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Topic Review

A Systematic Review of Deep Learning for Intelligent Transportation Systems with Analysis and Perspectives

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Abstract: This systematic review critically examines the application of deep learning in intelligent transportation systems (ITS) over the past seven years. The review identifies and analyzes the most cited articles to determine the most productive authors, influential institutions, and prominent regions contributing to this field. We employ bibliometric and statistical analyses to uncover key trends, thematic patterns, and the evolution of research topics through the analysis of author-defined keywords and co-occurrence keyword networks. The study reveals significant shifts in research focus and methodology, highlighting the growing importance of deep learning in enhancing ITS efficiency and effectiveness. Our findings provide a comprehensive overview of the field's current state and project future research directions, offering valuable insights for researchers aiming to explore the untapped potential of deep learning within ITS.

Keywords: bibliometric analysis, deep learning, intelligent transportation systems, statistical analysis, systematic review, topic analysis

1 Introduction

In the aftermath of the COVID-19 pandemic, the digitization of society has become essential across numerous countries. This transformation is pivotal for the adoption of intelligent transportation systems (ITS) in large urban areas, increasingly aligned with the smart city paradigm [1]. ITS are indispensable in cities not only as a strategy to address immediate issues like traffic congestion, accidents, and pollution but also as a foundation for future urban mobility solutions [1]. These systems integrate diverse technologies such as big data, sensors, control systems, and advanced data processing, positioning ITS as a dynamic and critical field of research at the forefront of the transportation sector [2].

The application of ITS has shown potential to significantly enhance the safety, efficiency, and sustainability of urban transport networks. However, despite considerable advancements, the integration of deep learning technologies in ITS remains underexplored, particularly in terms of systematic evaluations of its effectiveness and adaptability in dynamic urban environments.

Elsevier's Scopus is one of the largest bibliographic reference databases in the world [3]. The Scopus database contains journals, books, and proceedings [4] from a variety of scientific disciplines, including science [5], technology [6], medicine [7], social sciences [8], and the humanities [9]. Scopus provides bibliographic data, abstracts, and excerpts from these sources, as well as a variety of analytical tools, including publication rankings, author ratings, and trend analysis. Further, Scopus is one of the bibliographic reference databases used extensively by academics, researchers, and practitioners to conduct literature searches and research quality assessments. One of the most notable aspects of Scopus is the Scopus Citation Index [10], which presents data regarding the total number of times an item has been cited. This enables Scopus users to track and evaluate the impact of their research with precision. The h-index, a quantitative indicator of a researcher's or author's output and influence as measured by citations, is just one example of the analytical data that Scopus provides. In addition to this, Scopus offers statistics regarding the authors, institutions, and countries in a certain field that is the most productive and is cited the most often. Researchers can identify relevant literature, evaluate the quality of research, and determine the significance of citations in their field of study, which in this case is it, thanks to the facilities offered by Scopus [11].

Most existing research predominantly focuses on isolated applications of deep learning in ITS without a comprehensive review of its broader implications and potential integrations. There is a notable gap in the systematic analysis of how deep learning can be holistically incorporated into ITS to address complex transportation challenges.

As shown in Figure 1, the average number of articles published in the Journal from the Scopus database over the previous seven years increased by about 10.29% from 2015 to 2022. Between 2021 and 2022, the number of publications in it research increased by 61%. This increase is the largest increase in research in 2021 and 2022. This indicates that it themed publications are becoming the current research trend.

Scientometrics [12] is a field of study that measures, analyses, and interprets scientific publications in order to quantify science and scientific research. it purpose is to measure the quantity and quality of scientific research and evaluate it impact and influence in certain areas. Scientometrics encompasses numerous facets, including quantitative analysis of publication data, citation, author collaboration, and collaboration networks. Using a variety of tools and methods, such as bibliometrics [13], webometrics [14], and altmetrics [15], scientometrics can provide crucial insights into research developments and trends in particular fields and aid in strategic decision-making. Use of bibliometrics as a tool for measuring and evaluating research in a wide range of research fields and topics [16].

In 2020, Zou *et al.* [17] implemented the use of scientometrics. Using the Web of Science (WoS) Core Collection database and knowledge domain mapping techniques, he analyzed

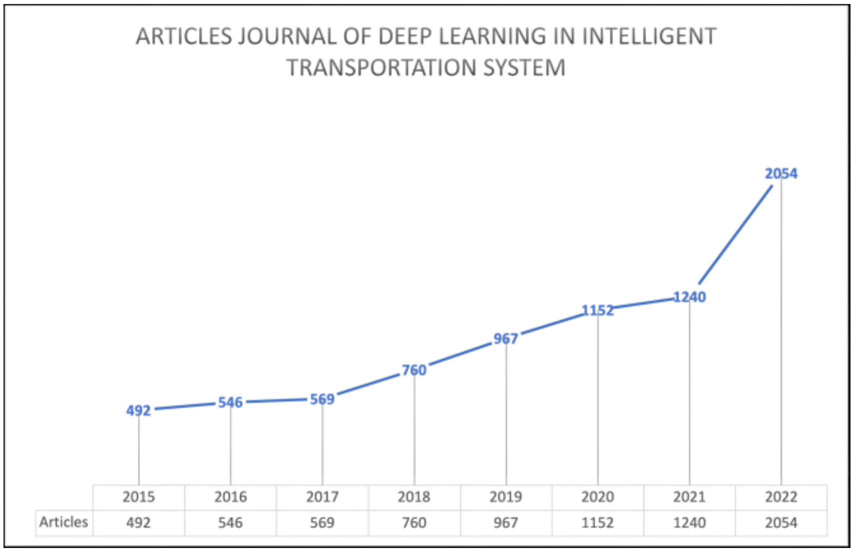


Figure 1: Publication (journal articles) enhancement at ITS.

the publication history of the journal Accident Analysis & Prevention (AA&P) from 1969 to 2018. The findings of the study revealed the countries and organizations of origin, core authors, highly cited publications, and influential publications. Also, the study found an important factor that will help guide future research and AA&P in new directions, especially when it comes to using frequency and severity analysis to model how often and how bad accidents are. In the age of smart, connected, and self-driving transportation systems, his research introduces the idea of a modified Haddon matrix [18] as a new way to look at how road safety is changing.

