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A Systematic Review on Data-Driven Traffic Management for Sustainable Urban Transport

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ABSTRACT

The rapid growth of urban areas has intensified challenges in traffic management, including congestion, air pollution, and high energy consumption. To address these issues, cities must adopt sustainable transport solutions that balance environmental, economic, and social factors while leveraging data-driven innovations. This review examines recent studies on optimizing traffic management through artificial intelligence and machine learning techniques. By applying a structured search strategy and strict inclusion criteria, we synthesize key findings from relevant academic sources. The results indicate that AI-driven approaches can significantly improve traffic flow, reduce congestion, and enhance transportation efficiency. Techniques such as machine learning and deep reinforcement learning show strong potential in predicting traffic patterns and optimizing signal control systems. However, challenges remain, particularly in ensuring data quality, integrating diverse data sources, processing information in real time, and scaling these solutions effectively. While data-driven traffic management strategies are promising, further research is needed to develop robust integration frameworks, refine scalable AI models, and enhance real-time analytics. Additionally, a deeper assessment of long-term sustainability impacts will be crucial in shaping the future of intelligent urban traffic management. This study provides a foundation for future research aimed at optimizing urban mobility through advanced data-driven methodologies.

Keywords - **Artificial Intelligence in Traffic, Data-Driven Traffic Management, Predictive Analytics for Urban Mobility, Sustainable Urban Transport, Traffic Optimization Algorithms, Traffic Signal Control**

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1. INTRODUCTION

The rapid urbanization of cities worldwide has led to significant challenges in managing traffic congestion, air pollution, and energy consumption [1]. Urban transport systems are critical to the functioning of cities, yet they often suffer from inefficiencies that result in negative environmental, economic, and social impacts. Traditional traffic management approaches are increasingly inadequate in addressing these issues, necessitating innovative, data-driven strategies. Addition- ally, increasing vehicle ownership exacerbates these problems, contributing to higher traffic congestion and environmental pollution [2].

Sustainable urban transport aims to create efficient, accessible, and environmentally friendly transportation systems [3]. It is essential for reducing greenhouse gas emissions, lowering energy consumption, and improving the overall quality of life in urban areas. Achieving sustainability in urban transport requires a holistic approach that integrates environmental, economic, and social considerations [4]. Data-driven approaches, leveraging advancements in AI, machine learning, and information and communication technology (ICT), have emerged as powerful tools to optimize traffic management, reduce emissions, and enhance the quality of life for urban residents [5].
Numerous studies have explored the application of data-driven techniques in traffic management, utilizing various data sources such as traffic sensors, GPS data, IoT devices, traffic cameras, and social media feeds [6, 7]. Advanced analytics techniques, including machine learning, artificial intelligence, and optimization algorithms, have been employed to enhance traffic flow, reduce congestion, and improve overall transportation efficiency. Research has demonstrated the potential of these techniques to predict traffic patterns, optimize traffic signal timings, and implement adaptive traffic signal control using Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL), leading to significant reductions in congestion and emissions [8–10].
Despite these advancements, several gaps remain in the current research. Data quality and availability continue to be significant challenges, with many studies relying on specific data sources that may not provide a comprehensive view of traffic conditions [10]. Integrating diverse data sources into cohesive traffic management systems poses technical challenges, requiring sophisticated algorithms and robust ICT infrastructure [7]. Additionally, real-time data processing and scalability remain critical issues, as current systems often struggle with the vast amounts of data required for timely decision-making [6]. Furthermore, there is a need for more advanced traffic signal control systems that can adapt in real-time to dynamic traffic conditions [9].
This study aims to address these gaps by providing a systematic review of data-driven traffic management strategies for sustainable urban transport. The specific objectives are to:
1) Provide a comprehensive overview of the various data sources and analytics techniques employed in data-driven traffic management systems.
2) Analyze the effectiveness of these approaches in optimizing traffic flow while promoting environmental sustainability.

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3) Identify potential gaps and limitations in current traffic management optimization techniques specific to achieving sustainable urban transport.
4) Explore the challenges and opportunities of implementing data-driven strategies in real-world traffic management scenarios.
5) Highlight emerging trends and future directions in data-driven traffic management, including potential applications for next-generation transportation systems.

This study contributes to the growing body of literature on sustainable urban transport by synthesizing current knowledge and identifying areas for future research. By addressing the identified gaps, this research aims to enhance the effectiveness of data-driven traffic management strategies, thereby contributing to the development of more sustainable and efficient urban transportation systems. The findings have practical implications for policymakers, urban planners, and transportation authorities, providing evidence-based recommendations for implementing effective and sustainable traffic management strategies.

The rest of this paper is structured as follows: Section 2 describes the systematic review methodology, including the research questions, search strategy, and criteria for inclusion and exclusion of studies. Section 3 explores sustainability factors in traffic management, focusing on environmental, economic, and social dimensions. Section 4 discusses technical solutions for optimizing data-driven traffic management, highlighting predictive, adaptive, and optimization-based approaches. Section 5 reviews key applications of these solutions and examines case studies that demonstrate their effectiveness. Section 6 identifies gaps in current research and suggests future directions. Finally, Section 7 summarizes the main findings and provides recommendations for future research and policy directions.

2. SURVEY METHODS

This section outlines the systematic approach adopted to identify, select, and analyze relevant studies for this review on data-driven traffic management optimization for sustainable urban transport. The methodology includes a comprehensive search strategy, clear inclusion and exclusion criteria, and a detailed data extraction and analysis process.

2.1. Research Questions

Following the design science [11], the study starts with the general question" How can data-driven traffic management achieve sustainable urban transport?", which is subsequently divided into four Research Questions (RQs). The study ex- amines the available literature to address the research questions, summarizing and analyzing the data. Research questions include:

1) How do existing data-driven traffic management approaches consider environmental sustainability and emission re- duction goals within urban transport systems? (Addressed in 3.4).
2) What are the different data sources and analytics techniques used in data-driven traffic management strategies, and how do they contribute to optimizing traffic flow for sustainable urban transport? (Addressed in 4.3).
3) How can data-driven strategies be effectively implemented in real-world traffic management systems for sustainable urban transport? (Addressed in 5.5).
4) What are the limitations of current traffic management optimization techniques, and how might emerging trends and future directions address these gaps to achieve sustainable urban transport? (Addressed in 6.5).

2.2. Search Strategy and Database Selection

To ensure transparency and integrity in our systematic review, we strictly complied to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [12]. The PRISMA standard checklist facilitates the clear and thorough documentation of the systematic review process. This includes choosing studies, identifying the research focus, implementing a search strategy, extracting data, and summarizing findings. A systematic search was conducted across multiple academic databases including DBLP, IEEE Xplore, ScienceDirect, SpringerLink, Web of Science, and Google Scholar to ensure comprehensive coverage of the relevant literature. These databases were selected for their extensive coverage of engineering, computer science, and transportation research. The search was conducted between January and March 2024, covering publications from 2019 to 2024 to capture the most recent advancements in this rapidly evolving field. The search strategy employed a combination of keywords related to data-driven traffic management, such as "data-driven traffic management", "traffic optimization", "sustainable urban transport", "environmental sustainability in traffic management", "AI in traffic management", "traffic management", "data-driven", "machine learning", "intelligent transportation systems", and "urban traffic optimization". Boolean operators (AND, OR) were used to refine the search and combine different keywords effectively. The initial search yielded 487 potentially relevant studies for review.

2.3. Inclusion and Exclusion Criteria

To ensure the relevance and quality of the selected studies, the following inclusion and exclusion criteria were applied:

2.3.1. Inclusion Criteria

- Studies published in peer-reviewed journals or conference proceedings.
- Research focusing on data-driven approaches to traffic management.
- Studies addressing sustainability factors such as emission reduction, energy consumption, and pollution reduction.
- Papers published between 2019 and 2024 to capture the most recent advancements.

2.3.2. Exclusion Criteria

- Studies not available in English.
- Studies not directly addressing data-driven techniques or sustainability.
- Papers that did not provide empirical data or case studies.

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- Research focusing solely on non-urban settings or non-traffic-related issues.
- Papers with titles containing" cars,"" vehicles," or" autonomous vehicles" (focusing on broader urban transport)

Table 1: All Related Works and Their Catalogs

Dimensions	Approach/Category	Count	References
Sustainability Factors in Traffic Management	Environmental Impact	19	[8–10, 13–28]
	Economic Efficiency	14	[6, 8, 14, 15, 22, 23, 29–36]
	Social Aspects	12	[6, 14, 15, 17, 18, 20, 22, 30, 34, 37–39]
Data-Driven Traffic Management	Predictive Traffic Management	16	[6, 8, 10, 13, 15, 20, 25, 28–31, 38–42]
	Adaptive Traffic Management	12	[10, 15–17, 21–24, 26, 30, 34, 43]
	Optimization-Based Traffic Management	14	[14–17, 22, 28, 31–34, 44–47]
Applications in Data-Driven Traffic Management	Traffic Signal Control	13	[7–10, 15, 16, 24, 26, 29, 34, 35, 38, 43]
	Urban Passenger Transport	11	[6, 13–15, 17, 21, 27, 30, 33, 39, 48]
	Freight and Heavy Vehicle Management	8	[23, 31, 36, 37, 41, 44, 45, 47]
	Special Applications and Short-Term Traffic Management	7	[6, 17, 30, 34, 39, 49, 50]

2.3.3. Study Selection Process

The study selection process followed PRISMA guidelines and comprised multiple stages:

- Identification (n=487): The initial database search identified 487 potentially relevant articles based on the search strategy described above.
- Screening (n=363): After removing 124 duplicates, 363 unique studies underwent title and abstract screening. Two reviewers independently screened titles and abstracts against the inclusion criteria.
- Eligibility Assessment (n=89): Following title and abstract screening, 274 studies were excluded (not focused on data-driven approaches: n=156; insufficient sustainability focus: n=98; outside timeframe: n=20). The remaining 89 studies underwent full-text review for detailed eligibility assessment.
- Final Inclusion (n=43): After detailed full-text assessment, 46 studies were excluded for the following reasons: not focused on data-driven approaches (n=18), insufficient sustainability focus (n=15), not peer-reviewed or insufficient methodological detail (n=8), and not available in English (n=5). This resulted in 43 studies included in the final synthesis. The extracted data were categorized into three dimensions: sustainability factors, technical solutions, and Applications. This structured approach facilitated comprehensive analysis, ensuring that the research questions and objectives were thoroughly addressed. The grouping of the 43 studies across these dimensions is summarized in Table 1.

