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AI on the Road – A Review of Technologies Enhancing Urban Traffic Safety and Efficiency

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Review
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ABSTRACT

Traffic management is becoming increasingly complicated, posing significant challenges to traditional systems. Adapting the intelligent transportation system (ITS) can resolve this issue. The present study identified peer-reviewed literature published between 2014 and 2023 in the most significant libraries, i.e. Google Scholar, Science Direct, ASCE Library, IEEE and others, to address this issue. Following that, 130 primary studies were identified, and the selected literature conducted systematic analysis. Research findings of RQ: 1 revealed that about 30% of total published articles between the year 2014-23 explored both efficiency and safety shows the significance of the study. To achieve the second objective RQ: 2 this study proposes a solution to improve traffic safety and risk management on the city's key roadways. The study technique involves gathering data from various sources, including traffic cameras, sensors and vehicle tracking devices. Artificial driving (AD) models are capable of accurately predicting traffic patterns. Intelligent network connections facilitate seamless real-time data sharing between vehicles and buildings. This study thoroughly examines safety by analysing collision rates and reaction times and then compares the results to the outcomes when traditional traffic management (TTM) approach were implemented. Furthermore, it deals with exploring adaptive traffic control and predictive analytics as methods to address safety issues proactively. Case studies demonstrate the positive impact of AD and smart network connectivity on enhancing road safety in urban areas. The review concludes with a discussion of issues raised and recommendations for future research to improve safety assessments and risk management in metro regions with shifting arterial traffic flow.

KEYWORDS

artificial intelligence (AI); intelligent transportation systems (ITS); traffic safety; risk management; artificial driving (AD); smart network connections.

1. INTRODUCTION

Traffic patterns have become increasingly complex as a result of urban population growth, higher vehicle density and shifting public transit demands [1]. Innovative remedies are necessary to enhance efficiency, safety and sustainability [2]. Increased vehicle traffic stresses existing infrastructure and TTM systems, resulting in traffic congestion and safety problems. Cities are progressively becoming economic and social hubs [3]. To conquer these difficulties, innovative technologies that are able to adapt to the changing dynamics of urban traffic are urgently required [4]. The transport efficiency tool calculates an appropriate speed and route to the destination based on traffic congestion data [5]. These technologies strive to offer solutions that exceed the limitations of existing traffic control systems.

The integration of AD and intelligent network connections can bring about a significant shift in traffic management [6]. AD refers to the utilisation of complex models and algorithms, i.e. machine learning, deep learning, reinforced learning and sensor fusion techniques, e.g. liDAR, cameras to anticipate driver conduct in intricate urban settings and unanticipated features of human driving [7]. Utilising AD enhances the modelling of traffic dynamics and enables a more precise representation. This enables the creation and evaluation of innovative traffic control solutions within a secure virtual setting. AD is a highly effective tool for achieving this objective [8-10]. Furthermore, a smooth and uninterrupted integration between vehicles and the surrounding infrastructure is necessary. Automobiles can establish a connection with traffic signals, sensors and other vehicles, allowing them to communicate with each other [11].

The outcome is a dynamic ecosystem that can rapidly adjust to varying environmental conditions. The combination of advanced network connectivity and artificial intelligence (AI) is introducing a new era of traffic control. This transformation is attributed to the integration of these two technologies [12]. The current approach to managing traffic at urban arterial crossings involves the use of advanced simulations and real-time communication, which enables proactive and flexible traffic control. This innovative concept has the potential to greatly enhance the movement of vehicles on the road [13].

This research aims to comprehensively examine how AD models and intelligent network connections can effectively address the growing complexities of urban traffic management. By delving deep into these technologies and their impact on traffic flow, the research seeks to identify appropriate solutions to these pressing issues. This paper contributes to the field by providing a thorough analysis of these emerging technologies and their potential to transform traffic management. The goal of this paper is to conduct a systematic literature review (SLR) on AD models and intelligent network connections in the context of urban traffic management. This SLR will involve a comprehensive search and analysis of existing research to identify the state-of-the-art, potential benefits and remaining challenges in this field.

1.1 Main elements

Urban traffic patterns are becoming increasingly complex due to rising vehicle ownership, diverse transportation modes and evolving urban landscapes. This results in congestion, safety risks and inefficient traffic flow. A thorough understanding of these challenges is crucial for developing effective solutions. Existing research highlights the negative impact of increasing traffic density, diverse transportation modes and changing urban environments on traffic flow and safety. Studies have identified key factors contributing to safety issues, including accident rates, high-traffic volume zones and interactions between different transport modes. Risk factors like pedestrian areas, accident-prone intersections and congestion zones require special attention for safety assessments and risk management strategies [14, 15].

While research recognises the challenges, there is a lack of comprehensive studies examining the synergy of technological solutions like AD and intelligent network connections. Most studies focus on individual technologies (e.g. AI or network connectivity) without considering their combined impact on the complex urban traffic environment. Research on integrating AI driving models with intelligent network connections for real-time traffic management and proactive risk prediction remains limited [4, 16-23].

Existing research often focuses on passive safety measures (e.g. seatbelts), neglecting the potential of AI-powered adaptive traffic management and predictive risk analytics for proactive safety improvements. Existing research provides valuable insights into urban traffic challenges and safety concerns. However, a critical gap exists in the comprehensive investigation of how synergistic application of AD models and intelligent network connections can revolutionise urban traffic management. This research aims to bridge this gap by exploring the potential of this integrated approach for:

- **Adaptive traffic management**: Utilising real-time data and AI to dynamically adjust traffic signals and optimise traffic flow based on changing conditions [24].
- **Proactive risk prediction**: Leveraging AI-powered models and real-time data from intelligent networks to anticipate potential hazards and implement preventive measures before they escalate [25].

1.2 Research goal

The study reviews prior studies and summarises how AI, real-time data and simulations might improve urban traffic safety and efficiency while highlighting limitations and suggesting future research. *Table 1* shows our technical research questions (RQs) to focus the investigation.

Table 1 – Research questions

Question no.	Research question
RQ1	To what extent can the integration of data analysis techniques and advanced artificial intelligence algorithms improve safety and efficiency in urban traffic management?
RQ2	How can real-time traffic data from sensors and simulations improve both traffic flow and safety in cities?
RQ3	What are the potential limitations and future research directions to improve traffic safety in cities while adopting real-time data and simulation techniques?

1.3 Contribution and layout

This SLR offers a valuable assessment of existing research, aiming to advance the knowledge base for transportation and computer science professionals interested in data analytics and artificial AI for traffic management.

- The study identified 140 relevant articles on the safety, efficiency and case studies of AVs published up to early December 2023. This comprehensive collection can serve as a foundation for future research in this field.
- Following a quality assessment based on predefined criteria, 130 noteworthy articles were selected for further analysis. These studies provide a strong comparative base for future research endeavours.
- A meticulous examination of data from the 130 studies was conducted. This analysis yielded valuable insights into the specific concepts and challenges surrounding the use of AI in AVs and CV systems for traffic control strategies.
- The study presents a meta-analysis of traffic management approaches and objectives, aiming to contribute to the advancement of ITS and new technologies.
- Limitations of the current research are identified, along with recommendations to guide further exploration in this domain.

Section 2 of this paper will adhere to the framework outlined in [26] to provide a detailed explanation of the rigorous selection process employed to identify primary research studies for analysis. Section 3 will delve into a comprehensive examination and analysis of the selected research publications. Section 4 will present the findings of the study, including recommendations for future research directions based on the initial research questions. Section 5 will conclude the articles with a concise summary of the key discoveries.

2. RESEARCH METHODOLOGY

This study employs a rigorous and comprehensive methodology known as a SLR. This established approach entails meticulous planning, execution of the review process and subsequent reporting of the identified findings. Adhering to the guidelines outlined in [26], the review process was iterated multiple times to ensure a complete examination of the available research.

2.1 Primary studies selection

To ensure the retrieval of the most recent research addressing the RQs, a comprehensive search was conducted in December 2023. A detailed search string was specifically constructed to target elements such as titles, abstracts and keywords. This targeted approach aimed to identify articles directly relevant to the research focus.