In 2021, Liu *et al.* used scientometrics to do a visual scientometric review of the progress of research in the transportation field on traffic forecasting. His research uses CiteSpace and VOSviewer to find new developments and new research trends in the field. In this study, 1536 bibliographies with references extracted from the Web of Science were used to construct a network of authors, institutions, keywords, and co-citations. The visualization's results show how research in the field has changed over time by pointing out authors, institutions, articles, and trends. Eleni I. Vlahogianni is the author whose work is cited the most often. Most journal articles come from China and the United States. In addition to these, notable institutions and articles were found. Keywords like "artificial neural networks," "convolutional neural networks," "spatiotemporal correlation," "traffic patterns," and "feature selection" are examples of new ways of writing about networks. The sudden increase in the number of citations of documents shows that using combined models and studying traffic flow forecasts in unusual situations is becoming a new trend. His research gives people who study transportation a useful tool for making predictions about traffic [19].

Another scientometric study conducted in 2022 by Mirhashemi *et al.* involved the bibliometric analysis of studies on pedestrian safety conducted prior to October 2021 using a science mapping methodology. For his research, a database of 6,311 papers on the safety of pedestrians was taken from the Web of Science Core Collection. In it analysis, a descriptive analysis is done of annual publications, the most cited papers, and the most prolific authors, as well as sources, affiliations, and countries. A science mapping strategy was used to show pedestrian safety research's social, intellectual, and conceptual structure. The VOSviewer and Bibliometric R packages were used for this. The findings indicate that there are seven primary research areas and five primary research areas related to pedestrian safety, as well as several prominent themes in recent years, such as "autonomous vehicles", "pedestrian detection", and "collision avoidance" [20].

From past works, it's easy and quick to figure out how knowledge and research in the ITS field have changed over time and where they stand now. Due to the fast growth of technology in areas like artificial intelligent (AI) [21], big data [22], IoT [23], and deep learning [24] that are closely related to transportation IT systems research, topics and methods for it have become more varied since 2015. Also, more academic and industrial researchers are getting excited about it research and applications. Given that we are currently approaching the end of the decade, the most recent analysis of the it literature (2015-2021) was conducted in 2022. With the significant impact of it over the past seven years, we are interested in identifying the most influential research outcomes, the major contributors to the field, the current research focus and future directions, and how these factors work together to advance the field.

This paper aims to bridge this gap by providing a systematic review of the application of deep learning within the realm of ITS. Using extensive bibliometric analysis sourced from Elsevier's Scopus database—one of the largest bibliographic reference databases globally—this study not only tracks the evolution of this integration but also identifies the most impactful research outputs, leading contributors, and predominant research trends over the last seven years. Our analysis includes a quantitative and qualitative assessment of publications, utilizing scientometric and bibliometric methodologies to map out the development and impact of research in this field.

This review promises to advance the understanding of deep learning applications in ITS by highlighting innovative approaches and pinpointing future research opportunities that could further revolutionize this critical field. It analyzes high-impact research papers, prolific authors, institutions, and countries from 2015 to 2022, thereby providing a valuable resource for scholars in the field. Additionally, it determines research trends and topic evolution in ITS, offering insights into the current research focus and suggesting future directions.

2 Methodology

2.1 Data

This dataset contains articles published in the Scopus database over the past seven years (20152022). Scopus is the most widely used and trusted database of publications for scientific analysis. "Deep Learning for Intelligent Transportation Systems" was the search term [25–27]. For each article's metadata, the following information is collected: Author(s), Document title, Year of Publication, EID or ScopusID, Source title, Volume, issues, pages, Citation count, Source and document type, Publication stage, DOI, Abstract, and Keyword are all required. This dataset was collected from 2015 to 2023 which was collected on February 19, 2023. During this time period, Scopus published 20,000 document articles from 4,693 article sources, with the following document types: 8,335 articles, book 57, book chapter 550, conference paper 10,209, conference review 257, data paper 4, editorial 70, erratum 39, letter 3, note 2, retracted 9, review 451, short survey 12, and two pieces not detected by the source. Before the analysis could begin, several problems with the raw data from the Scopus database had to be fixed. Most of these problems were caused by inconsistent and different ways of writing authors' names, including their first and last names and middle initials. Other studies have encountered and addressed similar problems. Another difficulty was distinguishing between authors with the same initials and last names. To fix this problem, the authors checked, double-checked, and compared the data with different databases by hand to make sure that publications by the same author were merged. We don't look at other kinds of data because we only care about research papers that go through regular peer review.

Table 1: Dataset published in Scopus database (2015-2022)

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Sources (Journals, Books, *etc.*)	1,307
Documents	8,066
DOCUMENT TYPES	
article	8,066
DOCUMENT CONTENTS	
Author's Keywords	18,396

Finally, this data set was obtained from 8066 English language journal articles (dataset's link) shown in Table 1. From the 8.066 article documents, they were derived from 1.307 selected journal sources and there were 18.396 keywords written by the researchers. The selection of journal articles was based on the review process given to each article that entered the journal, this was to see the methods of deep learning that are widely used by researchers around the world today.

2.2 Method

Recent developments in data collection, analytics, and graphical mapping have greatly increased the ability to analyze a large number of scientific publications. Several tools have been used to analyze scientific networks, including R-Studio Bibliometrix [28] and VOSviewer [29]. In this study, the authors evaluated and selected R-Studio because of it flexibility and functionality in representing bibliometric networks, especially in statistical analysis. To construct the network, bibliographic database files from the Scopus database were used as inputs in R-Studio. This study's methods for analyzing the literature of Scopus-indexed articles fall into three categories: statistical analysis [30], topic analysis [31], and thematic map [32].

The authors first did a statistical analysis with the most influential papers, top authors and organizations, and top countries as independent variables. The second analysis centered on articles that cited the 8,066 Scopus Database-published papers. The analysis included the leading authors, organizations, and journals that cited the Scopus papers, as well as the temporal evolution of these citations over the 7th year of 2015-2022. In order to determine the significance of Scopus-indexed articles, various bibliometric indicators are employed to assess the productivity and impact of authors, institutions, and countries/regions. By analyzing the statistical frequency and co-occurrence networks of author-defined keywords, important topics and patterns of change can be identified.

R-Studio constructs and visualizes the network. Each author may define an article's keywords differently. To get reliable analysis results, it is necessary to combine synonyms and identical terms with the keywords. A theme flow map is created to illustrate the evolution of the ten most important keywords. We make a co-authorship network and pull out community structures from large networks to find patterns of collaboration between authors, institutions, and countries/regions. R-Studio visualizes the network so that our results are more understandable.

2.3 Literature Review Process

To enhance the transparency and replicability of our systematic review, The outlined of the procedures followed during the literature collection and analysis phases. This subsection details shown Figure 2, the flow of the literature review, ensuring that our approach is both systematic and measurable.

Figure 2: Flowchart of literature review process.

