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Systematic Review

Leveraging Advanced Technologies for (Smart) Transportation Planning: A Systematic Review

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Abstract: Transportation systems worldwide are facing numerous challenges, including congestion, environmental impacts, and safety concerns. This study used a systematic literature review to investigate how advanced technologies (e.g., IoT, AI, digital twins, and optimization methods) support smart transportation planning. Specifically, this study examines the interrelationships between transportation challenges, proposed solutions, and enabling technologies, providing insights into how these innovations support smart mobility initiatives. A systematic literature review, following PRISMA guidelines, identified 26 peer-reviewed articles published between 2013 and 2024, including studies that examined smart transportation technologies. To quantitatively assess relationships among key concepts, a Sentence BERT-based natural language processing approach was employed to compute alignment scores between transportation challenges, technological solutions, and implementation strategies. The findings highlight the fact that real-time data collection, predictive analytics, and digital twin simulations significantly enhance traffic flow, safety, and operational efficiency while mitigating environmental impacts. The analysis further reveals strong correlations between traffic congestion and public transit optimization, reinforcing the effectiveness of integrated, data-driven strategies. Additionally, IoT-based sensor networks and AI-driven decision-support systems are shown to play a critical role in sustainable urban mobility by enabling proactive congestion management, multimodal transportation planning, and emission reduction strategies. From a policy perspective, this study underscores the need for investment in urban-scale data infrastructures, the integration of digital twin modeling into long-term planning frameworks, and the alignment of optimization tools with public transit improvements to foster equitable and efficient mobility. These findings offer actionable recommendations for policymakers, engineers, and planners, guiding data-driven resource allocation and legislative strategies that support sustainable, adaptive, and technologically advanced transportation ecosystems.

Keywords: smart transportation planning; transportation technologies; systematic literature review

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1. Introduction

Urban transportation systems are vital to economic prosperity and social connectivity as they facilitate the movement of people and goods [1]. However, the rapid expansion of urban populations has exacerbated long-standing transportation challenges, including severe congestion, rising greenhouse gas emissions, traffic-related safety risks, and inefficiencies in public transit systems. These issues not only hinder urban mobility but also compromise environmental sustainability and public health. Addressing these growing challenges has become a critical priority for cities striving toward sustainable development. Effective transportation planning, which forms the backbone of livable, resilient, and economically vibrant urban areas, is, therefore, essential to overcoming these obstacles [2,3].

In response, cities worldwide are increasingly adopting advanced technologies to transform their transportation systems. Emerging solutions, ranging from real-time data analysis and traffic forecasting models to Internet of Things (IoT) frameworks and decision-support tools, are reshaping traffic management practices [4–6]. These advanced technologies aim to enhance the efficiency of transportation networks by alleviating congestion, optimizing resource allocation, and improving overall mobility [7,8]. As a result, cities are taking meaningful steps toward building smart mobility environments where technology plays an integral role in addressing dynamic urban mobility demands.

Smart transportation systems aim to represent an innovative approach to improving the efficiency, safety, and sustainability of transportation networks [9,10]. These systems integrate interconnected technologies, including the IoT, digital twins, and automated decision-support systems, to enhance real-time mobility management. The IoT refers to a network of interconnected sensors and devices that facilitate real-time data collection and exchange, improving traffic management and vehicle coordination [11]. Also, digital twins are virtual representations of physical transportation systems that synchronize with real-world data to simulate and optimize network conditions [12]. Automated decision-support systems leverage artificial intelligence and optimization algorithms to analyze complex traffic patterns and recommend data-driven interventions in real time [13]. Through the integration of real-time data, predictive modeling, and adaptive responses, smart transportation systems provide actionable insights that empower decision-makers to address urban mobility challenges. By positioning technology as a cornerstone of sustainable city development, these systems offer scalable solutions that meet the demands of rapidly evolving urban landscapes [9,10].

Despite market expansion and notable advancements in the functionality of the platforms on offer, a comprehensive and holistic understanding of how these technologies are applied to transportation planning remains limited [5,14,15]. Existing studies often focus on isolated applications or specific modes of transportation, leading to fragmented insights into their broader benefits and limitations [16]. This narrow scope hinders efforts to address interconnected challenges such as congestion, safety, and environmental sustainability. As a result, planners, policymakers, and researchers lack a clear framework for implementing effective, data-driven strategies at scale. Without a more coordinated perspective on how advanced technologies can be integrated, it remains difficult to fully assess their potential to transform transportation systems and tackle complex issues on a broader level.

To address these gaps, this study examines the role of emerging technologies in advancing transportation planning and operations by analyzing their interrelationships and contributions to smart mobility solutions. The primary objective is to investigate how IoT, AI, digital twins, and optimization algorithms collectively support transportation planning while identifying key challenges and opportunities associated with their implementation. Through a systematic literature review, this study evaluates the extent to which these technologies mitigate congestion, enhance safety, and improve overall system efficiency. We further explore the alignment between transportation challenges, technological solutions, and strategic decision-making frameworks, highlighting areas where integration remains limited or underexplored. To support this synthesis, we employ a Sentence-BERT

(Bidirectional Encoder Representations from Transformers) model to systematically identify semantic relationships between transportation challenges, proposed solutions, and enabling technologies. This approach provides a structured means of analyzing existing research, offering deeper insights into how various innovations contribute to urban mobility solutions.

By providing a holistic framework, this study aims to uncover the synergies and limitations of advanced transportation technologies, offering practical guidance for designing integrated solutions. The findings of this study hold significant value for planners and policymakers, helping them to develop data-driven strategies that align with broader societal and environmental objectives.

2. Systematic Literature Review

The methodological framework for this study adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [17]. The screening process was structured based on the approach outlined by Xiao and Watson (2019) [18]. Adhering to these standards, a systematic and transparent procedure was employed to identify, screen, and evaluate studies for inclusion in this review.

2.1. Search Strategy

A comprehensive search was conducted across three major academic databases—Web of Science, Scopus, and Google Scholar—to identify peer-reviewed studies relevant to smart transportation systems. These databases were selected for their multidisciplinary coverage of transportation systems, big data analytics, and smart city technologies. The search was designed to include studies published between 2013 and August 2024, a period that captures the emergence and proliferation of transformative technologies, such as digital twins, big data analytics platforms, and decision-support systems, in transportation planning [19,20]. However, after applying the inclusion and exclusion criteria, the final set of reviewed articles covered the period from 2016 to 2024.

The search queries were tailored for precision and relevance, incorporating keywords that address both technological innovations and transportation challenges. These terms were selected to ensure comprehensive coverage of studies focusing on emerging transportation planning technologies and their applications in addressing key transportation issues. Key search terms included combinations such as "Digital twin", "Virtual twin", "Digital*", "Technolog*", "Big data", and "Decision-support systems", alongside terms related to transportation planning, such as "Transportation management", "Traffic management", "Transportation system", and "Traffic system". The inclusion of Boolean operators and field-specific searches ensured precision and relevance across the selected databases.

In Web of Science, the search query targeted terms related to advanced technologies and decision-support systems in the topic field, while limiting transportation-focused keywords to the title field. Specifically, the query was formulated as follows: "Digital twin OR Virtual twin OR Digital* OR Technolog* OR Big data (Topic) AND Transportation planning OR Traffic planning OR Transportation management OR Traffic management OR Transportation system OR Traffic system (Title) AND Decision support system OR DSS OR Decision-making OR Decision* (Topic)".

For Scopus, the search extended to titles, abstracts, and keywords to encompass studies with broader contexts but highly relevant content. The query was structured as follows: "(TITLE-ABS-KEY ("Digital twin" OR "Virtual twin" OR Digital* OR Technolog* OR "Big data") AND TITLE ("Transportation planning" OR "Traffic planning" OR "Transportation management" OR "Traffic management" OR "Transportation system" OR "Traffic system") AND TITLE-ABS-KEY ("Decision support system" OR DSS OR "Decision-making" OR Decision*))".

The Google Scholar search was conducted with more focused criteria to ensure precision, which was necessary to avoid an overwhelming number of irrelevant results and to target studies directly relevant to the intersection of transportation challenges and technological innovations. Queries were restricted to the title field, combining transportation-related terms with technological keywords and decision-support systems. Filters were applied to exclude patents and citations while limiting the results to articles published between 2013 and August 2024.

This initial search yielded 1793 studies across the three databases. After removing duplicate records (n = 285) and excluding non-peer-reviewed materials, such as conference proceedings and book chapters, and non-empirical research (n = 369), 1139 studies remained for further screening.

2.2. Screening Process

The screening process involved two stages—title review followed by abstract review—aimed at identifying studies relevant to technology-enabled transportation planning. Studies were deemed within scope if they explicitly examined transportation challenges, such as congestion management, traffic flow optimization, public transit efficiency, or environmental sustainability, through the application of advanced technologies, including digital twins, big data analytics, IoT systems, and decision-support tools. Conversely, studies that focused exclusively on conventional transportation methods, infrastructure design without a technological component, or general discussions of transportation policy without addressing technological applications were excluded.

To reduce bias, two independent researchers performed the screening in parallel [18], assigning a relevance score of 1 (low), 2 (moderate), or 3 (high). Studies with a combined score of 3 or higher advanced to the next review stage. Any discrepancies were resolved through discussion until a consensus was reached.

Titles and abstracts were screened according to the following criteria. First, studies were required to include terms explicitly related to transportation planning and management. Articles addressing general transportation technologies without a clear connection to planning or management contexts were excluded. Second, studies were required to reference specific advanced technologies, including but not limited to digital twins, big data analytics, IoT-enabled infrastructure, machine learning algorithms, automated decision-support systems, and predictive modeling tools. Studies that did not mention or integrate at least one of these technologies within the context of transportation planning or management were excluded. Third, this review focused exclusively on road transportation systems, leading to the exclusion of research related to non-road modes, such as aviation, maritime, or rail transport. Additionally, studies deemed out of context, either methodologically or thematically, were excluded. Finally, articles identified as review studies were removed, as the scope of this review was limited to primary empirical research.

After the title review, 735 articles were excluded, leaving 404 for the abstract review. The subsequent abstract review excluded 279 more articles, reducing the pool to 125 for full-text analysis.

2.3. Quality Assessment

A full-text review of the studies was conducted to ensure their methodological rigor, data transparency, and contextual relevance. The quality assessment followed a structured approach based on four key dimensions: relevance, data reliability, internal validity, and applicability [21,22]. This process ensured that only studies of sufficient quality were included for further analysis.

Relevance was assessed to determine whether each study addressed critical transportation challenges and the role of advanced technologies in resolving them. Specifically, the studies were required to engage with transportation planning or management while incorporating technologies such as big data analytics, digital twins, or decision-support systems. Articles that failed to address both thematic and technological relevance were excluded.