("ITS" OR "intelligent transportation system" OR "AI" OR "Artificial Intelligence" OR "traffic" + "management" OR "AV" OR "autonomous vehicle" OR "Safety" OR "Efficiency" OR "CVs" OR "connected vehicles" OR "traffic" + "cameras" OR "sensors" OR "case study" + "traffic management".)

The chosen search strategy encompassed seven electronic databases (as detailed in *Table 2*). An initial search retrieved 382 articles. Following the pre-defined inclusion/exclusion criteria outlined in **Section 2.2**, a multi-stage refinement process was employed. This process involved title, abstract and keyword analysis, reducing the initial pool to 140 articles. Subsequently, full-text screening against the established criteria identified 140 articles suitable for further analysis. To enhance the comprehensiveness of the search, a snowballing technique, detailed in [27], was implemented. This technique involved two stages: a backward snowball examining the reference lists of all included studies, followed by a forward snowball to identify additional relevant publications citing these studies. *Table 2* presents the scientific database and the URLs that are accessed during the comprehensive search of relevant articles.

Table 2 – Scientific database

Online scientific database	URL address
Google Scholar	https://scholar.google.com
ASCE Library	https://ascelibrary.org
Science Direct	https://www.sciencedirect.com
IEEE Xplore Digital Library	http://ieeexplore.ieee.org
Springer	https://link.springer.com
Scopus	https://www.elsevier.com/solutions/scopus
Web of Science	https://www.webofscience.com

2.2 Inclusion and exclusion criteria

This SLR examined traffic management systems that rely on computers and AI, including self-driving vehicles and connected vehicles. The focus was on how these technologies function at complex intersections and must deliver analytical findings that take applications and goals into account. Accepted studies had to analyse these systems in the context of real-world applications. Only English-language articles from reputable journals listed in Section 2.1 were included. Law enforcement and basic speed limit studies were excluded. See *Table 3* for primary inclusion and exclusion criteria.

Table 3 – Inclusion-exclusion criteria

Inclusion criteria	Exclusion criteria
The manuscript provides an analysis of the application and objectives of the study.	Articles that simply evaluate and compare the efficacy of current methodologies.
Peer-reviewed journal articles.	Research predominantly addresses the management challenges associated with solely human-driven vehicles.
Journal articles assessing connected and autonomous automobiles.	Technical reports or official government publications.
Journal articles that discussed case studies of traffic management.	Non-English articles.

2.3 Selection results

The initial search strategy employed keyword searches across titles, abstracts and keywords in seven reputable electronic databases (detailed in *Table 2*). This initial search retrieved a total of 382 articles. Subsequently, the inclusion/exclusion criteria outlined in Section 2.2 were applied, resulting in a refined set of 140 studies. Following a rigorous full-text review against the established criteria, 140 key studies were identified for further analysis. To enhance the comprehensiveness of the search and potentially identify relevant studies missed in the initial search, a snowballing technique, as detailed in [26], was implemented. This technique encompassed two stages: a backward snowball examining the reference lists of included studies and a forward snowball to identify additional publications citing these studies. Ultimately, this process yielded a final selection of 130 articles suitable for inclusion in this SLR. *Figure 1* illustrates the selection process for this initial sample.

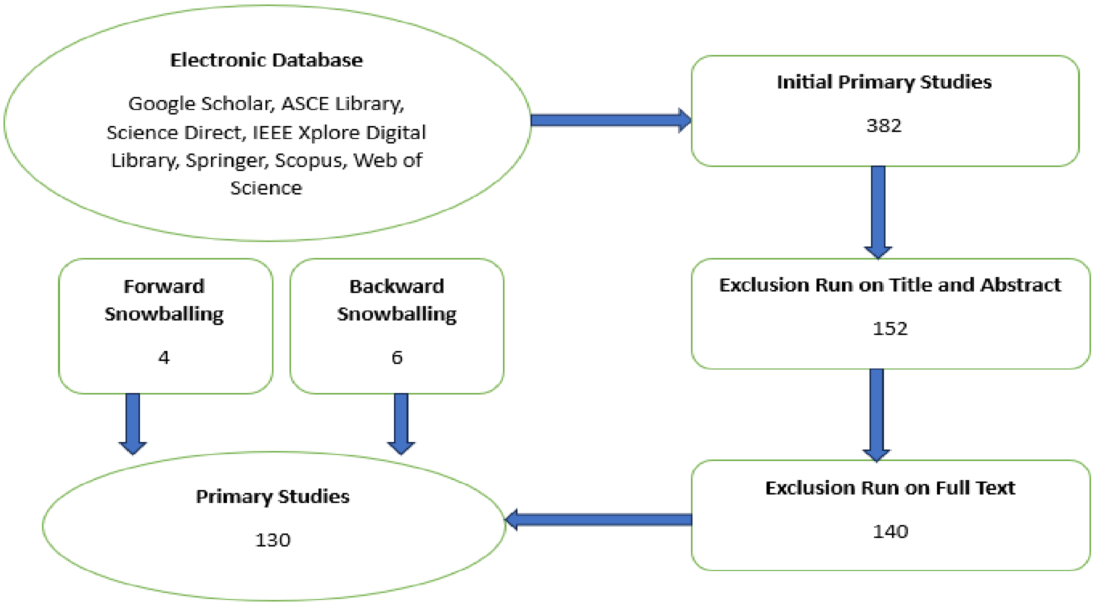

Figure 1 – Primary studies selection and inclusion criteria

2.4 Quality assessment

Adhering to established quality assessment guidelines [28], primary studies were evaluated for their alignment with the RQs. This systematic process ensured the selection of the most pertinent studies to address the research objectives. A random selection approach was eschewed in favour of a systematic methodology to identify a representative sample of studies for quality evaluation. *Figure 2* shows the distribution of primary studies published by different journals in the SLR conducted between January 2014 and December 2023.

— Traffic management: The study will discuss traffic control techniques while focusing on the safety and efficiency of connected and autonomous vehicles.
— Background: To answer RQ1 effectively, chosen publications must provide sufficient background information to understand the study's goals and the results of any experiments conducted.
— Application of real-time data: To answer RQ2, chosen publications must offer enough detail for the recommended approach to be implemented in a real-world traffic scenario.
— Performance evaluation and future perspective: To answer RQ3, chosen publications should include details about the evaluation environment and the models used to assess solutions' performance. These details will be used to evaluate the quality of primary studies found during the search process.
— Limitation: The study must focus on passenger vehicles and avoid solutions primarily designed for public transportation systems.

2.5 Data extraction

Following the quality assessment process, data extraction was conducted from the validated studies. This ensured the reliability and traceability of information informing this review. To establish a consistent data extraction approach, a pilot exercise was implemented on a representative sample of 140 studies drawn from the initial search results.

2.6 Data analysis

After data extraction, the information from the analysed studies was categorised into qualitative and quantitative groups. This facilitated the analysis of the data in relation to the RQs. This categorisation ensured a comprehensive examination of both qualitative and quantitative aspects of the research topic.

Existing research based on AI and ITS

Despite the increasing adoption of AVs and CVs and their potential applications in traffic management, few relevant studies were conducted between 2018 and 2023. *Figure 2* illustrates the limited number of studies selected for this review. However, the trend suggests a growing interest in integrating AI and ITS for traffic management solutions.

