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Published in:
Sustainability (Switzerland)

DOI:
10.3390/su16145879

sustainability

MDPI

Review

The Application of Machine Learning and Deep Learning in Intelligent Transportation: A Scientometric Analysis and Qualitative Review of Research Trends

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Abstract: Machine learning (ML) and deep learning (DL) have become very popular in the research community for addressing complex issues in intelligent transportation. This has resulted in many scientific papers being published across various transportation topics over the past decade. This paper conducts a systematic review of the intelligent transportation literature using a scientometric analysis, aiming to summarize what is already known, identify current research trends, evaluate academic impacts, and suggest future research directions. The study provides a detailed review by analyzing 113 journal articles from the Web of Science (WoS) database. It examines the growth of publications over time, explores the collaboration patterns of key contributors, such as researchers, countries, and organizations, and employs techniques such as co-authorship analysis and keyword co-occurrence analysis to delve into the publication clusters and identify emerging research topics. Nine emerging sub-topics are identified and qualitatively discussed. The outcomes include recognizing pioneering researchers in intelligent transportation for potential collaboration opportunities, identifying reliable sources of information for publishing new work, and aiding researchers in selecting the best solutions for specific problems. These findings help researchers better understand the application of ML and DL in the intelligent transportation literature and guide research policymakers and editorial boards in selecting promising research topics for further research and development.

Keywords: machine learning; deep learning; intelligent transportation; scientometric analysis; qualitative review

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Citation: Zhang, J.; Wang, J.; Zang, H.; Ma, N.; Skitmore, M.; Qu, Z.; Skulmoski, G.; Chen, J. The Application of Machine Learning and Deep Learning in Intelligent Transportation: A Scientometric Analysis and Qualitative Review of Research Trends. *Sustainability* **2024**, *16*, 5879. https://doi.org/10.3390/su16145879

Academic Editor: Maria Vittoria Corazza

Received: 18 May 2024
Revised: 4 July 2024
Accepted: 8 July 2024
Published: 10 July 2024

1. Introduction

By 2050, the global urban population is projected to reach around 66% to 70% [1,2]. This rapid urbanization is likely to profoundly impact environmental sustainability, city management, and urban safety. To address the challenges this poses, several countries have introduced the concept of "smart cities" as a strategy to manage resources and optimize energy usage effectively. Central to the smart-city framework are such sectors as intelligent transportation, cybersecurity, and smart grids, which are significantly influenced by the integration of machine learning (ML) and deep learning (DL). These technologies enhance efficiency and scalability in smart city initiatives.

Machine learning and deep learning are two core subfields within the field of artificial intelligence that, although they share similar goals and theoretical foundations, differ significantly in terms of technical implementation, data dependency, hardware requirements, feature engineering, execution time, and interpretability. Machine learning involves a series of algorithms that perform specific tasks by learning patterns from data, while deep learning focuses on using neural network models, especially deep networks with multiple hidden layers, to learn complex representations of data. Deep-learning models require large amounts of data and high-performance hardware, typically take longer to execute, and are less interpretable [3].

Intelligent transportation systems (ITS) represent a synergy of smart devices, control systems, and information technology. These generate a substantial volume of data, playing a pivotal role in the success of smart cities [4]. Intelligent transportation solutions can enhance traffic-flow management by monitoring traffic patterns and optimizing traffic-signal timing. The overarching goal is to promote sustainable transportation modes, using ITS to provide real-time information and traffic management systems (TMS) to manage congestion. These systems aim to enhance safety and encourage environmental sustainability by minimizing the consumption of fuels and reducing energy use [5].

Despite considerable research into various applications of ML and DL in intelligent transportation, the studies vary widely, with research areas including traffic-flow prediction [6], authors conduct a brief survey to explore the various fundamental and important aspects of smart cities. Some of the important challenges discussed were designing a data-based solution to manage the transportation organization of a smart city through the use of machine-learning algorithms. ITS [7], congestion management [8], smart parking solutions [9], and enhancements to public transportation [10]. This may challenge some researchers and policymakers to understand the field comprehensively.

Moreover, while these studies contribute valuable insights, they have prominent limitations [10]. Primarily, many rely on traditional qualitative literature reviews that the cognitive biases and interpretative limits of the researchers may influence. Furthermore, while the use of ML and DL in intelligent transportation has attracted significant interest, a holistic review of their applications remains absent [5]. In addition, there is a lack of quantitative analysis and generalization across studies, which would benefit from aggregating the findings from a substantial corpus of the literature over an extended period. This gap emphasizes the need for more systematic and comprehensive research approaches.

To address the identified research gaps, this study uses a scientometric analysis complemented by visualization techniques to quantitatively assess the maturity and utilization of ML and DL across various research domains within intelligent transportation, drawing on a robust dataset of the long-term literature [11]. A scientometric analysis is a quantitative research method using mathematical and statistical methods to study the output, distribution, citations, author cooperation patterns, and other characteristics of scientific literature. It can help researchers understand research trends and trends in specific fields and evaluate the influence of research results [12]. The contributions are twofold. First, a foundation is provided for future studies to use optimal solutions for specific challenges based on established studies, facilitating further exploration within their respective fields. Second, the study details the specific content and growing trends in applying scientometric methods to this research area, offering a systematic review and summarizing the current state of knowledge.

The structure of this paper is as follows. Section 2 outlines the research methodology, including bibliometric methods and the software tools used. Section 3 presents the analysis and findings. Section 4 discusses these findings in a qualitative context. Finally, Section 5 concludes by discussing conclusive remarks, theoretical contributions, practical implications, and research limitations.

2. Research Methods

Scientometric analysis helps researchers find findings relevant to the literature that would not be possible with other methods. Bibliometrics or scientometrics are usually used in scientific mapping research [13]. While the focus of bibliometrics is on the literature itself, scientometrics provides a broader approach that includes bibliometrics tools, methods, and data to analyze the literature and its outputs to identify underlying insight patterns and trends in the field [14]. A scientometric analysis is carried out using the widely recognized three-step approach [15–18] illustrated in Figure 1. The initial data-collection stage involves acquiring bibliographic data from the Web of Science (WoS) Core Collection database. The second stage focuses on selecting the appropriate analysis methods and software tools. Microsoft Excel is a widely used spreadsheet software that provides powerful data processing and analysis capabilities. In scientometrics analysis, it is necessary to organize, clean, and analyze the data first, and the table function of Excel can facilitate these operations. VOSviewer (1.6.20) is a tool specifically designed to create and visualize bibliometric networks. It can help researchers analyze and display the citations, co-citations, and cooperative relationships in the literature [15,17,18]. The final stage, data analysis and discovery, is divided into three sub-stages: (1) analyzing publication outputs to understand trends over time; (2) performing scientific mapping through keyword analysis and evaluating the impact of significant publications; and (3) quantitatively assessing the maturity and application of ML and data analytics across various research fields. This structured approach facilitates a comprehensive examination of intelligent transportation research's evolution and current state.

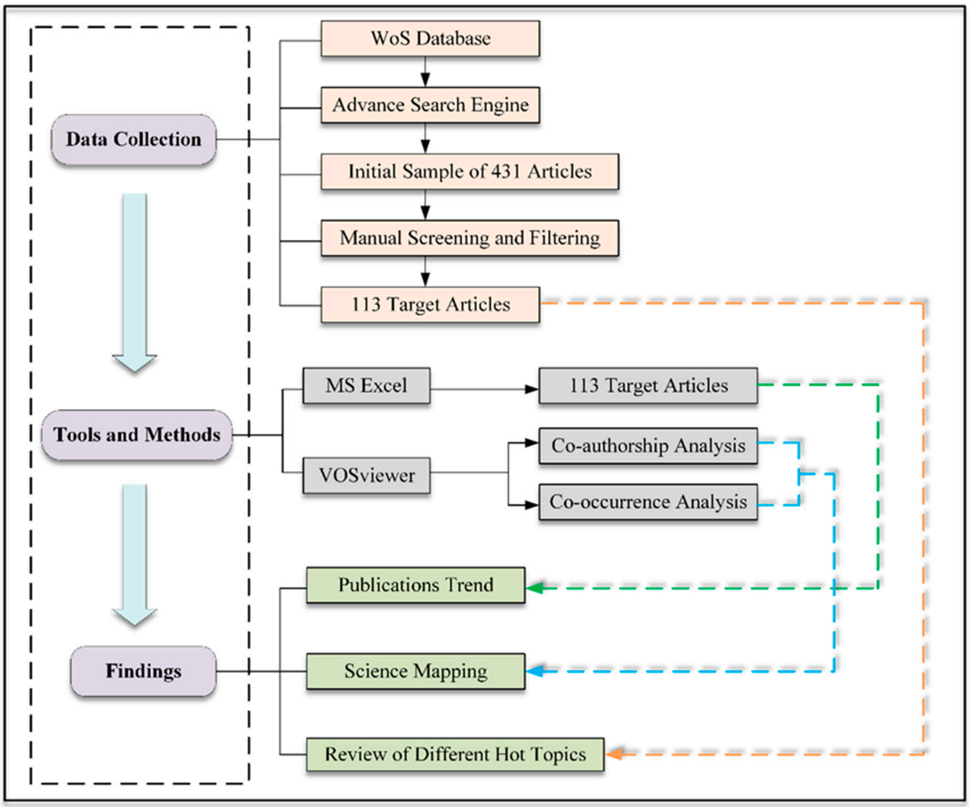

Figure 1. Three-step approach flowchart for scientometric analysis.

2.1. Data Collection

The data source was restricted to the Web of Science (WoS) database. The decision to use a single data source, WoS, was driven by its assurance of bibliographic data completeness and uniformity, including detailed information on authors, affiliations, countries, and cited references, as well as by the prevention of duplication risks that could arise from using multiple databases [19–21].

The initial screening involved a comprehensive search of papers published up to February 2024 using the following Boolean search strategy: ("data analysis" OR "data science" OR "machine learning" OR "deep learning") AND ("smart city" OR "smart urban" OR "transportation" OR "traffic"). This search yielded an initial set of 829 documents from the WoS database. When developing a Boolean search strategy, choose keywords carefully to ensure that they are highly relevant to the search target and avoid being too broad. Choosing these keywords would confine the retrieved articles to the scope of applying machine-learning or deep-learning techniques to transportation-related research topics.

To ensure the consistency and quality of the dataset, the manual screening and filtering phase restricted the document type to peer-reviewed journal articles. This decision stems from the recognition that journal articles typically represent the most prestigious and impactful forms of scholarly communication. Including other document types, such as "Proceedings Paper", "Review", "Editorial Material", "Book Chapter", and "Retracted Publication", could compromise the consistency of the dataset and skew the analysis. After excluding non-relevant document types, 431 articles remained.

In addition, this review does not include other modes of transportation, such as rail, air, and water. While the concepts of ITS, information technology, and digital technology can be applied to various transportation modes, our focus is on road/land transportation. Limiting the scope of ITS to road/land transportation rather than including other modes such as rail, air, and water has several significant advantages. Focusing on a single mode of transportation allows for a greater concentration of resources, technology, and research, leading to a significant increase in specialization and operational efficiency in this sector. Concentrating solely on road/land transportation simplifies transportation management and operations, effectively reducing the complexity of cross-sector coordination. Due to its narrower scope, the implementation and updating process of ITS will be faster and more adaptable to new technological changes.

Further scrutiny of titles and abstracts led to the exclusion of an additional 318 articles, primarily because their transportation modes were out of the scope of this review or they did not apply ML or DL techniques for intelligent transportation purposes. Ultimately, 113 articles that closely met the research criteria were selected. Comprehensive bibliographic data, including full records and cited references, were then retrieved for these selected articles.

2.2. Tools and Methods

This review uses scientometric econometric analysis and visualization techniques. The scientometric analysis presents research findings through visualization technology, making the data more intuitive and comprehensible. This approach aids researchers in identifying up-and-coming research topics and trends within the field. It also assists scientific institutions and governmental decision-makers in evaluating the effectiveness of research policies and allocating scientific resources.

Microsoft Excel and VOSviewer (1.6.20) [22,23] were used for tool selection. Microsoft Excel was used to map and visualize the thematic trends of the documents over time, providing insights into the literature's developmental trajectory. VOSviewer was used to conduct scientometric analysis, focusing on the co-authorship analysis of researchers, countries, and organizations, and keyword co-occurrence analysis. The relationships among researchers, countries, and organizations, and the connections between keywords, are elucidated by visualizing the co-authorship and keyword-occurrence networks. This visualization facilitates a clearer understanding of the research field's collaborative dynamics and thematic focus areas.

2.3. Findings

The findings from the scientometric analysis and visualization are qualitatively discussed, focusing on the development trends of the literature and co-authorship and keyword co-occurrence within the field. This approach systematically reviews and summarizes the evolution of the current knowledge base. A detailed examination is made of the application of ML and DL across various domains of intelligent transportation, offering insights from multiple perspectives. By analyzing these elements, the paper identifies and elaborates on the key trends and collaborations that characterize the current research landscape, providing a comprehensive overview of how these technologies are integrated into intelligent transportation systems.

3. Analysis and Findings

This section presents the analyses and findings of the literature regarding publication outputs, co-authorship, research cooperation, countries, organizations, and keyword co-occurrence.

3.1. Publication Outputs

The annual number of publications is a critical indicator of knowledge accumulation and the maturity of a specific research field [24,25]. As depicted in Figure 2, of the 113 publications reviewed, the number from 2015 to 2017 was relatively low, with only two articles comprising approximately 1.8% of the total publications in this field. From 2018 to 2021, the research activity in this domain intensified, and the number of published articles rose significantly to 34, representing 30.1% of the total. From January 2022 to February 2024, the volume of publications increased markedly, totaling 77, which accounts for 68.1% of the overall corpus.