The reliability of the data in each study was critically evaluated to ensure transparency and credibility. The evaluation considered whether data sources were explicitly identified and clearly presented. Studies were examined for the precise definition of variables and the application of systematic, reliable methods for data collection. Particular emphasis was placed on the documentation of data collection tools and procedures, as well as the overall transparency of the study, which served as a key indicator of the credibility of the findings.

Internal validity was evaluated to ensure that the research objectives and questions were clearly defined and logically aligned with the study design. The methodological soundness of each study was considered, focusing on whether the chosen design was robust and appropriate for deriving valid conclusions. Studies that demonstrated inconsistencies in their objectives, methodological flaws, or poorly substantiated conclusions were excluded.

The applicability of each study was examined to assess the generalizability of the findings. The sufficiency of the sample size was considered in relation to the study objectives, with a benchmark of $n > 100$ for quantitative studies and a threshold of 30 participants or more for group-based studies. These thresholds were selected based on established guidelines in empirical research, where a sample size greater than 100 is often regarded as sufficient to achieve statistical power and minimize sampling error in quantitative studies, and 30 participants is typically adequate for capturing group-level trends and interactions in group-based research [23]. Exceptions were made for qualitative research where smaller samples are methodologically appropriate. The degree to which the study findings could be generalized to broader settings, contexts, or populations was also evaluated.

Following the quality assessment, 99 studies were excluded, resulting in a final selection of 26 articles for the data extraction stage (see Table 1 for an overview). The overall process, including search, screening, and quality assessment, is summarized in Figure 1.

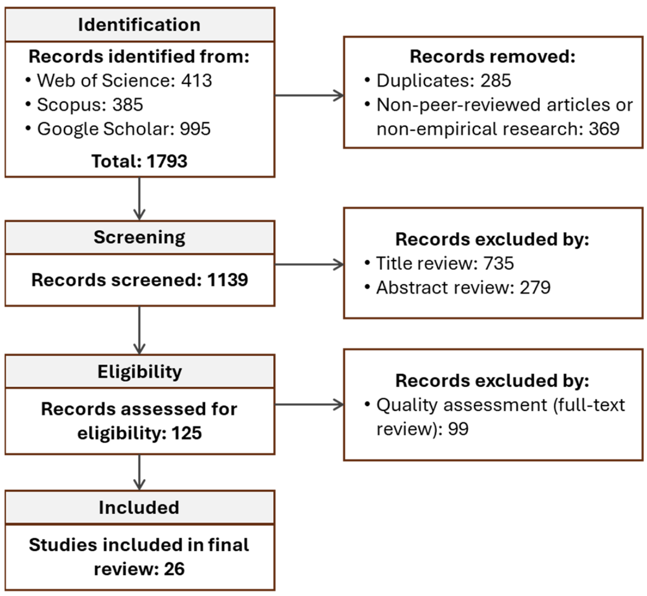

Figure 1. Overview of the study selection process.

Table 1. Summary of reviewed studies.

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Guan et al. (2016) [24]	Urban transport systems (Guangzhou, China)	• Congestion due to increased traffic flow • Decreased average travel speeds and imbalanced road network usage	• Deployment of an intelligent transportation system (ITS) for traffic flow optimization and decision support • Enhanced traffic management systems (e.g., signal control, event monitoring, emergency rescue, and electronic toll collection, dynamic navigation, parking information services, etc.) • Geographic Information System (GIS)-based decision support system for data management and analysis	• Integration of advanced information technology, data communication, electronic sensors, control systems, and computing technologies for real-time traffic management • Use of panel data for statistical analyses to evaluate transportation system performance
Chen et al. (2017) [25]	Rural contexts (Quinte West, Southeastern Ontario, Canada)	• Inequitable access to essential services for rural populations, including healthcare and groceries • Rising operational costs for demand-responsive transport systems • Scarce resources and difficulty balancing multiple objectives, such as cost, coverage, and equity	• GIS-based decision support system for data management and analysis • Redesigned bus routes optimized for equity and cost • Applied a heuristic procedure for route optimization balancing cost and equity	• GIS for mapping population density and major points of interest across rural regions • Data envelopment analysis (DEA) for multi-objective optimization and efficiency assessment • Multi-objective utility analysis (MOUA) and conjoint analysis for equity evaluation • Dijkstra algorithm for path optimization

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Ata et al. (2019) [26]	Highway/Arterial networks (England, UK)	• Increasing vehicular density leading to congestion • Failure of classical approaches to ensure smooth and efficient traffic flow due to rising urban traffic demands • Adverse weather conditions affecting road traffic and safety • Ineffectiveness of conventional traffic management solutions in managing increasing vehicular density	• Dynamic congestion prediction using artificial neural networks (ANNs) • Real-time adjustments to signal timings based on congestion levels • Weather-integrated traffic management to enhance road safety and reduce delays	• Back Propagation Neural Networks (BPNN) for predicting traffic delays with input-output mapping • Levenberg–Marquardt algorithm for training multilayer perceptron networks with dataset division • Smart traffic control system architecture • Non-Linear Autoregressive with External Input (NARX) model for time-series traffic data analysis and simulation using MATLAB R2017a • IoT-based data acquisition from sensors deployed at intersections for real-time traffic monitoring and control
Babar & Arif (2019) [27]	Simulated environments (based on the data from Aarhus City, Denmark)	• Traffic congestion caused by insufficient real-time data processing • Challenges in integrating heterogeneous IoT data sources for transportation • High computational demands for managing large-scale data	• Real-time data analysis for traffic flow prediction and congestion management • Dynamic decision-making using real-time event detection and response systems • Development of a smart transportation system architecture using big data analytics for real-time processing	• Utilization of Apache Hadoop for large-scale data storage and processing • MapReduce programming for parallel processing mechanism to manage large datasets efficiently • IoT integration using traffic sensors, cameras, and GPS data aggregation for real-time monitoring • Noise reduction in data using statistical methods like Kalman filters

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Luo et al. (2019) [28]	Urban transport systems (Shenyang, China)	• Need for integration of real-time data to reduce uncertainty and improve response • Severe traffic congestion due to rapid urbanization and economic growth • Inefficiency in traditional public transport scheduling due to static timetables • Passenger dissatisfaction caused by long waiting times and irregular bus services • Unpredictable traffic conditions impacting resource allocation and vehicle routing	• Real-time passenger flow analysis and vehicle control optimization • Dynamic dispatching of buses based on real-time traffic and passenger data • Transport flow prediction using periodic pattern mining • Decision support system with evolutionary algorithms for scheduling optimization	• IoT-based framework which includes perception, network, and application layers • Sensors for GPS tracking, automatic passenger counting, and real-time traffic monitoring • Communication protocols like GSM, 4G, Zigbee, and Wi-Fi • Dynamic scheduling and optimization applications • Cloud computing for data processing and analysis • Optimization algorithms for vehicle dispatching • Meta-heuristic algorithms for complex scheduling problems
Nallaperuma et al. (2019) [29]	Highway/Arterial networks (Victoria, Australia)	• Real-time handling of dynamic and volatile traffic data streams • Lack of real-time machine learning algorithms to predict non-recurrent traffic incidents across entire road networks • Predicting traffic flow under diverse, evolving conditions	• Deep learning approach for real-time traffic flow prediction and impact propagation estimation across arterial road networks • Deep reinforcement learning model to optimize traffic control actions using real-time data • Social media data integration model to capture commuter sentiment and emotions during non-recurrent traffic events	• Bluetooth traffic monitoring system for trajectory data collection at arterial road junctions • Online learning techniques to manage high-volume and high-velocity data with data-driven processing triggers • Deep Neural Networks (DNNs) for forecasting traffic flow and identifying critical road segments • Deep Reinforcement Learning (DRL) for adaptive and intelligent traffic control systems • Long short-term memory (LSTM) architecture for capturing temporal traffic patterns • Sentiment analysis of social media data, extending traditional methods to extract deeper emotions

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Shengdong et al. (2019) [30]	Simulated environments (based on data from California, USA)	• Limited real-time adaptability of traditional traffic control systems • Inefficient handling of large-scale data for short-term prediction	• Integration of cloud computing, network control systems, and traffic management to provide technical support for traffic control • Edge computing to provide localized control for critical nodes in the ITS • Development of an intelligent transportation cyber-physical cloud control system for real-time data management and control • Traffic redistribution strategies to alleviate congestion in overburdened areas • Utilization of cloud computing for scalable traffic flow prediction, optimization, and scheduling	• Cyber-physical systems (CPS) for acquisition, transmission, and computation of traffic data in real time for the optimization, decision making, scheduling, planning, prediction, and control of the system • Traffic big data analytics for advanced data mining techniques for accurate and efficient traffic data processing • Deep Belief Network-Support Vector Regression (DBN-SVR) for large datasets • Back Propagation Bilateral Extreme Learning Machine (BP-BELM) for small-scale predictions • Edge computing for real-time, localized control • Cloud systems for large-scale computation and data storage
Dauletbak & Woo (2020) [31]	Highway/Arterial networks (Los Angeles County, California, USA)	• Severe congestion at key locations and during peak times • Insufficient predictive tools for identifying long-term traffic patterns • Data imbalance affecting accurate predictions of extreme congestion levels	• Predictive analytics for classifying jam severity and supporting real-time traffic management • Identification of traffic hotspots and peak times for infrastructure planning • Enhanced visualization for dynamic traffic analysis	• Navigation app data captured at millisecond intervals, providing raw traffic datasets for analysis • Hadoop big data system for storing and processing large-scale traffic datasets using distributed parallel computing • Hive ecosystem with HiveQL for data schema creation, cleaning, summarization, and sample dataset generation • Multiclass Decision Forest for classification of jam levels • Interactive visuals to illustrate traffic jams, time-based trends, and segmented information for better analysis