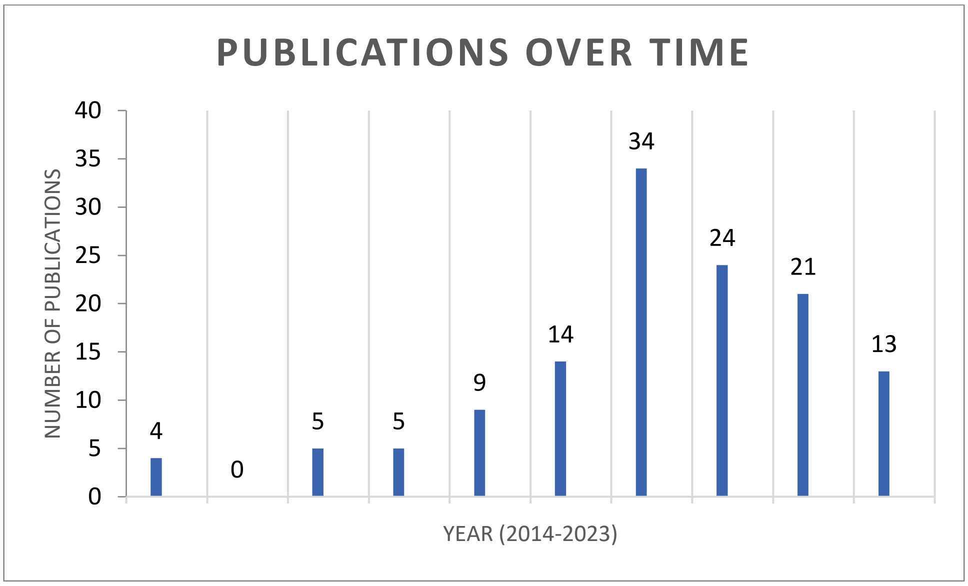

Figure 2 – Publications over time with the title AI and ITS between the years 2014–2023

Substantial keyword distribution

A diverse set of traffic management strategies were employed to search for the chosen primary articles. These strategies incorporated search terms related to autonomous vehicles. **Section 2.1** details the frequency and appropriate search terms typically used when researching motorised and ground vehicle procedures.

3. RESEARCH ANALYSIS

3.1 Traditional traffic safety methods

Traditional traffic safety research has primarily focused on three methods: road signs, legal enforcement and static traffic signal control. Accident analysis, particularly in urban settings, has been a common approach to identifying factors and patterns leading to collisions. Effective strategies to tackle common traffic problems at intersections and pedestrian crossings involve enforcing traffic regulations and improving physical infrastructure. These established methodologies have proven effective in reducing accidents and enhancing overall traffic safety standards, supported by evidence from multiple research studies [29]. However, limitations associated with traditional methods are becoming increasingly apparent as urban traffic continues to evolve. The growing number of vehicles and the expanding variety of transportation options pose challenges that traditional methods struggle to adapt to [30].

3.2 Intelligent transportation systems (ITS) for improved safety

In recent years, there has been a growing focus on exploring new technologies to address the shortcomings of existing systems. ITS utilise sensor technologies, data analytics and communication to enhance both traffic flow and safety. Advanced driver-assistance systems (ADAS) and vehicle-to-everything (V2X) connectivity are examples of ITS playing a crucial role by providing valuable information to drivers, ultimately improving road safety [31].

Numerous studies have explored the impact of emerging technologies on specific aspects of urban traffic safety. The implementation of intelligent crosswalks and autonomous braking systems are examples of contributing to pedestrian safety and reducing rear-end collisions, respectively. However, further research is necessary to fully understand the combined effects of various technologies on the safety of urban arterial traffic [32].

3.3 AI-driven autonomous vehicles and network connections for safety advancement

The integration of advanced network connections and AVs represents a significant shift in urban traffic safety. Machine learning-based AI driving models offer exceptional accuracy in predicting and simulating real-world traffic scenarios. This predictive capability empowers traffic management systems to take proactive measures, mitigating risks and addressing safety concerns before they arise. Intelligent network connections enable flexible communication between vehicles and the traffic control environment, facilitating faster response times, improved traffic light synchronisation, and better coordination among vehicles to prevent accidents. These advancements present an opportunity to establish a comprehensive and adaptable system for enhancing traffic safety in urban areas [33-35].

3.4 Combing major findings with future research directions

The literature review emphasises the importance of conducting comprehensive research that combines traditional methods with emerging technologies, with a particular focus on the potential of AD and smart network connections. This study aims to address the limited understanding regarding the impact of advanced technology on urban arterial traffic safety [36].

Table 4 provides a comprehensive assessment of major findings obtained from multiple studies on urban traffic safety. These investigations combine recent technological advancements with conventional study methodologies. *Table 4* **also** offers valuable insights into the challenges, achievements and potential areas for future exploration in the field of urban arterial traffic safety. It serves as a reference for gaining insights into various strategies used to tackle safety concerns, encompassing traditional methods (traffic lights, law enforcement) and advanced technologies (AI-driven models, smart transportation systems). By highlighting advancements made in urban traffic safety management and exploring how emerging technologies address limitations of existing methods, this synthesis paves the way for identifying areas where future technologies can improve upon current achievements [37-39].

In this section, the RQ1 from *Table 1* is addressed: a comprehensive literature review has been performed, and a dataset has been collected to analyse safety, efficiency, socioeconomic impact, environmental impacts and other factors discussed in those articles. The main findings of these articles are compiled in *Table 4*.

Table 4 – Review of important findings in the literature on urban transportation safety

Paper	**Year**	**Safety**	**Efficiency**	**Socio-economic**	**Environmental impact**	**other**	**The main findings of the research articles**
(29)	2023	✓			✓		Past traffic safety research has mainly focused on conventional methods like signage, enforcement and static signal control, emphasising accident analysis to understand crash causes and trends in urban environments.
(30)	2023	✓	✓	✓			Conventional traffic regulations, enhancements to physical structures (such as intersection layout), and multiple research studies demonstrate effectiveness in decreasing accidents. However, they face challenges in accommodating the constantly evolving complexities of expanding and diversified urban traffic.
(31)	2023	✓	✓				New research on “intelligent transportation systems” using sensors, data and communication explores improving traffic flow and safety through advanced driver assistance systems and vehicle-to-everything connectivity.
(32)	2022	✓	✓				Real-time traffic info and new tech (smart crossings, auto-braking) are studied for safety in cities, but more research is needed to see how these work together.
(33)	2022	✓	✓				Combining AI-powered vehicles with intelligent traffic networks creates a transformative approach to urban safety by enabling proactive risk prediction, real-time data exchange and optimised traffic control for accident prevention.
(34)	2023	✓					This research explores how to leverage new technologies to create a comprehensive safety framework for urban traffic, focusing on the potential of AI-powered driving and intelligent networks.
(35)	2021		✓				The inability of static traffic control to adapt to evolving traffic circumstances.
(36)	2021	✓					Restricting the use of passive safety measures is essential; proactive risk assessment is necessary.
(37)	2020		✓				Various modes of transportation influence the complexity of urban traffic patterns.
(38)	2021		✓				Intelligent transportation technologies help to optimise traffic flows.
(39)	2019	✓	✓				Data transfer in real time for adaptive traffic control strategies.
(40)	2020	✓					Using modern driver assistance systems helps to avoid rear-end collisions.