2.3.1 Databases searched

Our review primarily utilized the Scopus database due to its extensive coverage of peer-reviewed journals encompassing the fields of technology, science, and social sciences. This database was chosen for its comprehensive indexing, which includes a wide range of articles on ITS and deep learning technologies.

2.3.2 Search keywords

The search strategy was developed to capture all relevant studies. Keywords used included "intelligent transportation systems," "deep learning," "machine learning in transportation," "ITS applications," and "deep learning technologies." These keywords were combined using Boolean operators to ensure a comprehensive search output.

2.3.3 Inclusion and exclusion criteria

Studies were selected based on the following criteria: First, Inclusion Criteria: Articles published between 2015 and 2022. Articles that specifically discuss the application of deep learning in ITS. Articles available in full text and published in English. Second: Exclusion Criteria: Non-peer-reviewed articles such as editorials and opinion pieces. Studies not focusing on the core areas of deep learning or ITS. Duplicate studies or studies with incomplete data.

2.3.4 Study selection and data extraction

The initial search yielded a substantial number of articles, which were screened based on their titles and abstracts. The selected articles were then subjected to a full-text review to ascertain their relevance based on the inclusion and exclusion criteria. Data extracted from these articles included authors, publication year, objectives, methodologies, key findings, and conclusions. This information was tabulated to aid in comparative analysis and synthesis.

2.3.5 Item quality assessment

Each study was assessed for its methodological rigour and relevance to the review's scope. The quality assessment was based on a set of predefined criteria that evaluated the clarity of research objectives, the appropriateness of the methodology, and the depth of the analysis.

This structured approach ensures that our review is comprehensive, systematic, and contributes valuable insights into the application of deep learning technologies in ITS, addressing both current applications and future research directions.

Table 2: The top 20 cited publications in Scopus database from 2015 to 2022

Author	**Paper Title (Journal, Year)**	**Strength and Weakness**	**Total Citations**	**Avg. Citation / Year**
Yisheng *et al.* [33]	Traffic Flow Prediction With Big Data: A Deep Learning Approach **(, IEEE Trans Intell Transp Syst, 2015)**	**Strength:** High citation count indicates significant impact and recognition; uses big data for predictive accuracy. **Weakness:** Focuses narrowly on traffic flow prediction, which may not generalize to other ITS applications.	2,107	234.111

Lin *et al.* [34]	A Survey On Internet Of Things: Architecture, Enabling Technologies, Security And Privacy, And Applications **(IEEE Internet Things J, 2017)**	**Strength:** Comprehensive survey on IoT; addresses a wide range of technologies and their applications.	1,622	231.714
		Weakness: The broad scope may lack depth in specific areas critical to ITS.		
Zhao *et al.* [35]	LSTM Network: A Deep Learning Approach For Short-Term Traffic Forecast **(IET Intel Transport Syst, 2017)**	**Strength:** Applies LSTM networks specifically to short-term traffic forecasting, demonstrating practical applicability.	984	140.571
		Weakness: Limited to short-term forecasting; may not address long-term planning needs.		
González *et al.* [36]	A Review Of Motion Planning Techniques For Automated Vehicles **(IEEE Trans Intell Transp Syst, 2016)**	**Strength:** Reviews motion planning techniques which are crucial for automated vehicles.	866	108.25
		Weakness: As a review, it may lack original research or new methodologies.		
Zhao *et al.* [37]	T-GCN: A Temporal Graph Convolutional Network For Traffic Prediction **(IEEE Trans Intell Transp Syst, 2020)**	**Strength:** Introduces a novel Temporal Graph Convolutional Network approach, enhancing predictive accuracy.	743	185.75
		Weakness: The new model's complexity could limit its usability without extensive expertise.		
Kusiak [38]	Smart Manufacturing **(Int J Prod Res, 2018)**	**Strength:** Discusses smart manufacturing within ITS, a less commonly covered but crucial area.	636	106

		Weakness: May not directly apply to traditional ITS challenges like traffic management.		
Alonso-Mora *et al.* [39]	On-Demand High-Capacity Ride-Sharing Via Dynamic Trip-Vehicle Assignment **(Proc Natl Acad Sci USA, 2017)**	**Strength:** Innovative approach to high-capacity ride-sharing which is highly relevant in urban ITS applications.	619	88.429
		Weakness: The practical implementation of theoretical models may differ significantly in real-world settings.		
Shi *et al.* [40]	Automatic Road Crack Detection Using Random Structured Forests **(IEEE Trans Intell Transp Syst, 2016)**	**Strength:** Focuses on practical applications like road crack detection, offering direct benefits to infrastructure maintenance.	540	67.5
		Weakness: The scope is limited to detection and does not include repair or prevention strategies.		
Menouar *et al.*, [41]	UAV-Enabled Intelligent Transportation Systems For The Smart City: Applications And Challenges **(IEEE Commun Mag, 2017)**	**Strength:** Explores UAV applications in ITS, a cutting-edge and rapidly evolving area.	523	74.714
		Weakness: Challenges and regulatory issues concerning UAVs are not deeply explored.		
Martinez *et al.* [42]	Energy Management In Plug-In Hybrid Electric Vehicles: Recent Progress And A Connected Vehicles Perspective **(IEEE Trans Veh Technol, 2017)**	**Strength:** Discusses energy management in hybrid vehicles, crucial for sustainability in ITS.	493	70.429
		Weakness: Focused primarily on plug-in hybrid vehicles which are just one part of the broader ITS ecosystem.		

Abboud *et al.* [43]	Interworking Of DSRC And Cellular Network Technologies For V2X Communications: A Survey **(IEEE Trans Veh Technol, 2016)**	**Strength:** Surveys the integration of DSRC and cellular network technologies, critical for V2X communications. **Weakness:** As technology evolves, some of the discussed standards may become outdated.	466	58.25
Minoli *et al.* [44]	IoT Considerations, Requirements, And Architectures For Smart Buildings—Energy Optimization And Next-Generation Building Management Systems **(IEEE Internet Things J, 2017)**	**Strength:** Addresses IoT architectures for smart buildings, tying into broader smart city contexts that include ITS. **Weakness:** Specific ITS applications are only tangentially discussed.	465	66.429
Petit and Shladover [45]	Potential Cyberattacks On Automated Vehicles **(IEEE Trans Intell Transp Syst, 2015)**	**Strength:** Investigates potential cyberattacks on automated vehicles, a crucial security topic. **Weakness:** The focus on threats may not provide solutions or preventive measures.	441	49
Yurtsever *et al.* [46]	A Survey Of Autonomous Driving: Common Practices And Emerging Technologies **(IEEE Access, 2020)**	**Strength:** Provides a comprehensive survey of autonomous driving technologies. **Weakness:** Emerging technologies discussed may still be far from practical implementation.	407	101.75

