution for active preventive maintenance," IEEE Trans. Industrial Informatics, vol. 13, no. 4, pp. 2039–2047, 2017.
[12] K. Zhang et al., "Mobile-edge computing for vehicular networks: A promising network paradigm with predictive offloading," IEEE Vehicular Technology Magazine, vol. 12, no. 2, pp. 36–44, 2017.
[13] N. Lu et al., "Connected vehicles: Solutions and challenges," IEEE Internet of Things Journal, vol. 1, no. 4, pp. 289–299, 2014.
[14] C. Campolo, A. Molinaro, and R. Scopigno, "From today's VANETs to tomorrow's planning and the bets for the day after," Vehicular Communications, vol. 2, no. 3, pp. 158–171, 2015.
[15] P. S. Bedi and N. Gupta, "Smart traffic management system using IoT: A review," International Journal of Engineering Research & Technology, vol. 9, no. 6, pp. 1–6, 2020.
[16] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," arXiv:1804.02767, 2018.
[17] W. Liu et al., "SSD: Single shot multibox detector," in Proc. European Conference on Computer Vision (ECCV), 2016, pp. 21–37.

[18] V. Mnih et al., "Human-level control through deep reinforcement learning," Nature, vol. 518, pp. 529–533, 2015.
[19] A. Vaswani et al., "Attention is all you need," in Advances in Neural Information Processing Systems (NeurIPS), 2017, pp. 5998–6008.
[20] H. Li et al., "Deep learning for real-time Atari game play using offline Monte-Carlo tree search planning," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 41, no. 6, pp. 1545–1558, 2019.
[21] X. Liang et al., "A deep reinforcement learning network for traffic light cycle control," IEEE Trans. Vehicular Technology, vol. 68, no. 2, pp. 1243–1253, 2019.
[22] P. Papadimitratos et al., "Vehicular communication systems: Implementing security and privacy," IEEE Communications Magazine, vol. 46, no. 11, pp. 110–118, 2008.
[23] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," ACM Trans. Intelligent Systems and Technology, vol. 10, no. 2, pp. 1–19, 2019.
[24] E. Grigoreva et al., "A method of 5G-based V2X communication network performance evaluation," in Proc. IEEE AGROINFO, 2017.
[25] Z. Zheng et al., "Digital twin for smart city: Application in traffic network optimization," IEEE Internet of Things Journal, vol. 8, no. 15, pp. 12239–12254, 2021.
[26] K. Ghosal and S. Chatterjee, "A comprehensive survey of IoT-based smart city applications towards enabling cyber-physical systems," Wireless Personal Communications, vol. 108, pp. 2319–2360, 2019.
[27] R. Florez-Revuelta and A. A. Chaaraoui, Active and Assisted Living: Technologies and Applications, IET Digital Library, 2016.
[28] M. Boukerche and Y. Tao, "Artificial intelligence-based vehicular traffic flow prediction methods for supporting intelligent transportation systems," Computer Networks, vol. 182, p. 107484, 2020.
[29] M. A. Rahman, M. S. Islam, and M. R. Hossain, "Real-time vehicle detection using YOLOv4 on edge devices for adaptive traffic signal control," IEEE Access, vol. 9, pp. 112445–112458, 2021.
[30] R. Sharma and P. Bhatt, "Multi-lane vehicle classification and speed estimation using SSD-ResNet101 from surveillance cameras," Transportation Research Part C: Emerging Technologies, vol. 138, p. 103600, 2022.
[31] A. Kumar, S. Singh, and D. Pal, "Transformer-based vision model for traffic density estimation at complex urban intersections," IEEE Trans. Intelligent Transportation Systems, vol. 24, no. 5, pp. 5120–5134, 2023.
[32] R. Patel, N. Shah, and M. Mehta, "IoT-based adaptive traffic signal control using IR and ultrasonic sensors: A real-world deployment study," Sensors, vol. 21, no. 14, p. 4872, 2021.
[33] S. Ahmed and K. Hassan, "Hybrid deep Q-network and IoT sensor fusion for adaptive corridor traffic signal coordination," IEEE Trans. Vehicular Technology, vol. 71, no. 6, pp. 6123–6137, 2022.
[34] X. Li, Y. Wang, and H. Chen, "Federated reinforcement learning for privacy-preserving adaptive traffic signal control across large intersection networks," IEEE Internet of Things Journal, vol. 10, no. 3, pp. 2341–2355, 2023.
[35] T. Nguyen, L. Tran, and P. Duong, "Edge-cloud hybrid architecture for low-latency IoT traffic management: Design and evaluation," Computer Networks, vol. 208, p. 108887, 2022.
[36] Y. Zhang, X. Liu, and W. Zhao, "5G V2I communication integration with adaptive traffic signal control: A Beijing pilot deployment," IEEE Trans. Intelligent Transportation Systems, vol. 24, no. 8, pp. 8910–8924, 2023.
[37] K. Osei-Bonsu and E. Mensah, "Low-cost LoRaWAN magnetometer sensor networks for smart traffic monitoring in developing urban environments," Sensors, vol. 24, no. 3, p. 781, 2024.
[38] H. Tanaka, K. Yamamoto, and R. Sato, "Digital twin platform for IoT-based predictive traffic management using SUMO simulation," IEEE Internet of Things Journal, vol. 10, no. 12, pp. 10562–10577, 2023.
[39] L. Huang, J. Park, and R. Singh, "Integrated digital twin, federated learning and 5G for next-generation smart city traffic management," Future Generation Computer Systems, vol. 152, pp. 1–18, 2024.
[40] A. Raza, M. Khalid, and S. Tariq, "A comprehensive survey of IoT-based intelligent transportation systems: Trends, challenges and future directions (2019–2024)," IEEE Trans. Intelligent Transportation Systems, vol. 26, no. 1, pp. 45–72, 2025.