Paper	Year	Safety	Efficiency	Socio-economic	Environmental impact	other	The main findings of the research articles
(41)	2020	✓					Automatic braking systems reduce accidents, particularly those involving rear-end crashes.
(42)	2021	✓					Machine learning algorithms predict traffic behaviour in order to measure safety.
(43)	2020	✓					Smart crosswalks increase pedestrian safety.
(44, 45)	2020, 2022	✓	✓				There are flaws in the overall appraisal of technological initiatives.
(46)	2020	✓	✓				Limitations in the currently published literature on the revolutionary potential of AD.
(47)	2019		✓				Inconsistent traffic signal synchronisation substantially reduces urban traffic efficiency.
(48)	2020	✓	✓				The public is mostly unaware of the benefits and risks of automated driving technologies.
(49)	2020		✓				Connectivity challenges arise while implementing intelligent network connections in complex urban situations.
(50, 51)	2019		✓				The absence of standardisation impedes interoperability among various AD models and systems.
(51)	2021					✓	Inadequate legislative frameworks to ensure the ethical application of AI-driving technologies.
(52)	2020	✓	✓				Cybersecurity issues pose a threat to the reliability of smart network connections in urban traffic systems.
(53)	2022	✓					The adaptive traffic control legislation did not sufficiently consider socioeconomic factors.
(54)	2020			✓			Inevitable effects of AD models include over-reliance on automation and job displacement.
(55)	2021		✓				Challenges arise when attempting to optimise traffic flow in regions characterised by substantial variations in driving behaviour and road conditions.
(56)	2020	✓	✓				Popular suspicion of AD technology, as well as concerns about data privacy, impede widespread implementation.
(57)	2020		✓				The imperative for continuous research on the psychological dynamics of driver interaction with automated driving technologies.
(58)	2022	✓					Exploring the potential of blockchain technology to enhance the security of intelligent network connections.
(59)	2020		✓				Inefficiencies in handling traffic events underscore the need for better incident management systems.
(60)	2020				✓		The increased reliance on AD technology may have significant environmental consequences, necessitating the development of sustainable alternatives.
(61)	2022		✓				Evaluating the economic sustainability and effectiveness of implementing large-scale intelligent transportation systems (ITS) and AD technology.
(62)	2022				✓		AI can predict and mitigate the impacts of climate change on urban traffic flow.
(63)	2020		✓	✓			Challenges in assimilating AD technology with current infrastructure and urban planning systems.
(64)	2021			✓			Researching the impact of AD on the labour market and examining methods to enhance the skills and transition of individuals.
(65)	2023			✓			Social injustice may arise due to potential disparities in access to and advantages derived from AD technologies.
(66)	2019		✓				Exploring the connection between AD technologies and sustainable urban design techniques.
(67)	2020		✓	✓			Utilising AI to enhance urban quality of life and effectively regulate traffic flow in smart city efforts.
(68)	2021		✓		✓		Evaluating the impact of automated driving technology on traffic-related energy consumption and environmental sustainability.
(69)	2019			✓	✓		Acknowledging the cultural implications and degrees of AD technology adoption in many global metropolis environments.
(70)	2020		✓	✓			Potential applications for human-vehicle communication interfaces in the future and their potential influence on drivers' perception and utilisation of autonomous capabilities.
(71)	2022	✓	✓	✓			High-resolution, real-time traffic cameras provided valuable data on vehicle movement, traffic patterns and adherence to laws, enabling both quantitative and qualitative analysis of driver and pedestrian behaviour.

Paper	Year	Safety	Efficiency	Socio-economic	Environmental impact	other	The main findings of the research articles
(72)	2018	✓	✓				Traffic sensors like inductive loops provide detailed data on traffic volume, speed and usage, while advanced sensors like LiDAR and radar enhance safety by enabling better detection of pedestrians and bicycles.
(73)	2020	✓	✓				The utilisation of vehicle monitoring technology equipped with onboard sensors enables the provision of real-time traffic data, including speed, position and interactions. These data are utilised to enhance the precision and promptness of traffic management, with the ultimate goal of improving safety and efficiency.
(74)	2021	✓	✓				Powerful simulation tools with AI driving models recreate realistic urban traffic scenarios (road design, traffic lights, pedestrians) to explore safety improvements.
(75)	2022	✓	✓				Advanced AI and machine learning algorithms are incorporated into driving models to mimic the complexities of real-world driver behaviour, including decision-making, traffic signal response and adaptability to changing conditions.
(76)	2019		✓				Before using them, rigorous calibration and validation ensure AI driving models closely mimic real-world traffic scenarios captured by traffic cameras, sensors and connected vehicles.
(77)	2022		✓	✓			In order to integrate intelligent network connectivity into the system, it was imperative to provide seamless connectivity between autos and the urban infrastructure.
(78)	2022	✓	✓				To improve traffic flow (efficiency) and safety, traffic lights, signs and other components transmit real-time data and receive information about conditions, signal changes and hazards via two-way communication with connected vehicles.
(79)	2020	✓	✓				Vehicles with internet access communicate with nearby infrastructure (V2I) to share data on speed, position and potential hazards, improving both safety and traffic flow.
(80)	2022	✓	✓				Real-time data exchange between vehicles and infrastructure enables a responsive traffic management system that adapts control methods to current conditions in the urban arterial network, improving both safety and efficiency.
(81)	2022	✓					A comprehensive traffic safety assessment framework was established through data collection, the creation of AI driving models and intelligent network connections.
(82)	2018	✓	✓				Cutting-edge technology is used to create a proactive, adaptable traffic management strategy for urban safety and efficiency.
(83)	2020	✓					An accurate set of metrics assessed the safety of urban arterial traffic by observing and evaluating traffic behaviour and the way it reacted to issues.
(84)	2020	✓					Collision rates, calculated by accidents divided by total kilometres driven, offer a standardised measure for understanding traffic safety in urban arterial networks.
(85)	2022	✓					Including near-miss data alongside reported accidents helps proactively identify and reduce risk factors for improved traffic safety.
(86)	2020	✓					Analysing response times (emergency arrival, traffic control changes, driver adaptation) to incidents in urban traffic reveals a link between faster response and improved safety.

3.5 Traditional versus artificial traffic management approaches

To address RQ2, a comparison between the TTM approach and the AD approach was conducted while considering infrastructure, data analysis, approach against complex problem solving and flexibility in decisions, as shown in *Table 5*.

Table 5 – Comparison of TTM approach vs AD approach

Feature	Traditional traffic management approach	AD approach
Infrastructure	Static (signals, signage)	Dynamic (connected infrastructure, vehicles)
Data analysis	Limited, basic data collection	Extensive, real-time data analysis with AI
Approach	Reactive	Proactive
Flexibility	Limited, requires manual intervention	High, adapts to real-time conditions

TTM systems primarily rely on static infrastructure like traffic signals and basic data collection methods like loop detectors. These limited data restrict the ability to analyse complex traffic patterns and predict future conditions. Consequently, these systems struggle to adapt to real-time changes in traffic flow, leading to congestion and inefficiencies. Recognising these limitations, recent research has explored AI-driven traffic management approaches. AI systems leverage real-time data from various sources, including embedded sensors, traffic cameras and connected vehicles. Machine learning algorithms analyse this data to identify patterns, predict future traffic conditions and dynamically adjust traffic flow management strategies. A case study was discussed in [84] in which collision rates, calculated by accidents divided by total kilometres driven, offer a standardised measure for understanding traffic safety in urban arterial networks. [85] discussed near-miss data alongside reported accidents helps proactively identify and reduce risk factors for improved traffic safety. [85] Present the analysis of response times (emergency arrival, traffic control changes, driver adaptation) to incidents in urban traffic reveals a link between faster response and improved safety. In all three cases, they have covered six different situations: Intersection A, High Traffic Zone B, Pedestrian Crosswalk C, School Zone D, Residential Area E and Downtown F to identify the reduction in the percentage of collision rate and near-miss cases and increment in response time while adopting the AI driving approach.

Traditional traffic management approach (TTM)

The features presented in *Table 5*, considering the literature review, are discussed in detail as follows:

— Static infrastructure: TTM relies heavily on physical infrastructure like traffic signals, road markings and signage for traffic control [87]. These configurations are pre-defined based on historical traffic data or engineering estimates and often fail to adapt to real-time changes in traffic flow. For example, a busy intersection might have a fixed traffic light cycle that does not account for morning rush hour traffic volume or unexpected events like accidents, leading to congestion and frustration for drivers [88]. Additionally, installing and maintaining this infrastructure can be expensive and time-consuming, limiting the flexibility of TTM systems.
— Limited data collection: Traditional approaches often utilise basic data collection methods like traffic light timers or loop detectors embedded in the road surface. These methods provide limited data on traffic flow at specific points, such as vehicle count and speed [89]. These limited data restrict the ability to analyse complex traffic patterns, predict future conditions and make informed adjustments to traffic control measures. For instance, loop detectors can malfunction or be obscured by debris, leading to inaccurate data and potentially ineffective traffic signal timing adjustments.

Artificial driving (AI-assisted traffic management)

Figure 3 shows the flow chart of the working mechanism of the artificial driving approach to improve the efficiency and safety of traffic management systems.