Kumar and Vanajakshi [47]	Short-Term Traffic Flow Prediction Using Seasonal ARIMA Model With Limited Input Data **(Eur Transp Res Rev, 2015)**	**Strength:** Uses a seasonal ARIMA model for traffic prediction, applicable in various ITS scenarios.	389	43.222
		Weakness: Limited input data may affect the model's accuracy and applicability.		
Zheng *et al.* [48]	Heterogeneous Vehicular Networking: A Survey On Architecture, Challenges, And Solutions **(IEEE Commun Surv Tutor, 2015)**	**Strength:** Extensive survey on heterogeneous vehicular networking.	388	43.111
		Weakness: Focuses more on the architecture than on specific ITS applications.		
Lei *et al.* [49]	Blockchain-Based Dynamic Key Management For Heterogeneous Intelligent Transportation Systems **(IEEE Internet Things J, 2017)**	**Strength:** Introduces blockchain technology for dynamic key management in ITS, enhancing security.	386	55.143
		Weakness: The complexity and scalability of blockchain solutions can be challenging in larger ITS deployments.		
Yu [50]	Large-Scale Transportation Network Congestion Evolution Prediction Using Deep Learning Theory **(Plos One, 2015)**	**Strength:** Applies deep learning to predict large-scale transportation network congestion, a critical issue in ITS.	373	41.444
		Weakness: The application may require extensive computational resources not available in all regions.		

Zhang *et al.* [51]	Security And Privacy In Smart City Applications: Challenges And Solutions **(IEEE Commun Mag, 2017)**	**Strength:** Addresses crucial security and privacy issues in smart city applications, relevant to ITS.	371	53
		Weakness: Lacks specific case studies or empirical data to support the proposed solutions.		
Xu *et al.* [52]	Internet Of Vehicles In Big Data Era **(IEEE Caa J Autom Sin, 2018)**	**Strength:** Discusses the integration of Internet of Vehicles in the era of big data, providing insights into the future of vehicle communications. **Weakness:** The rapid evolution of technology may outpace the current findings, reducing their longevity.	368	61.333

3 Result and Discussion

3.1 Statistical Analysis

In this section, the authors focused on analyzing top leading authors, most influential papers, top organizations, and countries as independent variables. The interconnections among these variables are not taken into account in this analysis. The relationships between items are explored in the bibliographic and co-authorship analyses discussed in this section.

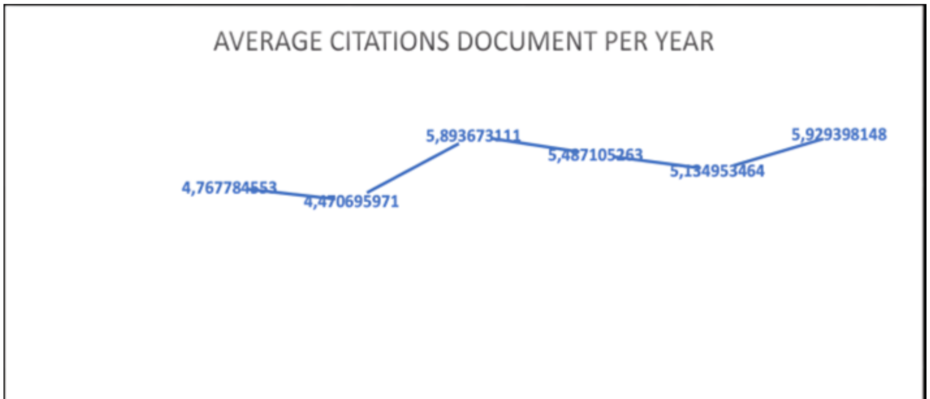
3.1.1 Article citation analysis

Figure 3, presents the average citation document article per year and the total number of citations received by the journal over 2015-2020. The number of citations steadily increased from 4.47 in 2016 to 5.89 in 2017, and 5.48 in 2018. It then significantly increased to 5.92 in 2020.

Based on these statistics, it can be concluded that during the period of 2015 to 2020, the average number of citations per year for ITS documents was 5. This indicates that there has been an increase in citations every year, and it research, especially on deep learning, has been extensively studied by researchers around the world.

The research paper with the most citations, as shown in Table 2 is a study from Yisheng *et al.* [33] entitled "Traffic Flow Prediction with Big Data: A Deep Learning Approach", with a total citation of 2107, and an average citation of 234 per year.

Nevertheless, Yisheng's [33] 2015 paper on traffic flow, which was published in IEEE Transactions on Intelligent Transportation Systems, Scopus Quartile 1, uses a deep learning method and a lot of data. Most citations have been given to this paper, which shows that



	2015	2016	2017	2018	2019	2020
Average Citation	4,767784553	4,470695971	5,893673111	5,487105263	5,134953464	5,929398148

Figure 3: Average citation document per year.

methods based on deep learning have been used in intelligent transportation research more often since 2015.

The second-most-cited article is "A Survey on the Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications" by Lin *et al.* [34]. This paper describes fog/edge computing integrated with the Internet of Things (IoT) to enable the placement of computing service devices at the network's edge to enhance the user experience and service resilience in the event of a failure. Fog/edge computing can give IoT applications faster response times and better service quality by taking advantage of the benefits of a distributed architecture and being close to the end user. Several real-world examples are given to show how fog/edge computing-based IoT can be used, such as smart grids, smart transportation, and smart cities. This article has been cited 1,622 times since 2017.

The interesting point in Table 2 data is the paper [47] entitled "A Survey of Autonomous Driving: Common Practices and Emerging Technologies", published in 2020, has an average citation per year of 101.75. This indicates that the trend of autonomous driving research is being widely studied for application in the industry.

3.1.2 Top leading authors

Figure 4 displays ten influential authors from 2015 to 2022 based on Scopus citations.

As shown in Figure 4, for 10 authors, every publication is cited more than twenty-five times. Wang *et al.* [53] and Zhang *et al.* [54] are the authors with the most cited papers, as their H-index is 29, indicating that their research papers have been cited 29 times. All of these researchers are from China and the most cited institution is also from China Beijing Jiaotong University is the institution with the greatest number of papers, with 495.

Moreover, the country/region with the 10 most cited papers in China (39765), followed by the United States (15013), India (5277), Korea (4924), the United Kingdom (4276), Canada (3128), Italy (234), Spain (2052), and Iran (2052).