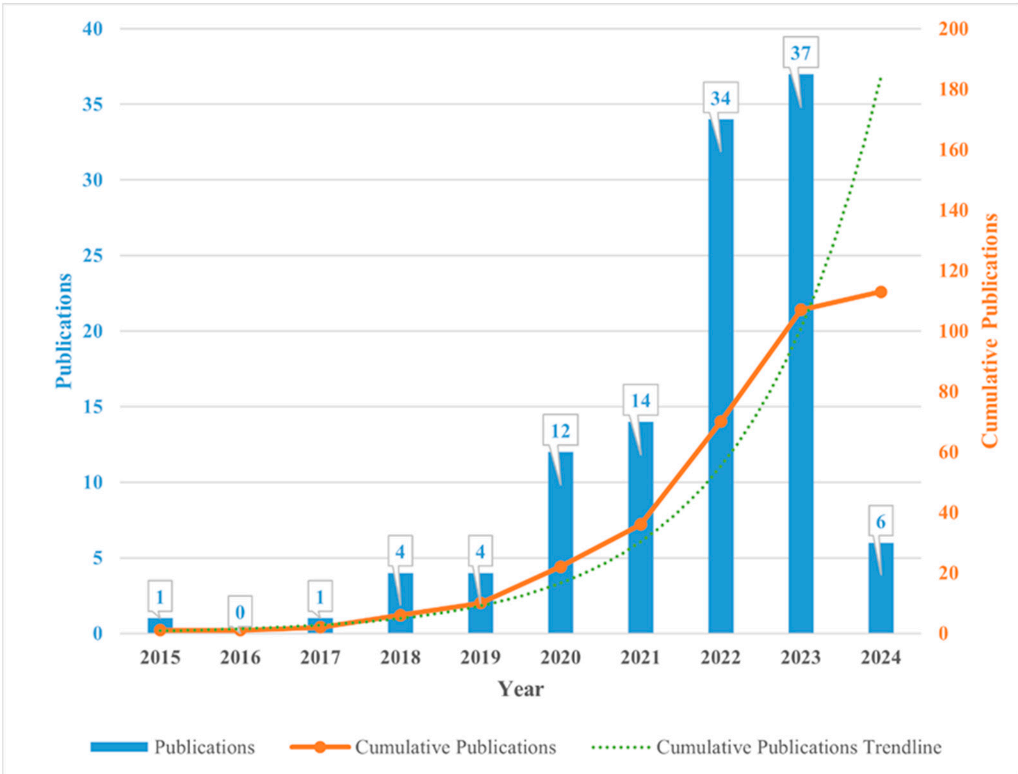

Figure 2. Annual publication trends from 2015 to 2024.

Overall, the trend analysis indicates that the number of publications has either increased or remained stable annually up to the search date of February 2024. The cumulative publishing trend line in Figure 2 illustrates a year-on-year increase in publications within this field. This trend suggests that the volume of publications will likely continue its upward trajectory in 2024 and beyond. The rapid expansion of publications highlights the growing breadth and interdisciplinarity of the intelligent transportation field, highlighting its potential as a fertile area for further development and exploration.

3.2. Co-Authorship

Tracing scientific collaboration patterns within a specific research field can facilitate access to expertise and enhance the breadth of knowledge. According to previous studies [4,24], these patterns can be effectively identified by analyzing co-authorship networks. Accordingly, the subsequent sub-sections detail the co-authorship networks among researchers, countries, and organizations, providing insights into the collaborative dynamics within the field.

3.2.1. Researcher Cooperation

Researchers are the architects of knowledge creation. Therefore, analyzing the complex cooperation among researchers can illuminate the characteristics of experts and pioneers in the field. An in-depth examination of their research and their social communication modes can elucidate the application areas of ML and DL within intelligent transportation. Utilizing 113 publications and the software tool VOSviewer, a visual representation of the collaboration network among researchers was constructed. For this analysis, the threshold is set to at least one document per author and at least 20 citations per author. Out of the 466 co-authors identified, 141 were selected for detailed analysis. In Figure 3, each node represents a different author, with links indicating collaborative relationships. The thickness of these links denotes the strength of collaboration, as measured by shared publications, while node size corresponds to each author's publication volume. The color gradient of the nodes reflects the average publication year of the authors' works.

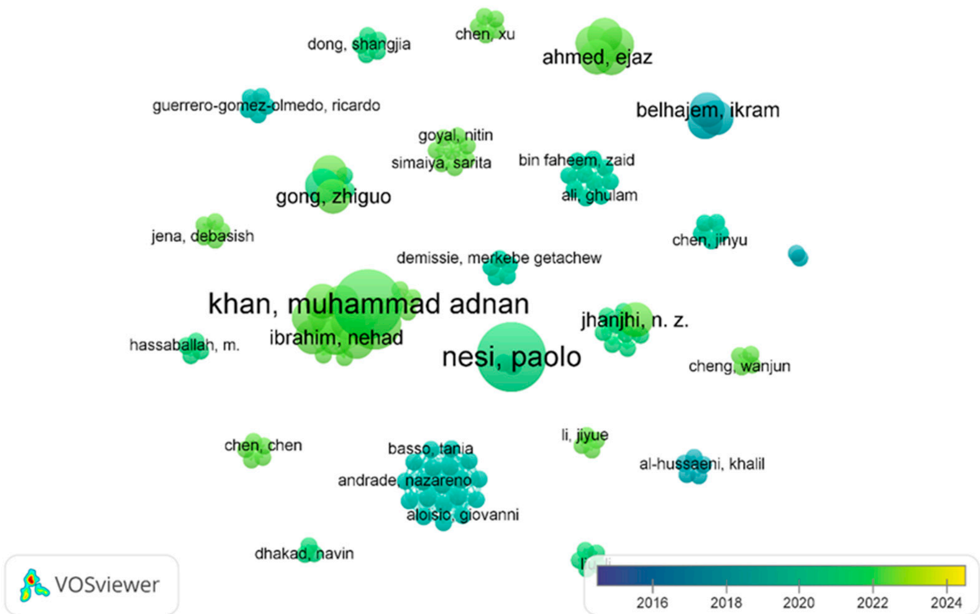

Figure 3. Co-authorship network for researchers.

Notably, leading researchers often form tightly knit research teams, resulting in several distinct cooperative networks. In terms of academic productivity and influence, Muhammad Adnan Khan emerges as the most cited author, with four academic works and 81 citations. Regarding active participation, researchers such as Nitin Goyal, Ning Zhang, and Wanjun Cheng stand out as dynamic contributors to recent publications in this domain.

3.2.2. Countries

Exploring international scientific cooperation is important for understanding the spatial distribution of publications and identifying key contributions in the field of ML and DL applications in intelligent transportation. VOSviewer generated a network of collaborative relationships between countries, as depicted in Figure 4. For this analysis, the threshold is set to at least one document per country and at least 20 citations per author. Consequently, out of 40 countries, only 22 met these criteria and were included in the analysis. In Figure 4, each country is represented by a node, with links between nodes indicating collaborative interactions. The thickness of these links denotes the strength of collaboration based on shared documents. Node size and color variations in Figure 4 follow the same scheme as Figure 3.

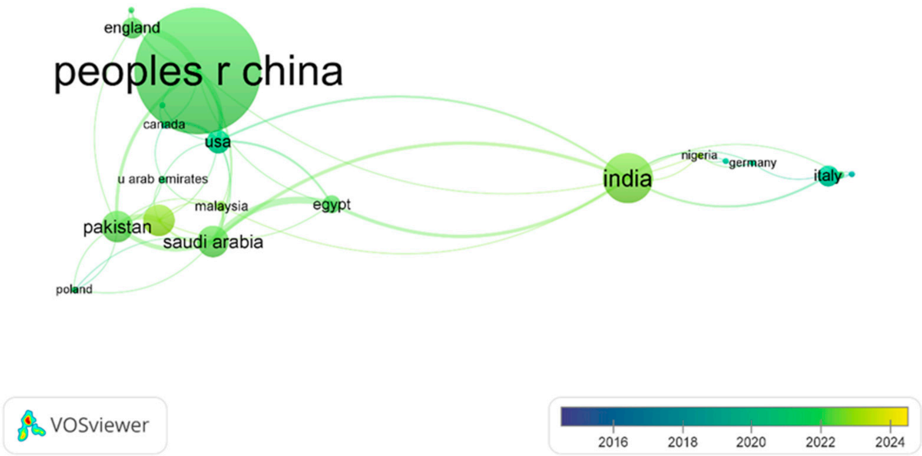

Figure 4. Co-authorship network for countries.

As illustrated in Figure 4, unlike the more fragmented researchers' network in Figure 3, the country networks are fully interconnected and have greater homogeneity. In terms of academic productivity and influence, China (48 publications, 521 citations), the United States (9 publications, 312 citations), and India (19 publications, 237 citations) stand out as the most prolific contributors, emphasizing their pivotal roles in advancing global research on ML and DL in intelligent transportation. Notably, India and South Korea are the most active contributors, with an average publication year of 2022 reflecting their dynamic engagement in this research area.

3.2.3. Organizations

Exploring scientific collaborations among organizations is important for sustaining future academic exchanges, optimizing funding allocation, and supporting research decision-making processes [24]. Utilizing VOSviewer, a network of collaborative relationships between organizations was constructed, as depicted in Figure 5. The network configuration—selection threshold, node size, and color changes—mirrors that of the national network analysis. For this analysis, the threshold is set to a minimum of one document per country and at least 20 citations per author. Out of 287 organizations, 94 met the criteria and were included in the analysis. Figure 5 highlights such significant contributors as the University of Macau (five publications, 117 citations), Dalian Polytechnic University (four publications, 70 citations), and the University of Florence (four publications, 78 citations) for their significant academic productivity.

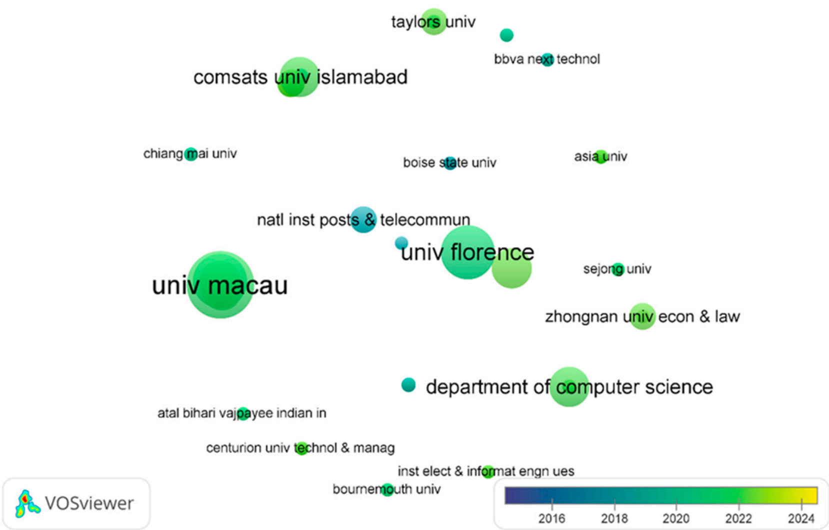

Figure 5. Co-authorship network for organizations.

In terms of research activity, Jiaquan University, Xi'an Jiaotong Liverpool University, and Zhongnan University of Economics and Law are identified as particularly active entities in this field, each with an average publication year of 2022. This indicates their dynamic involvement in the ongoing development of research in intelligent transportation.

3.3. Keyword Co-Occurrence

Keywords are concise phrases that encapsulate the core content or central concepts of publications. Analyzing keywords can reveal the primary interests and emerging topics within a specific research field [6]. The VOSviewer software generated a keyword co-occurrence network with a threshold of at least five occurrences per keyword. This process identified 110 keywords included in the analysis, as depicted in Figure 6. In this figure, each node represents a specific keyword, the links between nodes indicate the co-occurrence relationships of keywords, and the thicknesses of these links signify the strength of co-occurrence in mutual documents. The size and color variations of the nodes correspond to the frequency of the keywords and their respective clusters.

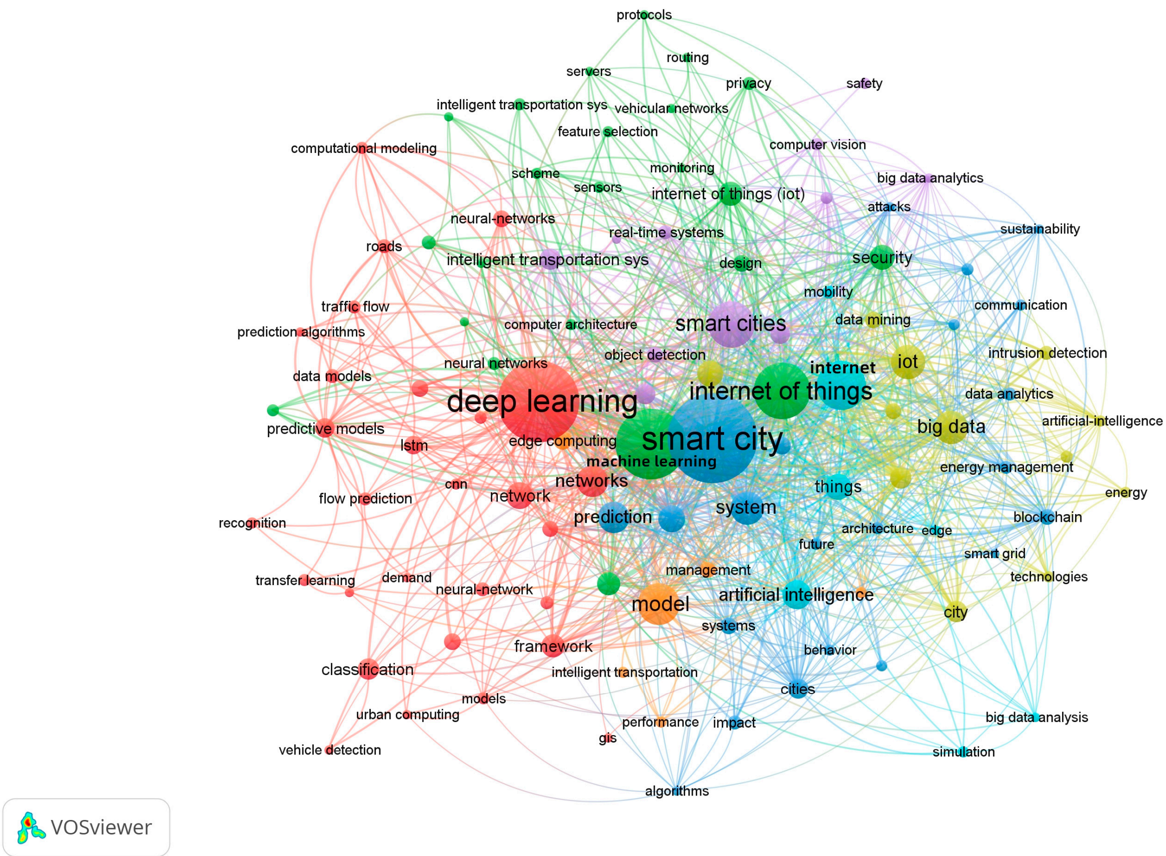

Figure 6. Keyword co-occurrence network and clusters.

