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Artificial intelligence, machine learning, and deep learning in intelligent transportation systems: A review for smart cities and sustainable mobility

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Abstract

With high urbanization rates, traffic congestion, road accidents, generation of carbon release, and transportation inefficiency, the problem of smart mobility growing through intelligent and sustainable transportation and designing is increasing in urban smart cities. Conventional transport systems are often incapable of responding to real-time conditions, dynamic traffic, as well as multimodal portable needs, which has seen a research gap in applying Artificial Intelligence, Machine Learning, and Deep Learning to Intelligent Transportation Systems. The purpose of this review is to critically assess the recent trends, applications, challenges and future opportunities of intelligent transportation technologies in smart cities and sustainable mobility. The review was oriented towards emerging themes such as traffic prediction and traffic flow optimization, intelligent traffic signal control, connected vehicles, autonomous vehicles, vehicle-to-everything communication, smart parking, accident prediction, driver behavior analysis, public transportation optimization, intelligent logistics and carbon emission reduction. In addition, the incorporation of the Internet of Things, Edge Computing, Big Data Analytics, Digital Twin technologies, Explainable Artificial Intelligence, Federated Learning, and Generative Artificial Intelligence is broadening the horizons of smart transportation and sustainable urban development. The review ends by stating that Intelligent Transport Systems that are empowered by Artificial Intelligence can be instrumental to the realization of resilient, efficient, low-carbon, and data-driven urban mobility ecosystems. Nevertheless, issues of cybersecurity, personal data privacy, explainability of the model, infrastructure shortages, and integration of policies still pose significant obstacles to large-scale use in the future.

Keywords: Machine learning, Deep learning, Autonomous vehicles, Artificial intelligence, Edge computing, Cloud computing.

1. Introduction

Growth in urban populations, rise in vehicles ownership, growth in traffic congestion and rise in environmental concerns have further escalated the necessity of having smarter, responsive, and sustainable transportation systems. Conventional transportation systems are usually ill-equipped to cope with dynamic travel demand, traffic variability, risk of accidents, fuel usage and carbon emission in a high populated urban environment [1-2]. Due to this fact, Intelligent Transportation Systems became an essential element of Smart Cities and Sustainable Mobility, which allow monitoring, making intelligent decisions, and planning transportation in real-time. The transportation industry is rapidly being disrupted through the application of Artificial Intelligence, Machine Learning and Deep Learning, which can be used as predictive analytics, adaptive traffic control, intelligent routing, smart parking, accident prediction and road safety. The integration of Intelligent Transportation Systems and Internet of Things technology, Connected Vehicles, Autonomous Vehicles, Vehicle-to-Everything Communication, Edge Computing, Cloud Computing, and Big Data Analytics has produced novel possibilities to build highly responsive, data-driven, and resilient transportation eco-systems. In recent

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times, there has been evidence that Artificial Intelligence will become the backbone of new mobility systems that enhance more efficient, safer, cleaner, and traversible urban transportation networks.

The current Intelligent Transportation System landscape indicates notable advances in terms of implementing the use of both Machine Learning and Deep Learning models to various transportation functions. Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, Reinforcement Learning, Graph neural networks, and Computer Vision are becoming popular for Traffic Prediction, Traffic Flow Optimization, Intelligent Traffic Signal Control, Vehicle Trajectory Prediction and Semantic Segmentation, Traffic State Estimation and Public Transit Optimization [2]. The trend of recent research as well shows the increased relevance of Explainable Artificial Intelligence, Federated Learning, Generative Artificial Intelligence, Large Language Models, and Digital Twin technologies in Intelligent Transportation Systems. Graph Neural Networks are especially useful in modeling the complex traffic network and enhancing the ability to predict the demand and manage the parking spots as well as safer transportation, whereas Large Language Models are becoming one of the promising tools to analyze the traffic, spot the traffic signs, recognize the crowd, and assist the autonomous driving. Parallel to this, Deep Reinforcement Learning is currently receiving significant interest within adaptive traffic signal control, and autonomous vehicle navigation due to its capability to act as a learner within dynamic and uncertain environments. These new technologies are transforming the transportation industry beyond a fixed infrastructure management where it transforms into predictive, context-aware, and autonomous mobility systems.

Regardless of significant advancements in transportation systems based on Artificial Intelligence, there still are a number of challenges and gaps in literature that prevent their use in the real world and on a larger scale. Most of the current literature investigates isolated systems like Traffic forecasting, smart parking or self-driven vehicles, however, relatively less has been done in constructions of an integrated system encompassing Traffic Management, Sustainable Mobility, Public Transportation, Intelligent Logistics, Carbon Emission Reduction, and Smart Governance within a coherent Intelligent Transportation System. Even the existing reviews are inclined to focus on one specific technology, i. e. Machine Learning, Internet of Things, Blockchain, or Computer Vision, instead of analyzing the overall convergence of Artificial Intelligence, Deep Learning, Edge Computing, Vehicular Networks, Mobility-as-a-Service, and Transportation Resilience. Also, major issues persist in the areas of Cybersecurity, Data Privacy, model interpretability, algorithmic bias, interoperability and infrastructure preparedness and the absence of standardized regulations on the application of Artificial Intelligence in transportation settings. The new issues of climate resilience, energy efficiency, ethical rules of Artificial Intelligence governance, and the inclusion of 5G and 6G communication technologies also underscore the necessity to conduct a more detailed and forward-looking examination of Intelligent Transportation Systems.

The escalating trend toward Sustainable Urban Development and Green Transportation has made Artificial Intelligence even more vital to building more environmentally-responsible mobility systems. ITS is currently being developed to not only help alleviate traffic congestion and enhance travel efficiency, but also assist in Carbon Emission Reduction, Electric Vehicles, Shared Mobility, Public Transportation, and Multi-Modal Transportation integration [2-4]. Predictive analytics, Real-time Monitoring, Adaptive Traffic Control, and demand-based routing are also assisting the city to lessen fuel usage, maximize transit services, and help persuade individuals to utilize low-emission transport options. Active bus scheduling, demand-responsive routing, and real-time passenger information systems are some of the elements in which artificial intelligence-driven public transportation systems are becoming more responsive to tackle what leads to the dependency of private vehicles and even facilitate the goals of the carbon-neutral mobility. The developments are particularly applicable to countries which are quickly becoming urbanized where traffic jams and inefficient transportation practices have continued to create significant economic, environmental and social burdens.

The goal of this paper is to cover the basic aspects of the literature review on Artificial Intelligence, Machine Learning, Deep learning application in Intelligent Transportation Systems to Smart Cities and Sustainable Mobility. Based on the PRISMA framework, the review reviews systematically the development, use, facilitating technologies, issues, and prospects of the intelligent transportation research. Traffic Prediction, Intelligent Traffic Signal Control, Smart Parking, Connected Vehicles, Autonomous Vehicles, Driver Behavior Analysis, Accident Prediction, Public Transit Optimization, Intelligent Logistics, Cybersecurity, Transportation Resilience, and Sustainable Mobility are some of the key themes of the paper. It also analyzes the new research directions such as Graph Neural Networks, Large Language Models, Generative Artificial Intelligence, Explainable Artificial Intelligence, Federated Learning, Edge Computing, and Digital Twin technologies. The key impact of this paper is that this will help to integrate fractured literature in a cohesive framework that relates Artificial Intelligence-based transportation technologies to Smart Cities, Urban Analytics, Sustainable Urban Development, and long-term mobility resilience. The review also sees the most crucial gaps in research and prospects in the future that can assist in creating safer, more efficient, more transparent, and more sustainable transportation ecosystems.

2. Methodology

This systematic literature review has been approached by following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework to identify, screen, and synthesize the related studies on the topic application of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in Intelligent Transportation Systems (ITS) to ensure transparency, reproducibility, and rigor. A systematic search of four large academic databases was conducted (Scopus, Web of Science, IEEE Xplore, and PubMed), with a focus on the research published between January and December 2019 to retrieve the most up-to-date and most dynamic research in this field. These Boolean search queries were used in both Scopus and Web of Science: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network") AND (intelligent transportation system" OR smart mobility" OR autonomous These queries were modified into an IEEE Xplore and PubMed query using their respective controlled vocabulary and thesaurus terms. A search in the first database identified a total of 4,217 records(Scopus: 1,384; Web of Science: 1,102; IEEE Xplore: 1,243; PubMed: 488), but 74 records were found through citation searching and gray literature sources to provide a total of 4,291 records. After automated, manual elimination of 537 duplicate records, 3754 unique records were then subject to the title and abstract screening phase where 2 891 records were then filtered out as being rather obviously irrelevant to the topic of the research. The rest 937 reports were identified to be in full-text, out of which 47 reports were not available and therefore, 890 reports were evaluated to be in full-text eligibility. The inclusion criteria were: The articles were peer-reviewed journal articles or conference papers published between 2019 and 2025; explicit application of AI, ML, or DL techniques in an ITS or smart urban mobility setting; empirically verifiable or computationally reproducible results. A study was filtered out in case it did not have a definite AI/ML/DL methodology, was not within the publication date, was not written in English, or had only abstracts of a conference without detailed methods. After full-text screening a total of 757 studies were eliminated because of the following reasons: not focusing on ITS (284), no AI/ML/DL methodology (198), exceeding the date limit (47), non-English (63), abstract-only conference papers (112) and 29 other types were excluded to include 133 studies in this review.

3. Results and discussions

3.1 Artificial intelligence techniques

Machine Learning for Traffic Prediction and Traffic Flow Optimization

Due to its capacity to examine extensive transportation data and spot concealed trends in traffic, Machine Learning has turned into one of the most popular methods of using Artificial Intelligence in Intelligent Transportation Systems. The often non-linear, dynamic and temporal nature of traffic behavior can be difficult to capture in a traditional statistical model, whereas, with a Machine Learning model, traffic behavior can learn continuously and based on both historical and real-time information [5-6]. Demand Prediction, Traffic Prediction, Traffic Congestion analysis and Traffic State Estimation are some of the areas where algorithms like Decision Trees, Random Forest, the Support Vector Machine, K-Nearest Neighbors, and Gradient Boosting have been heavily exploited. The inputs that are used in these models include vehicle numbers, velocity, climate, occupation of the road, the details of religious events and social movements to enhance transportation planning and control over traffic jams. Traffic Flow Optimization: TFO is a Smart City initiative that will become more common moving forward because of reducing congestion, reducing travel time, reducing fuel expenditures, and enhancing transportation resilience through the application of AI to machine learning. The increasing supply of Internet of Things sensors, GPS information, car networks, and networked infrastructure have become key contributors to the efficiency ofMachine Learning in transportation. Real-Time Monitoring systems are also being enhanced with the integration of Machine Learning models to offer dynamic route recommendations, congestion notifications, and adaptive mobility services. Machine Learning is used to enable energy efficient routing of Electric vehicles in sustainable mobility applications, predicting demand of public transportation, and Multi-Modal Transportation optimization. More recent studies reveal that hybrid Machine Learning systems, which introduce several algorithms to achieve greater predictive accuracy, are increasingly more widely implemented into complex traffic systems with high variability and uncertainty.