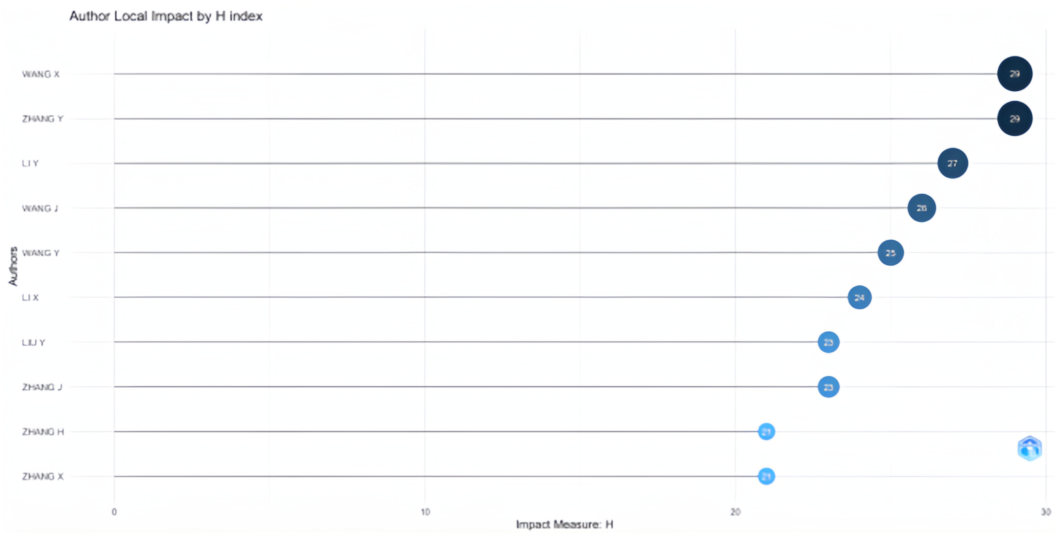


Figure 4: Author impact as measured by H index Scopus.

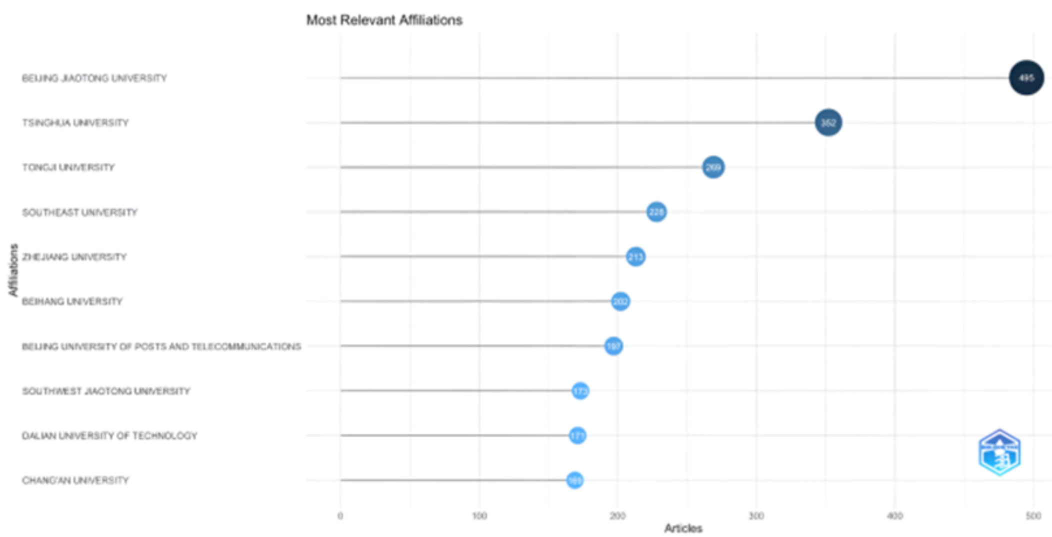


Figure 5: Authors' affiliations.

3.2 Topic Analysis

3.2.1 Trend topics research

Intelligent transportation system (890), deep learning (444), machine learning (229), VANET (241), Internet of Things (207), security (192), traffic prediction (76), roads (74), feature extraction (70), and others, are the trending topics that can be extracted from the

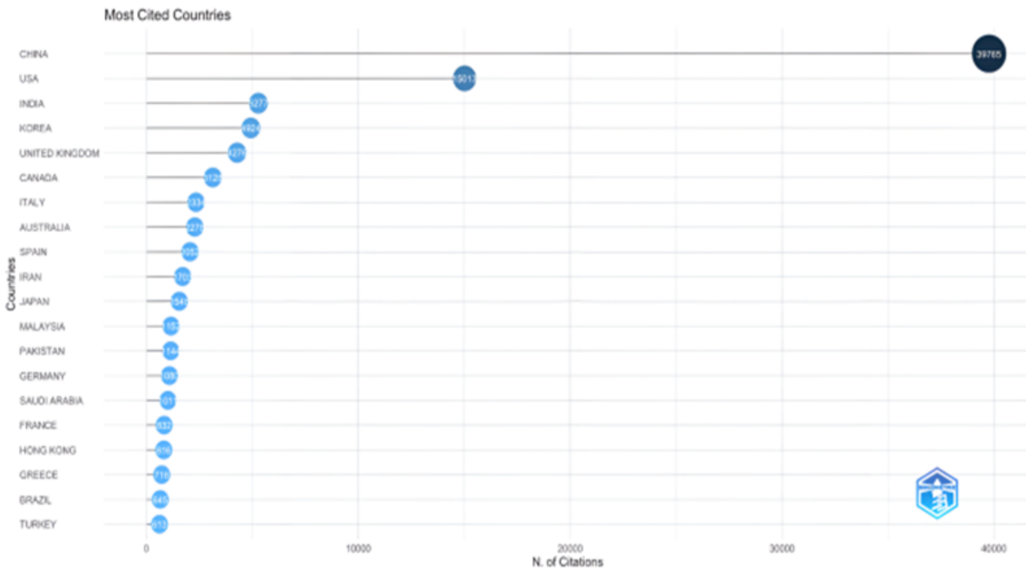


Figure 6: Top most cited countries.

Scopus metadata of this research paper with the highest frequency of occurrence in keyword authors.

