

Systematic Review

# Revolutionizing Urban Mobility: A Systematic Review of AI, IoT, and Predictive Analytics in Adaptive Traffic Control Systems for Road Networks

Carmen Gheorghe \*  and Adrian Soica 

Department of Automotive and Transport Engineering, Transilvania University of Brasov, 500036 Brasov, Romania; a.soica@unitbv.ro

\* Correspondence: carmen.gheorghe@unitbv.ro

**Abstract:** Urban mobility has undergone and continues to undergo a profound transformation driven by the convergence of artificial intelligence (AI), the Internet of Things (IoT), and predictive analytics in recent years. These technologies are redefining adaptive traffic control systems, enabling real-time decision-making and increasing the efficiency and safety of road networks. The main questions addressed in the review explore how the integration of advanced technologies such as IoT, AI in traffic systems, are useful in optimizing traffic flows, vehicle coordination and infrastructure adaptability in increasingly complex traffic environments. The integration of IoT-enabled devices and AI-based algorithms has been essential to enable data-driven approaches to urban traffic control. Predictive analytics improves emergency response mechanisms, improves traffic signal operations, and supports the deployment of autonomous and connected vehicles. Among the various methodologies evaluated, AI-based models combined with IoT sensors demonstrated superior performance, reducing average traffic delays by up to 30% and improving safety metrics in various urban environments. This systematic review underscores the transformative potential of integrating AI, IoT, and predictive analytics into urban traffic management, offering a blueprint for smarter, more sustainable urban transportation solutions.

**Keywords:** AI; IoT; ATCS; predictive; analytics; traffic; adaptive; system



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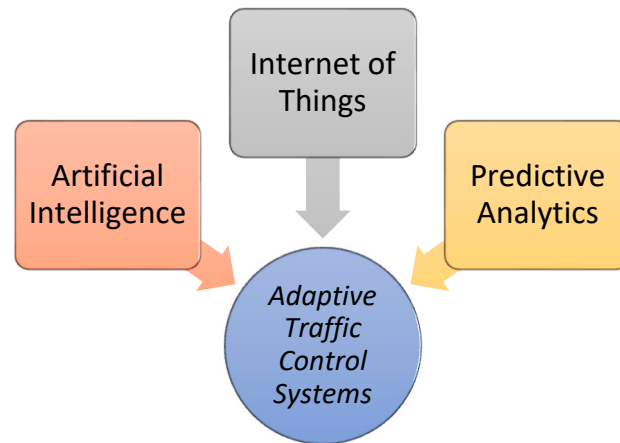
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## 1. Introduction

Urban mobility, and especially traffic congestion, is a well known, critical issue in urban areas, significantly impacting economic efficiency, public health, and overall productivity. With increasing urbanization and population growth, congestion has become a persistent problem, leading to delays, air pollution, accidents, and a reduced quality of life [1]. This situation requires innovative solutions to improve traffic management and reduce inefficiencies in the urban transportation systems [2]. Adaptive traffic signal control systems (ATCSs) integrate advanced technologies like Vehicle-to-Everything (V2X) communication, the Internet of Things (IoT), and predictive analytics, giving a promising approach to overcome these challenges [3].

Figure 1 presents the visual representation of the relationship between ATCS and AI, IoT and predictive analytics.



**Figure 1.** The relationship between AI, IoT, and predictive analytics and adaptive traffic control systems.

Urban traffic management relies mostly on traffic signal control systems to regulate traffic flow at intersections, which are the main points of congestion in urban traffic [4]. However, traditional fixed-timing signals are often ineffective in addressing dynamic traffic conditions. These outdated systems fail to adapt to real-time variations in traffic density, resulting in inefficient flow and increased delays. So, integrating the predictive analytics and real-time monitoring into traffic signal control systems can improve their response rate and efficiency.

Modern ATCS elevates V2X communication to facilitate information exchange between vehicles and road infrastructure. There are technologies, such as dedicated short-range communication (DSRC), that allow vehicles to share real-time data regarding speed, position, and traffic conditions with traffic management systems. This communication enables adaptive signal control that responds dynamically to traffic fluctuations, optimizing the flow at intersections and reducing congestion [5].

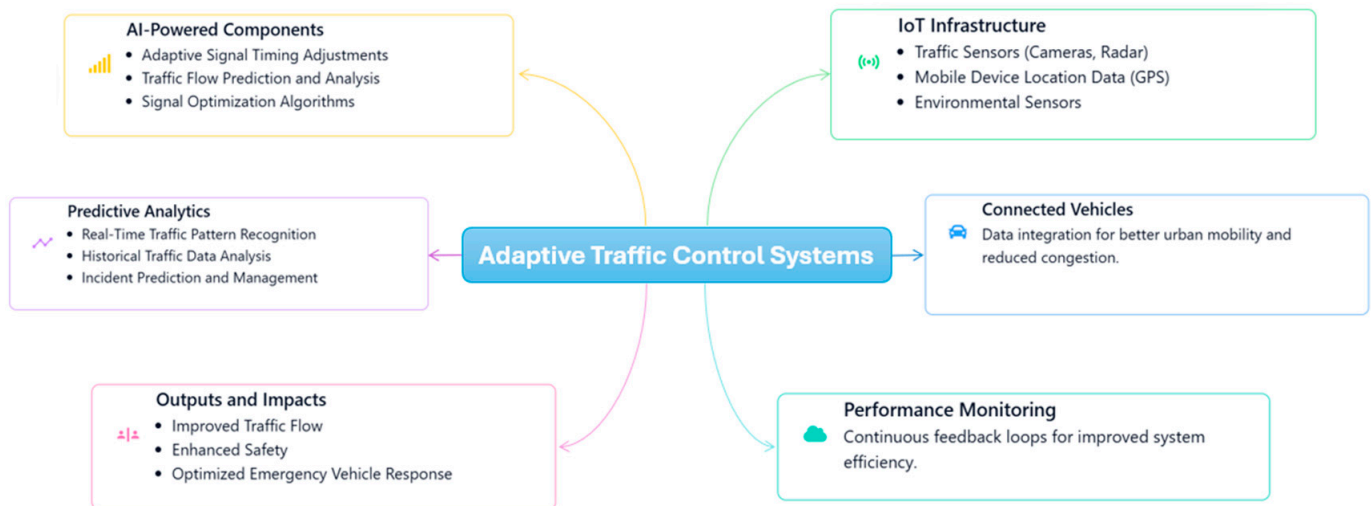
IoT integration boosts the capabilities of ATCS by enabling continuous data collection and analysis from sensors embedded in vehicles, roadways, and intersections. These sensors provide critical information about traffic density, pedestrian movements, and environmental conditions. IoT-enabled systems can use this data to adjust traffic signal timing dynamically, ensuring smoother transitions and minimizing delays during peak hours or emergencies [6]. Predictive analytics plays an important role in improving the performance of ATCS. By analyzing the historical and real-time traffic data, predictive models can forecast road traffic patterns and optimize signal timings proactively. Thus, traffic flow predictions can guide the synchronization of traffic lights across multiple intersections, creating “green waves” that facilitate uninterrupted travel for vehicles [7–9]. This predictive capability reduces congestion and boosts fuel efficiency, contributing to lower emissions and improved air quality.

Intersections are important in urban traffic management because, among other things, they serve as convergence points for multiple roads. Adaptive changes in signal timing based on real-time traffic density can significantly improve intersection efficiency. Synchronizing traffic lights at consecutive junctions using green signal delays ensures smoother flow and minimizes congestion, especially in densely populated metropolitan areas [10,11].