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Chen et al. (2021) [32]	Highway/Arterial networks (Taiwan)	• High variability in freight travel time due to stochastic events (e.g., congestion, weather) • Lack of robust short-term predictive models for real-time logistics • Difficulties in processing large-scale, heterogeneous IoT data in real-time	• Data-driven predictive analytics combining real-time traffic data with stochastic modeling to enhance travel time reliability • Adaptive logistics management by integrating predictive analytics into routing and scheduling • Enhanced response speed and operational efficiency in Logistics 4.0	• Traffic IoT integrating big data sources for logistics and transportation system improvements • Traffic sensors, GPS, and vehicle detectors • 5G-enabled Vehicle-to-Everything (V2X) for seamless connectivity and data exchange in transportation systems • Ensemble machine learning techniques, such as bagging and boosting, to enhance model performance by combining multiple predictors
Lemonde et al. (2021) [33]	Regional transport systems (Lisbon Metropolitan Area, Portugal)	• Lack of integration of multimodal traffic data with situational context for improved mobility management • Insufficient context-aware analysis to capture situational dynamics (e.g., large-scale events, traffic restrictions, weather, and urban planning changes) on mobility patterns	• Context-aware and multimodal traffic analysis principles for integrating urban data sources • Spatiotemporal and contextual modeling for emerging traffic trends and system optimization • Predictive traffic analysis using deep learning models such as recurrent neural networks and graph neural networks (GNNs) for short-term and long-term forecasting • Integration of automated fare collection systems to track cross-carrier passenger flows and infer comprehensive origin-destination matrices	• Urban data fusion techniques to enhance data consistency and completeness • Machine learning and analytics for predictive, prescriptive, and diagnostic analysis of multimodal traffic data • Spatiotemporal pattern mining and relational data mining techniques for understanding user-specific mobility patterns • Deployment of reinforcement learning and deep neural networks for optimizing public transport operations • Scenario-based simulation approaches to support decision-making in traffic management • Traffic dashboards and GIS-based multimodal data representation

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Muntean (2021) [34]	Urban transport systems (Birmingham, UK)	• Processing and analyzing large volumes of smart city data for timely decision-making • Traffic congestion and crowded parking due to high vehicle density and limited space • Inefficiency in traffic light operations	• Real-time traffic forecasting for flow optimization • Automated traffic management mechanism to prevent congestion and optimize urban mobility • Decision trees for fault detection and rapid decision-making • Parking occupancy prediction to assist in space allocation	• Multi-agent system (MAS) architecture designed for urban traffic management processes • K-nearest neighbor (KNN) for occupancy rates and Random Tree for traffic flow • Monitoring agents equipped with expert systems using the Jess rule engine for anomaly detection • Implementation within the Java Agent Development Framework (JADE) for inter-agent communication • Data mining tool for forecasting, classification, data pre-processing, and visualization
Rathore et al. (2021) [35]	Urban transport systems (Aarhus, Denmark, Madrid, Spain, and Cologne, Germany)	• Traffic congestion due to increased urbanization and vehicle density • Inefficient traffic management caused by the inability to process real-time data effectively • Delays in routing decisions for commuters and emergency services	• Real-time traffic analysis to identify congested routes and redistribute traffic • Traffic flow analysis using periodic pattern mining • Smart routing for commuters and emergency services using weighted graphs • Data-driven decision-making for urban planners to design better traffic systems	• CPS, which integrates IoT sensors and big data tools for real-time data collection and analysis • Graph algorithms that utilized Dijkstra's algorithm and maximum spanning tree techniques for traffic route optimization • Big data tools using Apache Spark 2.3.1 GraphX and Hadoop 2.6.5 for big data processing

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Sahil (2021) [36]	Simulated environments (used systematically generated synthetic datasets)	• Urban traffic congestion and long queues at intersections • Inability of legacy systems to process dynamic and real-time data	• Adaptive green light scheduling based on real-time traffic inflow data • Smart navigation system to guide vehicles along time-optimized routes and evenly distribute traffic across available paths • Real-time situation-aware traffic management to enhance road safety and improve overall traffic flow	• IoT for acquiring vehicle mobility data through onboard sensors, infrastructure-based sensors, and vehicle-to-infrastructure communication via Vehicular Ad-hoc Networks (VANETs) • Edge computing for low-latency, location-aware, and real-time processing of mobility data • Cloud computing for data storage and large-scale processing of traffic data • The reverse edge layer facilitates time-efficient smart navigation, ensuring the optimal distribution
Yu et al. (2021) [37]	Simulated environments (based on data from Jiangsu University, China)	• Safety risks in mixed traffic environments with autonomous and manual vehicles • Poor real-time performance and low accuracy in intention recognition systems • Limited data processing capabilities in traditional ITS frameworks	• 5G, edge computing, and AI-based deep learning traffic safety solution for mixed traffic • Use of normalized driving trajectory and natural-driving datasets • Decision-level fusion of historical and natural-driving data for higher recognition accuracy	• 5G technology for data collection and edge processing without centralized servers • TensorFlow framework for building long short-term memory networks • Moving average algorithm for smoothing driving trajectory data • LSTM network to handle data dependence and time sequence issues • Edge computing to support decentralized data processing, reducing the load on centralized servers

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Bachechi et al. (2022) [38]	Urban transport systems (Modena, Italy, and Santiago de Compostela, Spain)	• Traffic congestion impacts air quality and urban livability • Lack of tools for integrating traffic and pollution data in real-time • Sensor data anomalies reduce reliability for traffic modeling	• Trafair Traffic Dashboard to analyze and visualize real-time traffic sensor data and traffic flow simulations • Integration of traffic modeling with air quality impact analysis to provide actionable insights for city administrations • Scenario-based simulations to evaluate sustainable urban policies	• Microscopic traffic simulations and route generation from sensor data • Data cleaning using speed-flow correlation filters and anomaly detection with Seasonal-Trend Decomposition using Loess and Interquartile Range analysis • PostgreSQL database with PostGIS and Timescale extensions for efficient spatial and temporal data management • Anomaly detection algorithms applied to sensor data
Brazález et al. (2022) [39]	Urban transport systems (Madrid, Spain)	• Balancing mobility with health restrictions during a pandemic • Computing safe and fast routes considering changing alert levels and curfews • Integrating diverse data sources for decision-making	• Real-time computation of routes based on health data and mobility restrictions • Dynamic alert-level-based traffic control for urban areas • Modular architecture allowing easy adaptation to other emergencies	• Complex Event Processing (CEP) to detect real-time events and health risks using tools like MEdit4CEP • Fuzzy Inference System implemented to facilitate traffic restriction decisions • Colored Petri Net (CPN) models to mapping for route simulations, integrating alert levels and time restrictions • Deployment of the Pandemic intelligent transportation system to support authorities in making mobility decisions and ensuring efficient routing for drivers

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Chen et al. (2023) [40]	Urban transport systems (Taiwan)	• High variability and unpredictability of travel times due to traffic congestion, accidents, and roadwork • Inadequate performance of traditional predictive models under dynamic traffic conditions • Growing emphasis on green transportation necessitates efficient logistics and transportation planning	• Bi-directional time processing for enhanced predictive accuracy • Real-time vehicle routing optimization using predicted travel times • Integration of IoT data for continuous updates and system improvement	• Bi-Directional Isometric-Gated Recurrent Unit (BDIGRU) for chronological and retrospective information processing • IoT-based terminal technology for collecting vehicle operation and road condition data • Machine learning-based gradient descent optimization for real-time analytics • Integration of traffic data processing with enterprise resource management for cost-effective logistics optimization
Kušić et al. (2023) [41]	Highway/Arterial networks (Geneva, Switzerland)	• Inability of traditional traffic simulations to adapt to real-time changes • Ineffective testing of control strategies like variable speed limits in offline models • Difficulty in developing control strategies that perform consistently across varying traffic states in dynamic and stochastic environments such as motorways	• Development of a run-time synchronized digital twin model of the Geneva motorway using real-time traffic data from motorway counters • Safe and efficient testing of traffic management strategies using parallel Digital Twin Instances (DTIs) • Predictive analytics for early detection of traffic anomalies and optimization of traffic flows • Leveraging the open data and the microscopic traffic emulator to enhance simulation capabilities	• Simulation of Urban Mobility (SUMO) for modeling and simulating synchronized digital replicas of real motorway traffic • Dynamic Flow Calibration mechanism for real-time adjustment of traffic flow distributions • Real-time data collection from motorway traffic counters aggregated every minute and accessed via the Open Data Platform Mobility Switzerland (ODPMS) • Use of a central repository for storing and accessing high-resolution traffic data for real-time simulations
Montero-Lamas et al. (2023) [42]	Urban transport systems (Coruña, Spain)	• Increased bus travel times due to mixed traffic conditions • Delays caused by general traffic, ridership levels, and weather factors • Inefficiencies in calculating passenger time savings with traditional methods	• Exclusive bus lanes to mitigate traffic interference and reduce travel times • Utilizing sensor and management system data with high spatial and temporal detail to enhance analysis • Enhanced methodologies for calculating passenger time savings using big data • Alighting prediction algorithms to improve ridership data accuracy	• Bluetooth sensors for traffic flow and travel times • Inductive loops for road occupancy and flow rate • Statistical methods tailored to fit specific case studies for improved accuracy

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Rani & Sharma (2023) [43]	Simulated environments (used the CIC-IDS2017 dataset)	• Managing heterogeneous IoT traffic from interconnected devices in transportation networks • Effective network monitoring and management for Internet of Vehicles (IoV) systems • Preventing traffic congestion by utilizing ITS data for proactive forecasting • Security threats such as intrusions and attacks on vehicular networks	• Development of an intelligent intrusion detection system (IDS) for IoV-based vehicular networks using tree-based machine learning and ensemble learning techniques • Stacked ensemble learning approach for improved accuracy in intrusion detection • Feature selection to optimize network monitoring and reduce computational costs • Enhancing accuracy and attack detection capability	• Application of machine learning-based IDS for IoV within vehicular ad hoc networks • Use of tree-based learning techniques such as Decision Tree, Random Forest, Extra Tree, and XGBoost for classification and training • Stacking methodology to enhance classifier robustness and reliability by combining multiple learners
Tao et al. (2023) [44]	Urban transport systems (Hong Kong)	• Inefficiency in traditional traffic management methods • High carbon emissions and reliance on fossil fuels	• Traffic flow prediction models for real-time signal optimization and dynamic routing • Ensemble learning methods to improve the accuracy of traffic flow predictions • Optimizing traffic signal timing and resource allocation through precise forecasting	• Random Forest, Support Vector Regression (SVR), and ARIMA for traffic forecasting • Gradient boosting as ensemble learning techniques • Heat maps to visualize traffic flow distribution • Data-driven decision-making integrated into smart city systems
Wang et al. (2023) [45]	Urban transport systems (Beijing, China)	• Low network efficiency due to underutilized stops and poorly connected routes • Limited integration between subway and bus systems in traditional network planning • Inefficiencies in passenger flow management during peak hours	• Subway–bus double-layer network model to optimize public transportation routes and connections • Structural adjustments to add/remove stops based on demand and efficiency metrics • Simulation-driven decision-making to identify areas for network improvement	• Passenger flow and travel time data derived from IC card swipes • Weighted edge connections based on passenger flow and travel time • L-space modeling for connectivity analysis and C-space modeling for transfer optimization • Gephi for visualization, network efficiency calculations, and complex network analysis