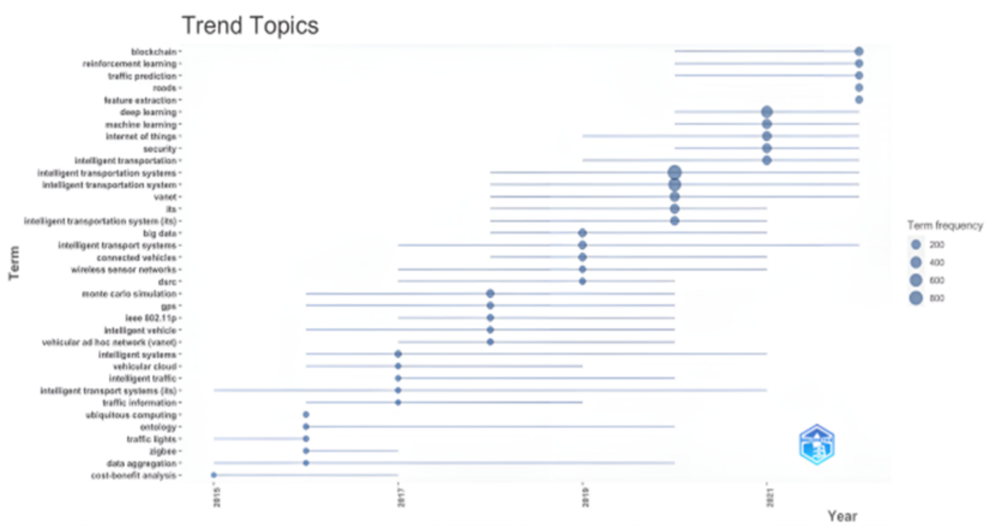


Figure 7: Frequency of trend-research topics.

The keyword "Intelligent Transportation Systems" appears the most, 893 times, followed by "Intelligent Transportation Systems" (640 times). These two keywords have the same meaning; the only difference is in the plural form of the sentences. Table 2 displays the 20 most frequently occurring keywords from 2015 to 2023. The top three keywords are "Intelligent Transportation Systems", "Deep Learning", and "VANET" respectively. The keyword "Intelligent Transportation Systems" appears the most, 893 times, followed by "Intelligent Transportation Systems" (640 times). These two keywords have the same meaning; the only difference is in the plural form of the sentences. Table 2 displays the 20 most frequently occurring keywords from 2015 to 2023. The top three keywords are "Intelligent Transportation Systems", "Deep Learning" and "VANET" respectively.

Table 3: Frequentist words

Words	**Occurrences**
intelligent transportation systems	893
intelligent transportation system	640
deep learning	445
VANET	241
machine learning	229
internet of things	207
its	194
security	194
intelligent transportation	177
smart city	148
intelligent transportation system (its)	147
blockchain	135
smart cities	126
transportation	120
internet of vehicles	119
intelligent transportation systems (its)	114
vehicular networks	113
autonomous vehicles	112
artificial intelligence	106
traffic flow prediction	100

To clearly show the trend of change from the top 20 keywords, we visualize the annual article count in the form of a graphic theme in Figure 8.

As depicted in Figure 8, research on ITS and deep learning, the two most prominent topics, exhibits an upward growth trend. Beginning in 2020, research on Machine Learning and the Internet of Things increased steadily until stabilizing in 2022. Similarly, research into VANET and security has not changed substantially between 2021 and 2022. It should be noted that deep learning began to be widely researched in 2022 with a significant increase since 2020.

3.2.2 Keyword network analysis

An R Studio-generated keyword co-occurrence network was created to demonstrate the research hotspots in it from 2015 to 2023, as shown in Figure 9. The Louvain clustering algorithm is used to determine the keyword co-occurrence threshold for the R study, with a normalization association, 50 nodes, a minimum number of edges of 2, and a repulsion force of 1. This is done to display the primary research keywords and their relationships. Figure 9 contains 49 keywords as its final visual representation. The size of a node represents a keyword link, whereas its color represents a cluster of topics that are related. Nodes

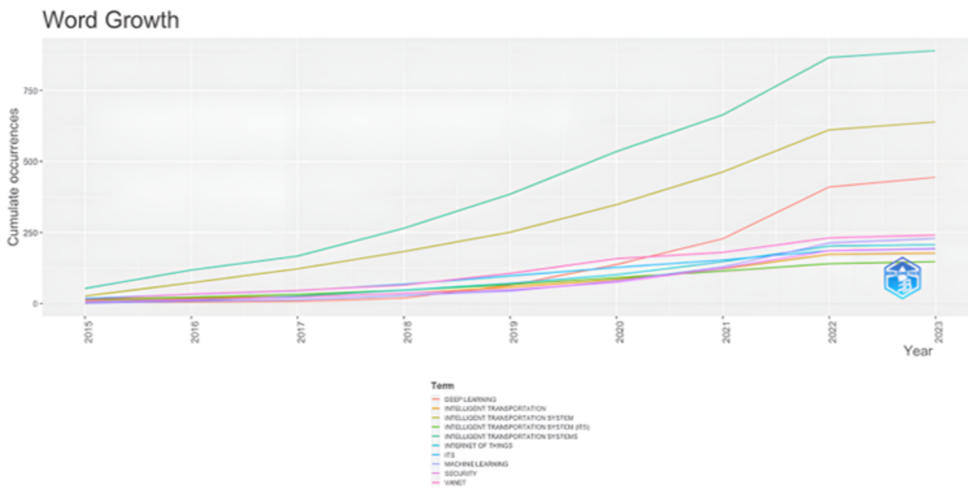


Figure 8: Word expansion.

with the same color are part of clusters with papers about the same subject. The distance between two keywords indicates the similarity of their subjects. How often two keywords appear together is shown by how wide the line between them. Figure 9's networks depict three distinct topic clusters.

Our experiment performed a brief analysis of these three research cluster topics by identifying the main keywords within each topic and discussing some research hotspots and trends associated with the emergence and development of new technologies from other industries/fields. Cluster 1 contains the most keywords with 18, including VANET, the internet of things, security, smart city, blockchain, the internet of vehicles, privacy, vehicular ad hoc networks, routing, cloud computing, edge computing, authentication, and clustering. In this cluster, research focuses primarily on the phrases internet of things and VANET. Intelligent transportation systems, machine learning, intelligent transportation, smart cities, vehicular networks, autonomous vehicles, big data, intelligent transport, reinforcement learning, connected, intelligent, internet of things, road safety, and route planning make up the largest cluster 2 with 16 keywords. In this cluster, the research focus is focused on intelligent transportation systems and machine learning. Intelligent transportation systems, deep learning, transportation, artificial intelligence, traffic flow prediction, optimization, vehicle detection, traffic prediction, convolutional neural networks, roads, traffic flow, object detection, feature extraction, computer vision, and neural networks make up the 15 keywords comprising cluster 3, which is the largest. In this cluster, the focus of research is mostly centered on intelligent transportation systems and deep learning.