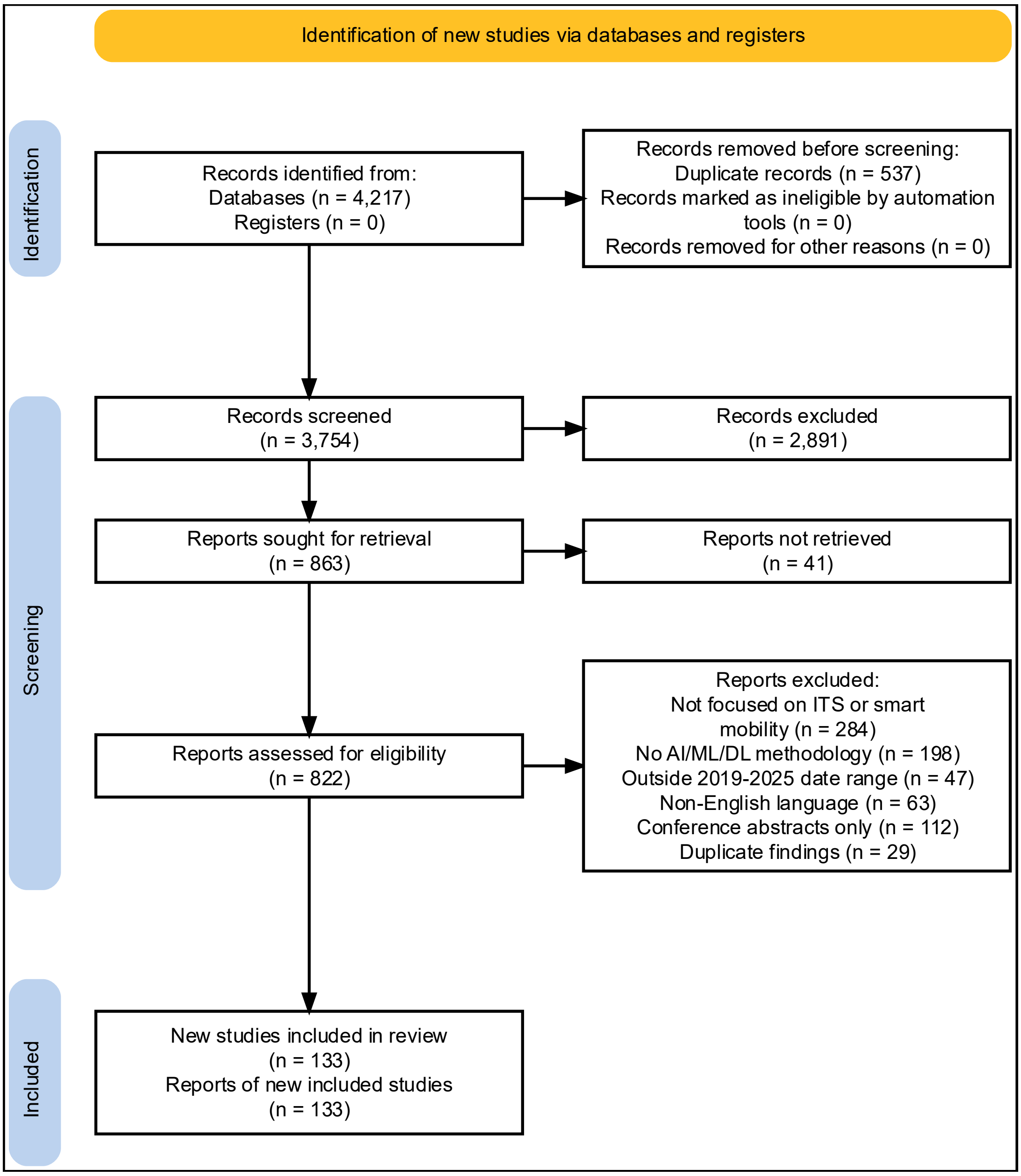

Fig. 1 PRISMA Framework

Deep Learning and Neural Networks in Intelligent Transportation Systems

Due to the capacities to handle huge amounts of both structured and unstructured transportation data, Deep Learning has become an innovative technology in Intelligent Transportation Systems. In contrast to traditional approaches to machine learning, Deep Learning models learn various complex features and patterns in traffic images and video feeds, sensor readings and mobility logs automatically by using multiple hidden layers. Applications of Neural Networks in Traffic Prediction, Road Safety, Analysis of driver behaviour, Accident Prediction and Smart Infrastructure monitoring are becoming increasingly popular. Deep Learning techniques are especially useful in transportation systems, in which real-time decision-making, data processing with multiple dimensions, and predictive performance are critical.

ANNs find extensive application in the domains of transportation demand forecasting, vehicle identification, estimates of traffic speed and prediction of travel time. These models have the capability to spot relationships which can be complicated between the variables of traffic and these can assist in better planning of transportation [7,8]. Deep Neural Networks are also significant in Intelligent Logistics, Smart Parking, and fleet management systems, which are optimization systems that optimize resource allocation, route planning, and delivery timelines with the support of DNN. Due to the increasingly data-intensive and interconnected transportation system, Deep Learning is likely to continue to play a central role in enabling predictive and autonomous mobility technologies.

Convolutional Neural Networks and Computer Vision for Road Safety

Due to their capacity to handle images and video feeds obtained via cameras, drones, roadside sensors, and other vehicle-mounted equipment, Convolutional Neural Networks and Computer Vision methods have become a vital part of Intelligent Transportation Systems. Convolutional Neural Networks have numerous applications in Object Detection, Vehicle Recognition, Pedestrian Detection, Lane Detection, Traffic Sign Recognition, Semantic Segmentation, and Accident Prediction. The techniques facilitate transportation systems in processing intricate road conditions, as well as aiding the generation of real-time decisions in both connected and autonomous vehicles. The Computer Vision technologies also find their application in the Smart Infrastructure and Road Safety applications which allow being used in improving traffic enforcement, detecting dangerous driving behavior, monitor the conditions in the road, and detect the accidents in real-time. Semantic Segmentation models are able to segment roads, pedestrians, vehicles, traffic lights and obstacles which can prove crucial in autonomous driving and smart navigation system. Recent progress in Deep Learning-based image processing systems has enhanced the accuracy of Computer Vision systems to operate in unfavorable weather, low light, and congested traffic conditions. These innovations have critical ramifications on Smart Cities since they make roads safer, reduce the number of accidents, and enable more effective transportation systems.

Recurrent Neural Networks, Long Short-Term Memory, and Gated Recurrent Units for Time Series Forecasting

The most popular Deep Learning architectures used in Time Series Forecasting in Intelligent Transportation Systems include Recurrent Neural Networks, Long Short-Term Memory networks and Gated Recurrent Units. These models can be used to forecast the speed of traffic, travel demand, road occupation, and vehicle movements since transportation data typically involves sequential and time-related data [9-12]. In particular, Long Short-Term Memory models could be argued to be quite useful due to their ability to address long-term dependencies in traffic dynamics and address the weakness of the conventional Recurrent Neural Networks. These Deep Learning algorithms are widely used in Traffic Prediction, Public Transportation scheduling, Vehicle Trajectory Prediction, and Traffic Congestion management. Long Short-Term Memory and Gated Recurrent Unit models can make precise predictions of transportation planning and operational management by utilizing recorded past traffic and weather forecasts, calendar occurrences, and road network information. Hybrid methods that use Long Short-Term Memory along with Convolutional Neural Networks or Graph Neural Networks are also attracting interest since they have the capabilities to jointly analyze the spatial and temporal dependencies of traffic. These models are especially applicable in Smart Cities where even the transportation systems need to be responsive in real-time and predictive in their adaptability.

Reinforcement Learning and Deep Reinforcement Learning for Adaptive Traffic Control

In Intelligent Traffic Signal Control and Adaptive Traffic Control, Reinforcement Learning and Deep Reinforcement Learning are coming to be regarded as a potent method of Artificial Intelligence. In contrast to supervised learning procedures, the Reinforcement Learning framework allows transportation systems to discover the way of operating and behavior on the basis of trial and error on the environment of dynamic traffic. The objective of these models is to maximize cumulative rewards in the form of less traffic jam, less time in transit, less fuel usage and efficiency in an intersection. Deep Reinforcement Learning comes in handy especially in situations with extensive complexities in traffic whereby conventional optimization techniques cannot rapidly reconfigure to evolving traffic situations. Reinforcement Learning-based intelligent traffic signal systems can respond to signal timing dynamically based on the vehicle density, length of a queue, pedestrian flow, and a moving vehicle in emergency cases. These systems make a lot of contributions to the Sustainable Mobility since it minimizes idle time, carbon emission and enhances the urban traffic. Advances in Reinforcement Learning are also applications in Autonomous Vehicles, Intelligent Routing and Mobility-as-a-Service platforms, where it assists in autonomous navigation, route choice, a decision on traffic management.

Graph Neural Networks for Traffic State Estimation and Urban Mobility Analysis

Graph Neural Networks have also become one of the most promising methods of Artificial Intelligence to represent transportation networks due to the ability to describe roads, crossroads, transit paths, and patterns of mobility as patterned graph networks. Graph Neural Networks, unlike traditional Machine Learning models, enable both spatial and time-dependence in transportation systems hence they are very useful in Traffic State Estimation, Traffic Prediction, Urban Analytics, and Demand Prediction. GNNs are actively applied to Smart Cities with the aim to study the connection of the road network, congestion hotspots, and optimization of the public transportation system. They are as well used in Vehicle Trajectory Prediction, Intelligent Routing and Shared Mobility systems to enhance route planning and mobility efficiency. Recent developmental tendencies indicate that an integration of Graph Neural Network with Long Short-Term Memory, Reinforcement Learning, and Digital Twin can, to great extent, boost the predictive capabilities of Intelligent Transportation Systems. Potential future citation These integrated models hold a high potential of future citation since they will deal with the increasing complexity of urban transportation systems and will also aid in more effective, scalable and adaptive solutions of mobility.

Transfer Learning and Federated Learning for Data-Efficient Transportation Systems

TLT Learning is becoming a more popular tool in Intelligent Transportation Systems to deal with the problem of scarce labeled data in transportation. A lot of transportation issues, including Traffic Sign Recognition, Accident Prediction, Driver Behavior Analysis, and Road Damage Detection, need a significant amount of annotated images and sensor data [7,13-15]. Transfer Learning allows using Deep Learning models that are pre-trained to implement specific transportation tasks that need lower computation costs and less training durations. This method is specifically useful in Smart Cities where different regions and uses of transportation data might not have equal availability. Another recent method that can be greatly applicable to transportation systems is Federated Learning since it provides the opportunity to train Machine Learning models on a variety of decentralized devices but not reveal any sensitive information to a poor server. Federated Learning in Connected Vehicles, Vehicular Networks, and Vehicle-to-Everything Communication systems Federated Learning aids in privacy-preserving traffic forecasting, driver actions, and accident detection. The growing importance of this approach is explained by the fact that transportation systems become sources of vast quantities of personal and place-based data, which provokes issues concerning Data Privacy and Cybersecurity. Federated Learning will likely impact the future of Intelligent Transportation Systems significantly as it promotes secure, distributed, and scalable deployment of Artificial Intelligence.