Figure 6 illustrates several high-frequency keywords such as "deep learning", "smart city", and "intelligent transportation". This is partly due to the Boolean operators applied during the literature search. Given that DL is a subset of ML and intelligent transportation falls under the broader category of smart cities, the recurrent appearance of these terms is expected. The keyword co-occurrence network highlights several topics that have attracted extensive attention, including "intelligent transportation system", "big data analysis", "traffic flow prediction", "security", and "anomaly detection". These topics form the theoretical foundation for analyzing the nine key up-and-coming research topics presented in Section 4.

The keyword clusters identified through the co-occurrence network analysis highlight distinct themes and technologies within the field of intelligent transportation.

Cluster #1 (red) is the largest cluster, encompassing 29 keywords. It focuses on the application of DL in traffic-flow prediction, utilizing various predictive tools and techniques, such as neural networks (NN), convolutional neural networks (CNN), and long short-term memory networks (LSTM).

Cluster #2 (green), comprising 23 keywords, addresses the integration of the Internet of Things (IoT), ML, and intelligent transportation systems. Security, privacy, service quality, routing, and monitoring are key aspects. The predominant tools and techniques involve IoT and NN.

Cluster #3 (blue) contains 22 keywords and emphasizes the role of data analysis and algorithms in intelligent transportation. This includes traffic-accident analysis, prediction, network security, and connectivity enhancements.

Cluster #4 (yellow), with 12 keywords, primarily focuses on the interplay between artificial intelligence, big data, cloud computing, and intrusion detection systems.

Cluster #5 (light purple), with 11 keywords, is centered on using big-data analysis and data visualization in intelligent transportation systems, covering such applications as object detection, road traffic monitoring, security, and real-time systems.

Cluster #6 (light blue) and Cluster #7 (orange) are smaller clusters containing seven and six keywords, respectively, and they explore advanced technologies, including artificial intelligence, big-data analysis, edge computing, and fog computing. These clusters highlight the evolving technological landscape and its implications for intelligent transportation systems.

While the seven clusters identified in the keyword co-occurrence analysis are distinctly defined, they are not isolated entities. Instead, these clusters are intricately intertwined, with significant overlapping. This complex interconnection highlights the close relationships of the clusters and reveals the complexity of their inherent linkages and interactions. The presence of overlapping areas not only challenges researchers to reconsider the distinctiveness of each cluster but also offers a valuable opportunity for a deeper examination of the mutual influences and interactions between these clusters. This integrated approach highlights the interdisciplinary nature of the field and the multifaceted applications of ML and DL in intelligent transportation. To achieve clearer distinctions, nine specific application areas were identified as more representative during a thorough review of the article's content and, therefore, needed to be separated.

4. Qualitative Discussion

This section outlines key insights regarding the application of ML and DL in intelligent transportation. The analysis of publication outputs reveals an upward trend in the number of annual documents, highlighting the growing interest in this domain as a promising area of research. This trend highlights the potential for ML and DL to address specific challenges within intelligent transportation.

To facilitate future research, this study uses rigorous scientific methods to systematically organize and summarize the development of the current knowledge base. This enables researchers and academics to further build upon prior work and explore their respective areas. Additionally, Table 1 presents a detailed examination of various types of ML and DL applications in intelligent transportation, providing a comprehensive overview that aids in selecting optimal solutions for specific problems within this field.

Table 1. List of emerging ML and DL topics.

Up-and-Coming Research Topics	Number of Publications
Traffic-Flow Prediction (TFP)	31
Public Transportation	19
Intelligent Traffic Data Transmission and Sharing	16
Intelligent Transportation System (ITS)	13
Smart Parking	12
Traffic Congestion	7
Vehicle Detection and Tracking	6
Vehicle Identification and License Plate Number Recognition	5
Traffic-Light and Streetlight System	4

4.1. Traffic-Flow Prediction

In intelligent transportation systems, traffic-flow prediction plays an important role. Accurate predictions enable traffic-management authorities to effectively plan and adjust resources, such as signal control and traffic guidance strategies. Such forecasting is important to the functionality of smart-city systems and public safety. However, traffic-flow prediction remains a challenging task [26]. This section provides an overview of recent advancements in traffic-flow prediction.

Table 2 details the methods, innovations, data preprocessing techniques, empirical conclusions, limitations, and future research directions from various studies in traffic-flow prediction. Analysis of this table reveals the use of diverse methods, including SVM, BiGRU, LSTM, GCN, RNN, and GAN, to address traffic-flow prediction challenges. Innovations include noise data, integration of trust authority principles, and dynamic correlation enhancements. Various data preprocessing methods are used to improve model performance and accuracy, such as min–max normalization, data interpolation, and data cleaning and conversion. Most of these studies demonstrate that the proposed models or methods surpass existing technologies or baseline models in terms of empirical results.

Table 2. Summary of the literature related to traffic-flow prediction.

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[27]	SMO, BiGRU	SMO algorithm for hyperparameter adjustment	Min–max normalization approach	SMOBGRU-TP model outperforms the existing technology	-	(1) Combine mixed DL models (2) Improve the efficiency of SMOBGRU-TP method
[28]	LSTM, RNN	Noise pollution and time-series data for better prediction	Data Interpolation	Adding noise data improves the performance by 13.48%	-	Reduce specialization of sensing infrastructure using feature profiles and AI technology
[29]	FL, GCNN	Trusted authority principle integrated into federated learning for model data protection	-	FDL-TF outperforms baseline solution	-	-
[30]	GCN	Study of superparameter optimization of T-GCN	Min–max normalization approach	The superparameter optimizer selects T-GCN's optimal hyperparameters		-

Table 2. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[31]	EC, DCRFNN	Short-term traffic-flow prediction model for 5g Internet of vehicles based on EC and DL	-	Ensure good unloading performance and high prediction performance	No suitable task-scheduling algorithm is proposed	Traffic-accident risk prediction
[32]	RNN, GCNN	Spatiotemporal correlation obtained from traffic network	-	Better than the most advanced baseline model	-	Consider external factors that determine traffic forecasts
[33]	FedSTN	Privacy issues addressed in distributed traffic data	-	FedSTN has a higher prediction accuracy	-	Real-time path planning through traffic-flow prediction
[34]	CONV-BI-LSTM	Traffic forecasting using Industry 4.0 and big-data analysis	-	CONV-BI-LSTM is the top choice for short-term prediction	-	-
[35]	PVHH, IDT, Ford-Fulkerson	Node intelligent prediction is performed on specific nodes	-	Good prediction effect	Problems in prediction accuracy and time	Study of time lag and unpredictable factors
[36]	EdRVFL, RF, GCN, BOA	Accurate counting of moving targets under different weather conditions	-	This method excels when connections are unavailable or too complex	-	-
[37]	LSTM	Utilization of large-scale taxi GPS trajectories and environmental information	-	Detection and tracking accuracy increase by 10%, cutting errors by approximately 50%	Weather conditions are described using only qualitative variables, such as sunny and rainy weather	Considering quantitative and human factors
[38]	RBM, SVM	Application of recurrent mixed density networks for short-term traffic-flow prediction	Map matching algorithm	O-Sense can effectively improve the accuracy of travel cost estimation	-	-
[39]	LSTM, MDN	Big-data architecture and real-time prediction model proposed	-	This method demonstrates significant superiority	-	-
[40]	LSTM, GRU	Traffic-flow prediction using technologies such as bagging and air pollution		When assessing January 2020 data, its predictions were highly accurate	COVID-19 impacts prediction accuracy after January 2020	Extend the initiative to the entirety of California

Table 2. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[41]	KNN	Dynamic correlation of transportation nodes integrated with spatiotemporal DL models	Mean/median method, Z-score, Min–max normalization	Reduce the error rate of traffic-congestion prediction by more than 30%	-	(1) Study of the impact of different seasons on traffic flow (2) Combine satellite traffic measurements with ground-sensor values
[42]	GCN, Spatiotemporal DL model	Adaptation to high mobility and frequent changes in the network	Z-score normalization	Outperforms state-of-the-art GNN baselines	-	(1) Integrate different GCN-based DL models (2) Integrate the captured features into traffic prediction
[43]	LSTM	Parameters and operation time reduced	Handling abnormal data	High accuracy is achieved in industrial 4.0 applications	-	-
[44]	CNN, GNN	High-precision traffic forecasting achieved	Linear interpolation method	Improved results in short- and long-term forecasting	Not considering all kinds of accidents	Consider more factors to improve the model
[45]	CNN, LSTM, AM, XGBoost	Traffic-flow estimation considering external factors	Min–max normalization approach	The model has low prediction error and performs well	Lack of fine-grained stop point identification for signaling users	-
[46]	DBN, POA	Initial step towards sensor practicability in urban management	Min–max normalization approach	AST2FP-OHDBN outperforms the current state-of-the-art DL model	-	Design hybrid metaheuristics to enhance prediction results
[47]	GNN, LSTM	Migration learning is used to address data scarcity		The MSE value of the model is 6.309, MAE value is 2.256, RMSE value is 2.511	Other weather factors and track characteristics are not considered during training	(1) Explore the optimal value of input parameters (2) Consider other factors affecting traffic flow
[48]	CNN, LSTM	Method proposed for analyzing cellular communication data	Min–max normalization approach	It is the best way to predict traffic flow through traffic counters on the road	SARIMA can only predict for one hour	Plan to test a new anomaly detection algorithm
[49]	LSTM	Hierarchical information considering spatial interaction	Min–max normalization approach	Mgat model is superior to the most advanced method	-	-

Table 2. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[50]	GCN, KNN	Complex dynamics and spatial relationship of mobile traffic demand captured	-	Enhance cellular network traffic prediction accuracy significantly		Expand the scope of data collection
[51]	GCN, GRU	Model learning mechanisms guided by prior domain knowledge	-	Model increased RMSE and MAPE by approximately 8.4–29.5% and 7.5–30.6%	Study of the impact of different spatial embedded networks	-
[52]	RNN, LSTM	End-to-end solution for capturing cross-domain knowledge automatically	Min–max normalization approach	GASTN can outperform the current state baseline with a faster running time	-	Explore a GCN method for mobile traffic prediction based on a spatial relationship graph
[53]	GAN	Parallel spatiotemporal DL network for learning features from time and space dimensions	Min–max normalization approach	This method has the highest accuracy, reaching 98.21%	-	Create a model that works effectively in both typical and unusual situations
[54]	DAN, LSTM	Complex patterns and dynamics of urban transportation systems captured	-	The model has excellent performance in spatiotemporal data migration learning	-	(1) Further apply ST-DAAN to traffic-flow prediction (2) POI recommendation tasks
[55]	CNN, LSTM	Trusted authority principle integrated into federated learning for model data protection	-	Parallel spatiotemporal DL network outperforms competitors	-	Advanced DL architecture for large-scale traffic-flow prediction
[56]	RBF	Study on superparameter optimization of T-GCN	Eliminate noise, outliers, and missing values	The method based on depth RBF is superior to the traditional traffic analysis method	The effectiveness of the model in various situations needs to be strictly tested	Study of the applicability of deep RBF networks in other fields

Research into traffic-flow prediction systems continues to face several persistent constraints (e.g., data privacy regulations), risks (e.g., technology integration challenges), and issues (e.g., inconsistent interoperability). These include concerns over data quality and dataset limitations, models' complexity and interpretability, models' generalization and stability, hyperparameter tuning and automation, real-time and dynamic adaptability, and the need for cross-city and cross-domain prediction capabilities. Addressing these constraints, risks, and issues necessitates a concerted effort to enhance model interpretability and stability, improve data preprocessing techniques, develop more efficient hyperparameter optimization methods, and devise real-time and dynamic traffic-flow prediction strategies. Collaborative interdisciplinary research that integrates expertise from traffic engineering, computer science, and data science is needed to advance the field of traffic-flow prediction systems and promote their practical implementation.

4.2. Public Transportation

Public transportation, a critical component of smart cities, plays a vital role in urban mobility and is pivotal for transportation planning, resource allocation, and demand management. Innovative approaches, such as carpooling and crowdsourcing, have emerged to address these needs. Additionally, urban ride hailing, buses, and bicycle sharing represent the majority of research in this area.