This comprehensive approach ensures that our research follows best practices in systematic literature review methodologies, which improves the study's rigor, transparency, and reliability. The inclusion and exclusion criteria were care- fully defined, and their implementation was meticulous, with strong and valid reasons. Fig.1 shows a comprehensive overview of the research framework presented in this paper. It includes every step of the work plan, from the preliminary planning stage to the literature review study's selection and exclusion criteria, and then the review and discussion of the findings. Furthermore, this figure emphasizes the scope of future work, providing a visual representation of the systematic approach used in this study.

2.4. Data Extraction and Analysis

The extracted data were systematically organized into three primary dimensions: sustainability factors, technical solutions, and applications. For each study, we extracted bibliographic details, study characteristics (geographic context, design, data sources), methodological approaches (AI/ML techniques, traffic management strategies), reported outcomes (sustainability metrics, performance improvements), and implementation details. The grouping of 43 studies across these dimensions is summarized in Table 1. For studies reporting quantitative outcomes, we extracted percentage improvements in emissions, congestion, energy consumption, and costs to provide a comprehensive view of demonstrated benefits.

2.5. Summary

This methodology ensures comprehensive database selection, clear inclusion/exclusion criteria, and systematic data extraction and analysis, providing a robust synthesis of data-driven traffic management optimization for sustainable urban transport. Subsequent sections address the research questions and objectives based on these findings.

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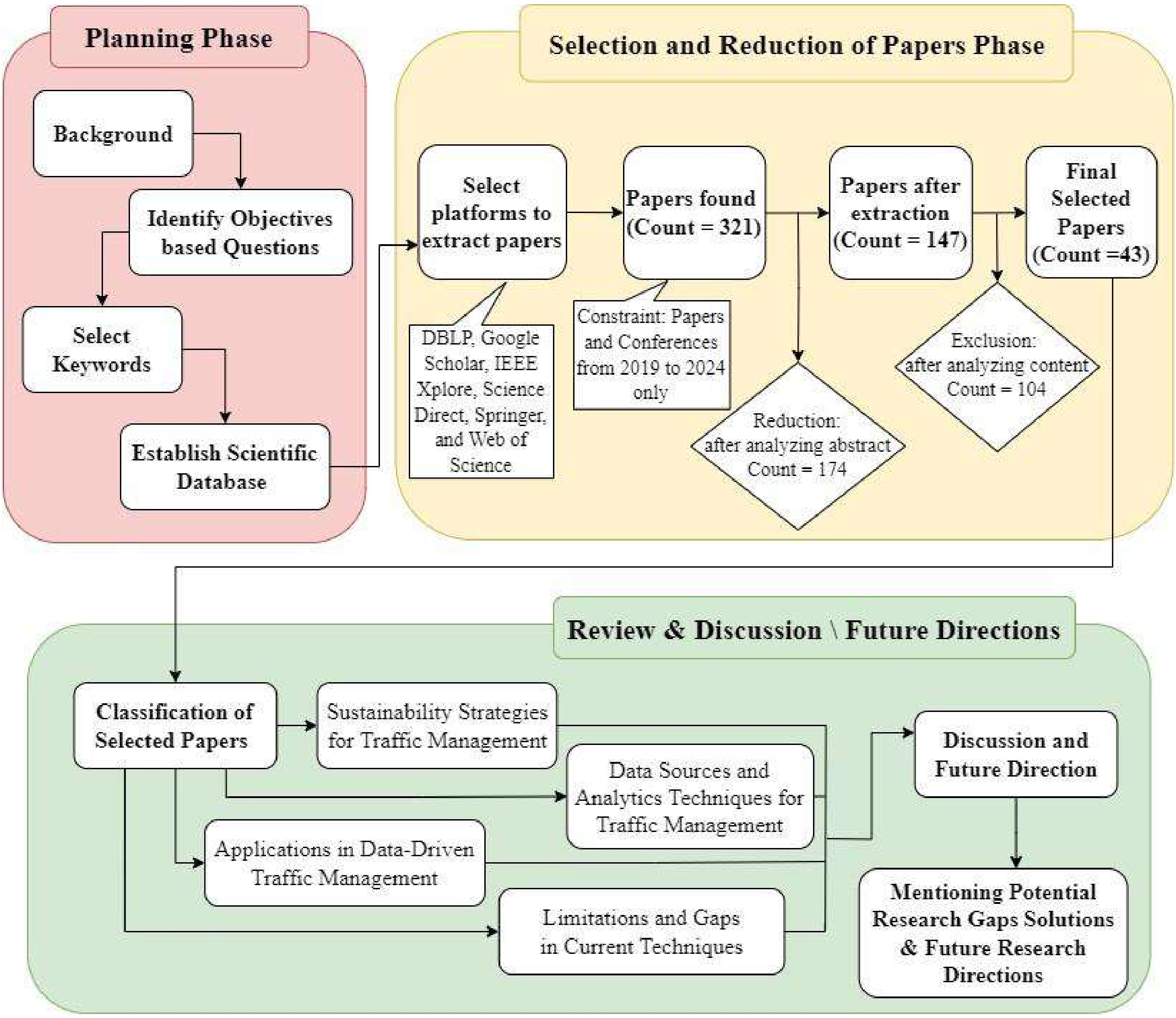

Figure 1: Research framework: A visual representation of the research framework based on PRISMA flow diagram, spanning from preliminary planning to selection criteria, review, and future work scope.

3. SUSTAINABILITY FACTORS IN TRAFFIC MANAGEMENT

This section discusses the various sustainability factors considered in data-driven traffic management. As shown in Fig.2, these factors are crucial for ensuring that urban transport systems optimize traffic flow while contributing to environ- mental, economic, and social sustainability. The factors were identified and categorized based on the reviewed studies, and this section examines how different traffic management strategies address these sustainability dimensions, providing relevant examples from the literature.

3.1. Environmental Impact

Minimizing the environmental impact of traffic is a central goal of sustainable urban transport, involving reducing emissions, pollution, and energy consumption - a major contributors to urban environmental degradation [16]. Data-driven traffic management strategies have emerged as effective tools for addressing these issues, leveraging machine learning, big data analytics, and IoT technologies to optimize traffic flow and decrease harmful environmental effects [51].

3.1.1. Emission Reduction

Emission reduction is critical for sustainable traffic management, with studies demonstrating significant decreases through optimized traffic flow and congestion mitigation [52]. Machine learning algorithms that dynamically adjust traffic signals have achieved substantial CO_2 reductions [8], while IoT and big data analytics enable real-time monitoring for lower emission levels across urban networks [6]. AI-based systems that adapt to real-time conditions reduce vehicle idling times [31], and integrating renewable energy sources into traffic infrastructure further decreases carbon footprints [25]. These data-driven techniques demonstrate substantial potential for creating cleaner urban environments. [31],

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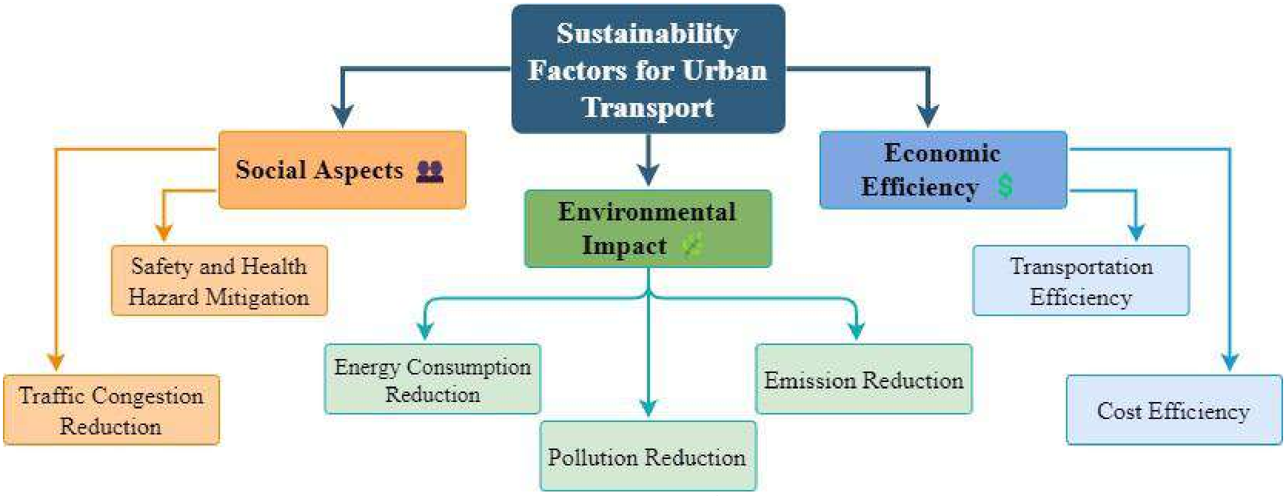

Figure 2: Sustainability Factors for Urban Transportation

3.1.2. Pollution Reduction

Reducing air and noise pollution is essential for sustainable traffic management. Optimizing traffic flow effectively reduces localized air pollution [8], while coordinated traffic signals decrease noise pollution and improve urban air quality [17]. Predictive modeling using deep learning forecasts pollution levels and adjusts traffic controls to mitigate hotspots [39], addressing health risks from traffic-related pollutants such as particulate matter and nitrogen oxides.

3.1.3. Energy Consumption Reduction

Optimizing energy consumption is essential for sustainability goals. Energy-efficient traffic signal control systems maintain traffic flow while reducing electricity consumption [24]. Integrating smart charging infrastructure for electric vehicles with traffic management systems decreases energy use during peak hours [28], contributing to a more sustainable urban energy profile.

3.1.4. Broader Environmental Impact Reduction

Comprehensive traffic management strategies integrate multiple sustainability measures. Long-term sustainable practices yield cumulative benefits including enhanced green infrastructure and improved air quality [18]. Combining various measures—eco-friendly vehicle technologies and green infrastructure—produces significant environmental gains [50], underscoring the need for holistic approaches to achieve broader sustainability objectives.