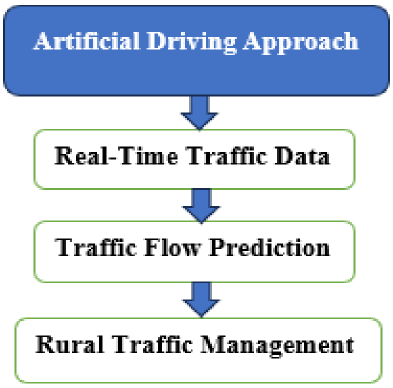

Figure 3 – AD approach working mechanism

Real-time data sources: AI-driven systems leverage real-time data from various sources, creating a comprehensive picture of traffic flow across the network:

— Embedded sensors: Sensors like radar, LiDAR (light detection and ranging) and magnetometers embedded in roadways can monitor traffic flow, vehicle speed, lane occupancy and even vehicle classification (vehicles, trucks, motorcycles) [90]. These detailed data allow for a more nuanced understanding of traffic conditions.

- Traffic cameras: Cameras mounted at intersections and along roadways capture real-time visual data on traffic conditions, including congestion, lane changes and incidents [90]. AI algorithms can analyse video feeds to detect accidents, disabled vehicles or unusual traffic patterns, enabling faster response times and proactive management.
- CVs: Vehicles equipped with vehicle-to-everything (V2X) communication technology can share information on their location, speed, direction and even intent (e.g. lane change) with the traffic management system [91]. These real-time data from individual vehicles provide a comprehensive picture of traffic flow dynamics across the network.

Machine learning and AI analysis: AD utilises machine learning algorithms and AI to analyse vast amounts of real-time traffic data. This analysis allows for:

- Identification of patterns: Machine learning algorithms can identify recurring patterns in traffic flow data, such as rush hour congestion or weekend travel patterns. This knowledge allows for proactive adjustments to traffic signals and infrastructure.
- Traffic flow prediction: AI models can be trained on historical and real-time data to predict future traffic conditions with increasing accuracy [92]. This predictive capability empowers traffic management systems to anticipate congestion and take preventive measures before it occurs.
- Dynamic adjustments: Based on real-time data and traffic flow predictions, AI can dynamically adjust traffic signals, activate variable speed limits or implement lane closures to optimise traffic flow and minimise congestion [93].

Implementation of intelligent traffic management system

Urban arterial traffic safety has been enhanced with the execution of adaptive traffic management systems that rely on real-time data. This action was undertaken in order to achieve the intended objective. These devices modify the timing and synchronisation of traffic lights according to the current traffic conditions. The adaptive control algorithms constantly examined data from traffic cameras, sensors and networked vehicles. The goal was to enhance signal phasing, alleviate overcrowding and decrease the possibility of incidents [94].

Intelligent network connection's functionality

An intelligent network connection was a crucial aspect in enhancing the effectiveness of adaptive traffic management. The traffic management systems collected real-time data on vehicle speeds, traffic density and any issues due to the seamless connection maintained between the automobiles and the infrastructure. The vehicles' capacity to communicate with the infrastructure enables this to be possible. The adaptive control systems effectively adjusted the traffic signals in response to the fluctuating patterns of urban traffic [95].

Use of predictive analytics

Predictive analytics originated as a proactive approach to risk management, aiming to identify and mitigate possible coercions to public safety before they worsen. In order to make prediction models utilising this approach, it is necessary to consider previous traffic data, patterns of events and environmental variables. The goal was to generate models. Predictive models facilitated the implementation of preventive measures, resulting in a decrease in accidents and an enhancement in overall safety [96].

Role of artificial driving models

Utilising AD models greatly enhanced the precision of risk prediction through the implementation of predictive analytics. These algorithms assess various traffic situations and driver actions to detect possible dangers. AD simulations yielded useful data for predictive analytics systems. This enhancement significantly enhanced the systems' capacity to forecast potential hazards in the future precisely. The integration of predictive analytics and AD models established a robust basis for proactive risk management endeavours. This originated from their cohesive professional rapport [97].

Integration with disaster response systems

The integration of emergency response systems with AI was critical for effectively handling accidents and crises. Vehicles equipped with sensors and communication technology transmitted real-time incident data to the emergency response systems. This continuous communication facilitated the immediate recognition and classification of situations, enabling swift and calculated responses to emergencies [98]. By facilitating better communication amid emergency systems and connected vehicles, the response time needed to address problems was significantly reduced. This efficiency was achieved by shortening the time required for responses. Immediate access to current data about the urgency of the situation, the exact location of vehicles, and the possible closing of roads enabled a more rapid and effective response. A synchronised emergency response framework was established, incorporating AD technology with smart network connections to improve safety in urban arterial traffic [99]. This framework aimed to apply this tech comprehensively. The application of adaptive traffic control, predictive analytics and emergency response technologies resulted in the creation of an extensive risk management strategy. This strategy was further enhanced by improved network connectivity and advanced AD models. The goal of these efforts was to lessen the impact of disasters and enhance safety in urban arterial environments. This was achieved by integrating real-time data with innovative concepts [100].

4. DISCUSSION

This section presents the analytical arrangements of the key studies identified to address all research questions outlined in *Table 1*. To ensure a comprehensive understanding of the reviewed material, detailed analytical charts addressing the technical questions are included. *Table 3* provides a consolidated summary of the relevant qualitative and quantitative data extracted from these studies.

4.1 RQ1: To what extent can the integration of data analysis techniques and advanced artificial intelligence algorithms improve safety and efficiency in urban traffic management?

This SLR investigates the potential of integrating data analysis techniques and advanced AI algorithms to improve safety and efficiency in urban traffic management. The analysis focused on published research from 2014 to 2023. *Figure 4* shows the number of published articles that addressed different parameters in their research findings.

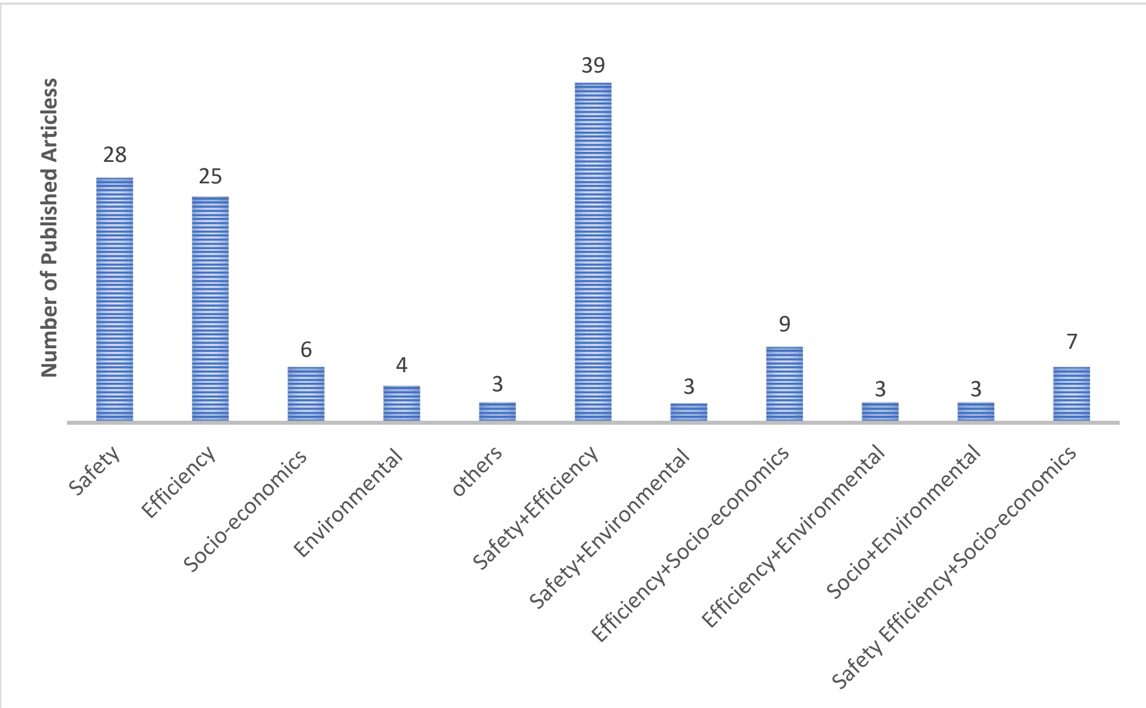

Figure 4 – Number of published articles (2014-2023) vs research findings

— An analysis of the included studies revealed a significant focus on research addressing both safety and efficiency (over 30% of total papers published between the years 2014-2023, as depicted in *Figure 4*). This increasing research trend highlights the interconnected nature of these goals in urban traffic management.