Table 3 comprehensively summarizes the research methods, innovations, data preprocessing techniques, empirical findings, limitations, and future research directions across various studies. The subsequent analysis provides a detailed examination of these aspects. Numerous studies have leveraged advanced DL models, such as GCN, CNN, LSTM, RESNET, DNN, and Bi LSTM, to model complex spatiotemporal relationships. These models, augmented by effective feature engineering and nonlinear capabilities, predict passenger flows and single-vehicle demand. Some researchers have introduced innovative methods and models, including TBI, RF, and MVST-NET, to enhance traffic prediction and exploit the potential of shared travel, achieving significant predictive performance.

Table 3. Summary of the literature related to public transportation.

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[57]	GCN, CNN, LSTM, Res Net	Modeling complex nonlinear spatiotemporal relationships		It shows different prediction accuracy in different regions	There are still deficiencies in the interpretation of the model	Consider improving LSTM and exploring layered attention
[58]	TBI	Passenger-flow forecast using vehicle GPS records	Data cleaning, matching, and organization	The method outperforms time-series-based predictions for long-term taxi flow.	-	Real-time prediction architecture based on TBI2Flow
[59]	DNN	Integration of feature engineering technology with deep neural network for effective forecasting	-	The performance gain of the model is 25-37%, which is higher than the most advanced model on the standard benchmark index	-	Expect to perform well in weather forecasting, traffic-speed forecasting, and many other fields
[60]	RF	Quantitative analysis method for regional shared travel potential mining	-	If carpooling is adopted, the emission-reduction effect can be well reflected	Did not take a personal attitude towards carpooling into consideration	Further investigate the attitude towards carpooling
[61]	XGBoost, CSTN	Extraction of micro and macro spatial characteristics from urban taxi service demand data	Min–max normalization approach	Multisensory stimulation attention and multi-periodic feature learning are shown to be effective.	-	(1) Expand MSSA by learning more cyclical patterns (2) Merge more context information

Table 3. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[62]	IDT	Taxi cruise recommendation strategy based on real-time and historical trajectory data		TR-RHT can accurately recommend the cruising route for cruising time reduction	-	-
[63]	DT, SVC, NB, LR, RF	Transit congestion detection method based on opportunity perception	-	Over 80% congestion can be detected when used by 8–12% of commuters	-	-
[64]	BuStop	Dwell position extraction from multimodal sensing using commuter's smartphones	-	The framework can accurately detect various dwell positions	-	-
[65]	FDA, BSVR	Quantification of uncertainty for robust performance improvement	-	FDA's predictions are highly accurate and effective at forecasting travel time distribution uncertainty	-	-
[66]	CheetahVIS	Dynamic bus routes provided to help users identify traffic flow		Proved the effectiveness of CheetahVIS	-	-
[67]	PubtraVis	New visualization tool developed for public transportation system operation	Data cleaning, reorganization, extraction, and filtering	PubtraVis is a highly beneficial and user-friendly tool	"Ease of use" needs improvement	(1) Use GTFS static data (2) Real-time data to develop additional visual analysis module
[68]	SVR, RF, Adaboost, GBRT, XGBoost, MLP	Improved accuracy in estimating car-hailing trip mobility	-	This model outperforms other benchmarks in estimating car-hailing trip mobility	Use diverse geographic context features to measure the replaceability of location	Consider individual travel behavior in mobility modeling
[69]	MVST-NET	Urban big data is used to predict shared bicycle travel behavior	Min–max normalization approach	The model has good performance in various tested models	-	Performance improvement of analytical methods to make them more interpretable
[70]	Bi-LSTM	Forecasting available bicycles and free slots at shared bicycle stations	-	It provides a powerful method for reliable and fast prediction of available bicycles	-	-

Table 3. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[71]	BSS	Bicycle rebalancing solution in bike sharing system (BSS)		The proposed method outperforms the relocation manager in terms of bicycle shortage and task difficulty	-	-
[72]	STOP	Framework proposed for predicting shared station occupancy using Bayesian and association classifiers	-	Shows the usefulness of maintenance actions based on short-term forecasts and readable models	-	Enrich station occupancy data
[73]	IRM, GNN, RNN	DL-based bicycle-demand forecasting model introduced		The model has higher R2, lower RMSE, and MAE and has a better prediction effect	This study is limited to possible influencing factors	Explore the impact of social population, traffic flow, and weather
[74]	Attention-Based Model, CNN	Advance prediction of potential destinations for rescheduling artificial bicycles		The proposed framework excels in precision, recall, and F1 compared to top-tier methods	-	Simulate other relevant factors to provide better prediction of shared bicycle destinations

Data preprocessing is a critical step in all research, involving data cleaning, matching, organization, and normalization to ensure the accuracy and effectiveness of model training and prediction. The empirical findings from these studies cover various applications, such as passenger-flow forecasting, shared travel potential exploration, and shared bicycle-demand prediction. Most studies report that the proposed methods outperform traditional approaches, demonstrating higher prediction accuracy and improved performance in practical applications.

4.3. Intelligent Traffic Data Transmission and Sharing

Traffic prediction is a critical application within smart cities, with accurate traffic information needed for effective traffic management. Various methodologies have been proposed to predict traffic flows using time-series data from traffic sensors.

Table 4 provides a detailed summary of the methods, innovations, data preprocessing techniques, empirical findings, limitations, and directions for future research across a series of studies. An analysis of this table reveals that various ML and DL models, such as logistic regression, ANN, DT, KNN, RF, RNN, GAN, SVM, and CNN, are used to address traffic-related issues. Some studies introduce novel models or methods, such as the ‘vehiclectron’ model for precise vehicle-count estimation on roads and a driver yawning detection method based on facial action recognition. The significance of data cleaning and transformation for enhancing model accuracy and stability is emphasized across many papers. Specific data standardization and normalization techniques, such as min–max normalization, are widely used. Many studies report on model accuracy and performance, with some decision-tree models achieving up to 71.44% accuracy, while other models have reached classification accuracies of 85%. Comparative analyses within these papers highlight that certain models excel in specific tasks.

Table 4. Summary of the literature related to intelligent traffic data transmission and sharing.

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[75]	Logistic Regression, ANN, DT, KNN, RF	Predict accident severity using various classification models	-	The average accuracy of the decision tree (DT) model is the highest, which is 71.44%	-	-
[76]	RNN, GAN, SVM, CNN, MMN	Solve traffic-accident detection issues with semi-supervised DL and different data patterns	-	GAN outperforms other models' accuracy and classification F1, with or without multimodal data	Focus only on traffic-sensor data and text data	Handle more types of data for other smart-city applications
[77]	DT, RF, MLR, NB	Discuss a paper on data models for road traffic accidents and propose prediction models		The results are relatively good (the accuracy is 60–80%)	-	Reduce the imbalance ratio of labels before inputting data sets into the model for training
[78]	BLM, SVM, XGBoost, XAI	Gather high-quality data to infer different factors in urban road traffic accidents	-	SVM shows the highest performance in accuracy and F1 score	-	-
[79]	XGBoost, CatBoost, LightGBM, DT, RF, Stacked DCL-X	Classify the injuries caused by vehicle–pedestrian and vehicle–obstacle collisions		The overlapping DCL-X model has better stability, less super parameters, and higher accuracy under different training data	-	-
[80]	Faster R-CNN	Introduce Faster R-CNN to extract IoT electronic data features	-	The faster R-CNN algorithm has stronger robustness and reliability in its data collection and analysis	Electronic traffic data are not clearly classified, and influence factors are not considered	(1) Accurately identify its projects (2) Optimize the designed model to obtain traffic information better
[81]	GAS, BSP	Address and overcome research challenges in IVN data processing	-	GPU-based graphics processing technology can achieve excellent performance on IVN data	-	Focus on other aspects of IVN data processing
[82]	Vehiclectron	Propose a new model to accurately estimate road vehicle cuboids using single-view sensors and road geometry information	-	Feasibility and applicability are confirmed via CCTV-captured real-road images	3D box estimation depends on the target-detection model	Provide accurate information in the field of intelligent traffic recognition and control

Table 4. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[83]	KDE	Build a traffic visualization management system based on improved ML algorithms	-	The method in this paper is critical for smart-city traffic management	-	-
[84]	BD	Discuss the application of BDA in constructing large-scale sensor data and modeling autonomous vehicles		The feasibility and effectiveness of the model are verified	-	Content-based sensor data management and process
[85]	ARI, KNN	Develop a method to predict the psychophysiological load affecting driving safety using vehicle manipulation data	Min–max normalization approach	Compared with previous models, the performance of this model is relatively low	-	(1) Collect data from different road environments (2) Evaluate the transferability of the proposed model
[86]	Bagging, Boosting, ANN	Develop a method to predict high-risk bus drivers as a benchmark for effective bus safety policies	-	The classification accuracy of the model reaches 85%	Focus only on the relationship between dangerous driving behavior and collision	The proposed neural network model can be further improved
[87]	3D- LTS	Propose a driver yawning detection method based on subtle facial motion recognition	-	It can detect yawning robustness in various external environments	Low image resolution and large camera vibration reduce the effectiveness of the method	Use better image preprocessing methods
[88]	CNN, SVM	Propose an ML algorithm based on smart devices and IoT network firewalls to protect data traffic	-	The hybrid DL model has effectiveness and high accuracy	-	-
[89]	EEMR, BUC, TAdam	Design efficient multi-hop routing for intelligent traffic wireless sensor networks	-	It provides a new reference for improving the transmission and sharing efficiency of intelligent transportation data	-	Use edge computing, principal component analysis, and other methods to achieve data dimensionality reduction and rapid processing

Table 4. *Cont.*

Articles	Approach	Research Innovation	Data Preprocessing	Empirical Conclusion	Limitations	Proposed Future
[7]	CNN	Develop a new framework based on artificial intelligence (AI) to predict traffic conditions on densely deployed IoT networks	-	Compared with the existing traditional CNN model, LTP-CNN has higher prediction efficiency	-	-

Research in intelligent transportation systems faces several risks, issues, and constraints. First, the inconsistency in model selection and comparison across studies complicates the identification of the most effective models for specific tasks. Second, a lack of detailed discussion on data preprocessing and feature engineering can adversely affect the models' accuracy and stability. The balance between model interpretability and accuracy, particularly with complex DL models, is also a critical consideration. Moreover, the validation and practical implementation of these methods in real-world smart-city environments are crucial for further research and development. Data privacy and security issues, particularly when handling large datasets, also need more rigorous research. Collaborative efforts across disciplines, focusing on sustainability and minimizing environmental impacts, are important for advancing research in intelligent transportation systems. Addressing these challenges will enrich the scope and depth of future studies in this field.

4.4. Intelligent Transportation System

The intelligent transportation system (ITS) forms the backbone of smart-city infrastructure, leveraging spatiotemporal traffic data to derive insights that are critical for intelligent transport dispatching and urban planning [9].

Table 5 provides a comprehensive summary of methods, research innovations, empirical findings, limitations, and future research directions across various studies in this field. An analysis of the table reveals extensive use of ML technologies, including LSTM, DT, RF, XGBoost, and CNN, often combined with DL to enhance ITS capabilities. The research innovations span several aspects of ITS, such as data analysis, traffic mode detection, path planning, traffic-flow estimation, and malicious traffic detection. These innovations offer fresh perspectives and approaches for ITS development. Many studies report high accuracy and low computational costs, demonstrating the methods' effectiveness and efficiency in ITS applications. Some studies also highlight the beneficial impacts of ITS implementations on traffic efficiency and air quality.

Table 5. Summary of the literature related to the intelligent transportation system.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[90]	LTSM	Establish ML framework for smart traffic, achieve optimal accuracy	Implementing intelligent transportation systems improves transportation and air quality	-	Explore the impact of intelligent transportation on the environment and supply chain
[91]	LSTM, Bayesian optimization	Apply DL for traffic pattern detection using smartphone data	Extensive experiments demonstrate a high recognition rate and efficiency	Training requires ample labeled data and computational complexity	The model is more robust to diverse user behaviors and optimized for its computational efficiency

Table 5. *Cont.*

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[92]	DT, RF, ET, XGBoost	Propose an intelligent traffic system for the IOV network with tree ML	High detection accuracy and low computational costs are key features	-	-
[93]	Hadoop, Spark DL	Introduce City Administration Dashboard for urban traffic analysis	Road network prediction accuracy reaches 94.05%	Suitability, data privacy, and security for specific city environments	-
[94]	CNN	Implement resource load balancing and DL for real-time scheduling	ATM system outperforms traditional traffic management methods	Applicability to the specific urban environment, generalization ability of model	Improve data processing and transmission efficiency
[95]	ATM	Enhance travel pattern extraction and path estimation with U-Net and GNN	RMSE, MAE, and MAPE are 4%, 20.49%, and 18%, respectively	Dependence on infrastructure and vehicle equipment	Consider a variety of traffic situations
[96]	U-Net, GNN	Identify malicious traffic in SDN-based Internet of Vehicles	Enhanced attack detection reduces latency and prevents buffer overflow issues	-	Extend the study to other urban traffic datasets
[97]	Fuzzy, logic	Introduce the ST-GCRN model for traffic-flow estimation	Bike-sharing system errors reduced by 98% and 63% in the estimation	-	-
[98]	GCN, LSTM	Propose MTLM model for travel time estimation	Real-world data sets have been extensively experimented on	-	-
[99]	MTLM	Batam City Government adopts smart mobility for sustainable transportation	Optimal implementation and sustainable approach are yet to be fully realized	-	Extend the datasets to other cities or transit systems
[100]	Qualitative analysis research method	SafePath algorithm ensures differential privacy with minimal data impact	SafePath enhances efficiency and scalability for large and sparse data situations	-	-
[101]	SafePath	Establish ML framework for smart traffic, achieve optimal accuracy	Implementing intelligent transportation systems improves transportation and air quality	-	-

Despite numerous advances, research and development challenges in the scope of ITS remain substantial. These include data privacy and security constraints and issues, algorithm interpretability, data quality and consistency, system integration and interoperability, and the practical application and sustainability of these systems. The key objectives for advancing ITS involve ensuring secure data storage and transmission, enhancing algorithm interpretability, maintaining high data quality and consistency, achieving effective system integration and interoperability, and promoting these technologies' practical application and long-term sustainability. Addressing these challenges comprehensively requires a multidimensional approach that considers technological, policy, social, and economic factors, which are important for the continued development of smart cities and the effective management of ITS.