The implementation of ATCS aligns closely with the broader vision of smart city development. Smart cities prioritize sustainable, data-driven solutions to urban challenges, and ATCS represents a key component of intelligent transportation systems. By integrating these advanced systems, cities can not only reduce congestion but also improve road safety and elevate the overall urban experience. Despite their potential, deploying ATCS systems

poses challenges, including high initial costs, the need for infrastructure upgrades, and the complexity of system integration. However, the long-term benefits, such as reduced congestion, lower emissions, and improved productivity, outweigh these challenges [12].

Recent advancements in machine learning and data analytics, including techniques like contrastive learning, offer further opportunities to improve ATCS [13,14]. By improving the representation and generalization capabilities of traffic flow forecasting models, these techniques enable more accurate predictions and better system performance. The combination of advanced analytics with robust infrastructure paves the way for more effective traffic management [15]. Thus, the integration of Vehicle-to-Infrastructure (V2I) communication, IoT, and predictive analytics into adaptive traffic signal control systems (ATCSs) represents a transformative approach to urban traffic management. These technologies provide real-time, data-driven solutions to traffic congestion, improving economic efficiency, environmental sustainability, and quality of life. As cities continue to grow and face increasing traffic challenges, ATCS will play an important role in shaping the future of intelligent and sustainable urban mobility systems. In Figure 2, the conceptual overview of ATCS is presented, including the outputs, impacts, and performance monitoring.



**Figure 2.** Conceptual overview of adaptive traffic control systems.

The organization of this review is as follows: Section 1 outlines the motivation and discusses related studies. Section 2 presents a summary of the methods and research strategies employed to identify the relevant literature. Section 3 examines the research domains. Section 4 provides a synthesis of the findings along with their limitations, while Section 5 delivers the conclusions and outlines directions for future research. This structured approach ensures a comprehensive and systematic examination of current research on ATCS implementations in urban mobility, improving the understanding of the technology's applications, progress, and potential areas for development within the traffic management sectors.

## 2. Materials and Methods

This section offers comprehensive details and essential guidelines to facilitate a literature review with a specific focus on the integration of artificial intelligence (AI), the Internet of Things (IoT), and predictive analytics in adaptive traffic control systems. The objective is to explore their application in enhancing urban mobility, emphasizing the critical aspects required for an in-depth and focused analysis.

### 2.1. Review Questions

The review questions are derived directly from the primary objectives of the review, serving as the foundation for structuring the literature search process. They are relevant in shaping the inclusion and exclusion criteria, ensuring that only the most relevant papers are considered for this systematic review. Furthermore, these questions provide a clear framework for interpreting and analyzing the findings, helping to maintain focus and consistency throughout the review process.

Outlined below are the specific questions formulated.

**Review Question 1:** What AI techniques are most used for traffic flow optimization, incident detection, and autonomous vehicle integration in ATCS?

Knowing the main AI techniques used in ATCS supports the researchers in the area-identifying process. So, this question explores the types of AI methods implemented in traffic management systems to improve the smooth flow of vehicles.

The main arguments for this question would be that adaptive AI methods help to adapt in real time to changing traffic conditions, making them an important factor in real-time traffic management and flow optimization. AI in incident detection is applied to reduce delays and ensure traffic safety. At the same time, the integration of autonomous vehicles in future urban mobility, which needs AI in facilitating communication between autonomous vehicles (AVs) and infrastructure, will help ease the transition to mixed traffic environments, both human-driven and autonomous vehicles. In Section 3.2, applications extracted from relevant published articles are presented to help formulate the answer to this question, further on Section 4.

**Review Question 2:** How is IoT technology, like smart sensors and Vehicles-to-Infrastructure (V2I) communication, implemented at intersections to improve traffic management?

This question examines the role of IoT devices like smart sensors in collecting and utilizing real-time traffic data at intersections to support adaptive traffic control strategies.

The main arguments to support this question would be that, for real-time traffic monitoring, IoT sensors provide the backbone, thus enabling data-driven decisions that improve intersection management, reducing traffic congestion. At the same time, V2I communication enables a real-time traffic control system, thus improving coordination between vehicles and traffic infrastructure. Thus, combining these technologies, the basis of intelligent transport systems (ITSs) is formed, which creates more efficient urban mobility. In Section 3.3, applications extracted from relevant published articles are presented to help formulate the answer to this question, further on Section 4.

**Review Question 3:** What predictive analytics methods are effective for forecasting congestion and weather-responsive controlling and event-based traffic management in urban traffic networks?

This question focuses on the predictive techniques used to anticipate traffic congestion, allowing for proactive traffic management interventions, but also analyzes the integration of weather-related data into traffic management systems to adaptively respond to conditions such as heavy rain, snow, or fog.

Predictive analytics is applied to proactive traffic management, allowing for the identification of potential congestion before it occurs and adjusting operations based on predicted future traffic conditions. Weather-aware systems incorporate weather data to inform adaptive traffic management decisions, thereby improving road safety. Thus, event-based traffic management optimizes traffic flow during challenging periods, ensuring a free flow of traffic. In Section 3.4, applications extracted from relevant published articles are presented to help formulate the answer to this question, further on Section 4.

## 2.2. Search Strategy

This section describes the methods used to identify, select, and evaluate relevant studies for inclusion in the review. It provides details on the databases and information sources consulted, the keywords employed, and the inclusion and exclusion criteria applied to ensure the selection of pertinent studies.

The published papers considered in this review were retrieved from Scopus and Clarivate Web of Science (WoS) online platforms in November and December 2024, using the following search query: “traffic AND system OR IoT AND AI OR predictive AND (adaptive AND traffic AND control AND system)”.

The keywords were chosen in order to generate results for using AI, IoT, and predictive analytics in ATCS in the timeframe from 2020 to 2024. The timeframe from 2020 to the end of 2024 captures the latest advancements and innovations in AI, IoT, and predictive analytics, ensuring the review includes cutting-edge research and technologies in adaptive traffic control systems. Also, this period reflects a significant evolution in these domains, marked by rapid progress in machine learning algorithms, IoT device integration, and predictive modeling techniques that have revolutionized urban traffic management. Studies from this timeframe emphasize refined and optimized implementations of these technologies, showcasing real-world applications and breakthroughs that improve the efficiency and effectiveness of traffic control systems.

The Clarivate Web of Science (WoS) and Scopus databases were selected for their extensive coverage of academic publications and their focus on indexing high-quality, peer-reviewed literature. Both databases are highly regarded for their citation tracking capabilities, which allow researchers to explore citation networks and identify influential works in specific fields. Additionally, their advanced search tools enable precise queries and filtering by various parameters, such as publication year, author, and journal. Using the selected search keywords, 6982 articles were retrieved from WoS, and 5582 articles were identified on Scopus.

To ensure a robust and consistent dataset, the search was restricted to peer-reviewed journal articles and conference papers published in English. Document types such as reviews, letters, book chapters, book reviews, and data papers were excluded. Detailed bibliographic information, including full records and cited references, was extracted from both databases and organized in Microsoft Excel for further analysis.

The process of review selection, using the PRISMA 2020 flow diagram template, is presented in Figure 3; also, this study was conducted in accordance with the PRISMA 2020 guidelines (see Supplementary Materials).

To preprocess the datasets and remove duplicate entries, the ScientoPy v2.1.0. [16] tool was employed. This powerful tool efficiently identifies and eliminates redundancies, ensuring the final dataset is accurate, comprehensive, and duplication-free. Following the preprocessing, a total of 3420 unique papers were retained.

Simultaneously, the application identifies topics related to published articles focusing on traffic systems. By utilizing ScientoPy and the author’s subjects (derived from all their keywords), a timeline was generated, as illustrated in Figure 4.

The classification of the related fields in Table 1 was based on the average growth rate (AGR), which measures the average difference in the number of articles published between two consecutive years (2024 and 2023), and the average documents per year (ADY), which calculates the average number of articles published over a specified timeframe (2020–2024) for topics related to the main field of adaptive traffic control systems.