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Xu et al. (2023) [46]	Urban transport systems (Chattanooga, Tennessee, USA)	• Lack of real-time integration of diverse urban data sources • Challenges in collecting and processing large-scale urban mobility data	• Cyber–physical traffic control for real-time signal timing optimization • Data-driven decision support using traffic simulations and predictive models • Interactive dashboards for exploring traffic, safety, and energy metrics	• Integration of diverse sensors, including Radar Detection Sensors and CCTV cameras, to provide traffic insights • Cloud-based infrastructure for large-scale data processing and management • Edge computing for distributed data processing at the source to reduce latency and enhance real-time responsiveness • Simulation tools for traffic dynamics and energy consumption modeling • Modular design ensuring system scalability and interoperability with IoT services
Callefi et al. (2024) [47]	Nation-wide transport systems (Brazil)	• Complexities of freight operations in route planning, resource allocation, and fleet management • Need for real-time data sharing and decision-making • High environmental impact due to emissions and inefficiencies	• Technology-driven fleet and route optimization • Real-time monitoring for cargo and emission control • Enhanced decision-making with integrated data systems	• IoT sensors, GPS, mobile and wireless communication technologies • Cloud computing for data analytics and storage • Fuzzy DEMATEL analysis to evaluate interdependencies among capabilities • Roadmap development to categorizes capabilities into base (core) and triggered (dependent) • Integration of ICT to enhance supply chain management and facilitate strategic decision-making

Table 1. *Cont.*

Study	Geographical Contexts	Transportation Challenges	Proposed Solutions	Enabling Technologies and Approaches
Dasgupta et al. (2024) [48]	Simulated environments (used the real-world traffic data but not specified particular locations)	• Delays at signalized intersections due to suboptimal traffic signal timing • Persistent traffic congestion negatively impacts fuel consumption, emissions, and public health • Lack of proactive traffic management tools that adapt to real-time demand	• Digital twin based adaptive traffic signal control (ATSC) framework for dynamic signal phase optimization • Real-time traffic demand prediction and simulation for proactive traffic management • Parallel simulations to assess various ATSC algorithms and trade-offs in delay reduction	• Simulation of real-world traffic flow, including road networks, vehicles, and traffic signals for digital twin • Parallel simulations, real-time data integration, and dynamic algorithm selection for the traffic simulation based on the digital twin • Data aggregation, synchronization, and visualization
Yang et al. (2024) [49]	Nation-wide transport systems (Taiwan)	• High fatality rates due to recurring violations, such as drunk driving and running red lights • Lack of integration between violation data and accident prevention strategies • Insufficient use of advanced sensor technologies in accident hotspots	• Installation of sensor-equipped cameras for real-time monitoring and enforcement • Big data analytics to identify accident-prone areas and common violation patterns • Enhanced enforcement through predictive models based on historical trends	• Hadoop distributed file system for splitting and storing large datasets across distributed locations • Spark for faster in-memory data processing and trend analysis • Tableau for dynamic dashboards and interactive trend analyses • LiDAR, CCD cameras, and radar for traffic monitoring

2.4. Data Extraction

Two independent researchers conducted the data extraction for the 26 selected studies to ensure accuracy and consistency. The extracted information included authors, publication year, transportation challenges, proposed solutions, and the enabling technologies and approaches relevant to each study. The extracted data were cross-verified by the authors, and discrepancies were resolved through discussion to ensure consensus.

To analyze the extracted data, a Sentence-BERT model was utilized. Sentence-BERT, a state-of-the-art deep-learning model for natural language processing, transforms text data into vector representations. Enhancing the original BERT model [50] significantly improves the efficiency and accuracy of text-to-vector conversion at both sentence and paragraph levels [51]. Precisely, the model used is an extension of the original Sentence-BERT developed by Reimers and Gurevych in 2019 [51], incorporating Microsoft's advanced Masked and Permuted Network approach [52], which effectively captures word order information within sentences. After generating sentence embeddings, cosine similarity was calculated to identify the similarity between texts:

$$\cos(X_i,\ Y_j) = \frac{X_i \cdot Y_j}{(\|X_i\| \times \|Y_j\|)}, \tag{1}$$

where cosine similarity, denoted as $\cos(X_i,\ Y_j)$, measures the similarity between the sentence embedding vectors X_i and Y_j. The value of $\cos(X_i,\ Y_j)$ ranges from -1 to 1, where -1 indicates completely opposite text vectors, and 1 indicates identical text vectors. The closer the value is to 1, the higher the similarity between the texts.

This process facilitates the identification of patterns and relationships among transportation challenges, proposed solutions, and associated technologies. Specifically, the analysis aimed to link particular solutions to the challenges they addressed and to determine the technologies most frequently employed. This approach provided a structured means of examining the interconnectedness of the reviewed studies, forming a robust foundation for the synthesis of findings presented in the subsequent sections.

3. Overview of Selected Studies

In this section, we summarize the characteristics of the selected studies, highlighting their publication years, geographic focus, and research domains, as presented in Table 2. The studies span from 2016 to 2024, reflecting the rapidly evolving and interdisciplinary nature of technology-enabled transportation research. Although the initial search covered the period from 2013 to 2024, no studies published between 2013 and 2015 met the inclusion criteria. An upward trend in research output was observed, peaking with seven publications in 2023, indicating growing recognition of advanced technologies as essential tools for addressing transportation challenges and fostering sustainable urban development.

The reviewed studies cover a range of spatial scales: urban, rural, regional, nationwide, and highway/arterial settings. Urban transport systems dominate, with 11 articles focused on cities in North America, Europe, and East Asia [24,28,33–35,38,39,42,44–46], primarily examining congestion management, public transit inefficiencies, and environmental sustainability. In contrast, only one study specifically addressed rural transportation, highlighting accessibility challenges in Southeastern Ontario, Canada [25]. Highways and arterial roads were investigated in five studies, which emphasized optimizing traffic flow, enhancing safety, and improving connectivity [26,29,31,32,41]. Six articles employed simulated environments—often calibrated with real-world data—to evaluate emerging methodologies and technologies [27,30,36,37,43,48]. Other studies adopted regional or nationwide perspectives, focusing on themes such as traffic safety, multimodal integration, and freight efficiency [33,47,49]. Diversity across spatial scales highlights the broad range of transportation challenges that advanced technologies seek to address.

Table 2. Descriptive summary of reviewed studies.

Category	Description
Total reviewed studies	26
Publication years	2016: 1, 2017: 1, 2019: 5, 2020: 1, 2021: 6, 2022: 2, 2023: 7, 2024: 3
Spatial scale	[Real world] Urban transport systems: 11, Rural contexts: 1, Highway/Arterial networks: 5, Nation-wide transport systems: 2, Regional transport systems: 1 [Virtual world] Simulated environments: 6
Transportation challenges *	Technical Capability and Real-Time Data Utilization: 21, Traffic Congestion: 13, Public Transit and Multimodal Transportation Systems: 4, Traffic Safety and Accidental Risks: 4, Environmental Impacts: 4, Transportation System Operation and Management: 7
Solutions *	Real-Time Traffic Monitoring and Control: 16, Predictive Analytics: 20, Optimization of Public Transit/Multimodal Systems: 6, Safety Enhancement and Risk Mitigation: 5, Dynamic Traffic Flow and Signal Management: 11, Scenario Planning and Strategic Simulations: 6
Technologies and approaches *	IoT-Based Data Collections: 19, Big Data Processing and Analytics: 16, Machine Learning and AI-Based Technologies: 12, Optimization and Decision Support Systems: 10, Digital Twins and Traffic Emulations: 7, Data Integration and Visualization: 9

* Some studies appear in multiple categories, so the counts and references may overlap.

A structured synthesis of these findings allows for a clearer understanding of research trends and methodological approaches. The reviewed studies apply diverse techniques, including empirical case studies, simulation-based analyses, machine-learning models, and optimization frameworks. Categorizing them based on their focus on transportation challenges, proposed solutions, and enabling technologies provides insights into dominant research priorities and gaps that require further exploration.

Building on this classification, the subsequent sections delve deeper into key thematic areas. Section 4 examines the major transportation challenges, outlining the mobility issues most frequently discussed in the literature. Section 5 focuses on technological solutions, identifying strategies designed to mitigate these challenges. Section 6 explores enabling technologies and methodological approaches, discussing the tools and frameworks used in transportation research. Section 7 synthesizes these insights, highlighting the interconnections between transportation challenges, solutions, and technologies while identifying dominant trends and areas where research is converging. Finally, Section 8 presents the concluding discussion, reflecting on broader implications for transportation research and policy development.

4. Identified Transportation Challenges

4.1. Technical Capability and Real-Time Data Utilization

Several studies highlight critical issues related to technical capability and real-time data utilization in smart transportation systems. The main issue is the integration of heterogeneous IoT data sources, which often creates data silos and interoperability problems that hamper seamless communication and decision-making [27–30,43]. Additionally, many legacy systems struggle to process dynamic, real-time data, resulting in suboptimal traffic management and extended response times [30,35–37,41,45,46]. Researchers further note a lack of robust predictive models, which undermines short-term traffic flow predictions and hinders efficient management of congestion in response to factors such as weather, road incidents, and special events [29,30,32,33,42,48,49].

Limited integration of multimodal traffic data with situational context also impedes effective transportation planning, underscoring the need to incorporate contextual information (e.g., real-time traffic restrictions and urban planning changes) [33,41]. Data reliability and accuracy remain pressing concerns, with sensor anomalies necessitating rigorous validation to ensure data quality [34,38,39,46,47]. Finally, interoperability gaps across transportation subsystems (e.g., buses and subways) create operational inefficiencies and negatively affect commuter experiences [28,33,45].

4.2. Traffic Congestion

Traffic congestion remains a central challenge in urban environments, impairing economic efficiency, environmental sustainability, and public health. Primary contributors include escalating vehicular density—driven by urbanization and rising vehicle ownership—and infrastructure limitations that fail to accommodate growing travel demand [24,26,28,35]. Inadequate real-time data processing curtails proactive congestion management measures, such as adaptive traffic signals and dynamic routing, while inefficiencies in traffic management systems further exacerbate the problem [27,34,43]. Severe congestion at key locations and during peak hours highlights the challenges of an overburdened transportation network that lacks the flexibility to accommodate fluctuating demand [31,36]. Long queues at intersections and inadequate signal timing contribute to further delays and inefficient traffic flow management [36].

Congestion also disrupts travel time reliability and impacts public transportation systems, particularly buses sharing mixed traffic lanes, leading to service irregularities and passenger dissatisfaction [42,44]. Beyond operational inefficiencies, the environmental impact of sustained congestion is significant, including higher fuel consumption and emissions that degrade air quality and contribute to respiratory ailments [38,48]. These findings stress the urgency of implementing measures that mitigate congestion and foster sustainable transportation alternatives.