Improved traffic flow and efficiency can contribute to safety, while enhanced safety measures, e.g. intelligent crosswalks and autonomous braking systems, can lead to smoother traffic flow.
— The reviewed literature also presented dedicated research efforts in specific areas. Approximately 22% of the research focused on safety improvements in urban traffic management. This research likely explores technologies like pedestrian detection systems, real-time hazard identification and driver assistance features. Another 20.3% of the research concentrated solely on improving traffic efficiency. This research may investigate areas like dynamic traffic signal optimisation, congestion prediction based on real-time data analysis and route planning algorithms.
— This distribution suggests a growing recognition of the need for a holistic approach that acknowledges the interdependence of safety and efficiency in urban traffic management. AI and data analysis offers the potential to develop comprehensive traffic management systems by enabling a deeper understanding of traffic patterns. This knowledge can then be used to create solutions that optimise traffic flow while simultaneously enhancing safety for all users (drivers, pedestrians, cyclists).

The results underscore the importance of further research that explores the combined effects of various AI and data-driven technologies on overall traffic safety and efficiency. Investigating how these technologies interact and potentially amplify positive outcomes on urban roadways is crucial for future advancements.

4.2 RQ2: How can real-time traffic data from sensors and simulations improve both traffic flow and safety in cities?

Real-time traffic data from sensors, cameras and other AI-based gadgets are studied, and a comprehensive review was presented in a few studies. [100-102] discussed the shortcomings of static signal plans and emphasised the need for dynamic approaches that can adapt to real-time traffic conditions. Similarly, [103-106] discussed the limitations of traditional traffic flow prediction methods. These methods often struggle to capture the nuances of traffic flow, leading to inaccurate predictions. AI-powered solutions offer the potential for significantly improved prediction accuracy. Another challenge lies in real-time traffic data collection and processing. [107-110] explore the limitations of traditional methods in this area. Inaccurate or delayed data can significantly hinder the effectiveness of traffic management strategies. A limited number of publications were found that discussed both traditional and AD approaches simultaneously. *Figure 5* shows the number of publications that cover these aspects:

— Traffic Signal Timing
— Traffic Flow Prediction
— Real-Time Traffic Data
— Urban Traffic Management
— Freeway Traffic Management
— Rural Traffic Management.

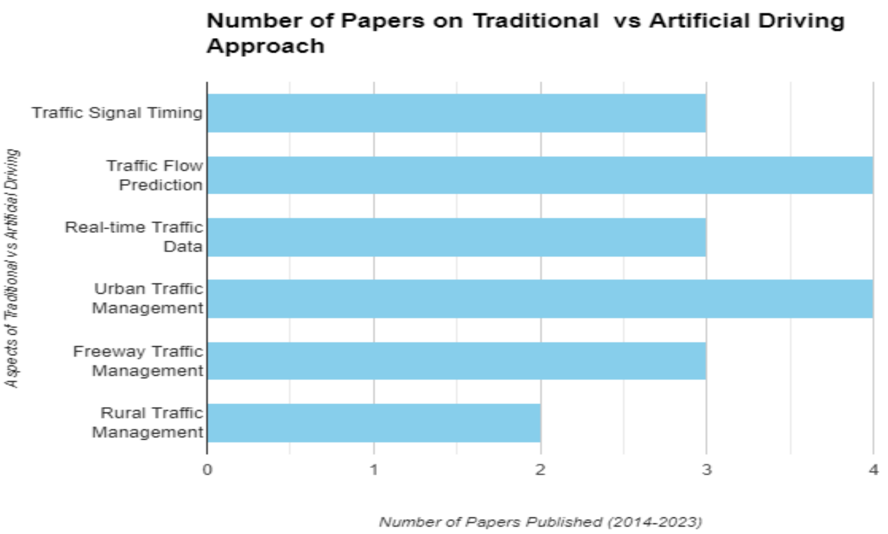

Figure 5 – Publications of traditional vs AD management approach

The focus then shifts to specific traffic environments. Articles [110, 111] explore the challenges of urban traffic management. These challenges include congestion prediction and management. Here, AI offers promising solutions for improved prediction and proactive measures to address congestion. [112-114] delve into the limitations of traditional freeway management systems. AI can play a crucial role in enabling proactive control measures for freeways. [115, 116] explore the limitations of traditional ITS solutions in rural areas. AD has proven to be highly effective in high-density traffic zones with high traffic volumes. The results from [85], illustrated in *Figure 6*, show a remarkable 76% decrease in accidents that occurred in Downtown F. These results provide insight into the various uses of AD and its revolutionary potential in a variety of urban settings. They also assert that efficiency and safety will both increase as technology develops further.

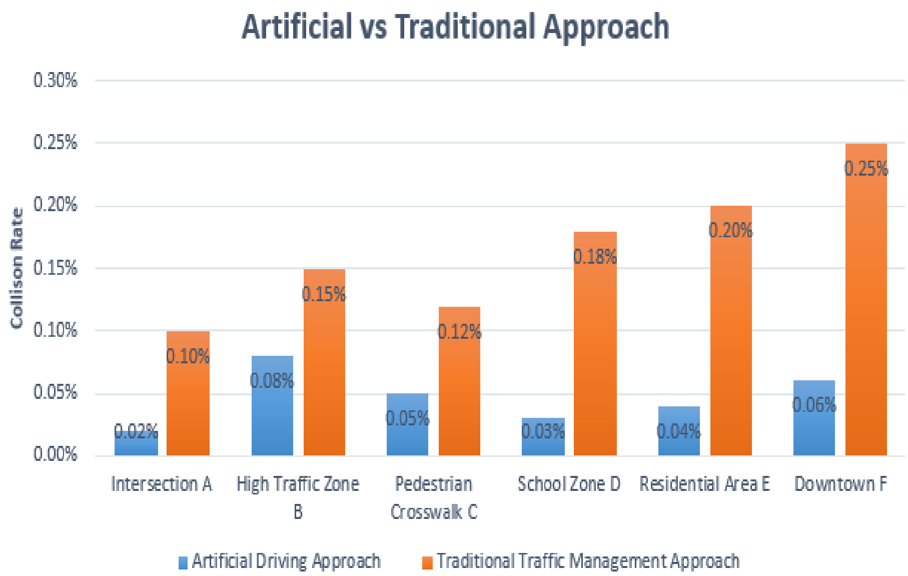

Figure 6 – Significant reduction in collision rates: a comparison between artificial and traditional approach

The comparison discussed in [85] presented in *Figure 7* shows that by the implementation of the AD approach, the number of near-miss cases was reduced to 5 instead of 15, 8 instead of 20, and 7 instead of 18 at Intersection, High Traffic Zone and Pedestrian Crosswalk, respectively.

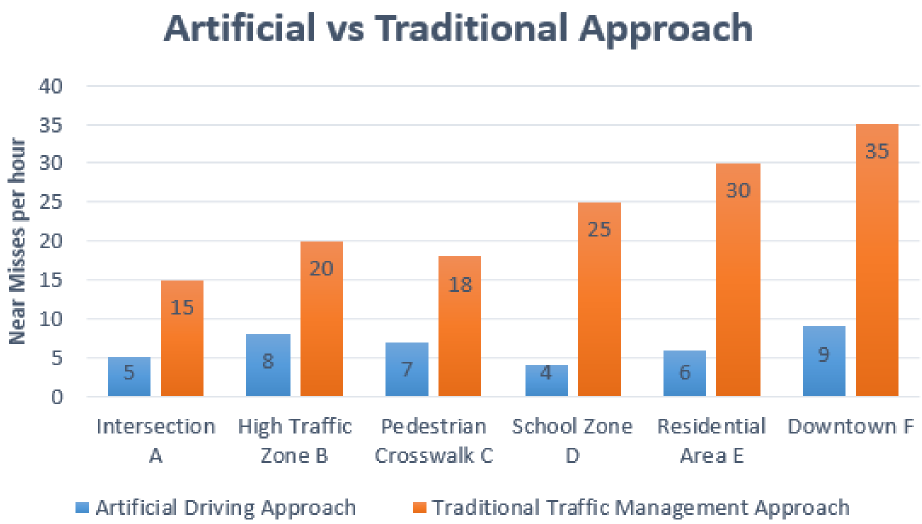

Figure 7 – Significant reduction in near-miss cases: a comparison between artificial and traditional approach

Reduction in response time was discussed in [86] and *Figure 8*. It illustrates that there is a considerable reduction in response time in High Traffic Zone B, Pedestrian Crosswalk C and the Downtown area, i.e. 50%, 55%, and 56%, respectively.