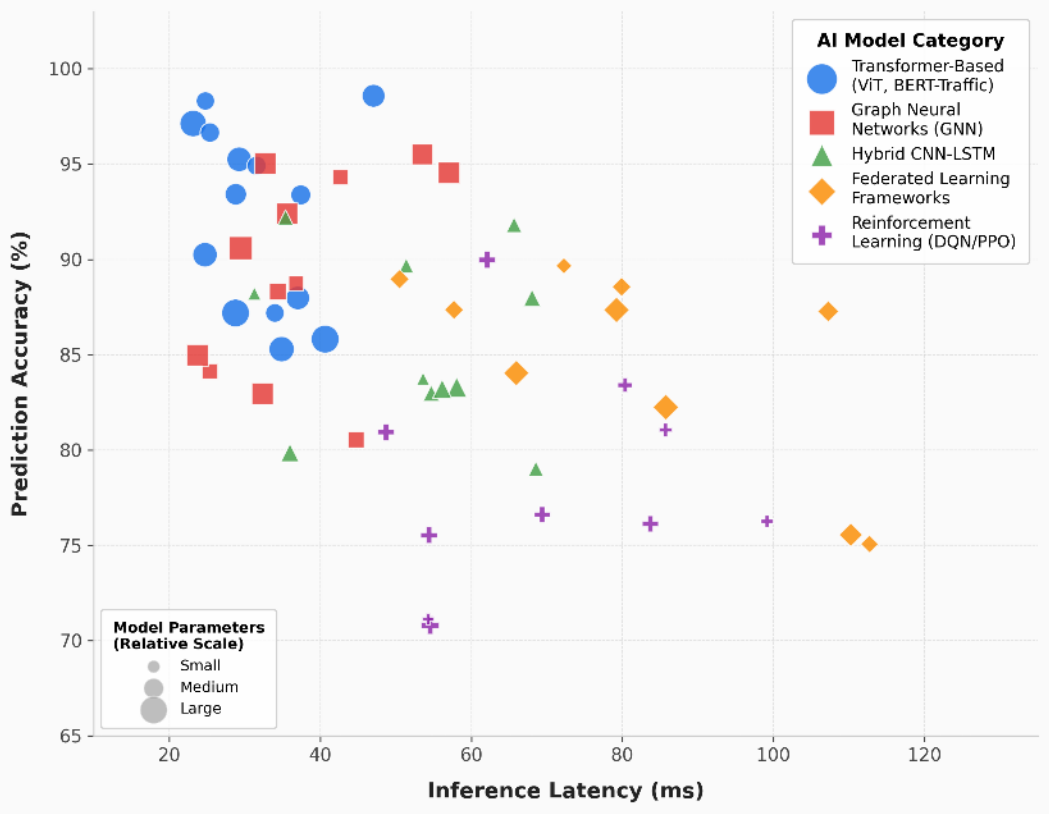

Fig. 2 Accuracy vs. Inference Latency Across AI Model Categories

Fig. 2 shows a scatter plot maps the trade-off between prediction accuracy (%) and inference latency (ms) for five major AI model categories deployed in ITS contexts: Transformer-Based models (including ViT and BERT-Traffic variants), Graph Neural Networks (GNN/GAT), Hybrid CNN-LSTM architectures, Federated Learning frameworks, and Reinforcement Learning agents (DQN/PPO). Each data point represents a distinct study or experimental result from the reviewed literature, with marker size proportionally encoding the relative scale of model parameters. The visualization reveals a clear Pareto frontier where Transformer-based and GNN models dominate the upper-left region, combining high accuracy with relatively low latency, making them the most operationally attractive for real-time ITS deployments. Federated and RL-based models occupy the lower-right region, reflecting their distributed computational overhead. This figure enables rapid visual benchmarking of model families and highlights the emerging efficiency of attention-based architectures for latency-critical smart mobility applications.

Explainable Artificial Intelligence for Transparency and Trust

Reliable Artificial Intelligence is now a relevant research topic in Intelligent Transportation Systems due to the fact that a large number of Machine Learning and Deep Learning models are commonly a subject of criticism as being black-box systems. In transportation safety-critical scenarios like Autonomous Vehicles, Accident Prediction, Intelligent Traffic Signal Control, and Driver Behaviour Analysis, the stakeholders demand transparent processes of decision-making by Artificial Intelligence models. Explainable Artificial Intelligence methods will seek to enhance the interpretability, accountability and trustworthiness of Machine Learning systems by explaining the most important variables and features that help in making predictions. Explainable Artificial Intelligence can also use its power in transportation systems to provide answers to issues like why a traffic management system chose a certain route, why a vehicle was labeled as dangerous, or why an accident risk score went up. The capabilities are specifically essential in Smart Governance, transportation regulation, and public trust. It is expected that Future Intelligent Transportation Systems will need Explainable Artificial

Intelligence systems to make sure that Artificial Intelligence-based decisions are clear, moral, and comply with the regulations.

Generative Artificial Intelligence and Large Language Models in Transportation

Both Generative Artificial Intelligence and Large Language Models are poised to become the most powerful technologies in Intelligent Transportation Systems. Generative Artificial Intelligence is able to generate synthetic transportation information, model traffic conditions, produce mobility predictions, and facilitate transportation decisions in data-deprived conditions [16]. Artificial traffic data are also most suitable in training Deep Learning models in motion of Autonomous Vehicles, Road Safety and Intelligent Traffic Signal Control without necessarily using real world data. Conversational mobility assistants, travel planning, traffic incident recap, and intelligent decision support are some of the transportation system applications of Large Language Models. Such models have the ability to process transportation papers, find data on the reports and give real-time advice to travelers and urban planners. Enhancing communication, interaction between users and transportation coordination, Large Language Models can be utilized in Smart Cities to aid in the management of Public Transportation, Mobility-as-a-Service promoting platforms, and Intelligent Logistics. Generative Artificial Intelligence has high potential of yearning citations in the future since despite its recent adoption in the transport industry it has the capability to change the transportation analytics, planning and decision making processes.

Digital Twin Technology and Artificial Intelligence Integration

Digital Twin technology is growing in significance in Intelligent Transportation Systems since it allows creating digital copies of transport networks, roads, intersections, vehicles, and infrastructure. Digital Twin systems can also model transport situations, assess infrastructure performance, and maximize traffic processes through incorporation of Artificial Intelligence, Machine Learning, Internet of Things, and Real-Time Monitoring data [9,16-18]. In Smart Cities, particularly, to facilitate proactive transportation planning, predictive maintenance and disaster response, Digital Twin models come in handy. The Digital Twin systems can assist transportation authorities to test new transportation policies, congestion reduction strategies, and consider the effect of road closures or infrastructure breakdowns and test them virtually and may implement them in the real environment after testing. The combination of Graph Neural Networks, Deep Reinforcement Learning, and Big Data Analytics in Digital Twin platforms is projected to produce extremely flexible and robust transportation systems that aid in Sustainable Urban Development and Transportation Resilience.

Edge Computing, Cloud Computing, and Big Data Analytics in Intelligent Transportation Systems

A fundamental technology used to implement Artificial Intelligence in Intelligent Transportation System involves Edge Computing, Cloud Computing, and Big Data Analytics. Connected Vehicles, Internet of Things, GPS sensors, surveillance cameras, mobile applications, and social media offer transportation networks enormous volumes of data. Cloud computing offers the processing power to store those massive datasets and process them, whereas Edge computing offers faster decision-making based on processing the data nearer the source. The Autonomous Vehicles, Intelligent Traffic Signal Control, and Road Safety applications are some of the areas that require Edge Computing due to the importance of low latency and real-time responsiveness. Mobility analytics, fleet management, and transportation planning at the city-wide level are becoming more widely implemented via cloud-based transportation solutions. Big Data Analytics enable transportation agencies to understand traffic behavior, detect trends and anomalies, predict demand and enhance service quality. Artificial Intelligence combined with Edge Computing and Cloud Computing is likely to enhance more scalable, efficient and responsive transportation systems in future Smart Cities.

Cybersecurity and Data Privacy in Artificial Intelligence-Based Transportation Systems

The issues of Cybersecurity and Data Privacy have become critical in Intelligent Transportation Systems as the transportation network is becoming more and more dependent on Connected Vehicles, Vehicle-to-Everything Communication, Cloud Computing, and artificial intelligence-based decision-making. The sector of transportation can fall victim to CADA worm attacks through traffic lights, autopilot connected automobiles, navigation systems, and mobility platforms [2,19-20]. These types of attacks may impair transportation activities, jeopardize passenger safety and confidence. The artificial intelligence is being applied more and more to detect cyber threats, identify abnormalities and enhance transportation security. Vehicular Networks and Connected Vehicles Machine Learning models can be used to analyze network traffic and detect suspicious activity, as well as to detect malicious behaviour. Simultaneously, transportation agencies need to make sure that Artificial Intelligence applications do not violate legal policies on privacy and safeguard confidential user information. In the future, Intelligent Transportation Systems will need powerful Cybersecurity systems, privacy-enabling Artificial Intelligence models, and secure communication channels to ensure secure and reliable transportation services.

Future Directions of Artificial Intelligence Techniques in Sustainable Mobility

The future of Artificial Intelligence in Intelligent Transportation Systems is probably influenced by the combination of various new technologies, such as 5G and 6G, Quantum Computing, Federated Learning, Explainable Artificial Intelligence, Digital Twin, Generative Artificial Intelligence, and Large Language Models. Transportation is seen as becoming more autonomous, connected, predictive, and sustainable in the future. Artificial Intelligence technologies will be more useful to Electric Vehicles, Shared Mobility, Mobility-as-a-Service, Public Transportation, Intelligent Logistics, and Green Transportation. The future transportation systems will demand greater level of integration of the Artificial Intelligence, Smart Governance, Urban Analytics, Transportation Planning and Sustainable Urban Development. Scholars are paying greater attention to the energy-efficient machine learning models, carbon-conscious traffic management, and fair transportation systems that assist a variety of residents. The focus of the studies in the future will be also most likely to include Transportation Resilience, climate adaptation, ethical Artificial Intelligence, and low-carbon mobility strategies. The Artificial Intelligence, Deep Learning, Internet of things, Edge computing, and sustainable mobility convergence have the possibility to revolutionize the future of Intelligent Transportation Systems by making them safer, more efficient, more resilient, and more environmentally sustainable transportation ecosystems.