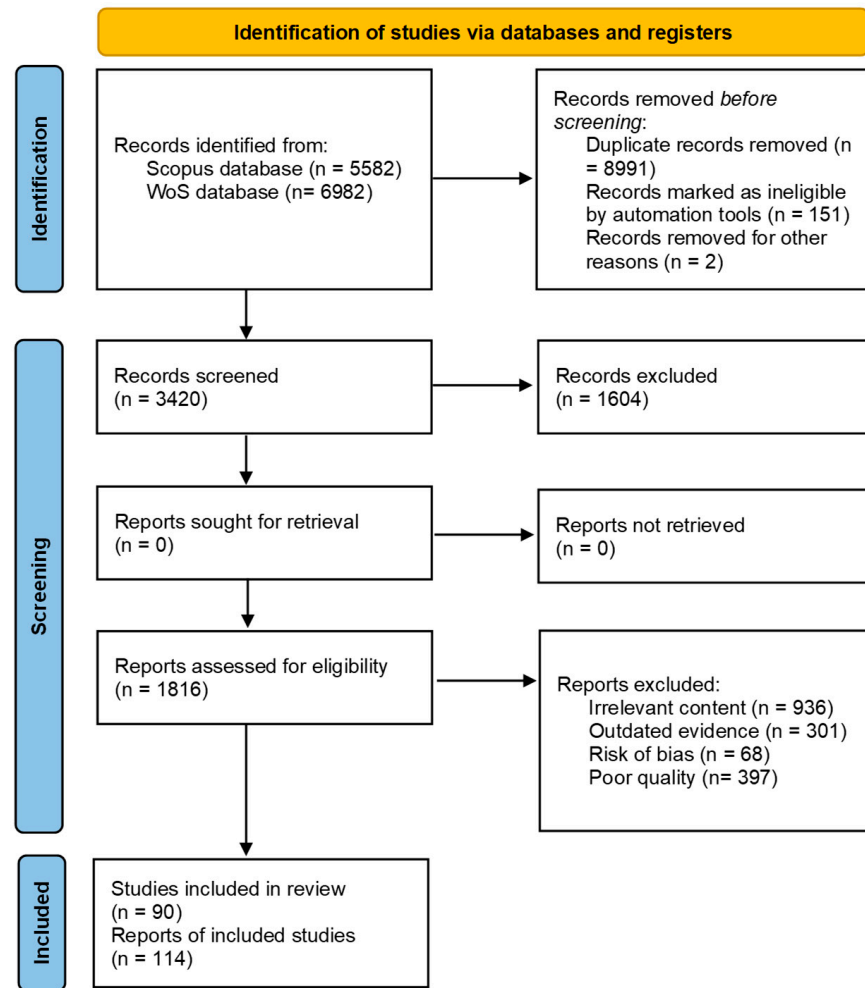


Figure 3. Review process flowchart.

After reviewing the most cited and relevant papers in the fields of ATCS and road traffic research, 114 papers remained for further discussion in the review.

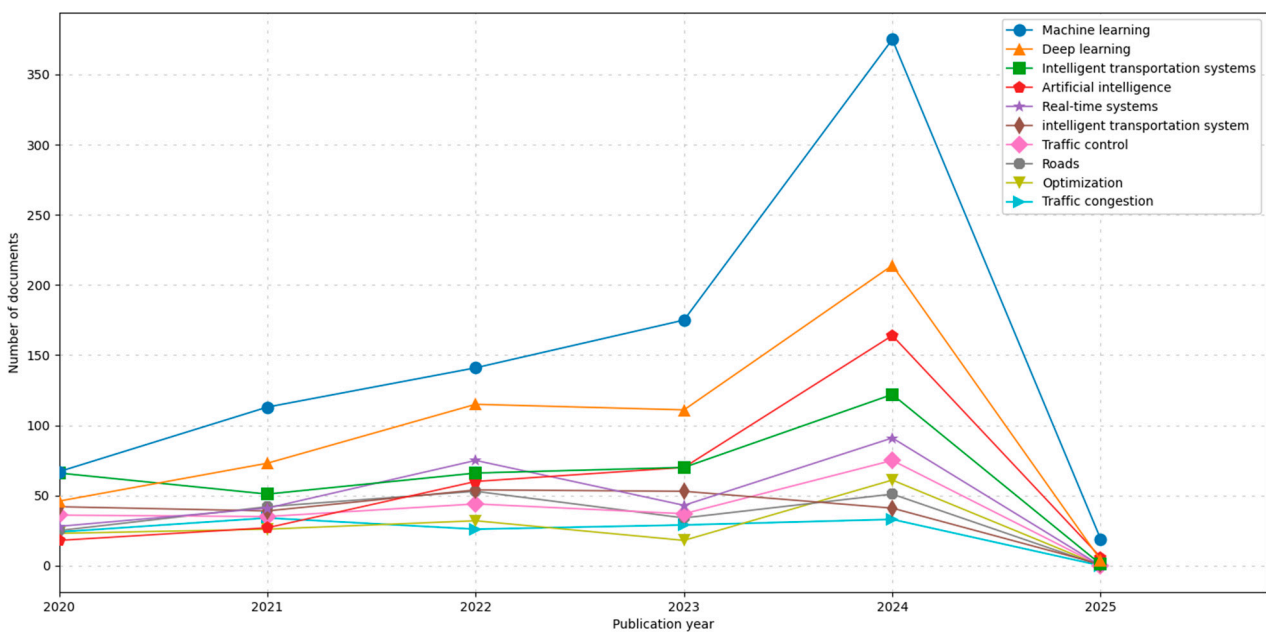


Figure 4. Trending and timeline for the top 10 topics.

We used the free version of Grammarly Inc. to ensure the manuscript was clear and accurate from the grammar and spelling perspective. This application is used to identify and correct grammatical and typographical errors. We manually reviewed the final version to ensure the accuracy of information where necessary.

**Table 1.** Top 10 subjects related to AI, IoT, and predictive analytics in ATCS.

Position	Related Subject	Total	AGR	ADY
1	Machine Learning	890	−78	197
2	Deep Learning	563	−53.5	109
3	Intelligent Transportation Systems	376	−34.5	61.5
4	Artificial Intelligence	345	−32	85
5	Real-Time systems	278	−21.5	45.5
6	Intelligent Transportation System	230	−26	21
7	Traffic Control	227	−18.5	37.5
8	Roads	205	−17	25.5
9	Optimization	160	−9	30.5
10	Traffic Congestion	146	−14.5	16.5

This section aimed to establish a framework that would create a connection between theoretical advances in AI, IoT, and predictive analytics and their practical implications for ATCS. By detailing the methodologies we used, we aimed to ensure that readers gain a comprehensive understanding of how the literature was systematically reviewed and analyzed to provide relevant information. The literature review was conducted using a stepwise approach, starting with the identification of the most relevant databases and search terms, followed by a systematic filtering process, described in Figure 2, to ensure the inclusion of high-quality, peer-reviewed studies. Keywords such as “adaptive traffic control”, “AI in urban mobility”, “IoT for traffic systems”, and “predictive analytics” were used to cover diverse but interconnected perspectives.

The methodologies described in this section represent the starting point for evaluating the practical results discussed in Section 3, thus creating the transition from theoretical exploration to applied findings in practice.

### 3. Results

The potential of using AI, IoT, and predictive analytics in adaptive traffic control systems has increased year after year, with constant improvements. This led to an increase in the number of scientists who chose to use AI, IoT, and predictive analytics for ATCS in fields such as traffic flow optimization, road incident detection, autonomous vehicle integration, smart sensors, V2X communication, emergency vehicle priority, congestion forecasting, event-based traffic management, and weather-responsive control.