When the co-occurrence network map image and the word growth image are put together with the analyst's data paper, the following trends can be seen: (1) As technologies like big data and machine learning continue to improve, the next phase of developing intelligent transportation systems will focus on AI-based vehicle infrastructure cooperative systems, smart vehicles, and autonomous vehicles. (2) As AI technology develops quickly, more and more algorithmic models will be able to be used to solve different traffic problems. Graph-based models and frameworks (GNN) are becoming more popular as a way

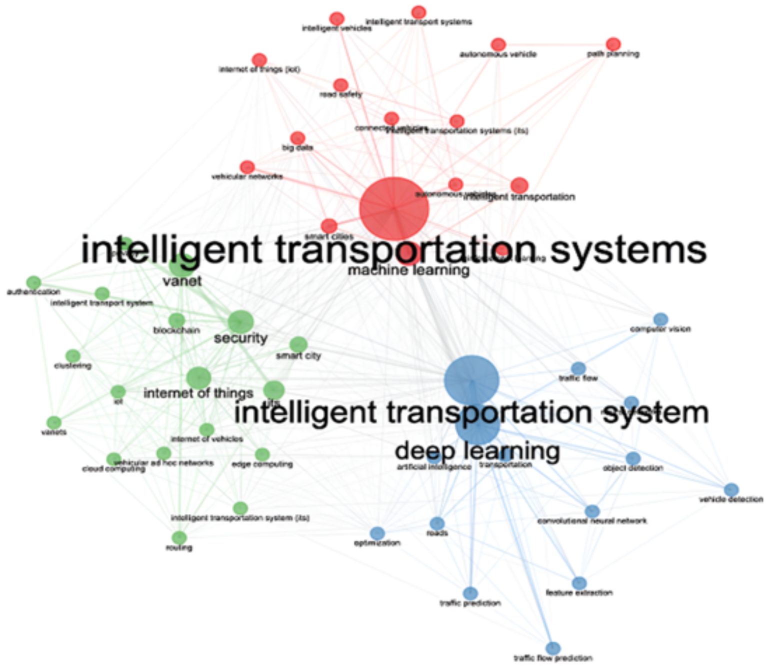


Figure 9: Map of the co-occurrence network.

to study and use things like traffic prediction. (3) The implementation of AI in ITS is in its infancy. Over the next ten years, one of the most important changes in it will be the rise of more specific, multidimensional, exhaustive, and in-depth research and applications.

Strictly speaking, autonomous and smart vehicles have become the research focus. This is partly because Tesla, Hyundai, and other companies have recently started selling automated vehicles. The fast-paced advancement of technology has brought about significant changes in the conventional automobile industry, with the focus now shifting to smart and connected cars. Equipped with sensors, controllers, actuators, and other sophisticated devices, smart connected vehicles incorporate modern communication and network technologies to facilitate the exchange and sharing of information between vehicles, roads, and clouds. They also feature complex environmental perception, intelligent decision-making, collaborative control, and other advanced functions. Moreover, research on the development of internet of things technology that will be applied in the smart city concept continues to be conducted in greater depth and does not lag in security issues if the digital era has already begun to be implemented, because privacy concerns should not be overlooked in the development of the technologically advanced smart city era.

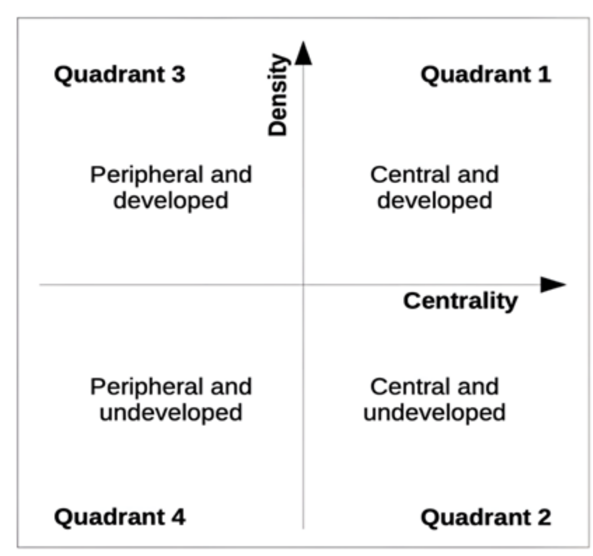


Figure 10: The matic map with 4 quadrants [55].

3.3 Thematic Map

A strategic diagram with a thematic map is presented in Figure 10 [55]. In recent years, researchers have reinterpreted this diagram for easier understanding. Cobo *et al*. [56] classified the diagram into four quadrants, with the first quadrant (central and developed) representing the motor themes, the second quadrant (central and undeveloped) representing the basic and transversal themes, the third quadrant (peripheral and developed) representing the highly developed and isolated themes, and the fourth quadrant (peripheral and undeveloped) representing the emerging or declining themes.

This analysis, as shown in Figure 11, is useful in providing knowledge to researchers and stakeholders regarding the potential of future research development of thematic areas within a field. we provide the thematic map of the field of deep learning in Intelligent Transportation Systems, which is basically divided into four quadrants (Q1 to Q4). The upper right quadrant (Q1) represents driving themes, the lower right quadrant (Q2) is underlying themes, the upper left quadrant (Q3) is the very specialized themes, and the lower left quadrant (Q4) is emerging or disappearing themes. Notably from the figure, a theme such as Transportation, Optimization, Monte Carlo Simulation; VANET, ITS, and Security in Q1. It is well-developed and capable of structuring the research field. But, the main point is in the central diagram, there are Intelligent Transportation Systems, Vehicular Networks, and Autonomous Vehicles in the leading theme within in the field. In the themes, Q4 appears to be emerging but transverses are intelligent transportation systems, deep learning, machine learning; Internet of Things, smart city, and smart cities, indicating that some of its components are basic and necessary for developing the field of the intelligent transportation system. The thematic analysis suggests that more efforts are needed to develop themes and their associated components.