4.5. Intelligent Parking Systems

As urbanization accelerates, the surge in vehicle numbers has exacerbated parking difficulties, becoming a significant issue in urban traffic management. Efficient parking infrastructures can prevent, mitigate, and resolve these risks and issues by enabling the identification of available parking spaces, thus, reducing carbon emissions from excessive fuel combustion, decreasing wait times, and alleviating traffic congestion [102]. Intelligent parking systems are becoming indispensable in urban areas [103]. Leveraging technologies such as the Internet of Things and big data, these systems facilitate the real-time monitoring and management of parking spaces, optimize resource allocation, and reduce the time drivers spend searching for parking, enhancing urban traffic flow and operational efficiency.

Table 6 summarizes multiple research studies on intelligent parking systems, encompassing methods, innovations, empirical findings, limitations, and future research directions. An analysis of this table highlights several key insights:

- diverse research methods: studies use various ML and DL techniques, including random forest (RF), CatBoost, LSTM, ANN, CNN, and SVM, supplemented with genetic algorithms and Bayesian regularized NN;
- varied innovative points: innovations use contextual data to predict parking utilization rates, integrate renewable energy sources for electric vehicle charging control, and improve intelligent parking rates through advanced DL;
- rich empirical conclusions: the results demonstrate that the proposed models and methods significantly enhance parking utilization rates, profitability, accuracy, and reliability.

Table 6. Summary of the literature related to smart parking.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[104]	RF, CatBoost	Evaluate RF and CatBoost for ML	Using context data has a positive impact on parking utilization prediction	-	Use POI data as context data
[105]	LSTM	Study of electric vehicle presence in urban IoT	Proper EV charging control boosts profits	-	Use renewable energy input in the model
[106]	LSTM	Identify optimal predictive model in ML and DL	The results obtained improve the existing results in the literature	-	-
[107]	ANN	Use ANN for parking-space data collection	The proposed method improves the intelligent parking rate through DL	-	Use genetic algorithm and neural network for training
[108]	LSTM	Develop a mobile smart parking app with DL	High accuracy and reliability	-	Investigate the influence of parking lots on traffic density under different parameters
[109]	CNN, LSTM, GA	Establish a parking-space availability system	Compared to existing states, this model has better performance	-	Study of traffic density under different parameters
[110]	ANN, SVM, ARIMA, RNN	Predict available parking in city garages	Bayesian regularized neural network is a reliable and fast time-period prediction method	-	-

Table 6. *Cont.*

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[111]	IoT	Address tourist city parking layout issues	Simple and easy to operate, with low requirements for data accuracy	-	-
[8]	CNN, ELM	Propose parking-spot detection with CNN and ELM	The CNN elm method outperforms other hybrid CNN models using different classifiers	-	Verify the performance of CNN-ELM on other parking datasets
[112]	IoT, LSTM	Predict parking availability via IoT, cloud, and sensors	The proposed model is superior to the most advanced prediction model at present	Only parking space occupancy information is considered without considering weather conditions and social events	Consider weather conditions, social event information, and parking-lot occupancy information

Research on intelligent parking systems faces numerous constraints, risks, and issues, including data privacy and security, technical integration and interoperability, cost-effectiveness and sustainability, user experience and acceptance, and compatibility with urban planning and policy frameworks. The implementation of critical success factors includes safeguarding user data, effectively integrating diverse technologies, minimizing costs, enhancing user experiences, and ensuring alignment with broader urban-planning objectives. Additionally, focusing on sustainability, social inclusivity, data governance, and transparency is important for advancing the development and application of intelligent parking systems in urban settings. By addressing these challenges comprehensively, intelligent parking systems can more effectively meet urban transportation management needs and contribute to the development of smarter cities.

4.6. Traffic Congestion

Smart cities have been evolving for nearly a decade, with reducing traffic congestion remaining a critical focus of their development [113]. Traffic congestion, a pervasive issue in urban transportation systems, leads to significant fuel waste and increases in accidents, traffic jams, and driver frustration. Managing traffic delays, especially during rush hours in metropolitan areas, is crucial due to the high volume of vehicles involved.

Table 7 comprehensively reviews methods, innovations, empirical results, limitations, and future directions in traffic-congestion research. Researchers have used various approaches to address this issue, including remote sensing, DL, and neuro-fuzzy systems. Applications of these technologies include IoT integration and advanced analytics, such as deep Q-learning, which enhance congestion prediction and optimize traffic flow. Although empirical outcomes indicate improved prediction capabilities and reduced wait times under various conditions, the studies also reveal performance limitations, data quality, and scalability challenges. The table recommends further development of communication protocols and expanding algorithm applicability across broader road networks to advance ITS and address persistent research gaps.

Table 7. Summary of the literature related to traffic congestion.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[113]	FITCCS-VN	Remote viewing of road traffic flow and vehicle volume	The system achieves an accuracy of 95% and a miss rate of 5%	-	
[114]	Logit, SVM	Common multivariate outlier detection methods	Outlier detection plays an important role in discovering useful and valuable information	-	(1) Identify variables with high discriminatory power (2) Apply the algorithms to various road types in a smart city
[115]	DNN	TC2S-DNN model integrates IoT and DL for congestion forecast	The performance of the TC2S-DNN model is reported to be better than previously published approaches	If the information is obtained in delay, or there is too much noise by the signal sensors. It can be influenced by the output of the proposed solution	-
[116]	Deep double-Q learning	Adaptive traffic signal adjustments based on vehicle types	The average waiting time at intersection points by up to 91.7%	The sampled data is biased and not exactly the same or the same distribution	-
[117]	Hybrid Neuro-Fuzzy	Enhance congestion prediction accuracy with IoT sensor data	The model has an even higher accuracy of 99.214% during the training phase	-	-
[118]	AFT	Apply survival analysis methods for congestion assessment	The results show a dramatic improvement in data quality and successful evaluation of traffic conditions with high reliability	-	Apply proposed methods for effective traffic control and management in smart cities
[119]	C-V2X network	Optimize cellular AP and vehicle throughput with user-AP associations	Results confirm the effectiveness and superiority of the traffic offloading method via DL in CV2X networks	-	-

Research on traffic congestion encounters several issues and constraints. Data collection and privacy concerns are prominent due to the reliance on in-vehicle sensors or IoT devices, highlighting the necessity for stringent data compliance and privacy safeguards. Moreover, the accuracy and practical application of models based on DL and NN require validation in real-world traffic scenarios, taking into account external factors such as weather and road conditions. Additional obstacles include integrating these proposed methods effectively into current traffic management systems, ensuring their cost-effectiveness and gaining social acceptance. Future research should enhance the reliability, practicality, and societal acceptance of intelligent traffic management systems to realize effective intelligent transportation management.

4.7. Vehicle Detection and Tracking

Moving-object detection and tracking have recently emerged as research hotspots in satellite video processing and analysis. In traditional approaches, moving-object detection is treated as a problem of foreground and background segmentation [120].

Table 8 provides a comprehensive summary of research papers focused on vehicle detection and tracking, encompassing methods, innovations, data preprocessing techniques, empirical findings, limitations, and directions for future research. The analysis indicates that studies have applied various methods, such as KEF, SVM, LSTM, GCN, RNN, and GAN, to address challenges in traffic-flow prediction. Innovations include incorporating noise data, trusted authority principles, and dynamic correlation. Various data preprocessing techniques, such as min–max normalization, data interpolation, cleaning, and conversion, have enhanced model performance and accuracy. Most studies have shown promising empirical results, surpassing existing technologies or baseline models in traffic-flow prediction.

Table 8. Summary of the literature related to vehicle detection and tracking.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[121]	EKF, NN, SVM	Integrating data from GPS augmentation and low-cost DR systems	EKF/SVM trained with particle-swarm optimization is more suitable for localization	GPS quality may decrease in actual situations	Research on vehicle prototype based on Arduino
[122]	-	Adapt to time-varying and unbalanced tracking workloads caused by traffic dynamics	Shows 100% tracking coverage and real-time assurance	-	-
[123]	EKF, SVM, RF	Using SVM to overcome the shortage of EKF when the GPS signal is interrupted	Experience 94% improvement over simple EKF prediction	When interrupted, GPS quality will decrease	(1) Test and improve this hybrid solution in case of GPS interruption (2) Combine this method with a distributed algorithm
[124]	EKF, SVM, Faster R-CNN	An intelligent vision sensor is preset for the detection and tracking of synchronous attitude estimation	Integrating vehicle position and attitude into EKF enhances tracking results	-	-
[125]	RetinaNet	Using RetinaNet architecture and Cars Overhead with Context dataset to find vehicles in satellite images	The model has good vehicle-detection accuracy and low detection time	-	(1) Expand experimental evaluation and conduct ablation experiments (2) Enhance the model with a street-detection model
[126]	DNN	A vehicle detection and tracking method in bad weather conditions is proposed	This method is superior to the most advanced method under adverse weather conditions	-	Some hard cases still need more attention and improvement

While innovative methods have been introduced to improve the systems in the domain of research on vehicle detection and tracking systems, several challenges remain. Some studies primarily focus on novel algorithms and models but encounter difficulties with computational complexity and real-time performance. Despite the significant advances facilitated by such technologies as DL, practical applications often require substantial computational resources and time to process large-scale data, which may limit the systems' practicality. Furthermore, while certain research performs well on specific datasets, the generalization ability across different environments or datasets needs further validation to ensure robust and safe vehicle detection and tracking systems operation. Future research should focus on enhancing the real-time capabilities of algorithms, improving generalization performance, and boosting system robustness to ensure more stable and reliable operation. By integrating sensor fusion, ML, and DL technologies, further improvements in system performance can be achieved, advancing the development of intelligent transportation systems.

4.8. Vehicle Identification and License Plate Number Recognition

In transportation and traffic management systems, vehicle recognition, particularly through reading license plates, is paramount [127]. Vehicle recognition involves the automatic identification of vehicles using computer-vision technology, which is extensively applied in traffic monitoring, intelligent parking management, and other areas. On the other hand, license plate number recognition focuses on the automatic detection and reading of vehicle license plates primarily through image processing and character recognition technologies.

Table 9 summarizes the research literature on intelligent parking systems, covering methods, innovations, empirical findings, limitations, and future research directions. An analysis of this data reveals (1) diversified research methods, where various studies have implemented different ML and DL techniques, such as the DLVLPNR model, RCNN, and deep active learning frameworks; (2) diversified innovation points, where innovations include using CNNs to capture and extract distinct vehicle features effectively, integrating Fast R-CNN with Extractive V2 and Tesseract OCR for enhanced license plate character recognition, and using memory space to aid active learning in vehicle-type recognition; and (3) abundant empirical conclusions, where the studies demonstrate that the proposed models or methods have yielded positive results, such as improved accuracy and reliability in empirical research.

Table 9. Summary of the vehicle identification and license plate number recognition literature.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[128]	CNN	CNN for vehicle feature extraction	The accuracy of the CNN model was evaluated based on the confidence values of the detected objects	The larger and lower size of the image can affect the validation process	(1) Expand the system to include more vehicle types (2) Improve the accuracy and robustness of the model
[129]	DLVLPNR model	Fast R-CNN with Inception V2 and Tesseract OCR for license plate recognition	The DL-VLPNR model can achieve optimal detection and recognition performance, as it attained the highest accuracy of 0.986	-	Handle more diverse conditions and integration into real-time applications for smart-city management
[130]	RCNN	Extending vehicle ID for counting and analysis	The average accuracy of the proposed method is 90.4%	Increasing the number after some time, the network goes into the stage of overfitting, and the accuracy of the network decreases	Optimize the method for enhanced performance
[131]	Deep active learning framework	Memory space for active learning in vehicle-type recognition	Over 90% accuracy for 20 vehicle types	The sample data is biased and does not have the same distribution	-

Research into vehicle and license plate recognition has advanced significantly in recent years, benefiting from the adoption of cutting-edge technologies and methodologies. However, issues persist, and areas for improvement remain. These include issues related to the quality and scale of datasets, the robustness of models against noise and lighting variations, the need for real-time performance and efficiency, and concerns over privacy and security. Additionally, the interpretability of DL models in these applications is important for building user trust and ensuring safety. Future research should concentrate on enhancing dataset quality, improving model robustness, optimizing real-time performance, addressing privacy and security concerns, and increasing model interpretability. Addressing these challenges will facilitate further advancements in vehicle and license plate recognition technologies, enhancing their effectiveness within intelligent transportation systems.

4.9. Traffic-Light and Streetlight System

With the evolution of smart cities, traffic-light control systems have become important for managing vehicle flow and addressing traffic congestion. A dynamic intelligent traffic-light control system (DITLCS) has been proposed, which dynamically adjusts traffic-light durations based on real-time traffic data [132].

Table 10 overviews recent advancements in traffic-signal and streetlight systems, highlighting innovative technological applications and key findings. These studies use various methodologies, such as reinforcement learning (RL) and Markov decision processes (MDP), to enhance the intelligence of traffic management systems.

Table 10. Summary of the literature related to traffic-light and streetlight systems.