3.2 Artificial intelligence methods

Supervised Machine Learning Methods for Traffic Prediction

Useful Artificial Intelligence Supervised Machine Learning Supervised Machine Learning is one of the most popular AI techniques used in Intelligent Transportation Systems due to its capacity to learn the relationships between the inputs and outputs of transportation based on the labeled datasets. The long-established supervised approaches that are common in use in Traffic Prediction, Traffic Congestion, Accident Prediction, Road Safety, and Transportation Planning are Linear Regression, Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, Naive Bayes, Gradient Boosting, Extreme Gradient Boosting, and K-Nearest Neighbors [9,21-23]. Such techniques prove especially useful when traffic tracking data of the past, weather data, vehicle numbers, GPS tracks, and road congestion data are presented in a format easily read by the computer. Smart Cities often apply supervised approaches in estimating the travel time, estimating the traffic density, optimizing the traffic signals, forecasting demand and intelligent route planning due to their relative interpretability and computational performance. The use of Random Forest and Gradient Boosting techniques has become such commonplace in Intelligent Transportation System due to their ability to capture nonlinear relationships among transportation variables despite their ability to withstand noise and missing values. DNA Support Vector Machines are well known in the field of Driver Behavior Analysis, anomaly detection and Road Safety assessment because of their classification capabilities of complex traffic patterns. Ensemble techniques are also gaining momentum due to the fact that they integrate the various predictive models in a bid to enhance the overall accuracy and eliminate errors in prediction. According to recent research in transportation, hybrid supervised Machine Learning systems are performing better in Public Transportation demand estimation, Intelligent Logistics, Smart Parking, and strategies to reduce Carbon Emissions, compared to traditional single-model approaches. Such advancements suggest that supervised Machine Learning remains a cornerstone Artificial Intelligence technique in Intelligent Transportation Systems.

Unsupervised Learning Methods for Mobility Pattern Discovery

Unsupervised Learning techniques are progressively significant in Intelligent Transportation Systems due to the fact that data of transportation often contains latent and uncharacterized structures, hidden mobility patterns as well as behavioral trends. In contrast, with supervised learning, unsupervised techniques detect the relationships within the data sets, without having the target labels. Common clustering algorithms that are applicable to Urban Analytics, Multi-Mode Transportation analysis, travel demand segmentation and mobility behavior identification include K-Means and Hierarchical Clustering, Density-Based Spatial Clustering, Gaussian MixtureModels and Self-Organizing Maps. Unsupervised Learning techniques are important in identifying abnormal states of traffic as well as location of congestions, driving style, and travel demand in cities among other applications. These methods are specifically applicable to Smart Cities since it will assist planners in comprehending some concealed mobility forces, as well as develop more effective transportation policies. There are also methods such as Principal Component Analysis of large transportation data and Autoencoders and Dimensionality Reduction, which simplify it and enhance the quality of computations. With the increasing data requirements of Intelligent Transportation Systems, unsupervised approaches will become more useful to detect latent traffic patterns, behavior patterns of passengers, and new transportation hazards.

Deep Learning Methods for High-Dimensional Transportation Data

Intelligent Transportation Systems have been revolutionized with Deep Learning methods since they are capable of automatically learning complex features in a high-dimensional data source like a traffic camera, sensors, GPS traces, LiDAR systems or a network of connected vehicles. Deep Neural Networks, Artificial Neural Networks, and Multilayer Perceptrons are prevalent in Traffic Flow Optimization, the planning of Public Transportation, Vehicle Trajectory Prediction, and Intelligent Routing since they are capable of modeling the overwhelming nonlinearities between the variables of transportation [24-26]. Deep Learning technologies are particularly valuable in the setting when transportation infrastructure has to manipulate a lot of real-time information at a high speed and precision. Such techniques are able to generate small mobility patterns which conventional Machine Learning models might overlook. Deep Learning finds its application in Smart Parking systems, freight demand prediction, Electric Vehicle charging prediction, and Road Safety improvement. Deep Learning algorithms are quickly being critical to support autonomous, predictive, and adaptive transportation ecosystems with transportation infrastructure becoming increasingly interconnected via Internet of Things devices and Vehicular Networks.

Convolutional Neural Networks for Computer Vision and Object Detection

Of the most significant Deep Learning approaches to the Intelligent Transportation System is Convolutional Neural Networks which are very effective in handling images and video streams. These are widely used in Computer Vision, Object Detection, Semantic Segmentation, Vehicle Recognition, Lane Detection, Pedestrian Detection, Traffic Sign Recognition and Road Damage Detection. Convolutional Neural Networks make the transportation system read the intricate scenes of the roads and offer real-time data as a means of Road Safety, Autonomous Vehicles, and Intelligent Traffic Management. Newer versions of Convolutional neural network design like ResNet, YOLO, Faster R-CNN, Mask R-CNN, and EfficientNet have been on the rise in the Smart City because of their high accuracy and speed in commerce with the transportation tracking system. Such models are capable of detecting dangerous road situations, monitoring illegal parking, and accidents, as well as automatically identifying the types of vehicles on the road. The latest advancements have also enhanced the durability of the Computer Vision systems in the unfavorable weather conditions, in low visibility, and during night traffic situations. Convolutional Neural Networks are also among the most relevant Artificial Intelligence techniques in Intelligent Transportation Systems since it helps maintain safer roads, enhanced surveillance, and more receptive mobility services.

Recurrent Neural Networks, Long Short-Term Memory, and Gated Recurrent Units for Time Series Forecasting

The transportation systems produce sequential and time-dependent data, and Recurrent Neural Networks, Long Short-Term Memory networks and Gated Recurrent Units are especially useful when it comes to Time Series Forecasting. They are commonly used in Traffic Prediction, Vehicle Trajectory Prediction, Public Transportation scheduling, Intelligent Logistics and Traffic State Estimation [8,27-30]. Long Short-term Memory models are particularly significant as they can include long-term traffic dependencies and seasonal patterns of traveling better than usual Recurrent Neural Networks. There is also the increased use of Gated Recurrent Units that do not need many computational resources but still have good predictive behavior. Combined approaches based on Long Short-Term Memory and Convolutional Neural Networks or Graph Neural Networks increasingly appear due to their ability to both examine extratemporal and intratemporal traffic dynamics. These mixed architectures have been more and more utilized in forecasting traffic velocity, congestion, state of parking and passenger demand within Smart Cities. Recent studies also show that Digital Twin frameworks, based on Long Short-Memory, can support predictive transportation management in 5G and 6G communications.

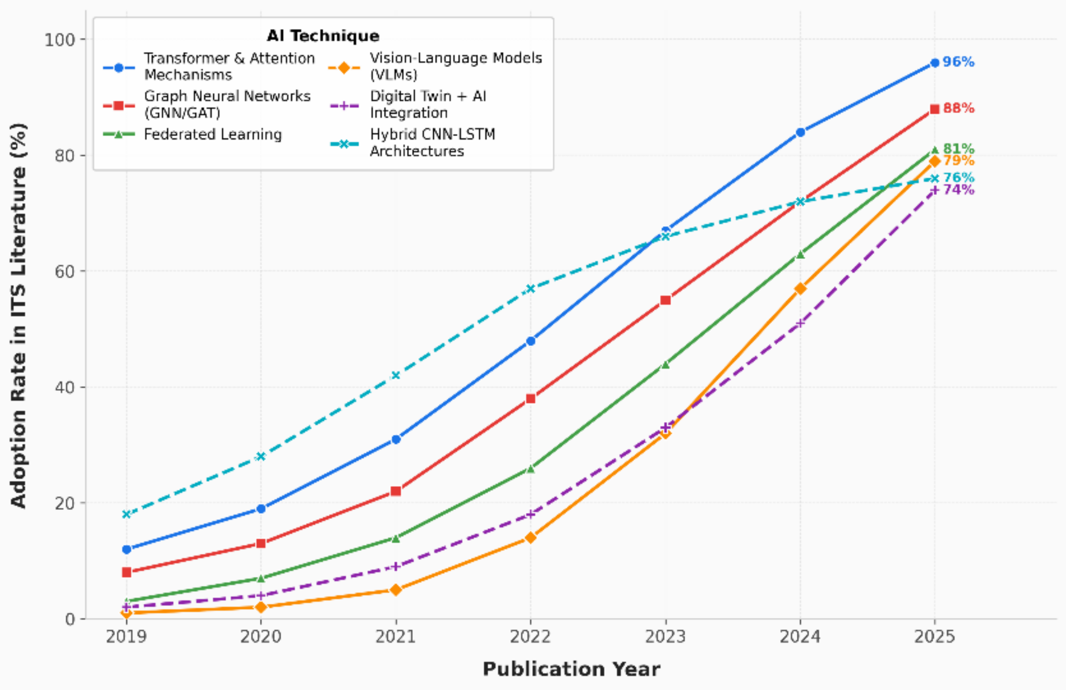

Fig. 3 Temporal Adoption Trends of AI Techniques in ITS Literature (2019-2025)

Fig. 3 represents multi-series line plot tracks the adoption rate (%) of six prominent AI techniques in ITS-related publications over the period 2019 to 2025, capturing the explosive growth of newer paradigms. Transformer and attention-based mechanisms dominate with the steepest growth trajectory, reaching 96% adoption by 2025, followed closely by Graph Neural Networks and Federated Learning frameworks. Vision-Language Models (VLMs) and Digital Twin-integrated AI systems show the most dramatic acceleration post-2022, consistent with the broader proliferation of large-scale foundation models. Hybrid CNN-LSTM architectures display a plateau after 2022, suggesting market maturation as more expressive models supersede them. The divergence between fast-rising and plateauing curves is a critical bibliometric signal for researchers and funding bodies seeking to anticipate the next wave of high-impact ITS research topics. This plot is particularly suited for trend analysis and strategic research gap identification in smart mobility reviews.

Reinforcement Learning and Deep Reinforcement Learning for Adaptive Traffic Control

Reinforcement Learning and Deep Reinforcement Learning are gaining relevance in Intelligent Transportation Systems as they provide transportation systems with opportunities to learn through exposure to dynamic traffic environments. These methods are widely used in Intelligent Traffic Signal

Control, Adaptive Traffic Control, Intelligent Routing, Autonomous Vehicles, and Mobility-as-a-Service platforms. The objectives of the Reinforcement Learning techniques are to optimise the long term benefits including less congestion, less time travelling, lesser carbon emissions, and better road utilisation. Deep Reinforcement Learning is especially useful to Smart Cities as it can adjust to evolving traffic situations in real-time and optimize traffic signal timing. To simulate transportation environments and verify laws in traffic management strategies, these methods are becoming part of Digital Twin systems and Real-Time Monitoring platforms to simulate transportation environments. Reinforcement Learning also finds common applications in autonomous vehicles to plan paths, choose lanes, and cooperatively drive. The future of transportation is projected to be dependent on a great deal of Reinforcement Learning due to the fact that it can enable adaptive, resilient and self-optimizing transportation networks. As of 2020, Reinforcement Learning is often coupled with Digital Twin Networks to do simulation-based optimization and resource management in the next-generation transportation infrastructure.