3.2. Economic Efficiency

Economic efficiency is another vital aspect of sustainable traffic management, aiming to reduce costs associated with traffic congestion and improve overall economic productivity in urban areas. Effective traffic management strategies can alleviate congestion, optimize resource use, and lead to substantial economic benefits by enhancing mobility and reducing the financial burdens of inefficient traffic systems [54].

3.2.1. Traffic Congestion Reduction

Reducing traffic congestion improves economic efficiency by decreasing lost time, productivity, fuel consumption, and vehicle maintenance costs [2]. Data-driven approaches yield considerable economic advantages. AI-driven predictive models optimizing signal timings achieve smoother traffic flow, reducing average travel time by 20% with significant cost savings for commuters and businesses [20]. Smart traffic management systems adapting to real-time conditions decrease peak-hour congestion, saving millions annually [47]. Integrated systems coordinating multiple transportation modes substantially improve traffic flow [36], while big data analytics dynamically managing congestion demonstrate 15% efficiency improvements [38]. Machine learning techniques predicting and alleviating traffic jams enhance efficiency and reduce economic losses [27]. These studies underscore the economic benefits of data-driven traffic management in reducing congestion and improving urban mobility.

3.2.2. Cost Efficiency

Improving cost efficiency minimizes congestion's financial burden and optimizes resource use, reducing costs for fuel consumption, vehicle wear, and infrastructure maintenance [53]. Big data-driven computational graph frameworks streamline processes, achieving up to 25% cost savings in traffic management operations [44]. AI-based optimization systems using edge computing reduce computational costs and enable faster response times [29]. Smart traffic solutions with automated adjustments based on real-time data substantially reduce management expenses [21], highlighting the importance of cost-efficient strategies for financial sustainability.

3.3. Social Aspects

Social aspects of sustainable traffic management focus on improving quality of life for urban residents by enhancing accessibility, safety, and public health [55]. Data-driven traffic management contributes to these goals through reduced congestion, improved air quality, and safer road conditions.

3.3.1. Transportation Efficiency and Safety

Efficient and safe transportation is key to sustainable cities [34]. Advanced technologies have shown real promise in achieving these goals. For example, [37] created an AI system that reduced accidents by 15% by predicting collisions and adjusting signals. Similarly, [48] found that Intelligent Transportation Systems (ITS) reduced accidents during peak hours through real-time traffic management. Machine learning has also helped improve safety by analyzing traffic patterns and adjusting controls, as seen in [30], where adaptive systems reduced crashes. Additionally, [34] explored how connected vehicle technology improves

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communication between cars and infrastructure, further enhancing safety.

3.3.2. Health Hazard Mitigation

Traffic-related pollution, like PM2.5 and nitrogen oxides, poses serious health risks, contributing to respiratory and heart problems [56]. Data-driven systems help reduce these risks by cutting down on pollution. For instance, [45] showed that smart traffic management reduced PM2.5 levels by 10%, improving air quality and public health. Likewise, [22] demonstrated that managing traffic flow reduces pollution during peak hours, highlighting the importance of integrating health-focused strategies into traffic management to protect public health and reduce healthcare costs.

3.4. Summary (RQ1)

This section addresses RQ1 by highlighting how data-driven traffic management is essential for environmental sustainability. By reducing emissions, pollution, and energy consumption, technologies like machine learning and real-time data analytics make traffic flow more efficient. While there are challenges with scaling these systems, they have the potential to significantly improve urban mobility and contribute to long-term environmental goals.

4. Technical Solutions for Data-Driven Traffic Management Optimization

As urban areas continue to grow, the complexity of managing traffic efficiently becomes increasingly challenging. Data-driven approaches have emerged as critical strategies for optimizing traffic management, providing insights that enhance decision-making processes [5]. These solutions leverage diverse data sources—such as traffic sensors, GPS data, IoT devices, and environmental conditions—to inform more intelligent traffic systems that improve flow, reduce congestion, and enhance safety.

Table 2: Data Types and Sources for Traffic Management Systems.

Data Types	**Sources**	**Key Characteristics**
Real-Time Traffic Data	Inductive loop detectors, GPS data, IoT sensors	Provides current traffic volumes, vehicle speeds, and incident data, crucial for dynamic traffic management.
Environmental Data	Weather stations, Road Weather Information Systems, air quality sensors	Monitors external factors such as weather and pollution that can affect traffic flow and safety.
Historical Traffic Data	Archived traffic flow data, congestion records, incident reports	Used for analyzing long-term traffic trends and building predictive models to forecast future conditions.
Vehicle-to-Infrastructure (V2I)	Smart traffic signals, roadside communication devices	Facilitates real-time communication between vehicles and infrastructure to optimize traffic flow and reduce fuel consumption.
Public Transportation Data	Public transit management systems, shared mobility platforms	Provides data on vehicle availability, routes, and passenger loads, contributing to the efficiency of multimodal transport systems.
Crowdsourced Data	Social media platforms, traffic apps	User-generated data offers real-time insights into incidents, road conditions, and traffic flow, complementing traditional sensor networks.

4.1. Data in Traffic Management

Effective traffic management relies on integrating data from multiple sources, enabling real-time monitoring, predictive analytics, and informed decision-making. The combination of various data types—such as traffic sensors, GPS data, and IoT devices—helps develop a comprehensive understanding of traffic patterns [57]. These insights allow for more adaptive and responsive traffic control systems, which are essential for improving traffic flow, reducing congestion, and enhancing road safety. Table 2 summarizes the main data types and their sources, highlighting the critical role each plays in modern traffic management systems.

Each of these data types contributes uniquely to enhancing traffic management by allowing systems to address different aspects of urban mobility. For instance, real-time traffic data enables adaptive signal control and rerouting during peak congestion periods, while historical traffic data allows urban planners to identify long-term trends that inform infrastructure improvements. Additionally, the use of environmental data ensures that external factors, such as adverse weather or high pollution levels, are accounted for in real-time traffic decisions.

The integration of these data sources is essential for developing a unified traffic management framework capable of real- time decision-making and long-term planning. Data fusion techniques, which combine information from different sources, play a key role in generating a more accurate and holistic view of traffic conditions. [21] discussed the benefits of data fusion in smart traffic management, noting that integrating real-time data with historical patterns improves traffic forecasts and system responsiveness.

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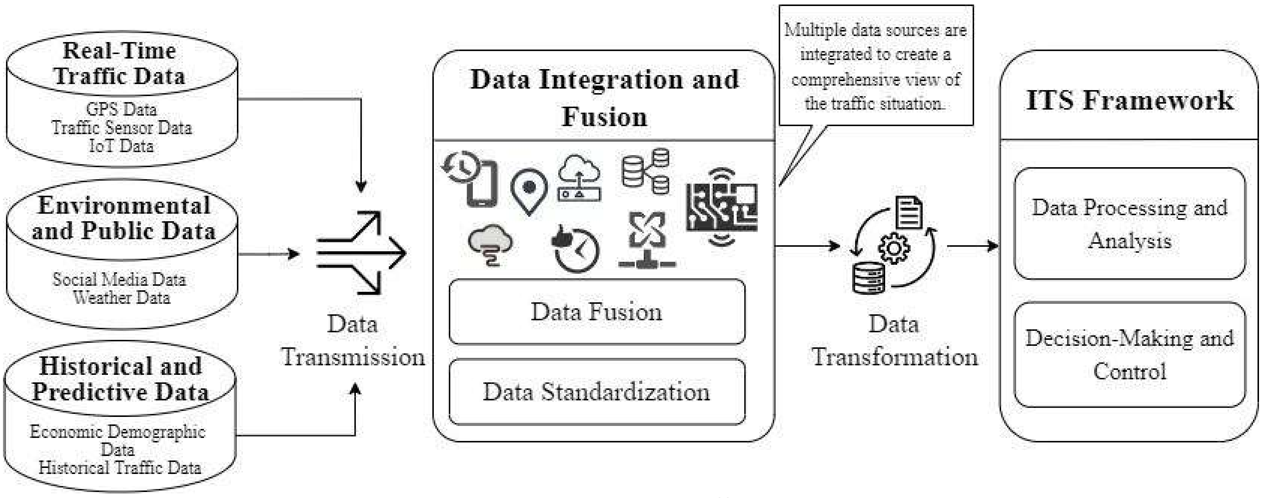

Figure 3: The Data Integration Framework Showcasing How Different Data Sources Are Combined and Utilized

Fig.3 illustrates the data integration framework used in ITS. The diagram shows how various types of data—including real-time, environmental, and historical data—are transmitted, standardized, and fused. This process creates a comprehensive view of the traffic situation, supporting decision-making processes such as adaptive signal control, route optimization, and incident management strategies. By harmonizing data from various streams, traffic management systems can dynamically adjust to changing traffic conditions, ensuring the effectiveness of traffic control measures even in rapidly evolving urban environments. [44] demonstrated that real-time data integration enables predictive models to adapt to traffic variations more effectively, thereby optimizing traffic flow, reducing congestion, and enhancing safety. The holistic approach illustrated in Fig.3 ensures that disparate data formats and sources are utilized effectively, providing actionable insights for decision-making processes within ITS.

4.2. Data-Driven Traffic Management Approaches

As cities grow and transportation needs increase, efficient traffic management becomes crucial. Traditional methods, relying on fixed signal timings and historical data, lack the flexibility needed for dynamic urban conditions. Data-driven approaches, using real-time data, predictive models, and optimization techniques, enable flexible decision-making that improves traffic flow, reduces congestion, and minimizes environmental impacts [58]. Below, we discuss key data-driven techniques, including predictive analytics and optimization algorithms.

4.2.1. Predictive Traffic Management

Predictive traffic management uses historical and real-time data to anticipate traffic conditions and proactively optimize flow. By forecasting congestion, adjusting signal timings, and suggesting alternative routes, these systems help avoid traffic issues before they escalate [58]. This is particularly useful in cities where dynamic factors like weather, accidents, and traffic demand constantly change mobility patterns.