#### 3.1. Citation Mapping

To enhance the visualization and analysis of relationships among citations in research papers, a citation mapping of articles indexed in Scopus and WoS was conducted. This approach highlights the networks and connections between cited works, making it ideal for exploring scholarly influence, identifying research trends, and mapping academic impact.

Since 2020, ATCS has seen rapid adoption in the road traffic and transport sector, experiencing exponential growth through 2024. Research output significantly increased after 2020, driven by continuous improvements in ATCS’s adaptability to different technical approaches. The upward trend remains evident when considering the number of publications in the final quarter of 2024 (as of the search date). Figure 5 shows the cumulative number of

citations per year, with a decline observed as expected, due to the time-dependent nature of citation accumulation.

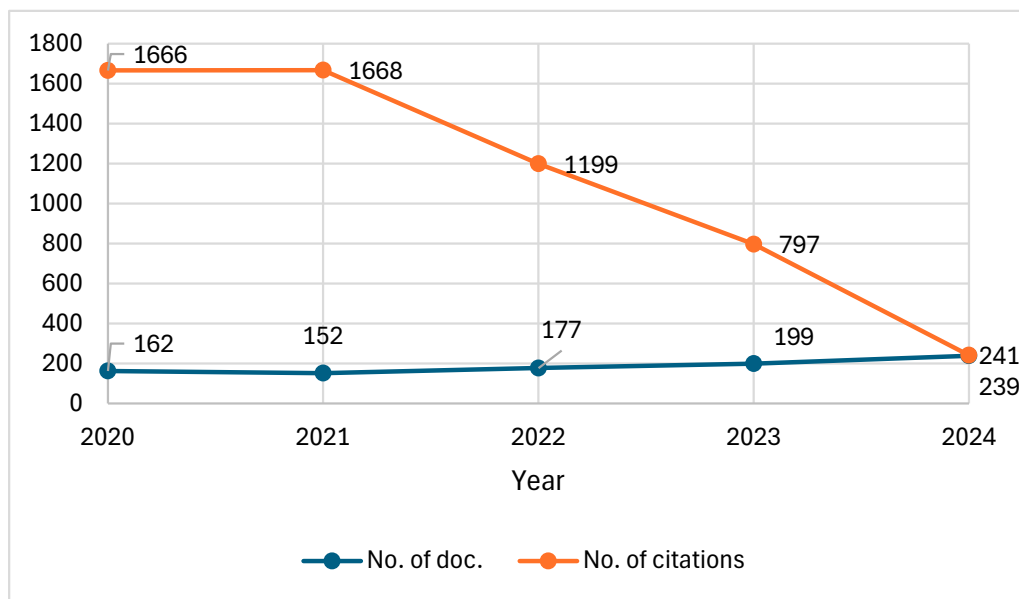


Figure 5. Academic publications and annual citation count from 2020 to 2024.

Figure 6 presents a pie chart with the percentage distribution of the identified papers by their type (conference, journal, or proceedings). Journal articles constitute 71.72% of the total number of papers considered after the screening step.

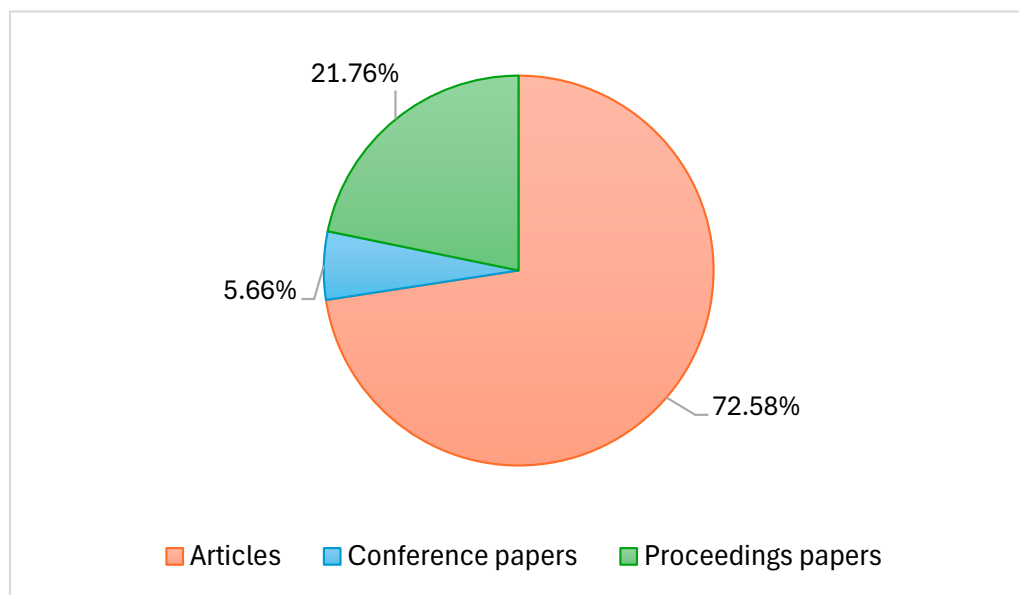


Figure 6. Percentage distribution of the papers considered.

In Figure 7, the network visualization of the keyword co-occurrence is presented, constructed using VOSviewer software v.1.6.20 [17]. The author-provided keywords that appear more than 15 times are 64. The top three keywords are: “machine learning” (occurrences: 754 and total link strength: 756), “deep learning” (occurrences: 347 and total link strength: 424), and “artificial intelligence” (occurrences: 306 and total link strength: 406).



A citation analysis was performed to evaluate the impact of the identified articles in the scientific literature. Using Scopus data, Table 2 presents the ten most cited studies related to ATCS applications in the road traffic domain.

**Table 2.** Top 10 most cited studies related to ATCS applications.

Position	Paper Title	Reference	No. of Citations
1	On the new era of urban traffic monitoring with massive drone data: The pNEUMA large-scale field experiment	[18]	172
2	Cooperative Deep Reinforcement Learning for Large-Scale Traffic Grid Signal Control	[19]	136
3	Traffic accident detection and condition analysis based on social networking data	[20]	111
4	Smart traffic monitoring system using Unmanned Aerial Vehicles (UAVs)	[21]	100
5	A future intelligent traffic system with mixed autonomous vehicles and human-driven vehicles	[22]	80
6	Predictive analytics on open big data for supporting smart transportation services	[23]	72
7	An End-to-End Recommendation System for Urban Traffic Controls and Management Under a Parallel Learning Framework	[24]	55
8	Analysis of road capacity and pollutant emissions: Impacts of Connected and automated vehicle platoons on traffic flow	[25]	47
9	Improved grey system models for predicting traffic parameters	[26]	46
10	Partial differential grey model based on control matrix and its application in short-term traffic flow prediction	[27]	40

The following sections delve into the AI, IoT, and predictive analysis used in ATCS for traffic flow optimization, road incident detection, autonomous vehicle integration, smart sensors, Vehicle-to-Everything (V2X) communication, emergency vehicle priority, congestion forecasting, event-based traffic management, and weather-responsive control.

### 3.2. Artificial Intelligence in ATCS

AI powers the decision-making and optimization algorithms in modern ATCS, enabling real-time adaptability and improved traffic flow management.

In terms of traffic flow optimization, machine learning algorithms analyze historical and real-time data to predict traffic patterns and dynamically adjust signal timings to minimize congestion.

Current research on AI-driven traffic management systems, employing techniques like fuzzy logic, reinforcement learning, deep neural networks, and evolutionary algorithms, highlights AI's potential to revolutionize the traffic landscape [28]. Thus, accurate analysis of traffic flow data is essential for vehicular applications [29,30]. Furthermore, the training models based on YOLO for intelligent vehicle detection are more and more popular all over the world nowadays [31].