Articles	Approach	Research Innovation	Empirical Conclusion	Limitations	Proposed Future
[133]	RL, DQN	A dynamic discount factor is embedded in the iterative Bellman equation to prevent bias in the estimation of the action value function	The trained agent outperforms the fixed timing plan, cutting total system delay by 20%	-	Apply DRL to multiple intersections
[134]	RL	Combining speed guidance system with traffic-signal control based on reinforcement learning	The proposed method is superior to a fixed timing plan and traditional drive control	-	(1) Add offset optimization to signal timing optimization (2) Use V2V communication and dynamic velocity guidance strategy
[135]	MDP, RL	KS-DDPG is proposed to achieve optimal control by enhancing the cooperation between traffic signals	KS-DDPG significantly boosts large-scale traffic network control and handles flow fluctuations effectively	All agents need to communicate, resulting in limited overall communication efficiency	Consider using heterogeneous vehicles to build a more realistic traffic flow

The intelligent traffic-signal system presented here offers significant potential for improving urban traffic management. However, its successful implementation faces several challenges. These include ensuring the real-time and accurate acquisition of traffic data, maintaining system stability across varying road conditions, balancing cost-effectiveness with technological sophistication, addressing privacy and security constraints and issues related to data collection, integrating the technology with the existing infrastructure and vehicle systems, and encouraging effective human–machine collaboration to ensure safe and efficient traffic flow. Addressing these constraints and issues is necessary for optimizing the system's performance and realizing its potential to enhance the efficiency and safety of urban transportation.

5. Conclusions

This study reviews the recent intelligent transportation research trends in smart cities, examining the impact of machine learning and deep learning on traffic-flow prediction, congestion management, smart parking, public transportation, traffic accidents, and driver safety. It also discusses current research challenges and future trends in smart cities, emphasizing the critical role of these technologies in improving traffic flow and safety.

In terms of theoretical contribution, this study aims to analyze and visualize intelligent transportation characteristics using a broad scope and extended timeframe methodology. The analysis and evaluation use quantitative methods, enhancing objectivity and reliability. The findings are presented in tabular and graphical formats, such as network maps and information sheets, with narrative explanations to provide a clearer understanding of the literature's social, conceptual, and intellectual structure. This approach allows for a comprehensive evaluation of intelligent transportation.

As a pivotal component of smart cities, the development of intelligent transportation is intricately linked to the future of the transportation industry. It has profound implications for urban management, environmental protection, and socio-economic development. Despite significant advancements, intelligent transportation systems (ITS) still encounter numerous issues and constraints. To function efficiently, these systems require integrating diverse technologies, such as the Internet of Things, big data, cloud computing, and artificial intelligence. Moreover, deploying various sensors and devices necessitates processing vast amounts of traffic data, which, in turn, demands robust data processing capabilities and efficient algorithmic support.

Furthermore, an ITS often involves handling extensive personal location and behavioral data, making data security and privacy protection critical. Additionally, these systems should encourage eco-friendly transportation modes to reduce greenhouse-gas emissions. Thus, the design and implementation of ITSs should consider their long-term environmental impacts to ensure the sustainable development of urban transportation.

Addressing the constraints, risks, and issues of technology integration, data processing, security and privacy, and environmental sustainability will be central to the future of intelligent transportation research. Key areas of focus will include:

- developing more sophisticated data processing algorithms and analysis models through the deep integration of big data and artificial intelligence to enhance traffic management and control;
- enhancing information security and privacy protection by innovating encryption technologies and anonymization methods to safeguard personal data;
- utilizing ML and other advanced technologies to improve the accuracy of traffic predictions, optimize traffic flow and accident prediction models, and facilitate more precise traffic decisions;
- pairing quantum technologies with AI to open new research, development, and implementation opportunities (e.g., combinatorial optimization);
- building cross-departmental data sharing and collaboration platforms to enhance overall efficiency and promote optimal information resource allocation;
- advancing the development of autonomous vehicle technologies, including autonomous navigation and safe obstacle avoidance systems, will be critical to driving the next wave of innovations in the transportation sector.

By focusing on these areas, future research can significantly advance intelligent transportation systems, encouraging revolutionary changes in the transportation industry and contributing to the broader goals of smart-city development.

Practically, the findings offer valuable insights for researchers, organizations, editorial boards, and practitioners, focusing on author collaboration, literature citations, keyword co-occurrence, and literature trend topic analysis, which can help identify collaboration opportunities and focus on promising research topics.

Despite its depth, this study has limitations due to its focus on the English literature, potential bias due to its reliance on the Web of Science database and the VOSviewer tool, and the subjective judgment of the author in selecting and interpreting the results. When interpreting the study's results, these limitations should be considered to ensure a comprehensive understanding of intelligent transportation.

Author Contributions: Conceptualization, J.Z., J.W., H.Z. and N.M.; methodology, J.Z., J.W., H.Z., N.M. and M.S.; validation, J.Z., J.W., H.Z., M.S. and Z.Q.; formal analysis, J.Z., J.W., H.Z. and N.M.; data curation, J.Z., H.Z. and Z.Q.; writing—original draft preparation, J.Z., J.W., H.Z. and N.M.; writing—review and editing, M.S., Z.Q., G.S. and J.C.; visualization, J.Z., H.Z., N.M. and Z.Q.; supervision, J.W., M.S., G.S. and J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Shandong Province Natural Science Foundation, grant number ZR2023QG168.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AM	Activation maximization
ANN	Artificial neural network
APY	Average year of publication
ARI	Adjusted rand index
ATM	Automatic topic modeling
BS	Batch size
BiGRU	Bidirectional gated recurrent unit
BOA	Butterfly optimization algorithm
BSP	Binary space partitioning
BSS	Blind source separation
BSVR	Bayesian support vector regression
BUC	Bottom-up clustering
CNN	Convolutional neural networks
CS	Citation score per author
CSTN	Continuous surface transition network
DAN	Deep adaptation network
DBN	Deep belief networks
DCRFNN	Dynamic convolutional recurrent fusion neural network
DL	Deep learning
DQN	Deep q-network
DT	Document type
EAI	Explainable artificial intelligence
EC	Evolutionary computation
EdRVFL	Enhanced random vector functional link
ELM	Extreme learning machine
FDA	Fisher discriminant analysis
FedSTN	Federated spatial transformer network
FL	Federated learning
GA	Genetic algorithm
GAN	Generative adversarial network
GAS	Gather-apply-scatter
GCN	Graph convolutional network
GCNN	Genetic convolutional neural network
GNN	Graph neural network
GRU	Gate recurrent unit
IDT	Intelligent data transform
IoT	Internet of Things
IRM	Invariant risk minimization

ITS	Intelligent transportation systems
KDE	Kernel density estimation
KNN	K-nearest neighbor
LR	Logistic regression
LSTM	Long short-term memory neural networks
MDN	Mixture density network
MDP	Markov decision process
ML	Machine learning
MLP	Multi-layer perceptron
MLR	Multiple linear regression
MMN	Mismatch negativity
MTLM	Multi-task learning model
MVSNET	Multi-view spatiotemporal network
NB	Naive bayes
NN	Neural networks
NP	Number of documents per author
POA	Probabilistic output analysis
POI	Point of interest
RBF	Radial basis function
RBM	Restricted Boltzmann machine
RCNN	Regions with convolutional neural networks
ResNet	Residual network
RF	Random forest
RNN	Recurrent neural network
SMO	Sequential minimal optimization
SVC	Support-vector classification
SVM	Support-vector machine
TBI	Target bearing indicator
TFP	Traffic-flow prediction
TMS	Traffic management systems
WoS	Web of Science

References

1. O'Dwyer, E.; Pan, I.; Acha, S.; Shah, N. Smart energy systems for sustainable smart cities: Current developments, trends and future directions. *Appl. Energy* **2019**, *237*, 581–597. [CrossRef]
2. Liu, Y.; Yang, C.; Jiang, L.; Xie, S.; Zhang, Y. Intelligent edge computing for IoT-based energy management in smart cities. *IEEE Netw.* **2019**, *33*, 111–117. [CrossRef]
3. Renaud, J.; Karam, R.; Salomon, M.; Couturier, R. Deep learning and gradient boosting for urban environmental noise monitoring in smart cities. *Expert Syst. Appl.* **2023**, *218*, 119568. [CrossRef]
4. Yu, D.; Xu, Z.; Pedrycz, W. Bibliometric analysis of rough sets research. *Appl. Soft Comput.* **2020**, *94*, 106467. [CrossRef]
5. Ravish, R.; Swamy, S.R. Intelligent traffic management: A review of challenges, solutions, and future perspectives. *Transp. Telecommun. J.* **2021**, *22*, 163–182. [CrossRef]
6. Zhai, Z.; Shan, M.; Darko, A.; Le, Y. Visualizing the knowledge domain of project governance: A scientometric review. *Adv. Civ. Eng.* **2020**, *2020*, 6813043. [CrossRef]
7. Ateya, A.A.; Soliman, N.F.; Alkanhel, R.; Alhussan, A.A.; Muthanna, A.; Koucheryavy, A. Lightweight deep learning-based model for traffic prediction in fog-enabled dense deployed IOT networks. *J. Electr. Eng. Technol.* **2023**, *18*, 2275–2285. [CrossRef]
8. Kaur, R.; Roul, R.K.; Batra, S. A hybrid deep learning CNN-ELM approach for parking space detection in Smart Cities. *Neural Comput. Appl.* **2023**, *35*, 13665–13683. [CrossRef]
9. Khan, N.A.; Nebel, J.C.; Khaddaj, S.; Brujic-Okretic, V. Scalable system for smart urban transport management. *J. Adv. Transp.* **2020**, *2020*, 8894705. [CrossRef]
10. Yan, G.; Chen, Y. The application of virtual reality technology on intelligent traffic construction and decision support in smart cities. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 3833562. [CrossRef]
11. Riahi, Y.; Saikouk, T.; Gunasekaran, A.; Badraoui, I. Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Syst. Appl.* **2021**, *173*, 114702. [CrossRef]
12. Cobo, M.J.; López-Herrera, A.G.; Herrera-Viedma, E.; Herrera, F. Science mapping software tools: Review, analysis, and cooperative study among tools. *J. Am. Soc. Inf. Sci. Technol.* **2011**, *62*, 1382–1402. [CrossRef]
13. Su, H.N.; Lee, P.C. Mapping knowledge structure by keyword co-occurrence: A first look at journal papers in Technology Foresight. *Scientometrics* **2010**, *85*, 65–79. [CrossRef]