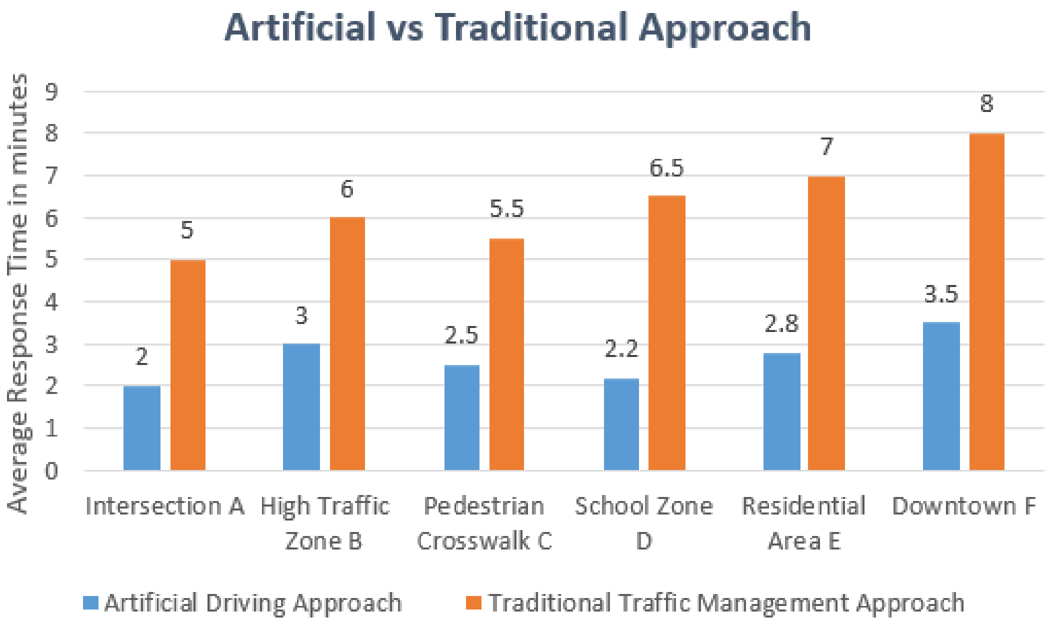

Figure 8 – Significant reduction in time response: a comparison between artificial and traditional approach

It is possible to demonstrate that in all six scenarios, AD performs better than traditional traffic control techniques. The use of AD technology has the potential to significantly decrease the occurrence of collisions, near misses and reaction times [84-86].

4.3 RQ3: What are the potential limitations and future research directions to enhance traffic safety in cities while adopting real-time data and simulation techniques?

Even though the investigation's conclusions were encouraging, there were a lot of difficulties encountered. The topics covered in this area included data security and privacy concerns, the need for interoperability across various platforms, and the public reception of tech in AD. The use of intelligent network connections also presented a number of significant issues. Creating a strong communication infrastructure and standardising communication protocols were two of these obstacles. These problems exposed the extent of the challenge associated with integrating state-of-the-art technology into older urban traffic management systems [117, 118]. *Table 6* offers a comprehensive overview of the challenges and future directions for AD technology. It highlights a range of critical areas that need to be addressed to ensure the safe, efficient, and widespread adoption of self-driving vehicles.

Table 6 – Hurdles and opportunities for adopting AI driving approach

Sr. no.	Category	Challenge/Future direction	Description
1	Data security and privacy	Enhanced dataencryption	Ensuring the utmost security and privacy of the vast quantities of data gathered in urban transportation networks by implementing cutting-edge encryption techniques.
2	Technology interoperability	Standardisation of technologies	Establishing industry-wide standards to ensure the seamless integration of diverse technologies with urban traffic control systems.
3	Perception by the general population	Public awareness campaigns	Launching public awareness campaigns to address concerns, build confidence and educate people about AD technologies.
4	Infrastructure development	Investment in communication networks	This highlights the need to invest in robust communication networks to ensure the seamless flow of real-time data through intelligent network connections.
5	AD models	Improved representation of driver behaviours	Improving AD models to accurately replicate the diverse driving behaviours found in urban traffic environments.
6	Analytics prediction	Advanced predictive analytics algorithms	Developing more complicated and reliable predictive analytics systems to detect better and handle safety risks.

Sr. no.	Category	Challenge/Future direction	Description
7	Sociopsychological aspects	Comprehending the concept of public trust	Researching the social and psychological determinants that impact individuals' confidence in autonomous vehicle technology to assist in making informed decisions.
8	Practicality and expandability	Technology scalability assessment	Evaluating the potential of smart network connectivity and AD technologies to adapt and function effectively in various urban environments.
9	Cooperation and involvement of relevant parties	Collaborative multilateral action	Encouraging collaboration between policymakers, business leaders and the public to create a cohesive and all-encompassing plan for traffic management in cities.
10	Continued system reliability	The resilience of synthetic driving systems	Lowering the frequency of system errors or malfunctions and guaranteeing the robustness and reliability of artificial drive systems under diverse environmental conditions.
11	Energy efficiency	Sustainable technology integration	Investigating methods of integrating intelligent network connection technology with automatic driving to conserve energy and advance sustainability.
12	Regulatory structure	Traffic technology regulations development	Establish comprehensive legislation to regulate AI technology usage, ensuring compliance with standard operating procedures and safety standards.
13	Continuous innovation	Research and development initiatives	Emphasising the importance of ongoing research and development to address emerging challenges and maintain a leading position in the field of technology.
14	Enhancing accessibility and inclusivity	Analysis of varied user demographics	Ensuring the accessibility and usefulness of AD technologies and intelligent network connections for diverse user groups, including those with disabilities.
15	Internet safety	Defence against cyber threats	Putting robust cybersecurity safeguards in place to prevent unauthorised access to urban traffic systems and potential hacker assaults.
16	Machine-human interface	Human-friendly interfaces	Facilitating interaction between automated driving systems and drivers through the development of user-friendly interfaces for machine-human communication.
17	Ownership and management of data	Implementation of data governance policies	Properly established standards about data ownership and administration are necessary to solve data governance issues and set criteria for moral data usage.
18	Considerations of ethics	Ethical implementation of AD technologies	Integrating moral issues with AI technology, such as accountability, fairness and prejudice.
19	Economic efficiency	Financial feasibility of implementations	Assessing the expenses and benefits of maintenance to determine the financial viability of utilising intelligent network connectivity and AD technologies.
20	User education and training	Training programs for users	Developing comprehensive training programs to teach drivers and stakeholders how to use and understand AD technologies.
21	Traffic system resilience	System resilience to adverse conditions	Enhancing urban transportation networks' resilience to adverse weather, accidents and unexpected disruptions.
22	Integration with public transport	Seamless integration with mass transit	Ensuring the seamless integration of AD technologies with public transit networks in order to provide a coherent and efficient urban mobility environment.
23	Data quality assurance	Monitoring the quality of data	Implementing robust procedures to monitor and assure the accuracy of data gathered from diverse sources, with the aim of minimising errors and enhancing overall reliability.
24	The availability of data	Data access policies	Encouraging transparency and fostering creativity by implementing open data laws that grant researchers, policymakers and the general public access to pertinent traffic data.
25	Engaging with the community	Engaging the community in decision making	Encouraging community involvement in decisions about implementing and installing autonomous vehicles in urban areas.
26	Ongoing maintenance	Routine maintenance Plans	Implementing routine maintenance schedules to ensure the longevity and optimal functioning of AD and intelligent network technologies.