A well-functioning roadway system is fundamental to both society and the economy. Some traffic events, like maintenance and accidents, can reduce roadway capacity and also can have immediate and perhaps lasting effects on traffic conditions. To understand

network behavior following disruptions, a traffic flow evolution model is used in [32]. The proposed model includes a parameter representing the information dissemination penetration rate, which can be adjusted by operators; thus, the study identifies the optimal information penetration rate to maximize network resilience while maintaining stability. Additionally, traffic sign recognition (TSR) is an important component of intelligent transportation systems (ITSs), enhancing road safety and improving traffic management [33]. Especially in the oversaturated intersections, where computer simulations demonstrate that the control performance is markedly superior to that of traditional traffic coordination under identical boundary inflow conditions. Compared to traditional centralized coordinated control, the rule-based real-time traffic signal control model is more adaptable to traffic flow fluctuations and effectively mitigates vehicle queuing spillover issues caused by such variations [34].

In [35] the development of a smart traffic light prototype based on vehicular traffic flow measurement was proposed for a stretch between two avenues in the city of Limeira, SP, Brazil, with a focus on the direction toward UNICAMP's School of Technology, and the final virtual traffic light system demonstrated vehicle counting accuracy rates of 75% for large vehicles, 90% for passenger cars, and 100% for motorcycles. The simulation of the smart traffic light implementation performed satisfactorily, as validated by the post-processing of recorded video. Also, in [36] is proposed a sensor-based technique functioning as an automaton to reduce the workload of traffic police. The model incorporates four sensors positioned at each side of a four-way intersection, designed to count vehicles on the roadways using IR sensors for data collection and an Arduino UNO board. The controller determines the flashing durations of subsequent traffic lights.

A low-cost visible light communication (VLC) framework for intelligent transportation systems (ITSs) has been developed in [37], featuring affordable transceivers, transmitter circuits with embedded systems, and receiver circuits using photodiodes to decode traffic light signals. Laboratory tests were conducted using a traffic light prototype to test the VLC framework, and the results were satisfactory. Because manual traffic surveillance is challenging, as traffic management centers manage numerous cameras across a network. Introducing automation can ease the workload of human operators, it can boost proactive decision-making and help mitigate the effects of incidents and recurring congestion on roadways [38], thus another proposed system [39] utilizes live images from cameras at traffic junctions to calculate traffic density using image processing and AI. It incorporates an algorithm to switch traffic lights based on vehicle density, aiming to reduce congestion, facilitate faster transit, and lower pollution levels.

In the context of incident detection and response in transport and traffic systems, it is important to note that these systems are complex infrastructures in modern cities, and the efficient operation of urban transport is important for the sustainability of other urban systems [40,41]. AI detects anomalies such as accidents or stalled vehicles and reroutes traffic accordingly. Modern city infrastructures rely heavily on complex, software-intensive systems, consisting of various elements such as software, sensors, actuators, and processes [42].

In traffic management applications, traffic flow and incidents can be detected from roadside images using AI cameras, with only high-level information being transmitted to the server to minimize network bandwidth and server resource usage [43,44]. The impact of road traffic incidents, such as accidents and vehicle breakdowns, has worsened over time, contributing to issues like serious injuries, economic losses, and lifelong disabilities [45,46]. An example of a system developed to reduce traffic accidents, fatalities, and injuries is the SAHER system, a smart traffic surveillance system based on unmanned aerial vehicles (UAVs) using 5G technology, that was introduced in Saudi Arabia [21]. Another example

is a system deployed in Phuket, Thailand, where an optimized architectural design for a traffic violation enforcement system was implemented using deep learning techniques [47].

Non-recurrent congestion, primarily caused by traffic incidents, can significantly affect the performance and operation of traffic systems, and optimizing the system performance after road incidents is challenging due to the uncertainty in traffic flow variations and the diverse responses of travelers to information [48]. However, selecting an appropriate response strategy with minimal delay can help mitigate incident impacts, improve traffic efficiency, and improve safety. The researchers in [49] propose STIME, a smart traffic incident management framework designed to assist traffic incident operators in choosing the most suitable response strategy during an incident. The testing was performed on a section of the Muscat expressway in Oman, with satisfactory results.

Another point to be mentioned is pedestrian crossing scenarios that involve complex human-vehicle interactions. The authors in [50] propose a novel approach using traffic scene graphs with improved vehicle-pedestrian interactions and a deep model combining Transformer and GCN for pedestrian collision risk assessment. Experiments on datasets show significant performance improvements, with the model achieving 94% accuracy.

Furthermore, autonomous vehicle integration in ATCS based on AI facilitates coordination between ATCS and autonomous vehicles, ensuring smooth navigation through intersections. A challenge in predicting the in-traffic performance of connected and autonomous vehicles (CAVs) is that CAV algorithms are often analyzed individually, while their interactions with surrounding traffic require a focus on traffic-network behaviors [51,52]. Vehicle movement through the intersection is controlled by green, red, and “white” signal indications. Traffic operations during green and red signals are like those at a typical intersection. However, during the white phase, connected, human-driven vehicles (CHVs) must follow connected and autonomous vehicles (CAVs) to pass the intersection safely. It is likely that soon, autonomous vehicles (AVs) and human-driven vehicles (HVs) will need to coexist within traffic systems [22]. The mobility and safety impacts of these behaviors are analyzed based on different CAV market penetration rates and demand levels. The findings show that more aggressive CAV behavior results in lower average delays but increases the average number of stops for CAVs [53,54].

As autonomous vehicles (AVs) become integrated into transportation systems, a transitional period will emerge, where semi-autonomous vehicles (semi-AVs), which still require an attentive driver, coexist with fully autonomous vehicles (fully-AVs) [55]. An autonomous driving environment requires continuous data streams and predictive measurements to enable real-time, critical decision-making in uncertain situations [56]. This specific environment promotes a self-organizing system, where vehicles are seamlessly connected, and traffic flow management must emerge through various services and intelligent decisions. To advance this vision, a traffic flow management model is proposed in [57], based on a novel two-phase approach for optimizing traffic during congestion. In the first phase, an adaptive traffic signal control using deep reinforcement learning (DRL) is employed to optimize flow at congested intersections. Simulation results show that the proposed approach improves performance efficiency by up to 31% compared to traditional pre-timed signals without re-routing. This kind of approach improves overall traffic flow, reduces delays, and minimizes traffic queues, offering a solution for intelligent infrastructure to handle congestion and balance traffic efficiently [58,59].

### 3.3. Internet of Things in ATCS

IoT enables interconnected devices and sensors to collect, transmit, and process real-time data essential for adaptive signal control.

IoT-enabled cameras and radar sensors at intersections monitor traffic density, pedestrian movement, and environmental conditions through smart sensors. In recent years, the sensing and computing capabilities of modern traffic intersections have significantly improved, yet current control policies do not fully leverage these advancements [8,60,61]. Coordination between intersections is achieved by incorporating a green wave concept into the objective function, which helps maximize vehicle throughput and minimize average waiting times, thereby reducing congestion and maintaining smooth traffic flow [62–64]. However, poorly managed intersections remain a major cause of growing traffic issues in urban areas, leading to suboptimal traffic flow and unnecessary deadlocks [65].

Real-time traffic signal acquisition and network transmission are critical components of intelligent transportation systems, enabling real-time traffic monitoring, management, and analysis in urban environments [66]. Recent advancements in sensor technologies, signal processing, and machine learning have allowed real-time traffic control systems to adapt to changing traffic conditions. A comprehensive system called LIDATS (live intersection data acquisition for traffic simulators) has been introduced in [67], combining live traffic signal acquisition, real-time data processing, and secure network transmission through hardware and software modules. The system's design and implementation, including signal acquisition hardware and a software platform for real-time processing, are detailed. Also, another approach was elaborated when the system utilized traffic measurement estimation at intersections, integrating computer vision techniques with traffic simulators for traffic signal evaluation. The proposed deep-visual tracking pipeline generates traffic measurements at various time frames using YOLOv4 [68].