Machine learning techniques, such as Long Short-Term Memory (LSTM) networks, excel in short-term traffic forecasting due to their ability to capture both long-term trends and short-term fluctuations. For instance, [50] found LSTM models to be more accurate than traditional time-series models like ARIMA in predicting congestion in urban areas, enabling real-time adjustments.

Convolutional Neural Networks (CNNs), typically used in image processing, have also been applied to predictive traffic management. By analyzing traffic data patterns, such as vehicle density at intersections, CNNs optimize signal timing and reduce waiting times, as demonstrated by [13]. These systems proactively adjust signals, minimizing delays.

The integration of diverse data sources—such as IoT sensors, GPS data, and environmental factors—further improves predictive accuracy. [44] showed that combining real-time data with historical patterns enhances the system's ability to adapt to evolving traffic conditions. This ensures traffic control measures remain effective in dynamic urban environments.

Predictive traffic management also supports environmental sustainability by reducing vehicle idling, fuel consumption, and emissions. [28] demonstrated that predictive systems in smart cities led to significant reductions in fuel use and carbon emissions by optimizing traffic signals and rerouting vehicles. These findings show how predictive models can improve both traffic efficiency and environmental sustainability.

By forecasting conditions and implementing preemptive measures, predictive traffic management enables cities to proactively address congestion, improve travel times, and reduce emissions, contributing to sustainable urban mobility.

4.2.2. Adaptive Traffic Management

Adaptive traffic management involves real-time adjustments to traffic systems in response to changing conditions. Unlike predictive systems, which forecast traffic patterns, adaptive systems continuously monitor traffic flow and adjust measures like signal timings, vehicle routing, and public transport schedules [58]. This approach is particularly useful in large cities where traffic can change unexpectedly due to accidents, road closures, or spikes in demand.

At the heart of adaptive traffic management is the ability to process real-time data from diverse sources, including IoT devices, cameras, and GPS. This enables systems to respond instantly to changing conditions, optimizing flow and minimizing delays. [29] highlighted how edge computing in adaptive systems reduces latency and speeds up decision-making, improving system responsiveness.

RL is one of the most effective techniques for adaptive traffic management. RL-based systems learn from real-time feedback and adjust behavior accordingly. [10] implemented an RL system in Nicosia, which dynamically adjusted signal timings, leading to shorter wait times and better fuel efficiency—demonstrating RL's potential to improve both traffic flow and sustainability.

Multi-agent systems, where each signal operates independently and communicates with others to optimize flow, are also key to adaptive traffic management. [15] applied multi-agent RL to manage traffic in large urban areas, showing that decentralization allows for scalability and better performance in complex networks. These systems reduce the computational complexity of centralized control systems.

The environmental benefits of adaptive traffic management are significant. By reducing congestion and optimizing signal timings, these systems lower vehicle idling times, cut fuel consumption, and reduce emissions. For example, [9] found that an RL-based system reduced CO2 emissions by 8.1% and decreased delays by 34%. These findings highlight how adaptive traffic management contributes to sustainable urban mobility.

Adaptive traffic management provides a dynamic solution for real-time traffic management. Techniques like RL and multi-agent systems can quickly respond to changes in traffic conditions, enhancing efficiency and supporting sustainability by lowering emissions and fuel consumption.

4.2.3. Optimization-Based Traffic Management

Optimization-based traffic management tackles complex, multi-objective problems in urban transport, such as reducing congestion, travel times, and emissions, while accounting for environmental and operational constraints. This approach uses advanced algorithms to dynamically adjust traffic measures, offering efficient solutions in changing traffic conditions, especially in urban areas with fluctuating demands.

Heuristic optimization methods like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are widely used in traffic management due to their ability to handle large solution spaces and balance multiple goals. For example, [22] used GA to optimize traffic signal timings, reducing travel times and fuel consumption by evolving strategies based on natural selection principles. This iterative process allows GA to adapt effectively to dynamic traffic systems, outperforming traditional methods.

PSO, inspired by the collective behavior of swarms, is another key technique. In PSO, each "particle" represents a potential solution, adjusting its position based on the best-performing solutions in the group. [22] showed that PSO optimized vehicle routing and signal control, leading to reductions in fuel consumption and emissions. PSO's ability to quickly adapt to changing traffic makes it ideal for real-time applications.

Multi-objective optimization is essential for balancing competing goals like travel time, emissions, and energy consumption. [39] applied a multi-objective framework during large public events, optimizing road occupancy, reducing travel times by 37.7%, and cutting emissions by 89.6%, demonstrating the potential of this approach to handle traffic surges while minimizing environmental impacts.

Dynamic traffic routing, where routes are adjusted based on real-time data, helps avoid congested areas and improves traffic flow. [23] implemented this in last-mile logistics, improving delivery efficiency and reducing fuel use by optimizing routes in real-time. This contributes to more sustainable urban logistics by minimizing travel distances and emissions.

The sustainability benefits of optimization-based traffic management are substantial. By optimizing signals, routing, and schedules, these systems reduce idling, fuel consumption, and emissions. [39] demonstrated a significant reduction in emissions during special event management, while [22] found that GA and PSO methods enhanced both environmental and operational sustainability.

Optimization-based traffic management offers a robust solution to urban traffic challenges, using advanced algorithms to improve flow, reduce environmental impacts, and optimize resource use.

Table 3: A Detailed Comparison of The Three Data-Driven Traffic Management Approaches

Approach	**Data Sources**	**Method**	**Impact to Sustainability**	**Limitations**	**Key Studies**
Predictive Traffic Management	Historical traffic data, real-time sensor data, IoT, GPS, weather data	Time-series models, Machine Learning Data Fusion	Reduced congestion, lower fuel consumption, improved travel times, decreased emissions	Struggles with non-linear traffic dynamics, requires large datasets for machine learning	[28, 42, 44, 50]
Adaptive Traffic Management	Real-time traffic data, weather data	RL, DRL, Multi-agent systems, Edge computing	Reduced waiting time, fuel consumption, and CO2 emissions, real-time adaptability	High computational complexity, scalability issues in large urban networks	[9, 10, 15]
Optimization-Based Traffic Management	Real-time traffic data, sensor data, GPS, environmental data	Heuristic Optimization, Multi-objective Optimization	Optimized vehicle routing, reduced travel times and emissions, improved public transport schedules	Optimization complexity grows with network size, trade-offs between objectives	[22, 23, 33, 39]

Optimization-based traffic management offers a robust approach for addressing complex traffic challenges by utilizing advanced algorithms to achieve efficient traffic control. These methods support sustainability goals by improving traffic flow, minimizing environmental impacts, and optimizing resource use in urban mobility systems.

The various traffic management approaches discussed in this section offer diverse strategies to address urban traffic challenges. To provide a clearer comparison, Table 3

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provides a detailed comparison of the three data-driven traffic management approaches; Predictive, Adaptive, and Optimization-Based, highlighting their data sources, methods, impact on sustainability, limitations, and key studies.

Fig.4 depicts the ITS framework, which incorporates data processing, analysis, and decision-making to facilitate traffic management. This framework utilizes integrated data from various sources, including real-time traffic data, environmental factors, and historical patterns, to support different traffic management approaches. The data-driven insights generated by this system allow for adaptive and predictive traffic control, optimizing signal timings, routing, and resource allocation in response to changing conditions.

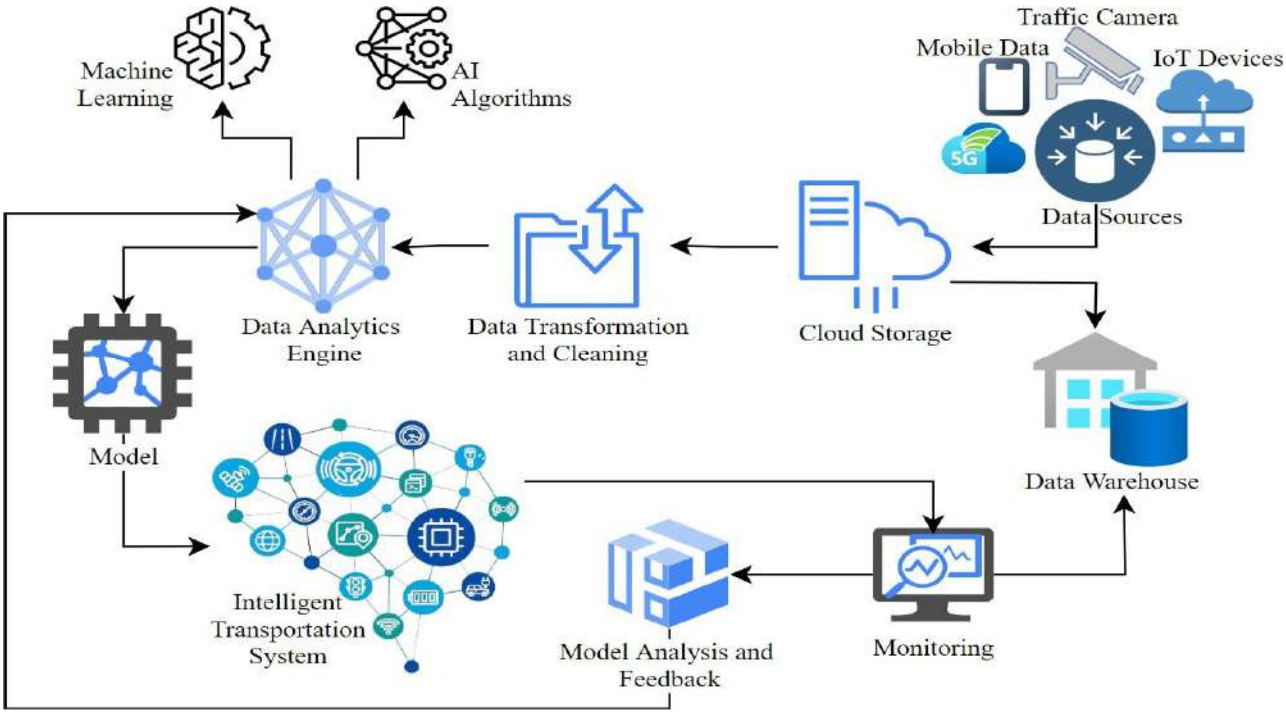

Figure 4: The Framework for ITS for Data-Driven Traffic Management, Depicting The Integration Of Various Data Sources, Analytics Engines, And AI Algorithms To Optimize Traffic Systems.