Sr. no.	Category	Challenge/Future direction	Description
27	Legal structure	Developing legal framework for autonomous vehicles	Developing and modifying regulatory frameworks to tackle concerns regarding accountability, insurance and responsibility in response to the increasing presence of autonomous vehicles on the road.
28	Environmental consequences	Evaluating environmental impact	Conducting thorough assessments of the environmental effects of AD systems, taking into consideration energy usage and emissions.
29	International norms	Collaboration on international standards	Promoting worldwide specifications for AD technology through international collaboration in order to foster consistency and interoperability across borders.
30	Sustainable cities	Integration with smart city initiatives	Assessing the possible applications of AD tech in smart city projects to support comprehensive and sustainable urban development.
31	Future of urban planning	Impact on development patterns and urban land use	AD technology could reshape urban planning by altering zoning, housing and commercial development. Reduced parking needs may free up space for new developments. Changes in commuting patterns could influence housing demand, potentially expanding residential areas. Commercial areas might shift to optimise access and logistics. Overall, autonomous vehicles could transform land use and urban planning.
32	Future approach	Redefining urban transportation landscapes	AD technology can create a more ecological, inclusive and efficient urban transportation ecosystem. It reduces emissions, enhances accessibility for people with disabilities and optimises traffic flow for faster travel and better resource management, promising a transformative impact on urban mobility.

Data security and privacy

The vast amount of data collected by autonomous vehicles necessitates robust encryption and clear data governance policies to address ownership, usage and ethical considerations. [119] explores various data security and privacy challenges in CVs and AVs including data collection, storage and usage. On the data side, concerns focus on security and privacy. The vast amount of data collected by AVs navigating urban environments needs robust encryption to prevent unauthorised access and misuse. Additionally, data governance policies are crucial to determine ownership, usage and ethical considerations surrounding the data.

Technology interoperability

Technical interoperability is another key challenge. Different manufacturers use varying technologies, and ensuring these systems seamlessly integrate with existing traffic control infrastructure is vital. Standardisation efforts will be essential for smooth operation and to avoid compatibility issues. Seamless integration of diverse autonomous vehicle technologies with existing traffic control infrastructure requires industry-wide standardisation efforts. [120] reviews recent efforts on standardisation for connected and autonomous vehicles, highlighting the importance of interoperability for seamless integration.

Public perception

Public perception is a significant hurdle. Building trust and educating the public about AD is crucial for widespread adoption. Public awareness campaigns can address safety concerns and showcase the potential benefits. [121] analyses research on public perception of autonomous vehicles, highlighting the need for trust-building and education.

Infrastructure development

Infrastructure development is another critical area. Reliable and robust communication networks are essential for real-time data exchange between AVs and urban traffic management systems. Investments in infrastructure will be necessary to support the seamless flow of information. Reliable and robust communication networks are essential for real-time data exchange between Avs and traffic management systems, requiring investment in infrastructure. [122] discusses infrastructure needs for AVs, including communication networks for real-time data exchange.

Improved perception by AVs

Current models require refinement to represent better the unpredictable driving behaviours encountered in real-world traffic conditions. Additionally, advanced predictive analytics algorithms are needed to enhance risk detection and safety. [123] explores using deep reinforcement learning to improve the situational awareness of autonomous vehicles in complex traffic environments. *Table 6* also emphasises the need for improved perception by autonomous vehicles. Current models need to be refined to represent better the diverse and unpredictable driving behaviours encountered in real-world urban traffic conditions. Additionally, advanced predictive analytics algorithms are required to enhance risk detection and improve overall safety.

Sociopsychological aspects

The social and psychological aspects of Vs are also crucial. Understanding public trust and addressing societal concerns are vital for successful implementation. Research in this area can inform policy decisions and promote public confidence. [124] analyses research on the social and psychological factors influencing public acceptance of autonomous vehicles. Research into these areas can inform policy decisions and promote public confidence.

Practicality and expandability

Assessing how well AD and smart network connectivity adapt to various urban environments (traffic patterns, weather) is crucial. While the primary focus is infrastructure, [125] also touches upon the need for autonomous vehicles to adapt to various urban environments. Beyond technical considerations, *Table* 6 explores the scalability of this technology. Evaluating how well AD and smart network connectivity can adapt to various urban environments is essential. This includes assessing the functionality in different city layouts, traffic patterns and weather conditions.

Collaboration

Effective collaboration between policymakers, businesses and the public is necessary for developing a cohesive plan for managing autonomous vehicles within urban traffic systems. [126] emphasises the importance of collaboration between stakeholders for the responsible and beneficial implementation of autonomous vehicles.

The continued reliability of AD systems is paramount. Minimising system errors and malfunctions under diverse environmental conditions is crucial. Additionally, cybersecurity measures are essential to safeguard urban traffic systems from cyberattacks and unauthorised access. Sustainability is another prominent theme. Integrating energy-efficient technologies can minimise the environmental impact of autonomous vehicles.

Furthermore, assessing the potential for AD to contribute to smart city initiatives can promote sustainable urban development. *Table 6* also studies the legal and regulatory frameworks that will need to evolve alongside AD technology. Establishing clear regulations for AI usage, traffic management and accident liability will be critical for safe and responsible implementation. The future of urban planning is an exciting potential consequence of autonomous vehicles. Reduced parking needs could free up space for new developments, while changes in commuting patterns might influence housing demand. Overall, this technology has the potential to reshape urban landscapes and create more efficient and sustainable cities.

5. CONCLUSION

This study highlights the potential of AD and intelligent network connections to improve urban traffic safety. Case studies demonstrate successes in adaptive management, predictive analytics and emergency response. Despite challenges, these technologies promise enhanced traffic safety and efficiency. Ongoing research, development and collaboration are crucial to overcoming obstacles. Advances in AI and intelligent networks can significantly enhance urban traffic management strategies.

— This comprehensive study reviewed a massive amount of research (382 publications from 2014-2023). After careful evaluation, they narrowed it down to 130 high-quality studies on traffic management. Interestingly, there has been a surge in research on this topic since 2018, suggesting growing interest in improving traffic management solutions.

— The study examined three research questions related to the integration of data analysis techniques and advanced AI algorithms in urban traffic management. A detailed literature review of published articles on AI and ITS between the years 2014-2023 revealed the answer to RQ: 1 that approximately 22% of research articles focused solely on safety, while around 20.3% of published articles concentrated on efficiency. Additionally, about 30% of published articles explored both efficiency and safety. Extensive research has been conducted over the past five years, as indicated by these statistics.

— In order to address RQ: 2 regarding the enhancement of traffic flow and safety, an analysis was conducted on real-time traffic data from sensors and simulations. This analysis involved comparing the artificial and traditional approaches in order to study collision rates, near-miss cases and the reduction in response time. The study found that implementing an AD approach led to a considerable decrease in incidents in Downtown F. The number of near-miss cases also decreased at intersections in High-Traffic Zone and Pedestrian Crosswalks. Additionally, there was a noticeable decline in response time in High Traffic Zone B, Pedestrian Crosswalk C and the Downtown area. AD proves to be highly effective in areas with dense traffic and high volumes.

— The current study identified 32 elements that offer a brief overview of the major obstacles and emerging trends in the domain of urban traffic management. These factors address the limitations and future research directions to improve traffic safety in cities while adopting real-time data and simulation techniques. The paper thoroughly discusses essential components such as building infrastructure, gaining public support, ensuring technology integration and maintaining information security, among other vital considerations.

ABBREVIATIONS

Here are the abbreviations used in this review paper.

ITS	Intelligent transportation system
AI	Artificial intelligence
AV	Autonomous vehicles
CV	Connected vehicles
SLR	Systematic literature review
IEEE	Institute of electrical and electronics engineers
V2V	Vehicle-to-vehicle
V2I	Vehicle to infrastructure
I2V	Infrastructure-to-vehicle
LiDAR	Light detection and ranging
TdPN	Temporal delay Petri net-based
SIoV	Social internet of vehicles
ENN	Elman neural network
IoV	Internet of vehicles
V2X	Vehicle-to-everything communication
RQ	Research question
AD	AD
TTM	TTM

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