Graph Neural Networks and Graph Transformers for Urban Mobility Analysis

GNN has emerged as one of the most impactful AI techniques in the context of Intelligent Transportation Systems since transportation networks can be naturally modeled as graphs that are made up of roads, intersections, transit lines, and vehicles. GNNs have been successfully applied in the fields of Traffic Prediction, Traffic State Estimation, Demand Prediction, Shared Mobility analysis, Intelligent Routing, and Vehicle Trajectory Prediction due to their ability to embrace both the spatial and temporal relationships in transportation networks [9,31-33]. The recent advancements in Graph Transformer and spatio-temporal Graph Neural Networks have made great contributions to the accuracy of traffic prediction and mobility study. Such techniques are finding increasing applications in Smart Cities to find the areas of congestion, optimize transport networks, and aid Public Transportation planning. Federated Learning and Digital Twin systems are also being incorporated with instantiations of Graph Neural Networks to provide transportation intelligence that is distributed, private, and adaptive. Recent surveys show that Graph Neural Networks are currently extending to areas outside of traffic prediction to include parking management, traffic light control, transportation safety, and autonomous vehicle control systems.

Transfer Learning and Federated Learning for Distributed Transportation Intelligence

Transfer Learning is gaining momentum in Intelligent Transportation Systems, as it enables Artificial Intelligence-trained models in one context to be adapted to a different transportation situation with little retraining. This approach is especially useful in Road Safety, Driver Behavior Analysis, Traffic Sign Recognition and Accident Prediction since labeled data of transportation is not always cheap and not readily available. Transfer Learning lowers the computer expenses and can instruct transportation agencies to roll out complex Deep Learning frameworks more successfully. Federated Learning already becomes one of the most significant privacy-saving techniques in Intelligent Transportation Systems since this approach allows Artificial Intelligence models to be trained on a wide range of devices and organizations without the need to store sensitive data in a single location. The Federated Learning is particularly applicable in Connected Vehicles, Vehicle-to-Everything Communication, Vehicular Networks, and Internet of Things systems where edge devices share transportation data. These techniques facilitate privacy-conscious traffic prediction, driver behavior modeling, and autonomous car coordination. Recent studies emphasize the fact that Federated Learning is more and more combined with Generative Artificial Intelligence, Graph Neural Networks, Edge Computing, and 6G-enabled Digital Twin solutions to enable safe and distributed and scaled transportation intelligence.

Explainable Artificial Intelligence and Neuro-Symbolic Methods for Trustworthy Transportation

Explainable Artificial Intelligence has been an important emphasis in Intelligent Transportation Systems since many Deep Learning and Machine Learning technologies are black-box systems. Stakeholders, especially in transportation systems like Autonomous Vehicles, Accident Prediction, Intelligent Traffic Signal Control and Driver Behavior Analysis, are often seeking clear explanations of the Artificial Intelligence decisions [34-36]. Explainable Artificial Intelligence can be used to explain the variables used to make a prediction, why a vehicle was considered a risk, or why a certain route was suggested.

Neuro-Symbolic Artificial Intelligence is becoming an exciting technique of combining the learning abilities of Neural Networks with the deductive abilities of symbolic mechanisms. These approaches are becoming useful in the rapidly developing systems of Autonomous Vehicles, transportation regulation, ethical Artificial Intelligence governance, and Road Safety due to their capability to enhance explainability and minimize hallucinations, as well as, make transportation choices guided by rules. The Neuro-Symbolic Artificial Intelligence will have its future significance in Intelligent Transportation Systems as it would be capable of developing more transparent, credible and policy integrated mobility systems.

Generative Artificial Intelligence, Large Language Models, and Agentic Artificial Intelligence

Generative Artificial Intelligence and Large Language Models are quickly becoming powerful tools in Intelligent Transportation Systems as they can generate synthetic transportation data, simulate mobility conditions, be able to provide a summary of traffic reports, and aid the planning of intelligent transportation. In future Accident Prediction, Intelligent Traffic Signal Control, Traffic Prediction, and the generation of synthetic data in Autonomous Vehicles, Generative Artificial Intelligence is especially beneficial [3,37-39]. Such techniques tend to be particularly useful in the cases when the actual data about transportation is scarce or sensitive and hard to gather. Conversational mobility assistants, Transportation decision support systems, traffic incident summary, and Intelligent Logistics platforms are all increasingly using Large Language Models. Alternatively, Agentic Artificial Intelligence is a radically promising domain as well since it allows different Artificial Intelligence agents to cooperate dynamically in the context of transportation networks. Recent research suggests that Generative Artificial Intelligence is now becoming additionally integrated with Digital Twin platforms, simulation tools, retrieval-augmented generation as well as scientific optimization systems to assurances in urban freight planning, Intelligent Logistics and low-carbon transportation plans. Federated Learning and spatio-temporal Graph Neural Networks to forecast traffic and reason about transportation are being combined with Large Language Models.

Digital Twin and World Model Methods for Transportation Simulation

Intelligent Transportation Systems are becoming highly reliant on Digital Twin approach as the approach develops virtual models of transportation infrastructure, transit vehicles, traffic networks, and mobility systems. Such approaches aid Real-Time Monitoring, predictive maintenance, traffic optimization, disaster response, and Transportation Resilience. Machine Learning, Deep Learning, Reinforcement Learning, and Graph Neural Networks are frequently used with Digital Twins to forecast what traffic might look like and how transportation policies would work before implementation. The new generation of Artificial Intelligence techniques that can acquire interactive and realistic transportation environments in the form of real-world data include World Models. Such techniques prove to be particularly useful when it comes to Autonomous Vehicles since they can create rare traffic situations, synthesize sensor data, and simulate hazardous real-life situations that are hard to test. The recent trend has observed that world models are being utilized in the fields of autonomous driving simulation and edge-case generation, which is critical in enhancing safety, robustness and reliability in Connected Vehicles and autonomous mobility systems.

Edge Computing, Quantum-Inspired Computing, and Future Artificial Intelligence Methods

The idea of Edge Computing has often become a relevant enabling approach in the Intelligent Transportation Systems since it enables Artificial Intelligence models to run on the transportation data at the point of origin without wholly depending on the centralized Cloud Computing facilities. This is particularly crucial to the Autonomous Vehicles, Intelligent Traffic Signal Control, Connected Vehicles, and Vehicle-to-Everything Communication where a low latency and real-time responsiveness is crucial [36,40-42]. Edge computing helps in making quicker traffic decisions, less communication delays and enhancing transport safety. The perspective of Intelligent Transportation Systems is quantum-Inspired Computing which can be considered as an approach to Artificial Intelligence due to their potential to address highly complicated optimization issues that are connected with the problems of route planning, optimization of traffic flows, allocation of resources and schedule optimization of transport. Most recent studies suggest that quantum-inspired Graph Transformers, Federated Learning and Digital Twin models could enable privacy aware, causal, and highly responsive transportation intelligence. The Future Intelligent Transport system is hoped to integrate Edge Computing, Quantum-Inspired Computing, Generative Artificial Intelligence, Graph Neural networks, Explainable Artificial Intelligence, and 6G-enabled Digital Twin systems to provide extremely resilient, efficient, and sustainable transportation systems.

3.3 Artificial intelligence technologies

Internet of Things and Sensor Technologies in Intelligent Transportation Systems

The Internet of Things is currently one of the best Artificial Intelligence technologies in the Intelligent Transportation Systems due to the opportunity of real-time collection of data of connected devices, vehicles, roads, intersections, traffic cameras, and environmental sensors. The application of the Internet of Things technologies in Smart Cities is extensivelywide-ranged in Traffic Management, Traffic Prediction, Smart Parking, Intelligent Traffic Signal Control, Public Transportation monitoring and Intelligent Logistics. Transportation data about speed, congestion, travel time, road occupancy, weather conditions, fuel consumption, and emissions is always created through sensors installed in road infrastructure, vehicles, parking systems and mobile devices. With this real-time data, the applications of Machine Learning, Deep Learning, and Predictive Analytics can be built to achieve sustainable mobility ecosystems. The combination of Internet of Things systems with Connected Vehicles, Vehicular Networks, and Vehicle-to-Everything Communication has considerably enhanced the capabilities of the transportation systems to respond dynamically to the changing traffic conditions. Transportation systems enabled by the Internet of Things, Adaptive Traffic Control, Intelligent Routing, Real-Time Monitoring, and Road Safety make use of continuous data streams to enable Artificial Intelligence models to identify the presence of congestion, concentrate on incidents and optimize the traffic flow. The current trends in Smart Infrastructure also suggest that Internet of Things are also becoming integrated with Digital Twin platforms and Edge Computing systems to become smarter, autonomous, and sustainable transportation networks.

Connected Vehicles and Vehicle-to-Everything Communication Technologies

Connected Vehicles and Vehicle-to-Everything Communication technology is starting to form the core of Intelligent Transportation Systems due to its ability to provide vehicles with the communication capabilities to interact with other vehicles, infrastructure along with roadside features, traffic lights, pedestrians, and cloud services. Vehicle-to-Everything Communications consist of Vehicle-to-Vehicle, Vehicle-to-Infrastructure, Vehicle-to-Pedestrian, Vehicle-to-Network communications, all of which enhance safer mobility systems, faster coordinated mobility systems and safer mobility systems [40,43-44]. There are several technologies that are especially significant to Smart Cities; they enhance Traffic Management, Road Safety, Intelligent Routing, and Accident Prediction. Connected Vehicles produce massive amounts of data pertaining to vehicle speed, location, braking, fuel use, driver behavior and traffic conditions. This data is used by Artificial Intelligence technologies to optimize traffic lights, detecting the risk of accidents, supporting Autonomous Vehicles, and making Public Transportation more efficient. V2EC is also gaining more relevance in Electric Vehicles, Intelligent Logistics, and Shared Mobility services as a means to coordinate in a seamless way the different options of transportation. It is believed that automated transportation systems of the future will heavily depend on 5G and 6G communication to achieve Intelligent Transportation Systems low-latency, high-speed, and efficient Vehicle-to-Everything Communication.

Cloud Computing and Edge Computing Technologies

Cloud Computing and Edge Computing are key technologies on which Artificial Intelligence applications can be built in Intelligent Transportation Systems. Connected Vehicles, Internet of Things devices, GPS, cameras, mobile apps, and social media platforms continually produce vast amounts of data in transportation systems. Cloud Computing is what is required to supply the computations and storage required to handle these large-scale transportation data sets, and Edge Computing is used to provide low-latency decision-making by operating on the data at or near its origin. Edge Computing is especially significant in the fields of Road Safety, Autonomous Vehicles, Intelligent Traffic Signal Control, and Adaptive Traffic Control due to the occurrence of numerous transportation decisions that require real-time effects. Any slackness in processing of data can lead to congestion of traffic, accidents, or ineffective mobility services. Edge Computing reduces the latency of communication and enhances the efficiency of computation in order to provide quicker Artificial Intelligence inference of traffic monitoring, traffic congestion detection, route planning, and driver assistance systems. Recent trends in research indicate that Edge Computing, Federated Learning, and Digital Twin systems may be combined to facilitate resilient, privacy-assuring and larger transportation networks.