4.3. Summary (RQ2)

This section addresses RQ2 by examining the diverse data sources and analytics techniques that underpin data-driven traffic management and their impact on optimizing traffic flow for sustainable urban transport. Techniques such as predictive modeling, adaptive traffic systems, and optimization algorithms leverage data from traffic sensors, GPS, and IoT devices, enabling real-time adaptability and improved decision-making. These strategies have shown effectiveness in improving traffic efficiency and reducing environmental impacts. However, challenges in multi-source data integration and achieving real-time scalability indicate areas for further research. This section underscores how data-driven approaches enhance urban mobility and contribute to sustainable transport systems through informed, data-supported optimizations.

5. Applications in Data-Driven Traffic Management

This section explores how data-driven strategies improve sustainable urban traffic management, focusing on traffic signal control, urban passenger transport, freight and heavy vehicle management, and short-term traffic adaptations. Each subsection highlights real-world applications that improve traffic efficiency, reduce emissions, and enhance mobility.

5.1. Traffic signal control

Traffic signal control is vital for reducing congestion, emissions, and enhancing safety [53]. Traditional fixed-timing signals no longer meet the needs of modern urban traffic, prompting cities to adopt dynamic, data-driven approaches [59].

RL has emerged as an effective solution for real-time optimization of signal timings. [43] demonstrated the success of RL in Orlando, Florida, where a Deep Q Network (DQN) system reduced vehicle wait times by 18–53% and decreased traffic conflicts by 19–25% across nine intersections. RL's flexibility extends beyond travel time optimization; for example, [10] integrated RL algorithms like Q-Learning and SARSA to optimize signals while minimizing CO_2 emissions, addressing both traffic efficiency and sustainability.

A multi-agent RL system, where agents communicate across intersections, further improves scalability and adaptability. Unlike single-agent systems that optimize signals at one intersection, multi-agent systems optimize traffic flow across an entire network. Fig 5 illustrates the difference between single-agent and multi-agent RL frameworks for traffic signal control. [9] found that RL systems in Nicosia reduced queue lengths by 17.7% and CO_2 emissions by 8.1%, outperforming traditional fixed-timing methods. Additionally, multi-agent RL systems have shown improved training stability and network capacity, especially in dynamic regions [60].

However, RL-based signal optimization has challenges. Training agents in large networks is computationally demanding, and real-time data inaccuracies can affect system

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performance. Hybrid approaches, combining RL with techniques like genetic algorithms, aim to enhance robustness and adaptability.

Real-world applications demonstrate RL's potential. In Nicosia, RL systems improved traffic flow and reduced delays, while [16] implemented an RL system in Naples that reduced congestion and emissions, showcasing RL's ability to create adaptive and sustainable urban traffic solutions.

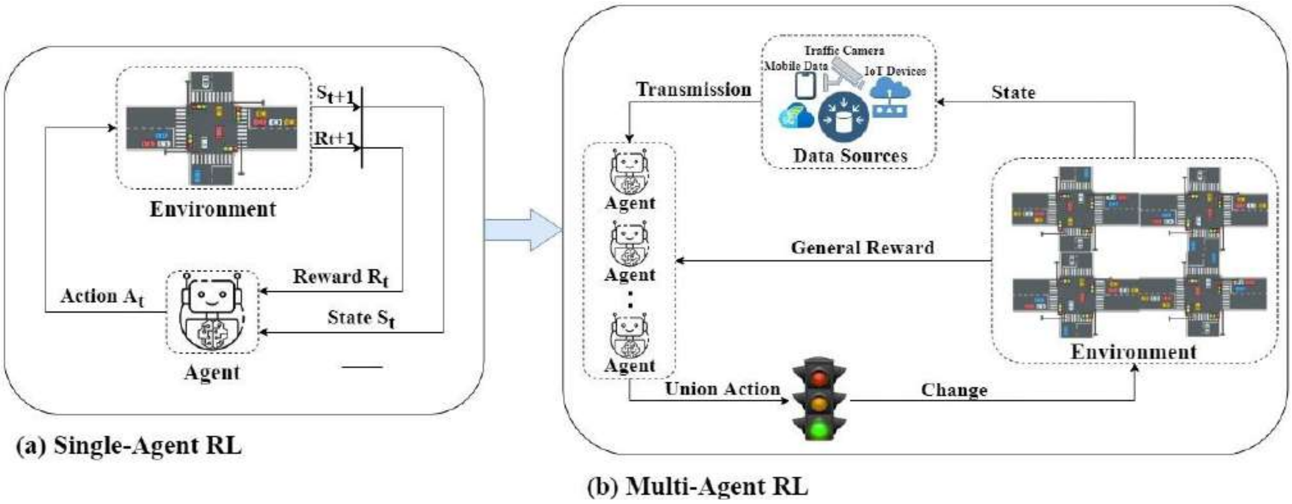

Figure 5: Single-Agent Vs. Multi-Agent RL Framework for Traffic Signal Control.

5.2. Urban Passenger Transport

Efficient urban passenger transport management—including buses, trams, and shuttles—is essential for reducing traffic congestion, lowering emissions, and improving passenger satisfaction [5]. Data-driven optimization and predictive techniques enhance public transport by improving scheduling, routing, and multi-modal network coordination to meet changing mobility demands [51].

A key method for optimizing transport is multi-objective optimization, which balances factors like reducing wait times, minimizing fuel consumption, and lowering emissions. For example, in Qingdao, China, a multi-objective optimization model improved bus scheduling efficiency by 23.7% while cutting emissions, contributing to the city's sustainability goals [33]. This approach addresses competing objectives, such as maximizing bus capacity and minimizing operational costs, leading to a more efficient and sustainable transport system.

Optimization has also been applied to improve last-mile shuttle services. In Shanghai, a data-driven framework used bicycle-sharing data to identify demand hotspots and dynamically adjust shuttle routes [30]. By incorporating Genetic Algorithms (GA) into the route optimization process, the system improved operational profits by 12-15% and reduced energy consumption, demonstrating the potential for data-driven optimization in last-mile connectivity and reducing the environmental impact. Figure 6 illustrates a data-driven framework for shuttle service design, which integrates multi-source data collection, cost-benefit analysis, and route optimization to enhance sustainable urban mobility.

Predictive models also play a vital role in adapting to real-time demand. In Naples, Italy, a machine learning-based system optimized bus schedules by predicting daily demand fluctuations [16]. This system dynamically adjusted bus dispatch times, reducing waiting times and improving punctuality, especially during off-peak hours. This optimization reduced fuel consumption, highlighting the dual benefits of improved efficiency and sustainability. While these data-driven approaches have shown success, challenges remain. Multi-objective optimization requires significant computational resources, and integrating real-time data from IoT sensors and GPS can lead to issues with data consistency and reliability, particularly in cities with emerging data infrastructures.

Despite these challenges, cities like Qingdao, Shanghai, and Naples demonstrate how data-driven strategies can transform urban mobility by optimizing schedules, adjusting routes dynamically, and integrating real-time data, improving service efficiency and sustainability

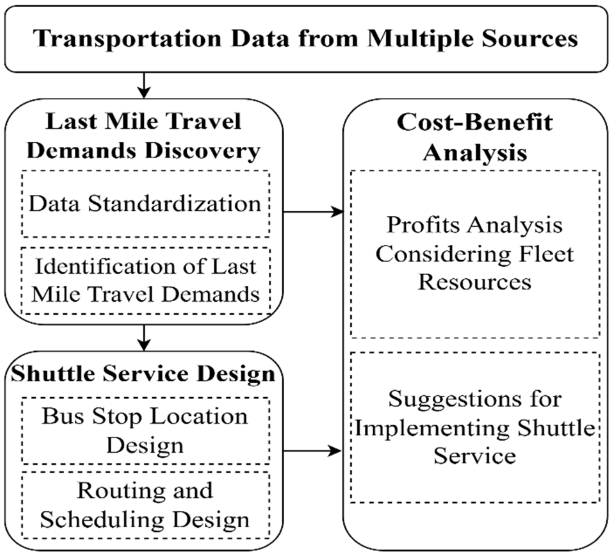

Figure 6: Data-Driven Framework for Shuttle Service Design

5.3. Freight and Heavy Vehicle Management

Managing freight traffic and heavy vehicles in urban areas is a major challenge, as these vehicles contribute to congestion, emissions, and road wear [53]. Traditional methods often struggle to adapt to changing conditions, leading to inefficiencies. Data-driven optimization techniques, such as

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predictive modeling and IoT-enabled systems, offer significant potential to improve the efficiency and sustainability of freight management.

One approach involves using IoT systems to optimize last-mile logistics by integrating real-time traffic data with machine learning. In Singapore, an IoT-based system adjusted delivery routes dynamically to avoid congestion, reducing travel distances by 5.5% and lowering delivery costs by 11% [23]. By continuously monitoring traffic with IoT sensors and GPS, the system minimized fuel use and emissions, aligning with environmental goals.

AI-driven systems also help optimize heavy vehicle movement in urban areas. In Italy, an AI system analyzed historical and real-time data to optimize delivery schedules, reducing stops and delays [36]. This approach improved fuel efficiency and reduced CO2 emissions by forecasting traffic conditions and adjusting routes. This demonstrates how predictive management benefits both the environment and operations.

Despite these successes, challenges remain. Real-time data from IoT sensors, GPS, and traffic cameras requires substantial computational resources. Data accuracy is also critical; any delays or inaccuracies can lead to poor routing decisions, which affect system performance [21].

Studies show that data-driven approaches outperform traditional methods in freight management. AI systems have led to notable reductions in travel times and emissions compared to conventional methods [10]. Optimization techniques, such as genetic algorithms, have been successfully used to improve route planning and minimize fuel consumption [22].

Data-driven methods offer substantial opportunities to enhance urban freight logistics, reducing emissions and operational costs. However, overcoming challenges related to data processing, real-time accuracy, and infrastructure investment is key for broader implementation.

5.4. Special Applications and Short-Term Traffic Management

Urban traffic management faces unique challenges during events and short-term surges, such as festivals, sports events, accidents, road closures, or peak-hour congestion. These situations can overwhelm infrastructure, causing delays and increased emissions [2]. Data-driven approaches, including multi-objective optimization, RL, and predictive modeling, effectively address these dynamic conditions.