Traffic lights are a key factor for efficient traffic management, particularly in congested cities [69]. Optimizing traffic flow helps reduce congestion, save time, and ensure smooth vehicle movement. Metaheuristic algorithms are effective in optimizing smart traffic management systems [70]. Key challenges in traffic management include overloaded vehicles moving beyond their designated zones and times, reckless driving, and ignoring road safety rules. The paper [71] proposes an Internet of Things (IoT)-based real-time intelligent traffic signal system (ITSS), which uses inductive loops and a programmable microcontroller to measure traffic density. Inter-communication within the centralized control unit adjusts traffic light timers and synchronizes with real-time traffic density to ensure smoother vehicle movement with minimal delay. The presented solution, with its automatic on-demand traffic signaling system, offers advantages over fixed systems.

In Vehicle-to-Infrastructure (V2I) communication, IoT allows vehicles to communicate with traffic signals, providing information such as speed, position, and expected arrival time. The advent of 5G communication networks has led to the emergence of numerous research areas, diversifying the spectrum of communicating objects. Two key areas being explored to optimize network performance are network function virtualization (NFV) and software-defined networking (SDN). One notable example is Cellular Vehicle-to-Everything (C-V2X), which enables end-to-end communication through network slices [72]. By sharing driving situation information through V2V, V2I, and V2X communication, C-V2X allows vehicles to receive guidance on previously unrecognized driving conditions, enhancing safety and situational awareness [73,74]. Additionally, this technology supports safer self-driving by sharing road environment information, such as tunnel data, road lines, and traffic facilities [74,75].

The rapid advancement of V2X communication and driving automation is poised to transform the transportation system. In the near future, human-driven vehicles (HVs), connected vehicles (CVs), and connected and automated vehicles (CAVs) will coexist [76]. V2X-based platoon management is expected to improve traffic capacity and fuel efficiency. Furthermore, the introduction of CAVs will generate vast amounts of data, which can

be used by traffic networks and fleet operators. This data will be passively collected by vehicles and infrastructure, exchanged via wireless communication, and shared through V2X technology [77].

Fully actuated signal controls were becoming increasingly popular in modern urban environments, aiming to reduce local congestion, synchronize flows, or prioritize specific types of vehicles [78]. This trend was expected to grow as more vehicles were anticipated to communicate via Vehicle-to-Infrastructure (V2I) communication. The presented dataset in [79] contained cleaned observations from a fully actuated signal control system that prioritized public transportation. Time series data of traffic signals regulating vehicle, public transportation, bicycle, and pedestrian traffic flows were available, showing when a traffic signal operated in a red or green phase in Zurich, Switzerland. Regarding the pedestrians, the approach in [80] predicts vehicle passage times at intersections using data from cameras and video detectors. By applying YOLOv3 and SORT, along with a fuzzy logic model, it reduces forced stops by optimizing speeds. Predictions are shared locally through V2X communication and scaled with the digital road model.

Regarding emergency vehicle priority, IoT devices prioritize ambulances or fire trucks by altering traffic light cycles to ensure their swift passage. Unwanted events on roads, like traffic incidents and congestion, can result in significant human and economic losses [81]. Efficient incident management requires the rapid dispatch of emergency vehicles (EVs) to the incident location, especially at peak hours [82]. To minimize incident clearance time, various approaches have been developed to provide a clear pathway for EVs using IoT [83]. One such solution involves a smart traffic light and dynamic navigational system that utilizes a minimum distance triggering algorithm to analyze and optimize the movement of EVs [84]. Traffic congestion remains a major global issue, negatively impacting both the economy and quality of life [85]. These challenges are compounded when considering emergency vehicles, such as ambulances, which often navigate intersections in a disorganized manner, increasing the risk of accidents during urgent responses [86,87].

In [88], the smart and prioritized emergency vehicle management system (SPEVMS) aimed to address traffic safety challenges and issues faced by emergency vehicles (EVs). A proposed methodology sought to facilitate EVs in reaching their destinations efficiently by utilizing vehicular ad hoc networks (VANETs) and simulations to minimize time lags or delays. SPEVMS also prioritized EVs based on the severity of the emergency and intended to ensure their swift transportation without significantly disrupting the flow of non-emergency vehicles. Another approach [89] incorporated IoT devices, including sensors and communication modules, into evacuation routes and centers to enable real-time data collection, processing, and communication. Results indicated that IoT significantly improved the efficiency of emergency evacuation systems by supporting informed decision-making, route optimization, and resource allocation. However, challenges such as cost, power consumption, and network coverage require attention in future implementations [84].

The authors in [90] present a method that utilizes wireless Vehicle-to-Infrastructure (V2I) communication between the emergency vehicle and the traffic light controller, incorporates an accurate estimate of queue length, and employs a mathematical model for queue discharge dynamics. Unlike conventional methods that activate preemption when the emergency vehicle reaches a fixed distance from the intersection, the proposed approach adjusts the activation timing based on real-time traffic conditions. This ensures that preemption duration is minimized, thereby reducing its impact on other traffic flows.

### 3.4. Predictive Analytics in ATCS

Predictive analytics uses historical and real-time data to forecast traffic patterns and proactively manage signal timing.

In congestion forecasting, advanced models predict traffic build-ups and adjust signal timings to prevent gridlock. One of the significant challenges in urban development for large cities is addressing traffic congestion. Despite efforts to enhance vehicle flow and improve the accuracy of traffic congestion estimation without overloading control networks, these issues remain under investigation [91]. Using artificial intelligence, a solution for inter-vehicle communication is proposed to estimate congestion levels and optimize traffic flow within transport systems. Traffic jams pose continuous socioeconomic and environmental challenges, necessitating an urgent and ambitious traffic management agenda. Existing traffic management systems (TMSs) often rely on beacon messages or proactive communication protocols to exchange vehicular traffic information, which becomes unsustainable as the number of vehicles increases during congestion [92,93]. To address these limitations, researchers propose a predictive congestion control system leveraging collaborative information sharing. Effective traffic signal control strategies are vital for managing urban traffic networks. Most optimization-based approaches update traffic signals at fixed intervals, balancing computational efficiency with control performance [94].

With connected vehicle (CV) technology, the next-generation transportation system is advancing through the deployment of intelligent traffic signal systems (I-SIG). The study presented in [95] analyzes congestion attacks and variations using machine learning, specifically the tree-regularized gated recurrent unit (TGRU) for explainable attack prediction. Experiments on real-world intersection data trained a TGRU-based model with 384 congestion attack samples, achieving 80% average precision. Another approach introduces a predictive traffic information module that utilizes historical traffic flow data to identify intersection patterns and enable proactive traffic signal control by forecasting future states. Experimental results show that the proposed method surpasses standard benchmarks at isolated intersections, improving traffic efficiency by over 20% and reducing environmental impacts by 18% [96].

Regarding event-based traffic management, the predictive tools prepare systems for traffic spikes during events like collisions or preorganized social events. Traffic safety remains a key concern for the sustainable development of urban transportation systems [97,98]. In recent years, fully connected long short-term memory (FC-LSTM) networks have been extensively used for forecasting urban traffic crashes. The growing availability of mobility data presents opportunities to study and predict human mobility patterns and behaviors at different levels [99]. The study in [100] explores the influence of historical accident data on predicting future traffic accident risks and examines its interaction with other variables, such as driver violations and vehicle characteristics.