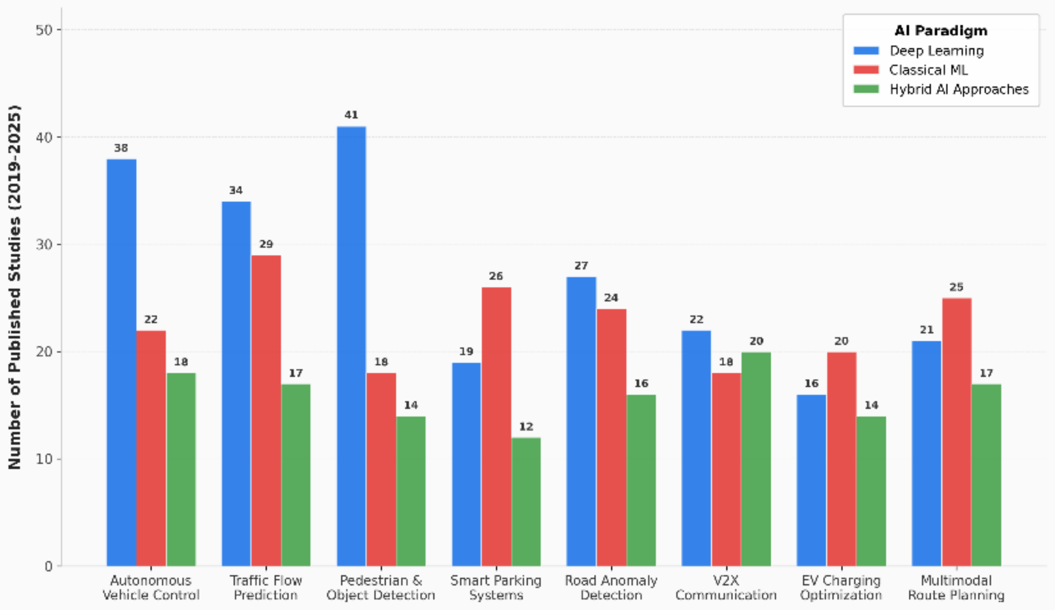

Fig. 4 Distribution of AI Paradigms Across ITS Application Domains (2019-2025)

Fig. 4 represent grouped bar chart compares the volume of published studies employing Deep Learning, Classical Machine Learning, and Hybrid AI approaches across eight prominent ITS application domains: autonomous vehicle control, traffic flow prediction, pedestrian and object detection, smart parking, road anomaly detection, V2X communication, EV charging optimization, and multimodal route planning. Deep Learning dominates pedestrian and object detection (41 studies) and autonomous vehicle control (38 studies), consistent with the visual processing demands of these tasks. Classical ML retains a competitive presence in traffic flow prediction and smart parking, where tabular and sensor data remain primary inputs. Hybrid AI approaches show consistent representation across all domains, with particular strength in V2X communication and route planning, reflecting the growing recognition that ensemble strategies outperform single-paradigm solutions in complex, heterogeneous transportation environments. This chart provides a comprehensive domain-level map of AI paradigm preferences within the ITS landscape.

Computer Vision and Intelligent Surveillance Technologies

The use of the Computer Vision technologies in Intelligent Transportation Systems has become an important concept as the transportation systems can now deduce images and video feeds provided by the surveillance cameras, drones, roadside sensors and the cameras attached in the vehicles. Applications of Computer Vision technologies have been broadly applied in Object Detection, Semantic Segmentation, Vehicle Recognition, Pedestrian Detection, Lane Detection, Traffic Sign Recognition, and Accident Prediction [3,45-48]. These technologies specifically hold significance in the field of Road Safety, Traffic Management, and Autonomous Vehicles in that they offer the visual insight needed to cognizant of changing road conditions. Recent Computer Visions technologies tend to use Convolutional Neural Networks, Graph Neural Networks and Mobility Foundation Models to enhance the accuracy of perception in feasible traffic settings. The Intelligent surveillance can be used to observe intersections, detect hazardous driving patterns, detect road-breaking regulations and real-time damage on the road. These technologies are also coming to gain prominence on Smart Parking, Public

Transportation security and Intelligent Toll Collection systems. Computer Vision and 5G-enabling Edge Computing, combined with Generative Artificial Intelligence, are also anticipated to be applied in Future Intelligent Transportation Systems to aid in quicker and more precise transportation tracking.

Autonomous Vehicle Technologies and Mobility Foundation Models

AV technologies are one of the most disruptive inventions in Intelligent Transportation Systems since they integrate Artificial Intelligence, Computer Vision, Deep Learning, sensor fusion, Vehicle-to-Everything Communication and Real-Time Monitoring and allow vehicles to be operated with a minimum amount of human intervention. AVs use cameras, LiDAR, radar, ultrasonic sensors, GPS, and massive-resolution maps to get acquainted with the situation on the road, identify objects and people, and make decisions in navigation. Recent trends show that Autonomous Vehicles are getting more beyond rule-based systems to Mobility Foundation Models, which can generalize across various driving conditions and types of vehicles. These Mobility Foundation Models are trained using large scale multimodal data or traffic videos, vehicle telemetry and aware of the environment which allows them to be more efficient in various road scenarios. The development of the foundation model-based driving systems is of particular significance to Smart Cities as it is capable of underpinning more versatile, larger, and efficient autonomous mobility services. Research based on local traffic conditions, the unpredictable nature of the road environment and intricate urban mobility issues are all rapidly advancing autonomous driving technologies in India through research partnerships.

Digital Twin Technologies for Smart Transportation

Digital Twin technology is currently emerging as one of the essential Artificial Intelligence technologies of Intelligent Transportation Systems as it generates virtual versions of roads, vehicles, traffic networks, transport systems, and communication infrastructure. Digital Twins automatically align with the actual transportation conditions in the real world with the help of Internet of Things sensor data, Connected Vehicles, Edge Computing systems, and Artificial Intelligence models [5,19,49-50]. This allows transportation agencies to model traffic conditions, forecast traffic jams, optimize traffic movement, and test transportation policies prior to implementation in the real world. Digital Twin technologies are becoming employed more in Traffic Prediction, Transportation Planning, Road Safety, disaster response, and Smart Infrastructure management. Recent work points to the adaptation of Digital Twin systems to more sophisticated systems like Single-Vehicle Digital Twins, Connected Vehicle Digital Twins, Environment Digital Twins, Network Digital Twins, Safety and Security Digital Twins, and Twin-of-Twins systems. These technologies apply specifically well to Sustainable Mobility as they allow the proactive planning of transportation, energy-efficient traffic management, and transportation resilience. Combining Deep Reinforcement Learning, Graph Neural Networks, Federated Learning, and Big Data Analytics into the Digital Twin platforms should enhance their predictive and operational abilities further.

Big Data Analytics and Predictive Analytics Technologies

Intelligent Transportation Systems cannot be successful without the role of Big Data Analytics technologies due to the creation of immense volumes of structured and unstructured information per second by transportation networks. This information is provided by traffic sensors, mobile apps, GPS trackers, smart infrastructure, surveillance, mass transit networks, and social media networks. The technologies of Big Data Analytics can assist transportation agencies to process such large volumes of data to detect areas with congestion, predict travel demand, optimize route planning, and enhance Road Safety. Delay in application Predictive Analytics technologies find application as Traffic Prediction, Demand Prediction, Public Transportation optimization, Vehicle Trajectory Prediction, and Intelligent Logistics. These technologies help transportation systems to predict future road conditions, demand of new passengers, and the risk of accidents instead of only responding to current situations. Recent advancements in Artificial Intelligence and Deep Learning have made Predictive Analytics technologies capable of handling high-frequency transportation data, and more precise mobility forecasts. These are some of the capabilities that are gaining relevance to Smart Cities since they aid in proactive transportation planning, alleviate traffic jams and enhance the overall efficiency of movement and mobility.

Federated Learning and Privacy-Preserving Technologies

The concept of Federated Learning has become one of the hottest future technologies in Intelligent Transportation Systems due to its ability to enable the training of Machine Learning models on a large scale, spanning many devices, without having to concentrate sensitive transportation information in a single location. Autonomous Vehicles, cell phones, roadside units and transportation platforms produce vast amounts of personal, locational and conductive information that pose certain threats to Data Privacy and Cybersecurity [29,51-53]. Federated Learning can alleviate these issues by enabling the transportation systems to train AI models locally and just send updated models instead of raw data. Applications of Federated Learning technologies to Driver Behavior Analysis, Traffic Prediction, Accident Detection, Connected Vehicles and Vehicle-to-Everything Communication systems are on the rise. These technologies enable privacy preserving transportation intelligence and minimizing communication overhead as well as enhancing scalability. Recent study reports that Federated Learning is also being combined with an Edges computing, Graph Neural Networks, Generative Artificial Intelligence and Digital Twin systems to ensure the secure, distributed and adaptive transportation ecosystems. With Intelligent Transportation Systems growing data-intensive, the Federated Learning will be deemed very significant in facilitating privacy-sensitive smart mobility solutions.

Explainable Artificial Intelligence and Trustworthy Technologies

Many Intelligent Transportation Systems are currently considering explainable Artificial Intelligence technologies since many Machine Learning and Deep Learning systems are black-box systems. In safety-important transportation systems like Autonomous Vehicles, Accident Prediction, Intelligent Traffic Signal Control, Driver Behavior Analysis, and Intelligent Routing, users and transportation agencies must know how Artificial Intelligence systems are able to make decisions. Explainable Artificial Intelligence technologies are designed to enhance transparency, accountability, interpretability, and trust in transportation. Such technologies may convey the reasons as to why a vehicle was considered dangerous, why a traffic light had to change its timing, or why a route suggestion was given. It is important to note that Explainable Artificial Intelligence is vital to Smart Governance, transportation policies, popular trust, and ethical implementation of Artificial Intelligence. The Future Intelligent Transportation Systems will need Explainable Artificial Intelligence frameworks that integrate Machine Learning, rule-of-thumb systems and the human control, to facilitate the safe and transparent transportation decisions. Explainable Artificial Intelligence will also become more relevant as Artificial Intelligence systems are more independent and multifaceted.

Generative Artificial Intelligence and Large Language Model Technologies

Generative Artificial Intelligence and Large Language Models are becoming promising technologies in Intelligent Transportation Systems due to their ability to generate synthetic transportation information, recreate traffic conditions, give advice on traveling, summarize events of traffic accidents and assist in transportation planning. The Generative Artificial Intelligence technologies are especially effective in the environment of the unavailability of transport data, incomplete data, or sensitive data [54-56]. Neural networks can be trained using synthetic transportation data to facilitate Deep Learning models in Autonomous Vehicles, Road Safety, Traffic Prediction and Intelligent Traffic Signal Control. The use of Large Language Models in conversational travel assistants, Intelligent Logistics systems, Public Transportation information services, and transportation decision support platforms are in increase. These technologies are able to process the transportation reports, process large-text datasets extracting useful insights and deliver personalized travel recommendations to users. Generative Artificial Intelligence also plays a role in Digital Twin simulations, transportation resilience analysis, and climate-conscience mobility planning. With increased integration of transportation systems into a multimodal mobility platform, Generative Artificial Intelligence and Large Language Models will be useful in offering more personalised, adaptive and intelligent transportation services.