Multi-objective optimization helps manage traffic during large events by balancing objectives like minimizing travel times, reducing road occupancy, and lowering emissions. In Tianjin, China, a multi-objective model improved travel times by 37.7% and reduced road occupancy by 89.6% during festivals and sports events [39], demonstrating how data-driven strategies can relieve pressure on urban infrastructure during high-demand periods.

RL is another valuable tool for managing short-term traffic fluctuations. In Orlando, Florida, a DQN-based system dynamically adjusted signal timings based on real-time data, reducing wait times at intersections and improving flow [43]. This flexibility is crucial for handling traffic surges due to accidents or sudden congestion.

Predictive modeling also plays a key role in managing congestion by enabling proactive measures. In Buxton, UK, an IoT-enabled system predicted congestion points with 95% accuracy, allowing city planners to reroute traffic in advance and prevent delays [20], thus enhancing urban mobility.

Despite their success, these approaches face challenges. Timely and accurate data is crucial, as delays or inaccuracies can hinder their effectiveness. Additionally, multi-objective optimization requires significant computational resources to process large data volumes and make real-time decisions [21]. Hybrid approaches combining RL, predictive modeling, and optimization are emerging as solutions to enable real-time adaptations while balancing multiple objectives.

Data-driven methods like multi-objective optimization, RL, and predictive modeling show strong potential in managing traffic during special events and short-term surges. They help optimize flow, reduce congestion, and support urban mobility in dynamic environments. However, addressing challenges related to data accuracy, computational demands, and scalability is key for successful implementation.

5.5. Summary (RQ3)

This section addresses RQ3 by examining the practical application of data-driven strategies in urban traffic management. It highlights how RL improves signal timing, predictive modeling enhances public transportation planning, and multi-objective optimization helps with real-time event routing, reducing traffic and pollution. IoT-based systems optimize freight routing, contributing to sustainable urban mobility. While these strategies show great potential, broader adoption requires overcoming challenges like data accuracy, computational needs, and scalability. The findings highlight promising approaches to sustainable and efficient urban mobility through data-driven traffic management.

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Table 4: Comparative Analysis of Data-Driven Traffic Management Approaches Across Urban Applications

Approach	Adaptability	Scalability	Sustainability	Data Requirements	Challenges	Study
RL	Highly adaptable for real-time decision-making, can adjust to traffic fluctuations	Limited scalability in large networks due to high computational costs	Moderate to high impact: significant reduction in emissions and fuel consumption	High: Requires continuous real-time data from multiple sensors	Computational complexity, high data requirements, real-time data transmission challenges	[9, 10]
AI-Driven Predictive Models	Low adaptability for real-time changes; better suited for proactive congestion forecasting	Good scalability for large urban networks but requires extensive data integration infrastructure	High impact: Reduced emissions through proactive traffic management	High: Requires large historical and real-time datasets, data integration challenges	Scalability issues as the network expands, data integration complexity	[40]
Multi-Objective Optimization	Moderate adaptability: effective for balancing multiple objectives in fixed scenarios like public transport	Good scalability in transport systems but can be resource-intensive for large-scale optimization	High impact: Significant reduction in emissions and fuel use	Moderate: Requires real-time inputs but can struggle with complex data sets and competing objectives	Complex to balance conflicting goals (e.g., travel time vs. emissions), high computational demands	[33]
Genetic Algorithms	Moderate adaptability for dynamic routing adjustments, but slower than RL for real-time changes	Good scalability, though computationally expensive for very large networks	Moderate impact: Some reduction in fuel consumption and operational efficiency improvements	Moderate: Handles real-time data but requires predefined objectives	Optimization complexity in real-time environments, challenges in handling large data volumes	[30]
AI-Driven Systems for Freight	Low adaptability for real-time changes; better suited for optimizing freight delivery schedules	Moderate scalability: suitable for freight management, but requires infrastructure for real-time tracking	Moderate impact: Reduced emissions through optimized routing and delivery schedules	High: Complex data sets from IoT, GPS, and traffic sensors	Data integration, scalability in highly congested urban areas	[36]
IoT-Enabled Systems	High adaptability: Can make real-time routing adjustments based on live traffic data	High scalability, especially when integrated with urban IoT infrastructure	High impact: Reduced emissions through optimized routing and improved last-mile logistics	High: Requires extensive real-time sensor data, GPS, and traffic data	Data transmission delays, high infrastructure costs	[21,23]
Multi-Objective Optimization for Special Events	Moderate adaptability: effective in fixed high-demand scenarios like large events but limited in rapidly changing environments	Good scalability: can manage large traffic surges during events but struggles with real-time fluctuations	High impact: Significant reduction in congestion and emissions during events	High: Requires real-time event-based data and forecasts	Requires high computational power for real-time optimization, reliant on accurate traffic predictions	[39]
DQN-Based RL System for Short-Term Surges	Highly adaptable: excels in responding to short-term traffic fluctuations (e.g., accidents, surges)	Limited scalability in larger networks, requires substantial computational power	High impact: Reduces emissions by dynamically adjusting signals in real time	High: Relies on continuous real-time data from multiple sources	Data availability, real-time adaptation challenges in larger networks	[43]
IoT-Enabled Prediction Systems	High adaptability: can predict bottlenecks and make proactive adjustments based on traffic conditions	High scalability: Suitable for large-scale urban environments	High impact: Reduced emissions through proactive rerouting	High: Needs reliable IoT sensor networks and accurate traffic forecasts	Data synchronization and accuracy in large networks	[20]

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6. Research Gaps and Potential Solutions

Despite advances in data-driven traffic management, several gaps remain, particularly in the areas of scalability, real-time data processing, and long-term sustainability. Addressing these gaps is crucial for improving the overall efficiency and resilience of urban transport systems.

6.1. Synthesis of Current Evidence

Our systematic review of 43 studies reveals substantial but highly variable reported benefits across different sustainability dimensions. Studies reported congestion reductions ranging from 8% to 45% (mean: 24%, median: 22%), CO_2 emissions reductions from 5% to 58% (mean: 29%, median: 25%), energy savings from 10% to 35% (mean: 19%, median: 18%), and cost savings from 12% to 38% (mean: 22%, median: 20%). This wide variability reflects differences in study contexts (urban morphology, baseline traffic conditions, existing infrastructure), methodological approaches (simulation-based vs. real-world testing, different algorithmic techniques), intervention types (signal optimization, routing, comprehensive traffic management systems), and measurement approaches (different simulation models, evaluation periods, metrics).

The heterogeneity underscores that data-driven traffic management effectiveness is highly context-dependent, and solutions optimized for one setting may require substantial adaptation for others. Notably, the predominance of simulation-based approaches across the reviewed literature suggests that while theoretical potential is well-demonstrated, more real-world validation studies are needed to build confidence in practical applicability and to understand how simulated benefits translate to operational deployments. These findings inform the research gaps and future directions discussed below, highlighting areas where the field must advance to realize the full potential of data-driven traffic management for sustainable urban transport.

6.2. Scalability of AI and Machine Learning Models

As urban areas grow and traffic networks become more complex, scaling AI-driven traffic management systems presents significant challenges. With increasing city intersections and traffic volumes, AI techniques, particularly RL, face limitations in managing real-time, city-wide traffic. Large-scale systems with many intersections can create computational bottlenecks, slowing down responses and reducing efficiency. Studies by [38, 43] show that while RL models perform well in isolated cases, extending them to larger networks poses challenges.

One solution to these computational constraints is hybrid traffic management frameworks combining rule-based systems and machine learning. In this setup, rule-based systems handle predictable conditions, such as off-peak traffic, while RL models are reserved for dynamic situations like traffic surges or accidents. This division allows RL to be used more efficiently, reducing computational strain and prioritizing resources only when needed. As suggested by [10], hybrid frameworks balance stability and adaptability, addressing traffic fluctuations without overwhelming the system.

Distributed RL further improves scalability by dividing control across city regions, each managed by an independent RL agent. This decentralized approach allows agents to optimize traffic in their areas while coordinating with neighboring agents. [15] demonstrated this with a scalable RL framework that reduces congestion by allowing agents to operate independently while sharing updates for broader network coordination. This split of responsibilities makes large-scale systems more feasible, even in densely populated cities.

Federated learning offers another advancement for scalability. This method keeps data local, on devices like traffic sensors and IoT nodes, instead of sending it to a central server. Local models are trained with region-specific data, and only the updates are sent to the central server, reducing data transfer and improving privacy. [21] highlighted the benefits of federated learning for decentralized urban mobility, noting its scalability and enhanced data privacy.

By leveraging hybrid frameworks, distributed RL, and federated learning, traffic management systems can become more scalable and resilient. These techniques help systems adapt to varying regional demands, balance computational loads, and provide real-time, data-driven solutions to urban traffic challenges. This makes AI-driven traffic management systems better equipped to enhance mobility and reduce congestion in modern cities.

6.3. Real-Time Data Processing and Decision-Making

Building on scalable frameworks, real-time data processing is crucial for dynamic, adaptive traffic management. As urban traffic networks grow and become more complex, the volume of data from traffic sensors, cameras, and other sources increases exponentially. Efficiently managing this real-time data is vital for optimizing traffic flow and responding to events like accidents, congestion, and surges. However, many existing systems rely on centralized data processing, which struggles to handle such vast amounts of real-time data. This limitation leads to delays and reduces the system's adaptability, compromising overall traffic management effectiveness [15, 39].

A hybrid approach that combines predictive AI models with RL provides a powerful solution. Predictive models forecast traffic patterns, while RL agents make dynamic adjustments in real time, allowing the system to proactively respond to anticipated conditions and adapt to unexpected events. This approach is also essential for demand-responsive last-mile solutions, such as shuttles and micro-transit services, which optimize routes based on peak demand, supporting smoother transitions between transit hubs and final destinations [21].

The process begins with data collection from sensors and cameras. Predictive AI models analyze this data to forecast traffic patterns, allowing the system to adjust signal timings before congestion occurs. Simultaneously, RL agents monitor real-time data, adjusting signals dynamically in response to traffic fluctuations, such as accidents or sudden congestion. This combination of proactive forecasting and real-time adaptation ensures efficient and responsive traffic management.