4.3. Public Transit and Multimodal Transportation Systems

Public transit and multimodal systems face interconnected challenges that restrict efficiency, accessibility, and overall effectiveness. Inequitable access is particularly acute in rural areas, where limited mobility options constrain access to essential services and exacerbate social inequalities [25]. This challenge is compounded by rising operational costs for demand-responsive transport systems and the difficulty in balancing multiple objectives, such as cost, coverage, and equity [25]. Operational inefficiencies, such as static timetables and unpredictably fluctuating traffic conditions, extend passenger wait times, reduce service reliability, and increase dissatisfaction [28]. Furthermore, a lack of integrated multimodal data hampers seamless transitions among various travel modes, while suboptimal passenger flow management during peak hours compounds congestion and service quality issues [33,45]. Consequently, planners seek integrated strategies to enhance network design, service frequency, and data sharing, ensuring that transit systems remain accessible, efficient, and adaptable to changing user demands [45].

4.4. Traffic Safety and Accidental Risks

Traffic safety and accidental risks remain substantial concerns in both conventional and increasingly connected or automated transport systems. Recurring traffic violations—such as drunk driving and red-light running—persist despite current enforcement, indicating an unmet need for integrating violation data into accident prevention measures [49]. The lack of advanced sensor deployment in accident-prone areas further limits the capacity to identify and address these violations proactively, leading to persistent safety risks [49]. Security threats in vehicular networks are another pressing concern, as increased connectivity in smart transportation systems introduces vulnerabilities to cyber intrusions and attacks, which can compromise vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, posing substantial risks to road users and critical infrastructure [43]. The need to balance mobility with health restrictions during crises, such as pandemics, presents unique challenges. Restrictions, including curfews and changing alert levels, disrupt traffic flow and necessitate real-time adjustments to route planning, complicating efforts to ensure both public safety and transportation efficiency [39]. Additionally, in the era of autonomous vehicles (AVs), safety risks in mixed-traffic environments may arise due to the coexistence of autonomous and human-driven vehicles, leading to unpredictable interactions and potential conflicts caused by differing driving behaviors and decision-making processes [37]. AVs operate based on pre-programmed algorithms, whereas human drivers rely on intuition and experience, increasing the likelihood of accidents in complex urban environments [37].

4.5. Environmental Impacts

Environmental concerns tied to transportation systems pose major barriers to sustainable urban development. Persistent congestion intensifies emissions of harmful pollutants, such as nitrogen oxides and particulate matter, degrading air quality and urban livability [38]. Reliance on fossil fuels contributes significantly to greenhouse gas emissions, climate change, and economic burdens associated with fuel consumption [44]. Poorly optimized logistics and traffic management practices exacerbate these challenges by increasing both travel distances and fuel consumption [47].

In response, numerous studies highlight a shift toward green transportation solutions, including enhanced public transit, active travel modes (e.g., walking and cycling), and smart mobility technologies [44]. Such strategies aim to lower environmental footprints and foster sustainable urban growth [44].

4.6. Transportation System Operation and Management

Effective operation and management of transportation systems are essential for ensuring efficiency, reliability, and sustainability. Nonetheless, resource limitations, legacy systems, and growing complexity create substantial operational hurdles. Studies point to constrained resources and the difficulty of balancing cost, coverage, and equity objectives, particularly in densely populated urban settings [25]. Conventional traffic management strategies are increasingly inadequate for handling modern, complex urban mobility, particularly as vehicle density rises [26,35]. One major contributor to inefficiency is the inadequate processing of real-time traffic data, which hinders the ability to implement adaptive traffic control measures [35]. Traffic light operations, in particular, remain inefficient, failing to respond effectively to fluctuating traffic volumes and dynamic demand patterns [34].

Furthermore, many systems are ill-equipped to incorporate real-time data and respond adaptively to fluctuating traffic conditions [36]. Traditional predictive models, which are typically designed for static or historical data, often prove ill-suited or exhibit inadequate performance when applied to dynamic, real-time traffic conditions. The complexity and unpredictability of streamed data can lead to delayed or suboptimal traffic flow management and inefficient resource utilization [44]. Freight operations add further intricacy, as route planning, resource allocation, and fleet management must account for cost, environmental impact, and service reliability [47]. Collectively, these findings illustrate the urgent need for data-driven, integrated strategies capable of addressing congestion, resource allocation, and technological interoperability challenges.

5. Proposed Solutions

5.1. Real-Time Traffic Monitoring and Control

Real-time traffic monitoring and control are pivotal for reducing congestion, improving road safety, and enhancing service reliability. ITS, equipped with sensors, cameras, and vehicle-tracking devices, allows for dynamic adjustments to traffic patterns [24,27,30,46]. Real-time data analysis and predictive modeling play a significant role in optimizing traffic flow and reducing congestion [29,32,34,36,39,40,47]. By integrating cloud computing—which centralizes data storage and large-scale processing in remote data centers—with edge computing—which brings computation and data analysis closer to the devices and sensors generating the data—transportation systems can significantly enhance real-time data processing and localized decision-making [30,41]. In particular, the implementation of such technology enhances the capability of real-time traffic monitoring and control [30].

Public transit services also benefit from real-time monitoring, which enables dynamic dispatch and helps minimize overcrowding by adjusting schedules in response to passenger demand [28,35]. The implementation of sensor-equipped cameras for real-time monitoring and enforcement has further enhanced compliance with traffic regulations and improved overall road safety [49]. Furthermore, digital twin models, providing synchronized virtual representations of transportation networks, facilitate continuous monitoring and real-time optimization of traffic flows [41]. Visualization tools (e.g., traffic dashboards) integrate live sensor data and modeling results, supporting evidence-based decision-making for congestion management [38].

5.2. Predictive Analytics

Predictive analytics has gained prominence in proactive decision-making for traffic management, congestion mitigation, and resource allocation. Studies demonstrate the utility of machine learning models, including artificial neural networks, deep learning, and graph-based learning techniques, for short-term and long-term traffic predictions [26,29,44]. In particular, GNNs have emerged as an advanced approach for predictive traffic analysis, leveraging the relational structure of road networks to enhance forecasting accuracy [33].

Advanced forecasting methods, such as spatiotemporal modeling and periodic pattern mining, refine prediction accuracy, supporting dynamic routing and infrastructure planning [28,33,46]. Relatedly, within this context, cloud and edge computing architectures are increasingly employed to manage large volumes of real-time data, improving scalability and the responsiveness of such predictive models [30,32,35,41]. By considering the locational properties of data capture and modeling outputs, these approaches tend to facilitate spatially informed analyses of traffic hotspots, accident-prone areas, and emerging demand trends [24,31,32].

Moreover, predictive analytics were shown to play a crucial role in parking management by forecasting occupancy levels and assisting in space allocation to reduce urban congestion [34]. Predictive analytics also addresses safety and cybersecurity issues by identifying risky driving behaviors and potentially malicious network activities [43,48,49]. Furthermore, real-time vehicle routing optimization has benefited from predictive models that leverage bi-directional time processing to enhance the accuracy of travel time forecasts [40]. The alignment of predictive models with environmental factors, such as air quality impact analysis, has also been explored to support sustainable urban development initiatives [38].

5.3. Optimization of Public Transit/Multimodal Systems

Enhancing public transit and multimodal networks is crucial for easing congestion, improving accessibility, and reducing environmental impacts. The proposed solutions focus on dynamic vehicle dispatch and route optimization, employing real-time passenger flow analysis to refine service schedules [28,35]. Network design adjustments, such as the introduction of dedicated bus lanes and the reconfiguration of underutilized routes, help mitigate congestion and deliver more predictable travel times [42,45].

Improved data integration enables better insights into cross-carrier passenger flows, supporting accurate origin–destination matrix estimation and more coherent multimodal planning [33]. Simulation-driven frameworks offer decision-makers the ability to test multiple service scenarios, optimizing the balance among service coverage, equity, and operational cost [45].

5.4. Safety Enhancement and Risk Mitigation

To address traffic safety challenges, researchers propose solutions using advanced technologies like AI, big data analytics, and real-time monitoring. Predictive modeling identifies collision-prone zones and patterns of traffic violations, enabling timely and targeted interventions [49]. AI-driven systems, particularly those leveraging 5G and edge computing, enhance situational awareness in mixed traffic environments, providing rapid response to evolving conditions [37].

Real-time route computation based on health alerts and mobility restrictions proves valuable for managing emergencies, such as pandemic-related lockdowns [39]. Decision-tree algorithms facilitate quick fault detection and corrective actions, while interactive dashboards offering live safety metrics support proactive risk management [34,46].

5.5. Dynamic Traffic Flow and Signal Management

Dynamic traffic flow and adaptive signal management strategies aim to optimize road network performance in real-time. Essential requirements involve the deployment of ITS to optimize traffic flow and provide decision support through enhanced traffic management functionalities, including signal control, event monitoring, and emergency response coordination [24]. Deep learning and deep reinforcement learning techniques forecast congestion and implement adaptive control actions in response to changing traffic conditions [29,44]. Adaptive green light scheduling, which modifies signal timing based on incoming traffic volumes, reduces delays and collision risks at intersections [26,36]. In urban environments, the implementation of dynamic alert-level-based traffic control has proven beneficial in adapting to fluctuating demand and emergencies [35].

The use of cyber–physical systems (CPSs) further enhances traffic signal optimization by integrating real-time sensor data with predictive analytics [46]. CPSs are integrated systems that connect physical components, such as sensors and actuators, with computational processes to monitor, control, and optimize real-world operations in real-time [35,46]. Additionally, digital twin technologies have been shown to enhance dynamic traffic control by synchronizing real-time data with virtual models of traffic networks, enabling continuous monitoring, predictive analysis, and optimized decision-making. By maintaining real-time digital counterparts of physical transportation systems, digital twins facilitate adaptive traffic management, operational improvements, and scenario-based simulations to enhance mobility and congestion control [41,46,48]. These models facilitate parallel simulations, enabling authorities to evaluate different adaptive traffic signal control algorithms and forecast system-wide effects [48]. Also, user-friendly visualization interfaces enhance operational decision-making by providing integrated insights into congestion patterns, sensor data, and simulation outcomes [38]. Automated traffic management mechanisms designed to prevent congestion and optimize urban mobility by redistributing traffic across the network have also been explored. These mechanisms utilize predictive analytics to preemptively detect congestion hotspots and recommend alternate routing strategies to minimize disruptions [34].

5.6. Scenario Planning and Strategic Simulations

Scenario-based planning and simulation-driven analyses are increasingly central to ensuring transportation resilience. Data-driven frameworks allow policymakers and planners to model diverse conditions, test infrastructure modifications, and evaluate policy interventions [35,46]. For instance, open data and microscopic traffic emulators help predict outcomes of traffic management strategies in virtual environments, minimizing real-world disruptions [41,48]. Simulation-driven decision-making has emerged as a powerful tool for identifying areas for network improvement and optimizing traffic management strategies [41].