14. Hosseini, M.R.; Martek, I.; Zavadskas, E.K.; Aibinu, A.A.; Arashpour, M.; Chileshe, N. Critical evaluation of off-site construction research: A Scientometric analysis. *Autom. Constr.* **2018**, *87*, 235–247. [CrossRef]
15. Wang, J.; Chen, J.; Hu, Y. A science mapping approach based review of model predictive control for smart building operation management. *J. Civ. Eng. Manag.* **2022**, *28*, 661–679. [CrossRef]
16. Jin, R.; Zou, P.X.; Piroozfar, P.; Wood, H.; Yang, Y.; Yan, L.; Han, Y. A science mapping approach based review of construction safety research. *Saf. Sci.* **2019**, *113*, 285–297. [CrossRef]
17. Wang, J.; Li, M.; Skitmore, M.; Chen, J. Predicting Construction Company Insolvent Failure: A Scientometric Analysis and Qualitative Review of Research Trends. *Sustainability* **2024**, *16*, 2290. [CrossRef]
18. Fu, C.; Wang, J.; Qu, Z.; Skitmore, M.; Yi, J.; Sun, Z.; Chen, J. Structural Equation Modeling in Technology Adoption and Use in the Construction Industry: A Scientometric Analysis and Qualitative Review. *Sustainability* **2024**, *16*, 3824. [CrossRef]
19. Zhou, K.; Wang, J.; Ashuri, B.; Chen, J. Discovering the Research Topics on Construction Safety and Health Using Semi-Supervised Topic Modeling. *Buildings* **2023**, *13*, 1169. [CrossRef]
20. Marzouk, M.; Elhakeem, A.; Adel, K. Artificial Neural Networks Applications in Construction and Building Engineering (1991–2021): Science Mapping and Visualization. *Appl. Soft Comput.* **2023**, *152*, 111174. [CrossRef]
21. Bornmann, L.; Thor, A.; Marx, W.; Schier, H. The application of bibliometrics to research evaluation in the humanities and social sciences: An exploratory study using normalized Google Scholar data for the publications of a research institute. *J. Assoc. Inf. Sci. Technol.* **2016**, *67*, 2778–2789. [CrossRef]
22. Van Eck, N.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]
23. Waltman, L.; Van Eck, N.J.; Noyons, E.C. A unified approach to mapping and clustering of bibliometric networks. *J. Informetr.* **2010**, *4*, 629–635. [CrossRef]
24. Yevu, S.K.; Ann, T.W.; Darko, A. Digitalization of construction supply chain and procurement in the built environment: Emerging technologies and opportunities for sustainable processes. *J. Clean. Prod.* **2021**, *322*, 129093. [CrossRef]
25. Muhuri, P.K.; Shukla, A.K.; Janmaijaya, M.; Basu, A. Applied soft computing: A bibliometric analysis of the publications and citations during (2004–2016). *Appl. Soft Comput.* **2018**, *69*, 381–392. [CrossRef]
26. Li, D.; Lin, C.; Gao, W.; Chen, Z.; Wang, Z.; Liu, G. Capsules TCN network for urban computing and intelligence in urban traffic prediction. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 6896579. [CrossRef]
27. Hamza, M.A.; Alsolai, H.; Alzahrani, J.S.; Alamgeer, M.; Sayed, M.M.; Zamani, A.S.; Yaseen, I.; Motwakel, A. Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic Prediction in Smart Cities. *Comput. Mater. Contin.* **2022**, *73*, 6563–6577.
28. Awan, F.M.; Minerva, R.; Crespi, N. Using noise pollution data for traffic prediction in smart cities: Experiments based on LSTM recurrent neural networks. *IEEE Sens. J.* **2021**, *21*, 20722–20729. [CrossRef]
29. Djenouri, Y.; Michalak, T.P.; Lin, J.C.W. Federated deep learning for smart city edge-based applications. *Future Gener. Comput. Syst.* **2023**, *147*, 350–359.
30. Chen, L.; Bei, L.; An, Y.; Zhang, K.; Cui, P. A Hyperparameters automatic optimization method of time graph convolution network model for traffic prediction. *Wirel. Netw.* **2021**, *27*, 4411–4419. [CrossRef]
31. Zhou, S.; Wei, C.; Song, C.; Pan, X.; Chang, W.; Yang, L. Short-term traffic flow prediction of the smart city using 5G internet of vehicles based on edge computing. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 2229–2238. [CrossRef]
32. Hussain, B.; Afzal, M.K.; Anjum, S.; Rao, I.; Kim, B.S. A Novel Graph Convolutional Gated Recurrent Unit Framework for Network-Based Traffic Prediction. *IEEE Access* **2023**, *11*, 130102–130118. [CrossRef]
33. Yuan, X.; Chen, J.; Yang, J.; Zhang, N.; Yang, T.; Han, T.; Taherkordi, A. Fedstn: Graph representation driven federated learning for edge computing enabled urban traffic flow prediction. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 8738–8748. [CrossRef]
34. Bilotta, S.; Collini, E.; Nesi, P.; Pantaleo, G. Short-term prediction of city traffic flow via convolutional deep learning. *IEEE Access* **2022**, *10*, 113086–113099. [CrossRef]
35. Gong, Y. Traffic Flow Prediction and Application of Smart City Based on Industry 4.0 and Big Data Analysis. *Math. Probl. Eng.* **2022**, *2022*, 5397861. [CrossRef]
36. Du, L.; Gao, R.; Suganthan, P.N.; Wang, D.Z. Graph ensemble deep random vector functional link network for traffic forecasting. *Appl. Soft Comput.* **2022**, *131*, 109809. [CrossRef]
37. Vijayalakshmi, B.; Ramar, K.; Jhanjhi, N.Z.; Verma, S.; Kaliappan, M.; Vijayalakshmi, K.; Vimal, S.; Kavita Ghosh, U. An attention-based deep learning model for traffic flow prediction using spatiotemporal features towards sustainable smart city. *Int. J. Commun. Syst.* **2021**, *34*, e4609. [CrossRef]
38. Zheng, Y.; Li, X.; Xu, L.; Wen, N. A deep learning–based approach for moving vehicle counting and short-term traffic prediction from video images. *Front. Environ. Sci.* **2022**, *10*, 905443. [CrossRef]
39. Niu, X.; Zhu, Y.; Cao, Q.; Zhang, X.; Xie, W.; Zheng, K. An online-traffic-prediction based route finding mechanism for smart city. *Int. J. Distrib. Sens. Netw.* **2015**, *11*, 970256. [CrossRef]
40. Chawla, P.; Hasurkar, R.; Bogadi, C.R.; Korlapati, N.S.; Rajendran, R.; Ravichandran, S.; Tolem, S.C.; Gao, J.Z. Real-time traffic congestion prediction using big data and machine learning techniques. *World J. Eng.* **2022**. *ahead-of-print*. [CrossRef]
41. Xu, X.; Mao, H.; Zhao, Y.; Lü, X. An urban traffic flow fusion network based on a causal spatiotemporal graph convolution network. *Appl. Sci.* **2022**, *12*, 7010. [CrossRef]

42. Han, S.Y.; Sun, Q.W.; Zhao, Q.; Han, R.Z.; Chen, Y.H. Traffic Forecasting Based on Integration of Adaptive Subgraph Reformulation and Spatio-Temporal Deep Learning Model. *Electronics* **2022**, *11*, 861. [CrossRef]
43. Chen, C.; Liu, L.; Wan, S.; Hui, X.; Pei, Q. Data dissemination for industry 4.0 applications in internet of vehicles based on short-term traffic prediction. *ACM Trans. Internet Technol. (TOIT)* **2021**, *22*, 1–18. [CrossRef]
44. Khan, N.U.; Shah, M.A.; Maple, C.; Ahmed, E.; Asghar, N. Traffic flow prediction: An intelligent scheme for forecasting traffic flow using air pollution data in smart cities with bagging ensemble. *Sustainability* **2022**, *14*, 4164. [CrossRef]
45. Cui, J.; Zhao, J. Construction of Dynamic Traffic Pattern Recognition and Prediction Model Based on Deep Learning in the Background of Intelligent Cities. *IEEE Access* **2023**, *12*, 1418–1433. [CrossRef]
46. Mohammed, G.P.; Alasmari, N.; Alsolai, H.; Alotaibi, S.S.; Alotaibi, N.; Mohsen, H. Autonomous short-term traffic flow prediction using pelican optimization with hybrid deep belief network in smart cities. *Appl. Sci.* **2022**, *12*, 10828. [CrossRef]
47. Almeida, A.; Brás, S.; Oliveira, I.; Sargento, S. Vehicular traffic flow prediction using deployed traffic counters in a city. *Future Gener. Comput. Syst.* **2022**, *128*, 429–442. [CrossRef]
48. Mo, J.; Gong, Z. Cross-city multi-granular adaptive transfer learning for traffic flow prediction. *IEEE Trans. Knowl. Data Eng.* **2022**, *35*, 11246–11258. [CrossRef]
49. Zhang, K.; Chuai, G.; Zhang, J.; Chen, X.; Si, Z.; Maimaiti, S. Dic-st: A hybrid prediction framework based on causal structure learning for cellular traffic and its application in urban computing. *Remote Sens.* **2022**, *14*, 1439. [CrossRef]
50. Yu, W.; Wu, S.; Huang, M. MmgFra: A multiscale multigraph learning framework for traffic prediction in smart cities. *Earth Sci. Inform.* **2023**, *16*, 2727–2739. [CrossRef]
51. He, K.; Chen, X.; Wu, Q.; Yu, S.; Zhou, Z. Graph attention spatial-temporal network with collaborative global-local learning for citywide mobile traffic prediction. *IEEE Trans. Mob. Comput.* **2020**, *21*, 1244–1256. [CrossRef]
52. Devadhas Sujakumari, P.; Dassan, P. Generative Adversarial Networks (GAN) and HDFS-Based Realtime Traffic Forecasting System Using CCTV Surveillance. *Symmetry* **2023**, *15*, 779. [CrossRef]
53. Wang, S.; Miao, H.; Li, J.; Cao, J. Spatio-temporal knowledge transfer for urban crowd flow prediction via deep attentive adaptation networks. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 4695–4705. [CrossRef]
54. Han, D.; Chen, J.; Sun, J. A parallel spatiotemporal deep learning network for highway traffic flow forecasting. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1550147719832792. [CrossRef]
55. Ismaeel, A.G.; Mary, J.; Chelliah, A.; Logeshwaran, J.; Mahmood, S.N.; Alani, S.; Shather, A.H. Enhancing Traffic Intelligence in Smart Cities Using Sustainable Deep Radial Function. *Sustainability* **2023**, *15*, 14441. [CrossRef]
56. Seng, K.P.; Ang, L.M.; Ngharamike, E.; Peter, E. Ridesharing and crowdsourcing for smart cities: Technologies, paradigms and use cases. *IEEE Access* **2023**, *11*, 18038–18081. [CrossRef]
57. Wu, Y.; Zhang, H.; Li, C.; Tao, S.; Yang, F. Urban ride-hailing demand prediction with multi-view information fusion deep learning framework. *Appl. Intell.* **2023**, *53*, 8879–8897. [CrossRef]
58. Kong, X.; Xia, F.; Fu, Z.; Yan, X.; Tolba, A.; Almakhadmeh, Z. TBI2Flow: Travel behavioral inertia based long-term taxi passenger flow prediction. *World Wide Web* **2020**, *23*, 1381–1405. [CrossRef]
59. Bhanu, M.; Priya, S.; Moreira, J.M.; Chandra, J. ST-A GP: Spatio-Temporal aggregator predictor model for multi-step taxi-demand prediction in cities. *Appl. Intell.* **2023**, *53*, 2110–2132. [CrossRef]
60. Zhang, H.; Chen, J.; Li, W.; Song, X.; Shibasaki, R. Mobile phone GPS data in urban ride-sharing: An assessment method for emission reduction potential. *Appl. Energy* **2020**, *269*, 115038. [CrossRef]
61. Liao, L.; Wang, Y.; Zou, F.; Bi, S.; Su, J.; Sun, Q. A multi-sensory stimulating attention model for cities' taxi service demand prediction. *Sci. Rep.* **2022**, *12*, 3065. [CrossRef] [PubMed]
62. Wang, T.; Shen, Z.; Cao, Y.; Xu, X.; Gong, H. Taxi-cruising recommendation via real-time information and historical trajectory data. *IEEE Trans. Intell. Transp. Syst.* **2021**, *24*, 7898–7910. [CrossRef]
63. Rajput, P.; Chaturvedi, M.; Patel, V. Opportunistic sensing based detection of crowdedness in public transport buses. *Pervasive Mob. Comput.* **2020**, *68*, 101246. [CrossRef]
64. Mandal, R.; Karmakar, P.; Chatterjee, S.; Das Spandan, D.; Pradhan, S.; Saha, S.; Chakraborty, S.; Nandi, S. Exploiting multi-modal contextual sensing for city-bus's stay location characterization: Towards sub-60 seconds accurate arrival time prediction. *ACM Trans. Internet Things* **2023**, *4*, 1–24. [CrossRef]
65. Huang, Y.P.; Chen, C.; Su, Z.C.; Chen, T.S.; Sumalee, A.; Pan, T.L.; Zhong, R.X. Bus arrival time prediction and reliability analysis: An experimental comparison of functional data analysis and Bayesian support vector regression. *Appl. Soft Comput.* **2021**, *111*, 107663. [CrossRef]
66. Ning, W.; Tang, Q.; Zhao, Y.; Yang, C.; Wang, X.; Wang, T.; Liu, H.; Zhang, C.; Zhou, Z.; Shen, Q.; et al. CheetahVIS: A visual analytical system for large urban bus data. *Proc. VLDB Endow.* **2020**, *13*, 2805–2808. [CrossRef]
67. Prommaharaj, P.; Phithakkitnukoon, S.; Demissie, M.G.; Kattan, L.; Ratti, C. Visualizing public transit system operation with GTFS data: A case study of Calgary, Canada. *Heliyon* **2020**, *6*, e03729. [CrossRef] [PubMed]
68. Chen, Y.; Geng, M.; Zeng, J.; Yang, D.; Zhang, L.; Chen, X.M. A novel ensemble model with conditional intervening opportunities for ride-hailing travel mobility estimation. *Phys. A Stat. Mech. Appl.* **2023**, *628*, 129167. [CrossRef]
69. Chai, J.; Song, J.; Fan, H.; Xu, Y.; Zhang, L.; Guo, B.; Xu, Y. ST-Bikes: Predicting Travel-Behaviors of Sharing-Bikes Exploiting Urban Big Data. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 7676–7686. [CrossRef]