5G, 6G, and Next-Generation Communication Technologies

5G and 6G communication technologies play an essential role in enabling Intelligent Transportation Systems since they offer high-speed low-latency and high-capacity communications capabilities suitable to Connected Vehicles, Autonomous Vehicles, Vehicle-to-Everything Communication, and Real-Time Monitoring. Logistical infrastructures are becoming more dependent on quick and stable communication systems to facilitate the operation of traffic lights, road accidents, self-driving, diagnosing cars remotely, and intelligent mobility. Intelligent Transportation Systems are also already being enhanced with the use of 5G technologies which facilitate instant data exchange among vehicles, infrastructures, and cloud systems. Nevertheless, 6G technologies would further enhance transportation systems with ultra-low latency and increased reliability, intelligent communication, and Digital Twin networks support. These new communication technologies will in particular be valuable in Mobility-as-a-Service, Shared Mobility, Electric Vehicles, and Autonomous Vehicles since all of them will be able to connect modes of transportation smoothly to each other. The Smart Cities of the future will largely rely on 5G and 6G technologies to facilitate intelligent, autonomous and sustainable transport ecosystem.

Cybersecurity Technologies for Intelligent Transportation Systems

The technologies involved in cybersecurity are gaining significance within Intelligent Transportation Systems since the transport networks could be subjected to cyberattacks to hack Connected Vehicles, traffic management systems, communication networks, and cloud environments. One of the possible impacts involves Cyberattacks that may undermine the Road Safety, disrupt the Public Transportation services, tamper with traffic lights, and reveal sensitive user information [57-59]. With all the advances in Intelligent Transportation Systems being more interconnected and automated, Cybersecurity technologies are increasingly required. Cybersecurity technologies associated with artificial intelligence are becoming more popular to detect anomalies, suspicious activity, and prevent cyberattacks within transportation networks. Vehicular Networks and Vehicle-to-Everything Communication systems The Machine Learning and Deep Learning models can handle network traffic, detect abnormal communication behavior and identify malicious traffic in the Vehicular Networks. Digital Twin platforms, Federated Learning, and Explainable Artificial Intelligence are also undertaking greater integration of the cybersecurity technologies to enhance resiliency and trust in transportation systems. The Intelligent Transportation Systems of the future will necessitate strong cybersecurity systems to maintain safety, security and reliability of transportation networks.

3.4 Artificial intelligence models

Artificial Neural Network Models for Transportation Forecasting

ANN models are still some of the most popular Artificial Intelligence models in Intelligent Transportation Systems due to their ability to model some complex nonlinear relationships between the variables in transportation systems. The classical transport networks produce dynamic data with great body in relation to the speed of traffic, number of vehicles on the road, progression of traffic demands, and the occupation of the road, weather, and driver dynamics [9,60-61]. Neural networks can handle these multidimensional data in parallel and generate very precise results to be used in Traffic Prediction, Traffic Congestion estimation, Demand Prediction and Intelligent Routing. These models are typical in Smart Cities as they enhance Traffic Management, Public Transportation scheduling, Intelligent Logistics and Sustainable Mobility planning. Artificial Neural Network models come in handy with such unstable traffic patterns that depend on various external events (accidents, road closures, weather conditions, or public events) as well. They are flexible in the sense that transportation authorities can develop predictive frameworks that can change with fluctuating mobility conditions on a real-time basis. The latest research also reveals that possibilities to implement Artificial Neural Networks along with Edge Computing, Internet of Things, and Big Data Analytics have become interconnected to serve Real-Time Monitoring and elastic transportation control systems. These advancements are enhancing the capacity of Intelligent Transportation Systems to provide more effective, resilient and ecologically friendly mobility services.

Convolutional Neural Network Models for Computer Vision

Convolutional Neural Network models are considered to be one of the most influential Deep Learning models in Intelligent Transportation Systems since they are constructed particularly aimed to analyze images and videos. Increasingly, transportation systems will deploy cameras, drones, LiDAR cameras, roadside cameras, vehicle-mounted cameras, and pedestrian sensors to gather real-time intelligence on roads, vehicles, pedestrians, traffic lights, and infrastructure [38,62-63]. Often used fields of Convolutional Neural Networks include Object Detection, Semantic Segmentation, Vehicle Recognition, Pedestrian Detection, Lane Detection, Traffic Sign Recognition and Accident Prediction. Recent Convolutional Neural Networks designs (ResNet, EfficientNet, YOLO, Faster R-CNN, and Mask R-CNN) have greatly enhanced the performance and performance of transportation perception systems. These models have extensive applications in Autonomous vehicles, Road safety, Smart parking, Smart Toll collection, and surveillance systems since they are able to interpret complex traffic environments at high specificity. New developments also indicate that Convolutional Neural Networks can perform more efficiently on low-light environments, bad weather or highly congested roads in urban areas. These features are particularly valuable to Smart Cities due to their capabilities in supporting safer transport systems and more reacting traffic management.

Recurrent Neural Network Models for Sequential Traffic Data

Recurrent Neural Networks have become very popular in Intelligent Transportation Systems due to the tendency of transportation data to be sequential, and time-dependent. The velocity of traffic, vehicle movement, travel demand and occupancy of roads operate constantly over time; therefore, Recurrent Neural Networks can be very useful in Time Series Forecasting and Traffic Predication. Such models can go through historical series of transportation information and in a way, discover long-term trends, which are applicable in the Traffic State Estimation, Public Transportation scheduling, and Intelligent Routing. RNNs are frequently used in transport-related problems where predicting and monitoring real-time control is needed. They are capable of predicting traffic congestion, abnormal traffic behavior, and aid Vehicle Trajectory Prediction in dynamic roads. Nevertheless, conventional Recurrent Neural Networks can be subjected to the problem of long-term dependencies and vanishing gradient. Consequently, new models like Long Short-Term Memory and Gated Recurrent Units have gained popularity in Intelligent Transportation Systems due to their ability to offer improved predictive capabilities and stability in long term predictions of traffic.

Long Short-Term Memory and Gated Recurrent Unit Models

Some of the most significant Deep Learning models to consider as part of Intelligent Transportation Systems are the Long Short-Term Memory and the Gated Recurrent Unit models since they can be used to address the critical issue of the transportation data and its temporal dependencies. The models are popularly applied in Traffic Prediction, Travel Time Estimation, Public Transportation demand, Vehicle Trajectory Prediction, and Traffic Congestion control [64-67]. Long Short-Term Memory models are especially suitable since they have gating mechanisms and memory type of cells that enable it to hold onto significant information in the long run. The models based on Gated Recurrent Unit are gaining popularity since fewer computational resources are required and the model used has high predictive power. Such models are particularly applicable to Edge Computing and Internet of Things-based transportation systems where the efficiency of computers is crucial. Hybrid Long Short-Term Memory/Gated Recurrent Unit models are also becoming popular since they are capable of incorporating spatial, time, and contextual transportation information. These are hybrid methods that are finding application in Smart Cities to predict demand of Electric Vehicles, predict occupancy of parking and Intelligent Logistics planning.

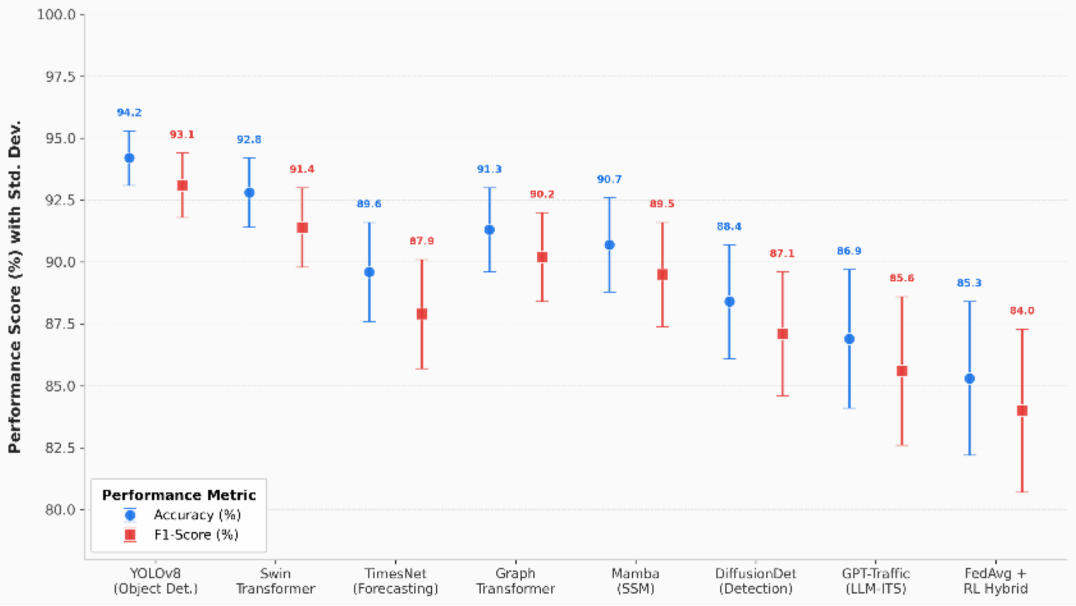

Fig. 5 Comparative Performance of Emerging AI Models in ITS Tasks

Fig. 5 explains error bar plot presents the mean accuracy and mean F1-score of eight state-of-the-art or emerging AI models benchmarked on ITS-related tasks, with standard deviation bars reflecting performance variability across multiple datasets and experimental configurations. Models assessed include YOLOv8, Swin Transformer, TimesNet, Graph Transformer, Mamba (state space model), DiffusionDet, GPT-Traffic (an LLM-adapted ITS model), and a FedAvg-RL hybrid. YOLOv8 achieves the highest mean accuracy (94.2%) and narrowest confidence interval, underscoring its maturity and robustness for object detection. Mamba and DiffusionDet represent the emerging frontier, offering competitive performance with increasing variance reflecting early-stage benchmarking diversity. LLM-based and federated approaches show the widest error bars, pointing to dataset heterogeneity and system configuration sensitivity as primary research challenges. The dual-metric presentation (accuracy and F1) ensures that class imbalance effects, common in ITS datasets, are appropriately captured, making this figure a reliable comparative reference for model selection in future ITS studies.

Graph Neural Network Models for Transportation Networks

Graph Neural Network models have proved to be one of the brightest of Artificial Intelligence models of Intelligent Transportation Systems since transportation systems are inherently networks of roads and intersections and transit routes and vehicle flows. Graph Neural Networks are unlike the classic Model of Machine Learning in that they can have a spatial-temporal association between transportation nodes. They are very useful in Traffic state estimation, Traffic prediction, Demand prediction, Intelligent Routing, Shared Mobility analysis and Public Transportation optimization. A survey of the research trends since 2019 indicates that GNNs have been especially relevant to traffic prediction, traffic light regulation, transportation safety, parking, and self-driving vehicles. Graph Neural Network models are particularly useful within the aspect of Smart Cities since it can be used to model transportation systems as graph models where roads are the nodes and travel connections in the cities the edges. This would enable the models to know the effects of congestion in a single locality on the traffic conditions in the surrounding areas. Long Short-Term Memory models, Federated Learning, and Digital Twin systems are won over by Graph Neural Networks to enhance the effectiveness of prediction and transportation resilience. These hybrid systems are anticipated to feature significantly in the future Intelligent Transportation Systems since they enable scalable, adaptive, and network-on-the-fly transportation intelligence.