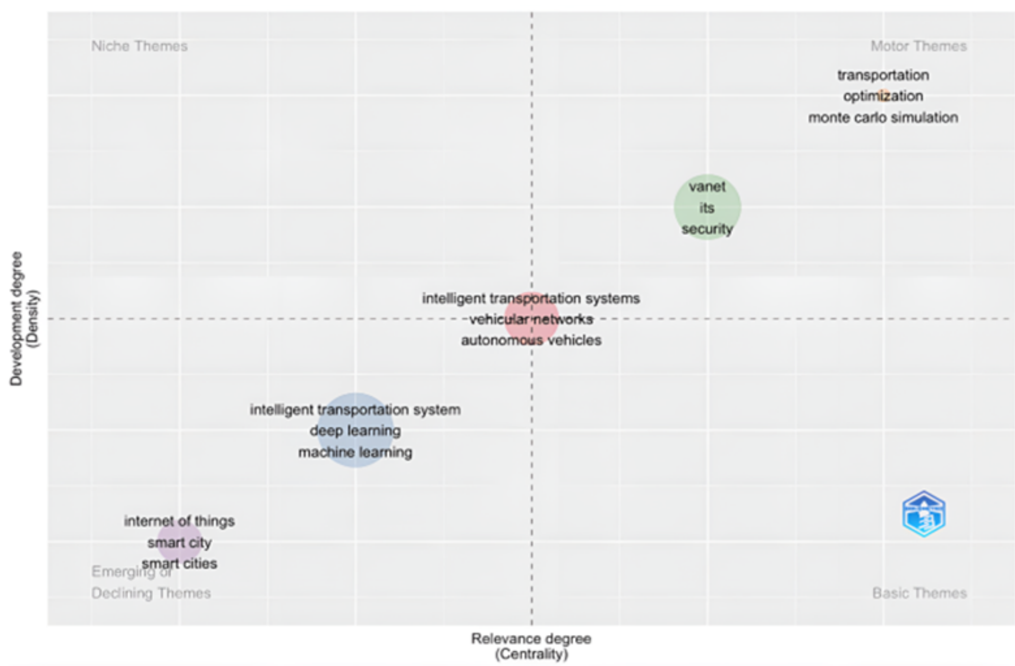


Figure 11: Thematic map of deep learning in intelligent transportation system.

3.4 Literature Review Result

A range of studies have explored the use of deep learning for object detection in intelligent transportation systems. Qiu *et al.*(2021) [57] and Liao (2022) [58] both highlight the effectiveness of convolutional neural networks (CNNs) in vehicle and road damage detection, respectively. Chen (2016) [59] and Pandey *et al.*(2018) [60] further emphasize the potential of deep features and YOLO, a real-time object detection system, in these applications. Kim *et al.*(2016) [61] and Sreelata and Roopa (2022) [62] extend this work to on-road object detection and heavy-construction vehicle detection, respectively, with the latter proposing a Single Shot Detector (SSD)-based system. Masmoudi *et al.*(2019) [63] provides a comprehensive comparison of learning models for video-based object detection, while Boukerche and Hou (2021) [64] offers a survey of deep learning-based object detection in traffic scenarios. These studies collectively underscore the promise of deep learning in enhancing object detection in intelligent transportation systems.

Building on this solid foundation, deep learning has become an indispensable tool in ITS, critically supporting applications from autonomous driving to smart city surveillance. Its methods, especially convolutional neural networks (CNNs), are prevalent for object detection tasks, with architectures like YOLO and Mask R-CNN offering real-time detection with high accuracy [65–68]. Moreover, IoT-enabled frameworks like PSPNet have demonstrated substantial effectiveness in smart surveillance, achieving notable accuracy rates [69]. Applications of deep learning also extend to vehicle detection and classification, where models like YOLOv5 have shown high precision and recall [70]. To overcome specific challenges in autonomous vehicle systems, such as detecting small or obstructed objects, enhanced models like an improved YOLOv4 have been developed [71] Furthermore, the exploration of deep learning-based range finding using monocular images presents a cost-effective alternative to traditional LiDAR and radar systems, promising effective results in object detection and distance estimation [72].

However, integrating deep learning into ITS is not without challenges. These include the need for large datasets and the integration of both local and global features to achieve accurate object detection. Despite these obstacles, deep learning continues to be a transformative force in ITS, driving advancements in vehicle detection, ranging, and overall traffic management. The synergy between deep learning models, IoT, and ITS infrastructure contributes to significant enhancements in transportation systems, making them safer and more efficient [73–76]. Ongoing research and development in this field are crucial, continually pushing the boundaries of what is achievable. In conclusion, while significant progress has been made, the field of deep learning within ITS continues to offer vast prospects for enhancement and innovation [57–120]. Future research should focus on merging novel deep learning methods with advanced sensor fusion techniques to create more adaptive and resilient detection systems capable of handling the dynamic nature of traffic and transportation infrastructures. These efforts will be crucial in pushing the boundaries of current technologies and in realizing the full potential of intelligent transportation solutions.

4 Conclusion

This article gives a complete bibliometric overview and visualization of the field of intelligent transportation systems over the last seven years (2015–2022) based on publications in Scopus-indexed databases. Statistical analysis and topic analysis are used to look at the evolution of ITS research from different points of view. The authors of a productivity and impact analysis use a statistical analysis of the number of citations to find articles that are seven years old but have been cited a lot. Then, the productivity and influence of authors, institutions, and countries are judged based on the number of articles they have written and the number of times those articles have been cited. Most articles talk about how deep learning can be used to predict traffic flow, which shows that technologies related to deep learning are being used more and more in research lately.

Based on the rankings of authors, institutions, and countries, China's influence in the ITS field has grown quickly, with 60 percent of articles coming from China and most articles coming from any country. Chinese academics and institutions dominated about half or more of the top 10 lists. In topic analysis, statistical frequency and co-occurrence networks are used and analyzed based on the keywords chosen by the author. This helps find important topics and patterns of change. In its research on problems, it is using more and more new technologies like big data, artificial intelligence, and the Internet of Things (IoT) to create a connected vehicle-infrastructure-pedestrian environment. It is also using more and more methods related to multi-source data. The findings of the analysis make this evident. Given how quickly science and technology change, it is hoped that a literature domain analysis like the one here will help researchers understand how it has changed and what its trends have been over the past seven years.

This evolving landscape of ITS, enriched by advanced technologies and multi-source data integration, underscores the necessity for ongoing research to leverage these advancements effectively. Despite considerable advancements in the application of deep learning within ITS, our systematic review has identified several promising areas for future investigation. One critical area involves the integration of real-time data processing with deep learning models to enhance decision-making processes in dynamic urban environments. Additionally, there is a need to explore the scalability of these models across different geographical regions and varied traffic conditions. Further research could also focus on the ethical implications and privacy concerns associated with the deployment of AI technologies in public spaces. Moreover, interdisciplinary studies combining insights from urban planning, cognitive science, and computer engineering could foster innovative solutions to persistent challenges in ITS. By addressing these gaps, researchers can significantly contribute to the evolution of smart transportation networks, ensuring they are more adaptive, secure, and efficient.

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