Predictive AI models, especially Long Short-Term Memory (LSTM) networks, anticipate traffic conditions and adjust signals in advance to prevent congestion, reducing the need for last-minute interventions. On the other hand, RL enables

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real-time adaptations. RL agents adjust signals based on current traffic conditions and respond to unexpected events, such as accidents or road closures, to minimize delays.

By integrating predictive AI for forecasting and RL for real-time control, this hybrid approach significantly improves traffic management systems, making them more efficient, adaptive, and responsive to the unpredictable nature of modern urban traffic.

6.4. Integration of Diverse Data Sources

Integrating diverse data sources is crucial for enhancing real-time decision-making in urban traffic management. Modern cities generate vast amounts of data from traffic sensors, GPS devices, IoT networks, and social media platforms. While each source provides valuable insights, the lack of integration across these data streams limits the effectiveness of traffic management systems. Without combining these datasets, systems struggle to offer comprehensive, real-time analyses, which hampers the development of adaptive control strategies.

Incorporating social media and crowdsourced data alongside traditional sensors and GPS enhances adaptability during events like public gatherings or unexpected incidents. These additional sources can provide early warning of congestion hotspots, enabling proactive traffic management. Furthermore, transfer learning allows cities with limited historical data to leverage models trained in similar environments, facilitating accurate forecasting and adaptive responses, even in data-scarce regions [25].

To address these challenges, advanced data fusion algorithms are essential. These algorithms integrate real-time and historical data, boosting the predictive capabilities of traffic systems. A cloud-based platform could serve as the backbone for this fusion, handling large-scale data integration while maintaining flexibility [17]. By implementing this solution, traffic management systems can provide more accurate predictions, optimize traffic flow dynamically, and respond more effectively to external factors like weather or accidents, ultimately contributing to more resilient and sustainable urban transport systems.

6.5. Long-Term Sustainability Assessments

While data-driven traffic management has shown short-term benefits, such as reducing congestion and emissions, there is a significant gap in long-term sustainability assessments. Current studies often overlook the broader impacts of these systems on urban environments, infrastructure durability, and energy consumption. Without evaluating these long-term factors, traffic management solutions may fail to align with sustainability goals.

To address this, future studies should incorporate comprehensive sustainability assessments that evaluate the impact of traffic management over extended periods. These assessments should include environmental impact, energy use, infrastructure costs, and their role in urban development plans. By considering these factors, traffic systems can align with long-term urban planning, ensuring that short-term improvements don’t compromise future sustainability. This approach will support solutions that not only meet immediate mobility needs but also enhance the long-term resilience and sustainability of urban transport systems.

Addressing these gaps will improve the efficiency, adaptability, and sustainability of data-driven traffic management systems. By resolving challenges like data integration, scalability, real-time processing, and long-term impact assessments, cities can build urban transport systems that meet the needs of growing populations while supporting sustainable development.

6.6. Summary (RQ4)

Emerging trends in traffic management tackle key limitations in current systems, advancing sustainable urban transport. Traditional models struggle with scalability, real-time data processing, and comprehensive data integration, reducing their effectiveness in complex urban networks. Hybrid models that combine rule-based systems with RL are improving scalability, while distributed RL frameworks enhance resource management in large cities. Integrating predictive models with RL improves real-time responsiveness, allowing systems to anticipate and adapt to changes. Multi-source data integration—from IoT to social media—fills gaps left by isolated data streams, enabling systems to respond to non-recurring events. Future research must focus on long-term sustainability by including environmental and infrastructure metrics to ensure systems support both immediate needs and urban resilience. These innovations offer comprehensive solutions, aligning traffic management with the goals of sustainable urban mobility.

CONCLUSION

This systematic review analyzes data-driven traffic management strategies aimed at advancing sustainable urban transport. It highlights the transformative potential of artificial intelligence, machine learning, and data analytics in addressing key urban challenges like congestion, emissions, and energy consumption. Organized around four research questions, the review synthesizes findings across three key areas:

- Sustainability in Traffic Management: Reducing environmental impact, improving economic efficiency, and providing social benefits are crucial for sustainable urban transport. AI-driven strategies show promise in reducing emissions, easing congestion, and improving efficiency. However, scalability and infrastructure readiness remain challenges that limit their broader impact.
- Data-Driven Techniques for Traffic Management: Case studies demonstrate the success of data-driven solutions like adaptive signal control using RL and IoT-enabled monitoring in smart cities. These systems improve traffic flow, reduce emissions, and enhance mobility. However, scalability and high implementation costs remain significant barriers.
- Applications in Real-World Urban Contexts: Comparative analyses of real-world applications highlight the benefits and limitations of data-driven traffic strategies. Integrated approaches combining various techniques show improved adaptability and efficiency, especially in diverse urban settings.

To advance sustainable traffic management, this review recommends developing robust data integration systems, exploring scalable AI models for real-time management, and establishing frameworks for long-term sustainability assessments. Incorporating emerging technologies such as autonomous vehicles and IoT can further optimize traffic management and support urban sustainability goals.

This review highlights that while data-driven approaches show promise, challenges related to scalability and operation must be addressed. Continued research is crucial to transition to smarter, more sustainable urban transportation systems

REFERENCES

[1]Othman B, De Nunzio G, Di Domenico D. Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation. Annual Reviews in Control. 2019. 48:292–311 [DOI: https://doi.org/10.1016/j.arcontrol.2019.09.003]

[2]Afrin T, and Yodo N. A survey of road traffic congestion measures towards a sustainable and resilient transportation system. Sustainability. 2020. 12(11) [DOI:10.3390/su12114660]

[3]Butler L, Yigitcanlar T, and Paz A. Smart urban mobility innovations: A comprehensive review and evaluation. IEEE Access. 2020. 8:196034–196049 [DOI:10.1109/ACCESS.2020.3034596]

[4]Goldman T, and Gorham R. Sustainable urban transport: Four innovative directions. Technology in Society. 2006. 28(1):261–273 [DOI: https://doi.org/10.1016/j.techsoc.2005.10.007] sustainable Cities

[5]Mahrez Z, Sabir E, Badidi E. Smart urban mobility: When mobility systems meet smart data. IEEE Transactions on Intelligent Transportation Systems. 2022. 23(7):6222–6239 [DOI:10.1109/TITS.2021.3084907]

[6]Dalal S, Seth B, Radulescu M. Optimized Deep Learning with Learning without Forgetting (LwF) for Weather Classification for Sustainable Transportation and Traffic Safety. Sustainability. 2023 3. 15(7):6070 [DOI: 10.3390/su15076070]

[7]Ismaeel AG, Mary J, Chelliah A. Enhancing Traffic Intelligence in Smart Cities Using Sustainable Deep Radial Function. Sustainability. 2023 10. 15(19):14441 [DOI:10.3390/su151914441]

[8]Chen L, Anandhan P, and S B. Analysis of performance-based issues in green transportation management systems in smart cities. EL. 2020 12. 38(5/6):963–977 [DOI:10.1108/EL-07-2020-0205]

[9]Ballis H, and Dimitriou L. Evaluation of Reinforcement Learning Traffic Signalling Strategies for Alternative Ob- jectives: Implementation in the Network of Nicosia, Cyprus. Transport and Telecommunication Journal. 2020 12. 21(4):295–302 [DOI:10.2478/ttj-2020-0024]

[10] Agand P, Iskrov A, and Chen M. Deep Reinforcement Learning-based Intelligent Traffic Signal Controls with Opti- mized CO2 emissions. 2023 10. arXiv:2310.13129 [cs, eess]

[11] Simon H, and Laird J. The Sciences of the Artificial, reissue of the third edition with a new introduction by John Laird. MIT Press. 2019.

[12] Moher D, Liberati A, Tetzlaff J. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLOS Medicine. 2009 7. 6(7): e1000097 [DOI: 10.1371/journal.pmed.1000097] publisher: Public Library of Science

[13] Batiebo MR, Kone T, N'Guessan BG. Optimising urban traffic management: A dynamic approach to traffic lights using artificial intelligence. International Journal of Innovation and Applied Studies. 2023. 41(2)

[14] Bibri SE, and Krogstie J. The emerging data–driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona. Energy Inform. 2020 12. 3(1):5 [DOI:10.1186/s42162-020-00108-6]

[15] Chamideh S, Ta¨rneberg W, and Kihl M. Scalable Intelligent Traffic Balancing: Advancing Efficiency, Safety, and Sustainability in Urban Transportation Through Machine Learning and AIM Integration. In: 2023 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT). Dubai, United Arab Emirates: IEEE. p. 72–79. [DOI:10.1109/GCAIoT61060.2023.10385120]

[16] De Luca S, Di Pace R, Memoli S. Sustainable Traffic Management in an Urban Area: An Integrated Frame- work for Real-Time Traffic Control and Route Guidance Design. Sustainability. 2020 1. 12(2):726 [DOI: 10.3390/su12020726]

[17] Ferna´ndez EI, Ku¨hne NG, Mulero NB. Advancing Sustainability Impact Assessment: A Comprehensive Tool for Low Emissions Zone Management. In: 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech). Split/Bol, Croatia: IEEE. p. 1–6. [DOI:10.23919/SpliTech58164.2023.10193202]

[18] Feizi A, Joo S, Kwigizile V. A pervasive framework toward sustainability and smart-growth: Assessing multifaceted transportation performance measures for smart cities. Journal of Transport & Health. 2020 12. 19:100956 [DOI: 10.1016/j.jth.2020.100956]

[19] Kar AK, Choudhary SK, and Singh VK. How can artificial intelligence impact sustainability: A systematic literature review? Journal of Cleaner Production. 2022 11. 376:134120 [DOI: 10.1016/j.jclepro.2022.134120]

[20] Majumdar S, Subhani MM, Roullier B. Congestion prediction for smart sustainable cities using IoT and machine learning approaches. Sustainable Cities and Society. 2021 1. 64:102500 [DOI: 10.1016/j.scs.2020.102500]

[21] Moumen I, Abouchabaka J, and Rafalia N. Enhancing urban mobility: integration of IoT road traffic data and artificial intelligence in smart city environment. IJEECS. 2023 11. 32(2):985 [DOI:10.11591/ijeecs.v32.i2.pp985- 993]