Researchers address the challenge of constructing a data-driven model to predict long-term crash risks for drivers, such as the likelihood of a crash in the next four weeks [101]. However, raw mobility data, despite being extensive, often lacks the explicit semantics or structure necessary for understanding and predicting such rare events. Additionally, an effective traffic management strategy involves applying special signal timing plans on alternative routes during road incidents [102]. Developing these plans requires estimating route diversion rates under incident conditions. Thus, most approaches employ a data analytics approach to estimate diversion rates and incorporate this information into the creation of optimized signal timing plans to manage traffic during road incidents [103]. The study in [104] introduces a reinforcement learning-based traffic predictive vehicle routing (RL-TPVR) algorithm to address traffic uncertainty, especially in non-recurrent congestion. By incorporating predictive state representation and reward modeling, RL-TPVR dynamically adjusts routes and reduces origin-to-destination travel time variability. Simulation results show its adaptability and superior performance compared to existing algorithms, making it effective for reliable navigation under uncertain traffic conditions.

Regarding the pedestrians as a human factor on the road, the study in [105] analyzes how built environment factors influence fault assignment in urban pedestrian crashes in the United States. Findings show pedestrians are more often faulted on high-speed, high-traffic roads with bus stops, while better crossings reduce pedestrian-blamed crashes at intersections. Disparities in crossing infrastructure and fault assignment vary across neighborhoods. The study calls for shifting from individual blame to systemic safety approaches, like Vision Zero, to promote equitable and safer road design.

In weather-responsive control, the predictive models analyze weather forecasts to adapt traffic lights during rain or snow, reducing accidents and delays. The increasing reliance on technology has elevated the role of artificial intelligence (AI), particularly machine learning (ML), which enables systems to learn from data using algorithms [106]. Predictive algorithms establish relationships in historical data to guide future decisions and solve real-world problems. Autonomous vehicles, driven by advancements like LiDAR (light detection and ranging) technology, represent a breakthrough in transportation by providing precise environmental mapping for improved safety and efficiency. However, LiDAR's accuracy is hindered by environmental conditions like dust and rain, impacting vehicle safety [107]. Additionally, AI and ML face challenges due to limited diverse datasets, highlighting the need for effective data generation methods [108].

As per example, in the 2019–2020 snow season, V2X systems using dedicated short-range communication (DSRC) were installed on snowplows and traffic signals in Utah. The study in [3] found snowplows requested signal preemption over 50% of the time, with preemption granted in 80% of cases. Signal coordination was impacted for less than 5 min. Snowplows on equipped routes had fewer speed disruptions and crashes compared to non-equipped routes. Drivers reported fewer stops and improved snow removal operations.

#### 4. Discussion

The primary objective of this study was to identify the most relevant research papers that explore the implementation of adaptive traffic control systems (ATCSs) in the road traffic domain, focusing on areas such as traffic flow optimization, integration with autonomous vehicles, and congestion forecasting. The adaptability and scalability of ATCS make it a promising technology for advancing road traffic management, enhancing safety, and fostering intelligent transportation systems. By incorporating ATCS-based solutions, the development of safer, more efficient, and intelligent traffic ecosystems is significantly accelerated. This research examines trends in AI, IoT, and predictive analytics applied in ATCS within a five-year period (2020–2024), analyzing each topic and article to highlight current challenges and identify future directions.

Review Question 1: What AI techniques are most used for traffic flow optimization, incident detection, and autonomous vehicle integration in adaptive traffic control systems?

AI techniques have proven instrumental in optimizing traffic flow, detecting incidents, and integrating autonomous vehicles in adaptive traffic control systems (ATCSs). For traffic flow optimization, AI techniques like fuzzy logic, reinforcement learning, and deep neural networks are employed to analyze real-time traffic data and adjust signal timing dynamically, effectively mitigating congestion and queuing issues [28,34]. Fuzzy logic is a rule-based approach that manages uncertainty and imprecision in data to adjust traffic signals in real time. Reinforcement learning (RL) is a machine learning method in which systems learn optimal signal synchronization strategies through trial and error, with feedback based on the results obtained, namely reduced congestion and improved traffic efficiency. Deep neural networks (DNNs) are AI models that use large datasets that analyze complex traffic patterns to make predictions and manage signal synchronization in real time. Addi-

tionally, traffic density analysis using live camera feeds and AI algorithms helps optimize signal switching based on vehicle density, reducing congestion and pollution [38,39].

For incident detection, AI-powered anomaly detection systems are used to identify accidents or stalled vehicles, enabling proactive traffic rerouting [40–42]. Techniques like image processing with roadside AI cameras and frameworks such as STIMF assist operators in selecting optimal response strategies to improve safety and minimize delays [43,44,49]. Advanced systems, including the SAHER UAV-based system with 5G technology, have been developed to monitor and reduce traffic incidents [21].

In the autonomous vehicle (AV) domain, deep reinforcement learning (DRL) models are applied for adaptive signal control, achieving up to 31% improvement in congestion management at intersections [57–59]. The introduction of a white signal phase, where connected, human-driven vehicles (CHVs) follow connected and autonomous vehicles (CAVs), exemplifies innovative traffic strategies to ensure smooth navigation during the transition to full automation [22,55]. These approaches collectively boost traffic efficiency, safety, and the seamless integration of AVs into urban traffic systems. A summary of the main applications of AI in ATCS can be found in Table 3.

**Table 3.** The main applications of AI in ATCS.

Technologies in ATCS	Application Field	Application Subcategory
AI in ATCS	Traffic flow optimization	AI traffic management [28–30,34] Smart traffic lights [35–37] Traffic density analysis [38,39]
	Road incident detection	AI incident detection [40–44] Pedestrian collision [50] Impact of road incidents [45,46,48]
	Autonomous vehicle integration	Autonomous vehicle interaction with traffic [22,51–54] Traffic optimization with reinforcement learning (DRL) [57–59] Transition to full automation [55,56]

Review Question 2: How is IoT technology, like smart sensors and Vehicle-to-Infrastructure (V2I) communication, implemented at intersections to improve traffic management?

IoT technology improves traffic management at intersections through the implementation of smart sensors and Vehicle-to-Infrastructure (V2I) communication systems. IoT-enabled cameras, radar sensors, and environmental sensors monitor traffic density, pedestrian movement, and road conditions, providing real-time data to optimize traffic flow [8,60,61]. By integrating the green wave concept into traffic signal systems, intersections can be coordinated to maximize vehicle throughput and reduce average waiting times [62–64]. V2I communication enables vehicles to share critical information, such as speed, position, and expected arrival time, with traffic signals, enhancing synchronization and reducing congestion [72]. Advanced systems combine live signal acquisition, real-time processing, and secure data transmission to adapt to changing traffic conditions dynamically [66,67]. IoT-powered adaptive signal controls prioritize specific vehicles, such as emergency vehicles or public transportation, ensuring efficient and safe passage while maintaining smooth traffic flow for others [78,88]. These technologies not only improve traffic efficiency but also contribute to fuel savings, reduced emissions, and improved safety at intersections [70,76]. A summary of the main applications of IoT in ATCS can be found in Table 4.

**Table 4.** The main applications of IoT in ATCS.

Technologies in ATCS	Application Field	Application Subcategory
IoT in ATCS	Smart sensors at intersections	IoT-enabled sensors [8,60,61] Green wave coordination [62–64] Real-time traffic signal acquisition [66–68] IoT-based intelligent traffic signal systems (ITSSs) [70,71]
	V2I communication	Cellular Vehicle-to-Everything (C-V2X) [72–77] Fully actuated signal controls [78,79] 5G and V2I communication [72,76]
	Emergency vehicle priority	IoT-based emergency vehicle priority systems [81–83] Smart traffic light [84,86,87] IoT for emergency evacuation systems [84,88,89]

Review Question 3: What predictive analytics methods are effective for forecasting congestion, weather-responsive controlling, and event-based traffic management in urban traffic networks?