70. Collini, E.; Nesi, P.; Pantaleo, G. Deep learning for short-term prediction of available bikes on bike-sharing stations. *IEEE Access* **2021**, *9*, 124337–124347. [CrossRef]
71. Lee, C.H.; Lee, J.W.; Jung, Y. Practical method to improve usage efficiency of bike-sharing systems. *ETRI J.* **2022**, *44*, 244–259. [CrossRef]
72. Cagliero, L.; Cerquitelli, T.; Chiusano, S.; Garza, P.; Xiao, X. Predicting critical conditions in bicycle sharing systems. *Computing* **2017**, *99*, 39–57. [CrossRef]
73. Ding, H.; Lu, Y.; Sze, N.N.; Li, H. Effect of dockless bike-sharing scheme on the demand for London Cycle Hire at the disaggregate level using a deep learning approach. *Transp. Res. Part A Policy Pract.* **2022**, *166*, 150–163. [CrossRef]
74. Wang, W.; Zhao, X.; Gong, Z.; Chen, Z.; Zhang, N.; Wei, W. An attention-based deep learning framework for trip destination prediction of sharing bike. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 4601–4610. [CrossRef]
75. Mohanta, B.K.; Jena, D.; Mohapatra, N.; Ramasubbareddy, S.; Rawal, B.S. Machine learning based accident prediction in secure IOT enable transportation system. *J. Intell. Fuzzy Syst.* **2022**, *42*, 713–725. [CrossRef]
76. Chen, Q.; Wang, W.; Huang, K.; De, S.; Coenen, F. Multi-modal generative adversarial networks for traffic event detection in smart cities. *Expert Syst. Appl.* **2021**, *177*, 114939. [CrossRef]
77. Pourroostaei Ardakani, S.; Liang, X.; Mengistu, K.T.; So, R.S.; Wei, X.; He, B.; Cheshmehzangi, A. Road car accident prediction using a machine-learning-enabled data analysis. *Sustainability* **2023**, *15*, 5939. [CrossRef]
78. Park, N.; Cho, J.; Park, J. Assessing crash severity of urban roads with data mining techniques using big data from in-vehicle dashcam. *Electron. Res. Arch.* **2024**, *32*, 584–607. [CrossRef]
79. Altaf, I.; Kaul, A. Classifying victim degree of injury in road traffic accidents: A novel stacked DCL-X approach. *Multimed. Tools Appl.* **2024**, *83*, 66691–66723. [CrossRef]
80. Cui, Y.; Lei, D. Optimizing Internet of Things-Based Intelligent Transportation System's Information Acquisition Using Deep Learning. *IEEE Access* **2023**, *11*, 11804–11810. [CrossRef]
81. Zheng, Z.; Bashir, A.K. Graph-enabled intelligent vehicular network data processing. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 4726–4735. [CrossRef]
82. Noh, B.; Lin, T.; Lee, S.; Jeong, T. Deep Learning and Geometry Flow Vector Using Estimating Vehicle Cuboid Technology in a Monovision Environment. *Sensors* **2023**, *23*, 7504. [CrossRef] [PubMed]
83. Zhang, Y.; Wang, H.; Wang, X. Research on the improvement of transportation efficiency of smart city by traffic visualization based on pattern recognition. *Neural Comput. Appl.* **2023**, *35*, 2211–2224. [CrossRef]
84. Gebremeskel, G.B. Leveraging big data analytics for intelligent transportation systems: Optimize the internet of vehicles data structure and modeling. *Int. J. Data Sci. Anal.* **2023**, 1–16. [CrossRef]
85. Jang, J.; Jung, A.; Oh, C.; Park, J.; Yun, D. Evaluating Driving Safety of Road Alignment Conditions by Predicted Driver's Psychophysiological Workload Using Vehicle Maneuvering Data. *Transp. Res. Rec.* **2024**, *2678*, 479–490. [CrossRef]
86. Cho, E.; Kim, Y.; Lee, S.; Oh, C. Prediction of high-risk bus drivers characterized by aggressive driving behavior. *J. Transp. Saf. Secur.* **2023**, 1–23. [CrossRef]
87. Yang, H.; Liu, L.; Min, W.; Yang, X.; Xiong, X. Driver yawning detection based on subtle facial action recognition. *IEEE Trans. Multimed.* **2020**, *23*, 572–583. [CrossRef]
88. Huang, Y.; Nazir, S.; Ma, X.; Kong, S.; Liu, Y. Acquiring data traffic for sustainable IoT and smart devices using machine learning algorithm. *Secur. Commun. Netw.* **2021**, *2021*, 1852466. [CrossRef]
89. Li, X.; Zhang, H.; Shen, Y.; Hao, L.; Shang, W. Intelligent traffic data transmission and sharing based on optimal gradient adaptive optimization algorithm. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 13330–13340. [CrossRef]
90. Tiwari, P. The machine learning framework for traffic management in smart cities. *Manag. Environ. Qual. Int. J.* **2024**, *35*, 445–462. [CrossRef]
91. Drosouli, I.; Voulodimos, A.; Miaoulis, G.; Mastorocostas, P.; Ghazanfarpour, D. Transportation mode detection using an optimized long short-term memory model on multimodal sensor data. *Entropy* **2021**, *23*, 1457. [CrossRef] [PubMed]
92. Rani, P.; Sharma, R. Intelligent transportation system for internet of vehicles based vehicular networks for smart cities. *Comput. Electr. Eng.* **2023**, *105*, 108543. [CrossRef]
93. Fiore, S.; Elia, D.; Pires, C.E.; Mestre, D.G.; Cappiello, C.; Vitali, M.; Andrade, N.; Braz, T.; Lezzi, D.; Moraes, R.; et al. An integrated big and fast data analytics platform for smart urban transportation management. *IEEE Access* **2019**, *7*, 117652–117677. [CrossRef]
94. Yu, M. Construction of regional intelligent transportation system in smart city road network via 5G network. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 2208–2216. [CrossRef]
95. Lilhore, U.K.; Imoize, A.L.; Li, C.T.; Simaiya, S.; Pani, S.K.; Goyal, N.; Kumar, A.; Lee, C.C. Design and implementation of an ML and IoT based adaptive traffic-management system for smart cities. *Sensors* **2022**, *22*, 2908. [CrossRef] [PubMed]
96. Vankdoth, S.R.; Arock, M. Deep intelligent transportation system for travel time estimation on spatio-temporal data. *Neural Comput. Appl.* **2023**, *35*, 19117–19129. [CrossRef]
97. Pitchai, M.P.; Ramachandran, M.; Al-Turjman, F.; Mostarda, L. Intelligent framework for secure transportation systems using software-defined-Internet of Vehicles. *Comput. Mater. Contin.* **2021**, *68*, 3947–3966. [CrossRef]
98. Drosouli, I.; Voulodimos, A.; Mastorocostas, P.; Miaoulis, G.; Ghazanfarpour, D. A Spatial-Temporal Graph Convolutional Recurrent Network for Transportation Flow Estimation. *Sensors* **2023**, *23*, 7534. [CrossRef]

99. Xu, S.; Zhang, R.; Cheng, W.; Xu, J. Mtlm: A multi-task learning model for travel time estimation. *GeoInformatica* **2022**, *26*, 379–395. [CrossRef]
100. Lodan, K.T.; Khairina, E.; Dompak, T.; Salsabila, L.; Fathani, A.T. Readiness of the Batam City Government in implementing sustainable transportation. *Masy. Kebud. Polit.* **2023**, *36*, 246–259. [CrossRef]
101. Al-Hussaeni, K.; Fung, B.C.; Iqbal, F.; Dagher, G.G.; Park, E.G. SafePath: Differentially-private publishing of passenger trajectories in transportation systems. *Comput. Netw.* **2018**, *143*, 126–139. [CrossRef]
102. Inam, S.; Mahmood, A.; Khatoon, S.; Alshamari, M.; Nawaz, N. Multisource data integration and comparative analysis of machine learning models for on-street parking prediction. *Sustainability* **2022**, *14*, 7317. [CrossRef]
103. Raj, A.; Shetty, S.D. Smart parking systems technologies, tools, and challenges for implementing in a smart city environment: A survey based on IoT & ML perspective. *Int. J. Mach. Learn. Cybern.* **2024**, *15*, 2673–2694.
104. Jelen, G.; Podobnik, V.; Babic, J. Contextual prediction of parking spot availability: A step towards sustainable parking. *J. Clean. Prod.* **2021**, *312*, 127684. [CrossRef]
105. Ding, X.; Gan, Q.; Shaker, M.P. Optimal management of parking lots as a big data for electric vehicles using internet of things and Long–Short term Memory. *Energy* **2023**, *268*, 126613. [CrossRef]
106. Bilotta, S.; Palesi, L.A.I.; Nesi, P. Predicting free parking slots via deep learning in short-mid terms explaining temporal impact of features. *IEEE Access* **2023**, *11*, 101678–101693. [CrossRef]
107. He, Y.; Li, X. Feasibility of Economic Forecasting Model Based on Intelligent Algorithm of Smart City. *Mob. Inf. Syst.* **2022**, *2022*, 9723190. [CrossRef]
108. Canli, H.; Toklu, S. Deep learning-based mobile application design for smart parking. *IEEE Access* **2021**, *9*, 61171–61183. [CrossRef]
109. Jakkaladiki, S.P.; Poulová, P.; Pražák, P.; Tesařová, B. Smart Parking System: Optimized Ensemble Deep Learning Model with Internet of Things for Smart Cities. *Scalable Comput. Pract. Exp.* **2023**, *24*, 1191–1201. [CrossRef]
110. Badii, C.; Nesi, P.; Paoli, I. Predicting available parking slots on critical and regular services by exploiting a range of open data. *IEEE Access* **2018**, *6*, 44059–44071. [CrossRef]
111. Ma, X.; Xue, H. Intelligent smart city parking facility layout optimization based on intelligent IoT analysis. *Comput. Commun.* **2020**, *153*, 145–151. [CrossRef]
112. Ali, G.; Ali, T.; Irfan, M.; Draz, U.; Sohail, M.; Glowacz, A.; Sulowicz, M.; Mielnik, R.; Faheem, Z.B.; Martis, C. IoT based smart parking system using deep long short memory network. *Electronics* **2020**, *9*, 1696. [CrossRef]
113. Saleem, M.; Abbas, S.; Ghazal, T.M.; Khan, M.A.; Sahawneh, N.; Ahmad, M. Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. *Egypt. Inform. J.* **2022**, *23*, 417–426. [CrossRef]
114. Blázquez, R.R.; Organero, M.M.; Fernández, L.S. Evaluation of outlier detection algorithms for traffic congestion assessment in smart city traffic data from vehicle sensors. *Int. J. Heavy Veh. Syst.* **2018**, *25*, 308–321. [CrossRef]
115. Siddiqui, S.; Ahmad, I.; Khan, M.; Khan, B.; Ali, M.; Naseer, I.; Parveen, K.; Usama, H. AIoT enabled traffic congestion control system using deep neural network. *EAI Endorsed Trans. Scalable Inf. Syst.* **2021**, *8*, e7. [CrossRef]
116. Kumar, R.; Sharma, N.V.K.; Chaurasiya, V.K. Adaptive traffic light control using deep reinforcement learning technique. *Multimed. Tools Appl.* **2024**, *83*, 13851–13872. [CrossRef]
117. Gollapalli, M.; Musleh, D.; Ibrahim, N.; Khan, M.A.; Abbas, S.; Atta, A.; Khan, M.A.; Farooqui, M.; Iqbal, T.; Ahmed, M.S.; et al. A Neuro-Fuzzy Approach to Road Traffic Congestion Prediction. *Comput. Mater. Contin.* **2022**, *73*, 295–310. [CrossRef]
118. Wang, Y.; Li, M.; Zhou, J.; Zheng, H. Sudden passenger flow characteristics and congestion control based on intelligent urban rail transit network. *Neural Comput. Appl.* **2022**, *34*, 6615–6624. [CrossRef]
119. Fan, B.; He, Z.; Wu, Y.; He, J.; Chen, Y.; Jiang, L. Deep learning empowered traffic offloading in intelligent software defined cellular V2X networks. *IEEE Trans. Veh. Technol.* **2020**, *69*, 13328–13340. [CrossRef]
120. Feng, J.; Zeng, D.; Jia, X.; Zhang, X.; Li, J.; Liang, Y.; Jiao, L. Cross-frame keypoint-based and spatial motion information-guided networks for moving vehicle detection and tracking in satellite videos. *ISPRS J. Photogramm. Remote Sens.* **2021**, *177*, 116–130. [CrossRef]
121. Belhajem, I.; Maissa, Y.B.; Tamtaoui, A. Improving low cost sensor based vehicle positioning with Machine Learning. *Control Eng. Pract.* **2018**, *74*, 168–176. [CrossRef]
122. Dong, Z.; Lu, Y.; Tong, G.; Shu, Y.; Wang, S.; Shi, W. Watchdog: Real-time vehicle tracking on geo-distributed edge nodes. *ACM Trans. Internet Things* **2023**, *4*, 1–23. [CrossRef]
123. Belhajem, I.; Maissa, Y.B.; Tamtaoui, A. Improving vehicle localization in a smart city with low cost sensor networks and support vector machines. *Mob. Netw. Appl.* **2018**, *23*, 854–863. [CrossRef]
124. López-Sastre, R.J.; Herranz-Perdiguero, C.; Guerrero-Gómez-Olmedo, R.; Oñoro-Rubio, D.; Maldonado-Bascón, S. Boosting multi-vehicle tracking with a joint object detection and viewpoint estimation sensor. *Sensors* **2019**, *19*, 4062. [CrossRef]
125. Stuparu, D.G.; Ciobanu, R.I.; Dobre, C. Vehicle detection in overhead satellite images using a one-stage object detection model. *Sensors* **2020**, *20*, 6485. [CrossRef] [PubMed]
126. Hassaballah, M.; Kenk, M.A.; Muhammad, K.; Minaee, S. Vehicle detection and tracking in adverse weather using a deep learning framework. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 4230–4242. [CrossRef]

127. Jesudoss, A. Entry and exit monitoring using license plate recognition. In Proceedings of the 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials, Chennai, India, 2–4 August 2017.
128. Trivedi, J.; Devi, M.S.; Dhara, D. Vehicle Classification Using the Convolution Neural Network Approach. *Zeszyty Naukowe Transp./Politech. Śląska* **2021**, *112*, 201–209. [CrossRef]
129. Vetriselvi, T.; Lydia, E.L.; Mohanty, S.N.; Alabdulkreem, E.; Al-Otaibi, S.; Al-Rasheed, A.; Mansour, R.F. Deep learning based license plate number recognition for smart cities. *CMC Comput. Mater Contin* **2022**, *70*, 2049–2064. [CrossRef]
130. Sharma, P.; Singh, A.; Singh, K.K.; Dhull, A. Vehicle identification using modified region based convolution network for intelligent transportation system. *Multimed. Tools Appl.* **2022**, *81*, 34893–34917. [CrossRef]
131. Huang, Y.; Liu, Z.; Jiang, M.; Yu, X.; Ding, X. Cost-effective vehicle type recognition in surveillance images with deep active learning and web data. *IEEE Trans. Intell. Transp. Syst.* **2019**, *21*, 79–86. [CrossRef]
132. Kumar, N.; Rahman, S.S.; Dhakad, N. Fuzzy inference enabled deep reinforcement learning-based traffic light control for intelligent transportation system. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 4919–4928. [CrossRef]
133. Wan, C.H.; Hwang, M.C. Value-based deep reinforcement learning for adaptive isolated intersection signal control. *IET Intell. Transp. Syst.* **2018**, *12*, 1005–1010. [CrossRef]
134. Maadi, S.; Stein, S.; Hong, J.; Murray-Smith, R. Real-time adaptive traffic signal control in a connected and automated vehicle environment: Optimisation of signal planning with reinforcement learning under vehicle speed guidance. *Sensors* **2022**, *22*, 7501. [CrossRef] [PubMed]
135. Li, Z.; Yu, H.; Zhang, G.; Dong, S.; Xu, C.Z. Network-wide traffic signal control optimization using a multi-agent deep reinforcement learning. *Transp. Res. Part C Emerg. Technol.* **2021**, *125*, 103059. [CrossRef]