[22] Nguyen TH, and Jung JJ. Swarm intelligence-based green optimization framework for sustainable transportation. Sustainable Cities and Society. 2021 8. 71:102947 [DOI: 10.1016/j.scs.2021.102947]

[23] Orsˇicˇ J, Jereb B, and Obrecht M. Sustainable Operations of Last Mile Logistics Based on Machine Learning Processes. Processes. 2022 11. 10(12):2524 [DOI:10.3390/pr10122524]

[24] Othmani T, Boubaker S, Rehimi F. Improving Energy Consumption Efficiency and Environmental Sustainability Through Smart Traffic Control Adaptation. In: 2023 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE). Sousse, Tunisia: IEEE. p. 1–6. [DOI:10.1109/ICAIGE58321.2023.10346256]

[25] Rauniyar A, Berge T, Kuijpers A. NEMO: Real-Time Noise and Exhaust Emissions Monitoring for Sustainable and Intelligent Transportation Systems. IEEE Sensors J.. 2023 10. 23(20):25497–25517 [DOI: 10.1109/JSEN.2023.3312861]

[26] Rimoldi A, Cenedese C, Padoan A. Urban traffic congestion control: a DeePC change. 2023 11. arXiv:2311.09851 [cs, eess, math, stat]

[27] Wu M, Yan B, Huang Y. Big Data-Driven Urban Management: Potential for Urban Sustainability. Land. 2022 5. 11(5):680 [DOI:10.3390/land11050680]

[28] Tao X, Cheng L, Zhang R. Towards Green Innovation in Smart Cities: Leveraging Traffic Flow Prediction with Machine Learning Algorithms for Sustainable Transportation Systems. Sustainability. 2023 12. 16(1):251 [DOI: 10.3390/su16010251]

[29] Chen C, Liu B, Wan S. An Edge Traffic Flow Detection Scheme Based on Deep Learning in an Intelligent Transportation System. IEEE Trans. Intell. Transport. Syst.. 2021 3. 22(3):1840–1852 [DOI:10.1109/TITS.2020.3025687]

[30] Shu P, Sun Y, Xie B. Data-driven shuttle service design for sustainable last mile transportation. Advanced Engineering Informatics. 2021 8. 49:101344 [DOI: 10.1016/j.aei.2021.101344]

[31] Peng T, Yang X, Xu Z. Constructing an Environmental Friendly Low-Carbon-Emission Intelligent Transportation System Based on Big Data and Machine Learning Methods. Sustainability. 2020 10. 12(19):8118 [DOI: 10.3390/su12198118]

[32] Jafarzadeh Ghoushchi S, Shaffiee Haghshenas S, Vahabzadeh S. Development of a robust hybrid framework for evaluating and ranking smartification measures for sustainable mobility: A case study of Sicilian roadways, Southern Italy. Expert Systems with Applications. 2024 5. 241:122595 [DOI: 10.1016/j.eswa.2023.122595]

[33] Li X, Zhan J, Pan F. A multi-objective optimization model of urban passenger transportation structure under low- carbon orientation considering participating subjects. Environ Sci Pollut Res. 2023 10. 30(54):115839–115854 [DOI: 10.1007/s11356-023-30423-w]

Volume: 17 Issue: 04 Pages: 6992-7007 (2026) ISSN: 0975-0290
https://doi.org/10.35444/IJANA.2025.17402

[34] Sˇosˇtaric´ M, Vidovic´ K, Jakovljevic´ M. Data-Driven Methodology for Sustainable Urban Mobility Assessment and Improvement. Sustainability. 2021 6. 13(13):7162 [DOI:10.3390/su13137162]

[35] Musa AA, Malami SI, Alanazi F. Sustainable Traffic Management for Smart Cities Using Internet-of-Things-Oriented Intelligent Transportation Systems (ITS): Challenges and Recommendations. Sustainability. 2023 6. 15(13):9859 [DOI:10.3390/su15139859]

[36] Russo F, and Comi A. Sustainable Urban Delivery: The Learning Process of Path Costs Enhanced by Information and Communication Technologies. Sustainability.2021-11. 13(23):13103 [DOI:10.3390/su132313103]

[37] Jia D, Chen H, Zheng Z. An Enhanced Predictive Cruise Control System Design with Data-Driven Traffic Prediction. IEEE Trans. Intell. Transport. Syst. 2022 7. 23(7):8170–8183 [DOI:10.1109/TITS.2021.3076494]

[38] Tsalikidis N, Mystakidis A, Koukaras P. Urban Traffic Congestion Prediction: A Multi-Step Approach Utilizing Sensor Data and Weather Information. Smart Cities. 2024 1. 7(1):233–253 [DOI:10.3390/smartcities7010010]

[39] Tian Y, Yang D, Wang J. Designing and planning sustainable customized bus service for departing attendees of planned special events: A two-phase methodology integrating data-driven and demand-responsive. Sustainable Cities and Society. 2023 9. 96:104630 [DOI: 10.1016/j.scs.2023.104630]

[40] Cheng ZA, Pang MS, and Pavlou PA. Mitigating Traffic Congestion: The Role of Intelligent Transportation Systems. Information Systems Research. 2020 9. 31(3):653–674 [DOI:10.1287/isre.2019.0894]

[41] Li Y, Lin H, and Jin J. Decision-making for sustainable urban transportation: A statistical exploration of innovative mobility solutions and reduced emissions. Sustainable Cities and Society. 2024 3. 102:105219 [DOI: 10.1016/j.scs.2024.105219]

[42] Zheng J, and Huang M. Traffic Flow Forecast Through Time Series Analysis Based on Deep Learning. IEEEAccess. 2020. 8:82562–82570 [DOI:10.1109/ACCESS.2020.2990738]

[43] Shabab KR, Ali SM, and Zaki MH. Deep Reinforcement Learning-Based Short-Term Traffic Signal Optimizing Using Disaggregated Vehicle Data. Data Sci. Transp. 2023 8. 5(2):13 [DOI:10.1007/s42421-023-00074-x]

[44] Bellini P, Bilotta S, Collini E. Data Sources and Models for Integrated Mobility and Transport Solutions. Sensors. 2024 1. 24(2):441 [DOI:10.3390/s24020441]

[45] Gutierrez-Franco E, Mejia-Argueta C, and Rabelo L. Data-Driven Methodology to Support Long-Lasting Logistics and Decision Making for Urban Last-Mile Operations. Sustainability. 2021 6. 13(11):6230 [DOI: 10.3390/su13116230]

[46] Ketter W, Schroer K, and Valogianni K. Information Systems Research for Smart Sustainable Mobility: A Frame- work and Call for Action. Information Systems Research. 2023 9. 34(3):1045–1065 [DOI:10.1287/isre.2022.1167]

[47] Resat HG. Design and Analysis of Novel Hybrid Multi-Objective Optimization Approach for Data-Driven Sustain- able Delivery Systems. IEEE Access.2020.8:90280–90293 [DOI:10.1109/ACCESS.2020.2994186]

[48] Qiao J. Smart City and Intelligent Upgrading of Urban Transportation System: based on Sustainable Investment Strategy. In: 2022 Second International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE). Bangalore, India: IEEE. p. 1–6.[DOI: 10.1109/ICATIECE56365.2022.10047675]

[49] Jagatheesaperumal SK, Bibri SE, Ganesan S. Artificial Intelligence for road quality assessment in smart cities: a machine learning approach to acoustic data analysis. Comput.Urban Sci. 2023 9. 3(1):28 [DOI:10.1007/s43762- 023-00104-y]

[50] Sun J, Guo J, Wu X. Analyzing the Impact of Traffic Congestion Mitigation: From an Explainable Neural Network Learning Framework to Marginal Effect Analyses. Sensors. 2019 5. 19(10):2254 [DOI:10.3390/s19102254]

[51] Dutta A, Jain M, Khan A. Deep reinforcement learning to maximize arterial usage during extreme congestion. 2023.

[52] Chen Z, Zan Z, and Jia S. Effect of urban traffic-restriction policy on improving air quality based on system dynamics and a non-homogeneous discrete grey model. Clean Technologies and Environmental Policy. 2022 Oct. 24(8):2365– 2384 [DOI:10.1007/s10098-022-02319-9]

[53] Sheikh MS, and Peng Y. A Comprehensive Review on Traffic Control Modeling for Obtaining Sustainable Objectives in a Freeway Traffic Environment. Journal of Advanced Transportation. 2022. 2022(1):1012206 [DOI: 10.1155/2022/1012206]eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1155/2022/1012206

[54] Sato K, Seo T, and Fuse T. Dynamic network congestion pricing based on deep reinforcement learning. 2022 Jun. arXiv:2206.12188 [eess]

[55] Spirin IV, Matantseva OY, and Grishaeva YM. The Strategy of Sustainable Development of Urban Transport. Atlantis Press. p. 2624–2628. [DOI:10.2991/aebmr.k.200312.369] iSSN: 2352-5428

[56] Khreis H. Chapter three - traffic, air pollution, and health. In: Nieuwenhuijsen MJ, and Khreis H. editors. Advances in Transportation and Health. Elsevier. 2020. p.59–104. DOI:https://doi.org/10.1016/B978-0-12-819136-1.00003-6

[57] P AB, and Sumathi R. Data sources for urban traffic prediction: A review on classification, comparison and technologies. In: 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS). p. 628–635. [DOI:10.1109/ICISS49785.2020.9316096]

[58] Liu X, and Rastgoftar H. Boundary control of traffic congestion modeled as a non-stationary stochastic process. In: 2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV). p.455–461. [DOI:10.1109/ICARCV57592.2022.10004375]

[59] Eom M, and Kim BI. The traffic signal control problem for intersections: a review. European Transport Research Review. 2020 Dec. 12(1):50 [DOI:10.1186/s12544-020-00440-8]

[60] Zhang Z, Wang Z, Ling Y, Li X. Evaluating Parameter Update Strategies in Deep Reinforcement Learning for Intelligent Traffic Signal Control. International Journal of Advanced Networking and Applications. 2025. 17(03):6885-6894.[DOI: 10.35444/IJANA.2025.17301]

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