Seasonal patterns in traffic, such as weekday rush hours, are captured through decomposition techniques, improving forecast accuracy for recurring events. Spectral analysis identifies periodic behaviors in traffic data, enabling predictions of peak congestion during festivals or holidays.

Multiple linear regression correlates traffic congestion with external factors, such as weather, time of day, and local events, providing actionable insights for planning. Polynomial regression improves predictions for non-linear relationships, such as sudden congestion increases during extreme weather. Also, logistic regression is used to classify traffic flow states, such as free-flowing, congested, or gridlocked, enabling more targeted interventions. LSTMs and GRUs (gated recurrent units) are specifically designed to handle sequential data, capturing long-term dependencies in traffic patterns to improve predictive accuracy. Hybrid models combining LSTMs with CNNs process spatial and temporal traffic data simultaneously, offering comprehensive forecasts for urban networks. These techniques are further enhanced by transfer learning, where pre-trained models are adapted to local conditions, reducing the time and data needed for implementation.

Predictive analytics integrate weather forecasts to adjust signal timings, speed limits, and route recommendations, minimizing delays during adverse conditions. Machine learning models analyze historical data on weather-induced traffic patterns to preemptively reroute traffic during snowstorms, heavy rain, or fog. Adaptive algorithms consider real-time weather updates to adjust traffic control measures dynamically, maintaining flow and safety. Event simulation models predict traffic impacts from planned events, such as road incidents and traffic rerouting, allowing for preemptive signal adjustments and detours. AI-driven systems monitor social media feeds and GPS data to detect unplanned events, like protests or road closures, and adapt traffic strategies in real-time. Crowd-sourced data from mobile apps and IoT devices provides additional insights into traffic disruptions, enhancing the accuracy of event-based predictions. A summary of the main applications of predictive analytics in ATCS can be found in Table 5.

**Table 5.** The main applications of predictive analytics in ATCS.

Technologies in ATCS	Application Field	Application Subcategory
Predictive analytics in ATCS	Congestion forecasting	AI-driven congestion estimation [91–93,95] Intelligent traffic signal systems (I-SIGs) [94,96]
	Event-based traffic management	Predictive tools for traffic spikes [97–101] Incident-based traffic signal optimization [102,103] Reinforcement learning for vehicle routing [104]
	Weather-responsive control	Predictive models for weather-responsive control [106–108] LiDAR technology [107] Weather-responsive V2X systems [3]

Predictive analytics is used in urban traffic management by analyzing historical and real-time data to forecast congestion, adapt to weather conditions, and effectively manage event-driven traffic fluctuations. Advanced models, such as fully connected long-term memory (FC-LSTM) networks, have proven effective in predicting traffic congestion and accident risks by analyzing historical accident data and driver behavior, allowing for targeted interventions [91,99,100]. For weather-adapted traffic control, predictive algorithms use weather forecasts to adjust the timing of traffic signals during adverse conditions, such as snow or rain, to increase road safety and reduce traffic delays [3,106]. Machine learning models, such as tree-regularized gated recurrent unit (TGRU), improve congestion forecasting by identifying attack patterns and enabling explainable decisions to optimize traffic flow [95,96]. In event-based traffic management, reinforcement learning algorithms such as RL-TPVR dynamically adapt routes to reduce travel time variability during non-recurring congestion caused by social or traffic incidents [104]. These methods, combined with collaborative information sharing, optimize signal timing plans and promote proactive traffic management strategies that can be adapted to real-world conditions [92,103].

#### 4.1. Challenges and Emerging Patterns in the Adoption of ATCS for Urban Mobility

Nowadays, in order to implement AI, IoT, and predictive analytics in adaptive traffic control systems, traffic engineers and specialists in electronics and computer science face several significant challenges. The first challenge, and one of the most important, is data privacy and security, as IoT devices used in traffic systems are vulnerable to cyberattacks [109]. System interoperability is a second issue, as the lack of standardization between IoT devices and AI platforms hinders communication and integration between technologies and vendors.

Ethical concerns in AI, such as algorithmic bias and lack of transparency, make it difficult to implement it in traffic systems, which can lead to unsafe decision-making. In addition, delays in real-time data transmission and processing can compromise the responsiveness needed for efficient traffic management. Thus, integrating AI, IoT, and predictive analytics into ATCS is challenging, as these models require constant updates and training to remain accurate in dynamic urban environments.

The integration of adaptive traffic control systems for urban mobility presents several emerging models that highlight their potentially transformative role in shaping the future of transport. First, integration with autonomous vehicles is becoming the basis of ATCS, as traffic control systems increasingly rely on Vehicle-to-Infrastructure (V2I) communication to optimize flow and reduce congestion. Another model with potential is the shift

towards multimodal traffic management, which will also consider pedestrians, cyclists, and public transport, not just cars, ensuring equitable access and efficient movement for all transport modes.

Sustainability and green mobility are emerging as priorities, with ATCS being used to reduce vehicle emissions by optimizing traffic flow and prioritizing green transport modes. Furthermore, there is a growing focus on equity and accessibility, as ATCS systems are designed to prioritize safe crossings for vulnerable road users, such as pedestrians and cyclists, and to improve accessibility for people with different disabilities.

Finally, the adoption of AI ethics frameworks is envisioned, which will become an integral part of ATCS development, thus ensuring transparency, fairness, and accountability in decision-making processes. Together, these models indicate that the adoption of ATCS is not only transforming urban mobility but also paving the way for smarter, more sustainable, and more inclusive transport systems for the future.

#### *4.2. Limitations of the Review*

This review is limited by the constraint of not being able to review every relevant paper found in the databases, leading to a selective representation rather than a thorough examination. Thus, all findings presented are based on a subset of studies selected from the available literature, highlighting the challenge of providing a fully comprehensive review due to the large number of publications. By focusing exclusively on AI, IoT, and predictive analytics in ATCS, the review may not provide comparisons with alternative methods of detecting moving or static objects, which may restrict insights into the comparative effectiveness or applicability of different approaches in road traffic management. Furthermore, this review did not consider non-technical factors, such as regulatory challenges, industry standards, or market dynamics, that may influence the adoption and implementation of ATCS in the road traffic and transportation sectors. Moreover, there may be a bias towards published research articles, possibly overlooking valuable information from the grey literature, industry reports, or unpublished studies, which could provide a more holistic understanding of ATCS applications and limitations in traffic management contexts.

## **5. Conclusions**

This review has provided a comprehensive overview of the state-of-the-art in AI-enabled adaptive traffic control systems. By synthesizing current research on the integration of AI, IoT, and predictive analytics, we have clarified the key advancements and challenges in this rapidly evolving field. The purpose of our analysis was to serve as a foundation for future development and implementation of intelligent transportation solutions.

The integration of artificial intelligence, advanced predictive models, and machine learning techniques is revolutionizing traffic management systems, enabling urban areas to improve traffic safety, optimize vehicle flow, and improve emergency response times. By leveraging these innovations, transportation infrastructure can become more efficient and reliable over time, thus addressing the growing challenges of urbanization and mobility. The inclusion of emerging technologies such as the Internet of Things (IoT), LiDAR, and AI-based approaches is the starting point for this transformation. These technologies provide intelligent yet sustainable transportation systems, thus ensuring a more seamless and predictive urban mobility experience.

Reinforcement learning and predictive model-based decision-making have also proven to be particularly effective in adapting traffic signal operations to dynamic and mixed traffic scenarios. Collaborative information-sharing frameworks and intelligent priority mechanisms for emergency vehicles are redefining urban emergency response systems, which are so necessary today, especially during peak hours when traffic is congested

due to commuting. These technologies minimize delays for emergency vehicles, improve coordination during critical incidents, and ensure that urban mobility remains resilient during emergencies. In addition, the development of congestion control systems based on collaborative information sharing supports better traffic flow in vehicle networks, addressing the challenges of growing urban populations.

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