Digital twins complement scenario planning by synchronizing real-time traffic data with virtual models to enable parallel simulations that assess various signal control algorithms, optimize network conditions, and support real-time decision-making [41,48]. Integrating traffic modeling with sustainability metrics (e.g., emissions or noise pollution) further enhances the ability to develop environmentally responsible policies [38].

6. Technologies and Approaches

6.1. IoT-Based Data Collections

IoT-based data collection is fundamental to real-time traffic monitoring and data-driven decision-making. Multiple types of sensors—ranging from GPS devices and radar systems to LiDAR and CCD cameras—capture traffic flows, road conditions, and travel times [26–29,32,36,42,44,45,47,49]. CPS and complex event processing frameworks integrate these heterogeneous data streams, enabling predictive analytics and responsive traffic management [30,35,39].

Emerging technologies, including 5G and edge computing, enhance data throughput and reduce latency, enabling faster decision-making [37]. Robust data cleaning and validation methods, such as speed-flow correlation filters and anomaly detection algorithms, further bolster data integrity [38]. In addition, scalable and interoperable IoT platforms are highlighted for their capacity to integrate diverse data sources spanning multiple transportation subsystems [41,46].

6.2. Big Data Processing and Analytics

Big data processing underpins modern operational transportation analytics, particularly in real-time traffic monitoring and control, by aggregating large-scale datasets from diverse sources, including transport-specific capture systems such as sensors, cameras, and mobile devices. Additionally, other data sources—such as surveys, administrative data, social media, and commercially relevant datasets—can complement these systems by providing broader contextual insights. Machine learning and statistical techniques are applied to uncover patterns and trends, while sentiment analysis of social media data offers additional perspectives on public opinion [29].

Urban data fusion techniques, including spatiotemporal pattern mining and relational data mining, enhance the consistency and completeness of transportation data [33]. However, data quality and cleaning remain significant concerns, requiring a balance between data engineering, which focuses on preprocessing and ensuring accuracy, and data science, which emphasizes deriving meaningful insights from the cleaned and structured data [38]. Integration with navigation app data and vehicle-to-everything (V2X) technologies further broadens the scope of data collection, capturing granular details of travel behavior [24,32].

Distributed computing frameworks, such as Apache Hadoop and Apache Spark, along with cloud computing environments, facilitate scalable storage, efficient processing, and real-time analytics [27,28,30,31,35,41,42,46,49]. Edge computing supplements these architectures by enabling on-site or near-site data processing, reducing transmission delays [36,46].

6.3. Machine Learning and AI-Based Technologies

Machine learning and AI techniques have proven effective in tasks ranging from short-term traffic flow forecasting to congestion classification. Unlike traditional methods that rely on static models and pre-defined rules, these techniques dynamically adapt to real-time data and complex, non-linear traffic behaviors. Deep learning, backpropagation neural networks, and decision tree algorithms have demonstrated superior performance in predicting traffic delays, identifying accident hotspots, and optimizing traffic operations by learning patterns directly from data [26,29,31,33]. Reinforcement learning, a key advancement over conventional optimization, has been explored for adaptive control of public transit operations, path planning, and dynamic traffic signal management, where decisions improve continuously through iterative feedback and real-time interactions [25,33,44].

Fuzzy inference systems, gradient-based optimization, and advanced ensemble algorithms represent another departure from traditional methods by providing flexible and scalable solutions to balance mobility demands with regulatory constraints, improving resource allocation and system responsiveness [39,43,44]. Furthermore, AI-driven monitoring agents integrated with anomaly detection mechanisms enable near-instantaneous adjustments to traffic management settings, a capability that traditional rule-based systems often lack [34,37,41].

6.4. Optimization and Decision Support Systems

Optimization techniques and decision support systems enable planners to evaluate various scenarios and select the most effective strategies by simulating and analyzing potential outcomes. These systems are typically deployed through web-based software platforms, GIS, or integrated decision-support dashboards that couple real-time data with optimization algorithms for practical, data-driven decision-making. In some contexts, they are implemented through abstract data science workflows designed to analyze complex network conditions and recommend solutions.

Data envelopment analysis (DEA) supports multi-objective optimization, particularly in evaluating the efficiency of multiple routes or resource allocation scenarios. Graph-based methods, such as maximum spanning trees and Dijkstra's algorithm, are applied to tasks like the traveling salesman problem and delivery route optimization, helping identify the most efficient paths through complex networks [25,35,36]. These methods are essential for applications such as urban freight delivery, public transit routing, and emergency response planning. These methods are essential for applications such as urban freight delivery, public transit routing, and emergency response planning.

CPS also offers a comprehensive framework by integrating real-time data acquisition, processing, and dynamic feedback to support decision-making processes. In this context, CPS applications go beyond traditional static systems by enabling adaptive and automated responses to fluctuating traffic conditions [30,35].

Dynamic scheduling and enterprise resource planning systems refer to software-based solutions designed to optimize the allocation of vehicles, personnel, and logistics resources in real-time. By integrating live traffic data, these systems improve vehicle dispatch, delivery scheduling, and fleet coordination, minimizing delays and maximizing operational efficiency [28,40].

For applications related to spatial optimization and decision support, agent-based approaches—such as those developed using the Java Agent Development Framework—provide a decentralized and cooperative decision-making framework. These methods differ from traditional centralized optimization techniques by simulating interactions between autonomous agents (e.g., vehicles or transit units), allowing for emergent behavior and real-time adaptability. Space modeling techniques, such as L-space and C-space, further support connectivity analyses in multimodal networks by modeling transportation nodes and routes to enhance flow optimization across various transport modes [34,45].

Finally, information and communication technology (ICT) solutions bolster coordination and interoperability by providing real-time communication channels among transportation stakeholders, such as logistics companies, public transit agencies, and traffic control centers. These technologies ensure that decision-making processes are well-coordinated and adaptable to dynamic transportation conditions [47].

6.5. Digital Twins and Traffic Emulations

Digital twin frameworks and traffic emulators complement each other by offering comprehensive virtual environments for transportation analysis. Traffic emulators simulate real-world traffic conditions, generating dynamic inputs that synchronize with digital twins—virtual representations of physical transportation systems that continuously integrate real-time data to optimize network conditions. This relationship enables continuous monitoring, real-time synchronization, and parallel simulations, bridging operational feedback with strategic decision-making.

Microscopic traffic models, colored Petri nets, and open-source tools (e.g., SUMO) serve as core components of traffic emulation, allowing researchers to test and refine routing strategies and congestion mitigation measures under controlled conditions [38,39,41,48]. The outputs from these emulators can be integrated into digital twin systems to improve real-time traffic management and long-term network planning, reinforcing their role as predictive and adaptive decision-support tools.

Integrating AI-based predictive models, such as Non-Linear Autoregressive with External Input (NARX), within digital twin systems enables the accurate simulation of complex interactions among vehicles, infrastructure, and travelers [26]. This integration provides dynamic capabilities that extend beyond traditional simulation models, supporting applications such as energy consumption analysis, environmental impact assessments, and infrastructure optimization. By combining emulation and real-world feedback, digital twins help policymakers align transportation initiatives with sustainability goals [46].

Scenario-based simulation approaches further enhance decision-making by incorporating GIS-based multimodal data representation and traffic dashboards, offering stakeholders actionable insights for optimizing traffic flow and improving resource allocation [33].

6.6. Data Integration and Visualization

Effective data integration and visualization techniques work together to transform raw information into actionable insights, enabling stakeholders to make informed decisions. Data integration focuses on harmonizing diverse data sources—such as geographic, temporal, and sensor-based data—into unified platforms, such as data lakes or distributed databases, to support real-time processing and analysis. Visualization tools then present these integrated datasets in user-friendly formats, turning complex information into intuitive visual outputs.

Heat maps, interactive dashboards, and specialized business intelligence tools (e.g., Tableau) offer dynamic representations of real-time network visualization tools (e.g., Gephi) and are particularly useful for route optimization and infrastructure planning as they allow for visual exploration of connectivity within transportation networks [45].

Spatial and temporal data integration methods—using platforms such as PostgreSQL with PostGIS and Timescale—enhance geographic and time-series analyses, ensuring that visual outputs are rooted in comprehensive, multi-dimensional data [38]. Advanced data mining techniques, including classification, clustering, sentiment analysis, and time-series forecasting, play a crucial role in refining predictive models and enhancing visualization accuracy [29,34,38,46]. By coupling robust data integration with effective visualization, stakeholders gain deeper insights into traffic dynamics, resource allocation, and infrastructure planning.

7. Interrelationships Among Challenges, Solutions, and Technologies

This chapter presents the results of the BERT analysis, with all numeric values in parentheses representing BERT Similarity Scores. The complete list of results is available in Appendix A. The BERT analysis highlights clear alignments between specific transportation challenges and proposed solutions, emphasizing the need for data-driven strategies and integrated planning. Figure 2 provides a visual representation of these relationships, mapping the interconnectedness among the three primary categories—challenges (orange nodes), solutions (green nodes), and technologies/approaches (blue nodes). Each line indicates a BERT-inferred similarity link, illustrating how strongly a particular challenge aligns with a solution or how a solution depends on specific technologies and approaches. The density of these connections underscores the multifaceted nature of modern transportation systems, where effective solutions require real-time data integration, robust forecasting, and coordinated decision-making.

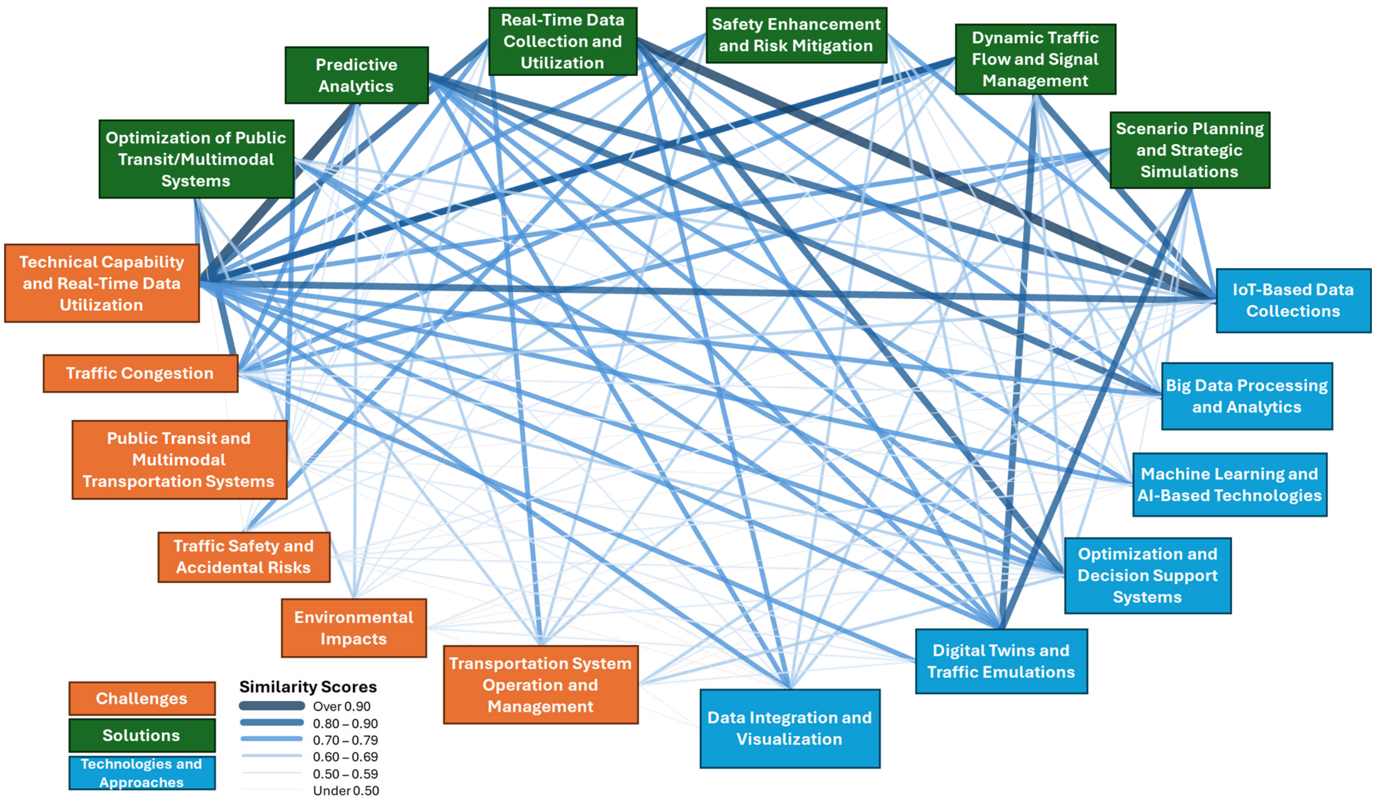

Figure 2. Integrative mapping of transportation issues, proposed solutions, and enabling technologies and approaches based on the results of BERT analysis.

In terms of the identified transportation challenges and proposed solutions, *Technical Capability and Real-Time Data Utilization* aligns strongly with *Predictive Analytics* (0.9285), showing that robust data-processing infrastructures are crucial for traffic forecasting and resource allocation. Likewise, *Traffic Congestion* demonstrates a strong connection to the *Optimization of Public Transit/Multimodal Systems* (0.8186) and *Predictive Analytics* (0.7641), implying that well-designed multimodal routes and accurate forecasting can alleviate congestion and improve operational efficiency.

Turning to *Public Transit and Multimodal Transportation Systems*, the strongest match (0.7737) appears with *Optimization of Public Transit/Multimodal Systems*, underscoring the importance of merging data insights into transit planning for better accessibility across modes. Meanwhile, *Traffic Safety and Accidental Risks* align closely (0.7527) with *Safety Enhancement and Risk Mitigation*, highlighting that proactive monitoring, real-time alerts, and targeted enforcement can significantly reduce accidents. For *Environmental Impacts*, the leading solutions include *Real-Time Data Collection and Utilization* (0.6773) and *Predictive Analytics* (0.6514), emphasizing how on-demand data and advanced forecasting can help lower emissions through adaptive traffic controls and optimized routing.

Viewing the solutions-technology linkage in detail clarifies how to implement these interventions. For instance, *Real-Time Data Collection and Utilization* shows a strong bond (0.9175) with *IoT-Based Data Collections*, reflecting the pivotal role of continuous, large-scale sensor data in on-the-fly traffic decisions. *Predictive Analytics* most closely depends on *Big Data Processing and Analytics* (0.8319) and *IoT-Based Data Collections* (0.8271), while *Scenario Planning and Strategic Simulations* pair closely with *Digital Twins and Traffic Emulations* (0.8771). Meanwhile, *Optimization of Public Transit/Multimodal Systems* aligns closely with *Optimization and Decision Support Systems* (0.7778), reinforcing the importance of data-driven algorithms for optimizing routes and schedules. For *Safety Enhancement and Risk Mitigation*, the strongest technological matches are *IoT-Based Data Collections* (0.7343) and *Data Integration and Visualization* (0.6609), indicating the role of real-time data and coherent visualization in identifying and addressing high-risk behavior.

Finally, the results show how certain technologies can effectively address the identified challenges. *IoT-Based Data Collections* strongly supports *Technical Capability and Real-Time Data Utilization* (0.8368) and *Traffic Congestion* (0.6577), demonstrating that real-time sensor networks are vital for dynamic traffic management. *Digital Twins and Traffic Emulations* stands out for *Technical Capability and Real-Time Data Utilization* (0.7959) and *Traffic Congestion* (0.7305), enabling scenario-based simulations that inform both short-term interventions and long-term planning. In addition, *Optimization and Decision Support Systems* shares a high correlation with *Transportation System Operation and Management* (0.6933) and *Public Transit and Multimodal Transportation Systems* (0.5791), indicating that algorithmic tools can enhance coordination and resource deployment across diverse network segments.

The interrelationships reinforce the value of an integrated approach that combines real-time data harvesting with robust machine-learning techniques and simulation models. While each solution may be directly aligned with a particular challenge, the high degree of overlap among different elements suggests that a truly resilient, smart transportation framework must capitalize on complementary technologies in tandem, for instance, pairing predictive analytics with IoT-based sensor networks or merging digital twins with decision support systems. Such a multifaceted strategy can address the layered nature of congestion, safety, and sustainability challenges, ultimately allowing urban planners, policymakers, and industry stakeholders to craft more adaptive and mobility solutions.

8. Conclusions

In this study, we conducted a systematic literature review to examine how emerging technologies—including the IoT, AI, digital twins, and optimization algorithms—are transforming transportation planning and operations. By synthesizing 26 peer-reviewed articles, the analysis highlighted a set of critical transportation challenges (e.g., traffic congestion, real-time data utilization, safety, and environmental impacts) and illuminated how advanced solutions such as real-time data monitoring, predictive analytics, and digital twin simulations can collectively address these issues. Leveraging a BERT-based approach, this study revealed notable alignments between specific challenges, solutions, and technologies, underscoring the centrality of integrated, data-driven strategies in smart transportation systems.

From a policy standpoint, the interrelationship analysis indicates several key recommendations. First, the results underscore the fact that IoT-based sensor networks and big data analytics should receive prioritized funding and legislative support, given their strong alignment with real-time data utilization and predictive capabilities. Policymakers can facilitate the rollout of urban-scale data infrastructures—for instance, by incentivizing public–private partnerships and providing open data platforms—to support better congestion management and enhance safety enforcement. Second, digital twin modeling should be integrated into policy frameworks for mid- to long-term urban planning, as it enables scenario-based simulations that can assess the impacts of multiple interventions (e.g., congestion charges, restricted traffic zones, infrastructure expansion) before substantial financial commitments are made. Third, aligning public transit and multimodal transportation improvements with optimization and decision support tools can promote equitable, efficient mobility services that reduce road congestion while extending service coverage. At the same time, AI-driven predictive analytics can guide targeted emission reduction measures and help policymakers design incentive systems for environmentally friendly travel behaviors. Collectively, these insights highlight the need for forward-thinking legislative agendas that incentivize both innovation and interagency data sharing, positioning advanced technologies as foundational elements of sustainable, equitable transportation ecosystems.

While these technologies offer significant opportunities for improving transportation systems, their implementation is accompanied by several challenges that must be addressed to ensure their practical effectiveness. IoT-based sensor networks require substantial investment in infrastructure deployment, maintenance, and cybersecurity protections to safeguard sensitive transportation data [53,54]. The complexity of integrating IoT data across multiple agencies and private entities further complicates adoption, necessitating standardized protocols for interoperability [55]. AI-driven decision-support systems, although powerful in predictive modeling and optimization, often suffer from issues related to algorithmic transparency and explainability [56,57]. The reliance on machine learning models in transportation planning raises concerns about the interpretability of AI-driven recommendations, making it difficult for policymakers to validate and implement them with confidence [58]. Additionally, digital twin technologies, while effective for scenario-based transportation planning, require continuous real-time data synchronization, which can be hindered by inconsistent data availability, legacy infrastructure, and high computational demands [12,59]. Optimization algorithms, despite their potential to enhance multimodal transportation coordination, are constrained by computational complexity and the need for high-resolution mobility data that may not always be accessible in practice [60,61].

Beyond technical barriers, regulatory and institutional challenges also impact the large-scale deployment of these technologies. The lack of standardized frameworks for data governance and technology interoperability leads to fragmentation across transportation systems, limiting scalability and cross-jurisdictional coordination [62]. Privacy and ethical concerns further complicate implementation, particularly when leveraging AI and IoT for mobility tracking and decision-making [63,64]. Addressing these constraints requires collaborative efforts between policymakers, technology developers, and urban planners to develop regulatory frameworks that ensure responsible, transparent, and secure integration of smart transportation technologies [65,66].

Despite the promising findings, this study has several limitations. First, although this review drew upon multiple databases, certain relevant studies may not have been captured due to search-term specificity or publication bias in the indexed sources. Additionally, the limited number of analyzed studies reflects the rigorous inclusion criteria used to focus on multi-technology applications rather than broader, single-technology discussions. While this approach ensures methodological consistency, it also means that some relevant but more general studies were excluded. Future research could expand the scope by incorporating a wider range of articles that explore emerging multi-technology applications, particularly in nascent fields. Also, this review focused predominantly on urban use cases, leaving the applicability of these technologies in rural, low-resource, or culturally diverse settings underexplored. Moreover, while the BERT-based analysis is effective in identifying alignment scores, it does not fully capture the complexities of real-world implementation, including regulatory constraints and data privacy concerns. As it primarily relies on textual embeddings and similarity measures, it lacks the ability to account for contextual factors, such as geographic, economic, and political variations, that influence the success of a given technology across different regions. Therefore, the interpretation of the results should be approached with caution, recognizing these inherent limitations. In addition, this review highlighted a key challenge in the lack of consistent definitions across the literature. This is particularly evident with terms like “digital twin”, which are used to describe a range of applications—from static simulations to fully synchronized, real-time virtual replicas. As a result, the literature may be discussing different concepts, complicating the synthesis of findings and the development of universally applicable recommendations. Future research should address these limitations by expanding the search scope to include more diverse geographic contexts, incorporating quantitative meta-analyses and expert interviews to deepen the methodological triangulation, and examining emergent issues related to data security, ethical concerns, and regulatory alignment. Furthermore, establishing clearer and more consistent definitions—particularly for key terms such as “digital twin” and “optimization algorithms”—would enhance cross-study comparability and improve the coherence of future research findings.

Nevertheless, this study synthesizes fragmented research into a more coherent framework, clarifying how key transportation challenges can be tackled through advanced technology-based solutions. By explicitly mapping the relationships among challenges, solutions, and underlying technologies, this study aids stakeholders in recognizing the multifaceted interactions at play in modern mobility networks. Policymakers, engineers, and planners can utilize the findings of this study to prioritize technology investments, enact supportive regulations, and forge cross-sectoral partnerships. Finally, the meta-level perspective—encompassing everything from IoT-based data collection to AI-enhanced analytics and digital twin simulations—strengthens the emerging discourse on integrated transportation planning, opening avenues for more holistic and adaptable solutions in the pursuit of sustainable, equitable, and efficient urban mobility.

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Appendix A

Table A1. The results of BERT analysis—Transportation challenges and proposed solutions.

Transportation Challenges	Proposed Solutions	Similarity Scores
Technical Capability and Real-Time Data Utilization	Predictive Analytics	0.9285
Technical Capability and Real-Time Data Utilization	Real-Time Data Collection and Utilization	0.8792
Technical Capability and Real-Time Data Utilization	Dynamic Traffic Flow and Signal Management	0.8236
Traffic Congestion	Optimization of Public Transit/Multimodal Systems	0.8186
Technical Capability and Real-Time Data Utilization	Optimization of Public Transit/Multimodal Systems	0.7776
Public Transit and Multimodal Transportation Systems	Optimization of Public Transit/Multimodal Systems	0.7737
Transportation System Operation and Management	Real-Time Data Collection and Utilization	0.7696
Technical Capability and Real-Time Data Utilization	Scenario Planning and Strategic Simulations	0.7688
Traffic Congestion	Predictive Analytics	0.7641
Traffic Congestion	Dynamic Traffic Flow and Signal Management	0.7613
Traffic Safety and Accidental Risks	Safety Enhancement and Risk Mitigation	0.7527
Traffic Congestion	Real-Time Data Collection and Utilization	0.7512
Technical Capability and Real-Time Data Utilization	Safety Enhancement and Risk Mitigation	0.7393
Traffic Congestion	Scenario Planning and Strategic Simulations	0.7153
Traffic Congestion	Safety Enhancement and Risk Mitigation	0.6961
Transportation System Operation and Management	Optimization of Public Transit/Multimodal Systems	0.6937
Environmental Impacts	Real-Time Data Collection and Utilization	0.6773
Transportation System Operation and Management	Dynamic Traffic Flow and Signal Management	0.6669
Transportation System Operation and Management	Predictive Analytics	0.6562
Environmental Impacts	Predictive Analytics	0.6514
Transportation System Operation and Management	Safety Enhancement and Risk Mitigation	0.6465
Traffic Safety and Accidental Risks	Dynamic Traffic Flow and Signal Management	0.6295
Environmental Impacts	Optimization of Public Transit/Multimodal Systems	0.6255
Transportation System Operation and Management	Scenario Planning and Strategic Simulations	0.6116
Traffic Safety and Accidental Risks	Real-Time Data Collection and Utilization	0.5918
Public Transit and Multimodal Transportation Systems	Real-Time Data Collection and Utilization	0.5892
Traffic Safety and Accidental Risks	Predictive Analytics	0.5875
Environmental Impacts	Scenario Planning and Strategic Simulations	0.5756
Environmental Impacts	Dynamic Traffic Flow and Signal Management	0.5711
Public Transit and Multimodal Transportation Systems	Predictive Analytics	0.5489
Environmental Impacts	Safety Enhancement and Risk Mitigation	0.5459
Traffic Safety and Accidental Risks	Scenario Planning and Strategic Simulations	0.5307
Public Transit and Multimodal Transportation Systems	Scenario Planning and Strategic Simulations	0.4916
Public Transit and Multimodal Transportation Systems	Dynamic Traffic Flow and Signal Management	0.4895
Traffic Safety and Accidental Risks	Optimization of Public Transit/Multimodal Systems	0.4759

Table A2. The results of BERT analysis—proposed solutions and enabling technologies and approaches.

Proposed Solutions	Enabling Technologies and Approaches	Similarity Scores
Real-Time Data Collection and Utilization	IoT-Based Data Collections	0.9175
Scenario Planning and Strategic Simulations	Digital Twins and Traffic Emulations	0.8771
Dynamic Traffic Flow and Signal Management	Digital Twins and Traffic Emulations	0.8357
Predictive Analytics	Big Data Processing and Analytics	0.8319
Predictive Analytics	IoT-Based Data Collections	0.8271
Dynamic Traffic Flow and Signal Management	IoT-Based Data Collections	0.8133
Real-Time Data Collection and Utilization	Optimization and Decision Support Systems	0.8040
Real-Time Data Collection and Utilization	Data Integration and Visualization	0.7984
Predictive Analytics	Machine Learning and AI-Based Technologies	0.7923
Real-Time Data Collection and Utilization	Big Data Processing and Analytics	0.7904
Real-Time Data Collection and Utilization	Digital Twins and Traffic Emulations	0.7867
Predictive Analytics	Digital Twins and Traffic Emulations	0.7828
Predictive Analytics	Data Integration and Visualization	0.7796
Optimization of Public Transit/Multimodal Systems	Optimization and Decision Support Systems	0.7778
Optimization of Public Transit/Multimodal Systems	Digital Twins and Traffic Emulations	0.7579
Scenario Planning and Strategic Simulations	IoT-Based Data Collections	0.7480
Predictive Analytics	Optimization and Decision Support Systems	0.7417
Safety Enhancement and Risk Mitigation	IoT-Based Data Collections	0.7343
Safety Enhancement and Risk Mitigation	Digital Twins and Traffic Emulations	0.6922
Safety Enhancement and Risk Mitigation	Data Integration and Visualization	0.6609
Optimization of Public Transit/Multimodal Systems	IoT-Based Data Collections	0.6604
Dynamic Traffic Flow and Signal Management	Big Data Processing and Analytics	0.6565
Safety Enhancement and Risk Mitigation	Optimization and Decision Support Systems	0.6564
Dynamic Traffic Flow and Signal Management	Data Integration and Visualization	0.6495
Dynamic Traffic Flow and Signal Management	Optimization and Decision Support Systems	0.6382
Dynamic Traffic Flow and Signal Management	Machine Learning and AI-Based Technologies	0.6363
Scenario Planning and Strategic Simulations	Data Integration and Visualization	0.6221
Safety Enhancement and Risk Mitigation	Big Data Processing and Analytics	0.6182
Scenario Planning and Strategic Simulations	Optimization and Decision Support Systems	0.6115
Scenario Planning and Strategic Simulations	Big Data Processing and Analytics	0.6037
Real-Time Data Collection and Utilization	Machine Learning and AI-Based Technologies	0.5988
Safety Enhancement and Risk Mitigation	Machine Learning and AI-Based Technologies	0.5781
Optimization of Public Transit/Multimodal Systems	Big Data Processing and Analytics	0.5771
Optimization of Public Transit/Multimodal Systems	Data Integration and Visualization	0.5554
Scenario Planning and Strategic Simulations	Machine Learning and AI-Based Technologies	0.5406

Table A3. The results of BERT analysis—transportation challenges and enabling technologies and approaches.

Transportation Challenges	Enabling Technologies and Approaches	Similarity Scores
Technical Capability and Real-Time Data Utilization	IoT-Based Data Collections	0.8368
Technical Capability and Real-Time Data Utilization	Digital Twins and Traffic Emulations	0.7959
Technical Capability and Real-Time Data Utilization	Big Data Processing and Analytics	0.7687
Traffic Congestion	Digital Twins and Traffic Emulations	0.7305
Technical Capability and Real-Time Data Utilization	Data Integration and Visualization	0.7258
Technical Capability and Real-Time Data Utilization	Optimization and Decision Support Systems	0.7149
Technical Capability and Real-Time Data Utilization	Machine Learning and AI-Based Technologies	0.7054
Transportation System Operation and Management	Optimization and Decision Support Systems	0.6933
Traffic Congestion	Optimization and Decision Support Systems	0.6636
Traffic Congestion	IoT-Based Data Collections	0.6577
Transportation System Operation and Management	IoT-Based Data Collections	0.6279
Transportation System Operation and Management	Digital Twins and Traffic Emulations	0.5924
Environmental Impacts	Digital Twins and Traffic Emulations	0.5886
Public Transit and Multimodal Transportation Systems	Optimization and Decision Support Systems	0.5791
Traffic Safety and Accidental Risks	IoT-Based Data Collections	0.5579
Environmental Impacts	Optimization and Decision Support Systems	0.5529

Table A3. *Cont.*

Transportation Challenges	Enabling Technologies and Approaches	Similarity Scores
Traffic Congestion	Machine Learning and AI-Based Technologies	0.5523
Traffic Congestion	Big Data Processing and Analytics	0.5515
Environmental Impacts	IoT-Based Data Collections	0.5411
Traffic Safety and Accidental Risks	Machine Learning and AI-Based Technologies	0.5278
Traffic Safety and Accidental Risks	Optimization and Decision Support Systems	0.5204
Public Transit and Multimodal Transportation Systems	Digital Twins and Traffic Emulations	0.5169
Traffic Safety and Accidental Risks	Digital Twins and Traffic Emulations	0.5119
Traffic Congestion	Data Integration and Visualization	0.5060
Transportation System Operation and Management	Big Data Processing and Analytics	0.5003
Public Transit and Multimodal Transportation Systems	IoT-Based Data Collections	0.4989
Transportation System Operation and Management	Data Integration and Visualization	0.4973
Environmental Impacts	Big Data Processing and Analytics	0.4753
Environmental Impacts	Data Integration and Visualization	0.4715
Traffic Safety and Accidental Risks	Big Data Processing and Analytics	0.4427
Environmental Impacts	Machine Learning and AI-Based Technologies	0.4152
Transportation System Operation and Management	Machine Learning and AI-Based Technologies	0.4095
Traffic Safety and Accidental Risks	Data Integration and Visualization	0.3999
Public Transit and Multimodal Transportation Systems	Big Data Processing and Analytics	0.3917
Public Transit and Multimodal Transportation Systems	Data Integration and Visualization	0.3622

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