Graph Convolutional Network, Graph Attention Network, and Graph Transformer Models

Graph Convolutional Network, Graph Attention Network, and Graph Transformer models are enhanced versions of Graph Neural Networks that are progressively becoming prevalent in Intelligent Transportation Systems. Graph Convolutional Networks are very efficient in the extraction of localized spatial data of transportation networks and can be applied broadly in Traffic Prediction and congestion analysis. Graph Attention Networks enhance this scheme (by attaching varying emphasis on importance of various transportation nodes and edges) to allow modeling of dynamic traffic interactions more accurately. Transformer models based on graphs are gaining a special significance due to the ability to learn both local and global transportation structures with large and complex road networks. These models are becoming popular in Smart Cities to carry out a large-scale Traffic State Estimation, Demand Prediction, Intelligent Routing and Public Transportation planning. According to recent literature, Graph Transformer architectures are more effective than other types of Graph Neural Network models in Network Digital Twins and next-generation 6G-enabled Intelligent Transportation Systems due to more often predictive accuracy and better scalability.

Reinforcement Learning and Deep Reinforcement Learning Models

Deep Reinforcement Learning and Reinforcement Learning models are becoming more popular in Intelligent Transportation Systems since they can acquire the best behaviour by interacting with real-time traffic systems. Intelligent Traffic Signal Control, Adaptive Traffic Control, Autonomous Vehicles, Intelligent Routing, and Mobility-as-a-Service systems are good locations to apply these models. Through reinforcement Learning models are constantly optimized in light of the long term rewards including reduced congestion, reduced travel time, reduced carbon emission and improved traffic efficiency. The models of Deep Reinforcement Learning are of particular importance to Smart Cities since they have the ability to deal with very complicated transportation settings with high populations of vehicles, intersections, and traffic lights. These models are finding more applications in Digital Twin settings whereby the transportation agencies can simulate and test traffic management strategies prior to their implementation in the real world. Connected Vehicles and autonomous driving systems use Reinforcement Learning to plan their paths, change lanes, and behave cooperatively with fellow vehicles as well. The above developments suggest that Reinforcement Learning will be an active source of developments in the development of adaptive and autonomous transportation systems.

Federated Learning Models for Privacy-Preserving Transportation

The importance of Federated Learning models is becoming very tangible in Intelligent Transportation Systems as they enable the use of Machine Learning algorithms to be taught using many devices without exposing any raw transportation data. Cvas, roadside devices, mobile apps, and IoT gadgets lead to the creation of vast quantities of sensitive data about their location, travel routes, driving habits, and passenger behavior [2,68-70]. Federated Learning may aid in solving Data Privacy and Cybersecurity issues by ensuring that this information is decentralized to stay that way and that transportation systems enjoy the benefits of collaborative model training. Applications of Federated Learning Are more popular in Traffic Prediction, Driver Behavior Analysis, Accident Detection, Vehicle-to-Everything Communication, and Connected Vehicle coordination. Recent discoveries denote Federated Learning to have a significant effect on enhancing the efficiency, scale as well as safety of the Intelligent Transportation Systems, and especially when combined with the Edge Computing, Digital Twins systems, and novel communication schemes. It is predicted that Federated Learning will get even more valuable in future Smart Cities since it can provide privacy-preserving, non-hazardous, and decentralized transportation intelligence.

Digital Twin Models for Transportation Simulation

The models known as Digital Twin models are gaining relevance when it comes to Intelligent Transportation Systems as they provide virtual representations of real-life transportation networks, vehicles, roads, traffic lights, and infrastructure. These models constantly link real-life transportation conditions with information on the Internet of Things sensors, Connected Vehicles, Edge Computers, and Real-Time Monitoring systems. Transportation agencies with Digital Twin models are able to model traffic conditions, experiment with new policies, assess congestion management approaches, and streamline transportation processes prior to making decisions in the real world. Traffic prediction, Intelligent Traffic Signal Control, Road Safety, Transportation Resilience and Autonomous Vehicle development are a few areas where Digital Twin models have been employed. Research has shown in recent times that Digital Twin systems are developing to be multi-layered and incorporate Federated Learning, Reinforcement Learning, Big Data Analytics, cooperative perception and 5G-enabled communication networks. Predictive simulation, adaptive control, and scenario-driven testing are easily facilitated by these systems and hence are of great utility in Smart Cities and Sustainable Mobility planning. The combination of digital Twin architectures and Machine Learning Operations has also been used more and more to automate the lifecycle management of predictive transportation models.

Foundation Models and Large Language Models for Mobility Intelligence

Two new paradigms in Intelligent Transportation Systems are Foundation Models and Large Language Models; these models have the ability to operate on large volumes of multimodal transportation data composed of text, images, sensor signals, maps, traffic videos, and vehicle telemetry. These models have a broad scope of transportation activities, and they are found to support Traffic Prediction, Road Safety analysis, Intelligent Routing, Public Transportation planning and transportation decision support [16,71-73]. The Foundation Models are becoming a new breed of mobility intelligence due to their ability to be generalized to various settings and applications of transportation. Machine Learning is evolving with Generative Artificial Intelligence and Foundation Models, which can create real-world text, pictures, and simulation using transportation data. Transport Large Language Models are used in large scale in transport systems in traveling assistants, traffic incident overviews, Intelligent Logistics coordination, and conversational mobility systems. These models are capable of processing transportation reports as well as identifying mobility trends and providing users and transportation planners with natural-language recommendations. Graph Neural Networks, Federated Learning, and online learning systems are also being merged with Foundation Models to enhance transportation forecasting and network intelligence. These changes imply that Foundation Models will grow in significance in future Smart Cities and Sustainable Mobility systems.

World Models and Neuro-Symbolic Models for Autonomous Transportation

The World Models have become one of the most promising Artificial Intelligence models in Intelligent Transportation Systems due to their ability to mimic the real-life conditions and forecast the behaviour of the transportation systems in various conditions. Such models are especially practical in the case of Autonomous Vehicles, Scenario-Based Simulation, Driver Behavior Analysis and Road Safety since they are capable of creating infrequent or dangerous traffic scenarios that are hard to test in real-world data. Independent driving systems can be enhanced in World Models, allowing them to train in simulated worlds and be ready to handle unpredicted road situations. Neuro-Symbolic Artificial Intelligence models are those models that use the pattern recognition of Neural Networks and the reasoning of symbolic systems. The models play a growing role in Intelligent Transportation Systems, as they enhance Explainable Artificial Intelligence, minimize uncertainty, and facilitate transportation choices that rely on rules. Autonomous Vehicles, Intelligent Traffic Signal Control systems and transportation policy systems are particularly useful in this field, as neuro-Symbolic demands transparency, reliability, and regulatory compliance. Future Intelligent Transport Systems will become more dependent upon World Models and Neuro-Symbolic Artificial Intelligence that will produce safer and more interpretable and adaptable mobility ecosystems.

Physics-Informed Neural Network Models for Transportation Systems

Physics-Informed Neural Network models are gaining popularity in Intelligent Transportation Systems since they incorporate physical principles, transportation regulations and mathematical constraints into Deep Learning models. In contrast to purely data-driven methods, Physics-Informed Neural Networks may enhance interpretability, predictability, and generalization since predictions in Artificial Intelligence are aligned with the real-world transportation dynamics [74-77]. Applications include traffic flow analysis, Vehicle Trajectory prediction, energy-efficient routing, and Autonomous Vehicle control, especially with these models. PINNs are now being deployed into Digital Tatinoms, Simulations of Transportation, and infrastructure monitors. The new trends indicate that Physics-Informed Neural Networks can be used to congestion control, predictive maintenance, and intelligent control in transport facilities, where physical limits and safety regulations are to be maintained. With the increased use of more sophisticated technologies in transport in Smart Cities, the PhysicsInformed Neural Networks are likely to gain relevance in the time, as they will be used to create strong and reliable, as well as explainable, Intelligent Transportation System.

3.5 Artificial intelligence applications

Traffic Prediction and Congestion Management Applications

Some of the most important applications of Artificial Intelligence in Intelligent Transportation Systems include Traffic Prediction and Traffic Congestion management since it tackles the largest urban mobility issue ever seen in Smart Cities. AI and ML as well as Deep Learning models are becoming more commonly applied in predicting traffic flow, congestion, and travel time, as well as road occupancy using GPS systems, Internet of Things sensors, Connected Vehicles, surveillance cameras and mobile technologies. Such systems have the ability to detect traffic behavior in advance and allow those in charge of the city to act in advance before the issue of excessive traffic is experienced. Traffic Prediction models are particularly pertinent in the fast developing city where traditional approaches to traffic planning cannot react promptly to the fluctuating needs in transportation. According to recent research, Artificial Intelligence-based traffic management systems can lower congestion drastically, enhance the predictability of the travel time and minimize fuel use with the help of real-time analytics and adaptive control systems. In the light of recent trends in AIoT-based smart traffic management systems, Artificial Intelligence has demonstrated itself capable of processing live video feeds of existing surveillance cameras to determine traffic density and dynamically set traffic lights. These systems are better than the traditional static traffic signal systems in that they allow a real-time Adaptive Traffic Control method and minimal waiting time at the intersections. These innovations are of particular value to Smart Cities since they offer economical and portable solutions to the growing traffic levels in the cities. Congestion management based on Artificial Intelligence is also becoming increasingly implemented with Predictive Analytics, Big Data Analytics, and Edge Computing to aid quicker decision-making and Transportation Resilience.

Intelligent Traffic Signal Control and Virtual Traffic Lights

One of the Artificial Intelligence applications most commonly used in Intelligent Transportation Systems is Intelligent Traffic Signal Control since traffic lights directly affect the congestion, emissions, and road efficiency. Intelligent Traffic Signal Control systems are powered by Artificial Intelligence algorithms and featured Linear Machine Learning, Reinforcement Learning, Deep Reinforcement Learning, and Computer Vision to manage traffic density in real-time and reassign the timing of a signal [78-81]. Such systems prove to be far more efficient compared to fixed time signal systems since they can give precedence to higher vehicle volumes of directions, emergency vehicles, transport vehicles and crossing pedestrians. The latest studies emphasize the value Intelligent Traffic Lights and Virtual Traffic Lights can bring to the traffic congestion issues and Sustainable Mobility of Smart Cities. Virtual Traffic Lights are also becoming a relatively new application since they adopt Vehicle-to-Everything Communication and Connected Vehicle networks rather than the more traditional physical traffic lights. These systems enable vehicles to talking directly with one another and organize intersections crossing without fundamentally depending on roadside facilities. Virtual Traffic Lights have great potential in future Autonomous Vehicles and Smart Infrastructure because they decrease the costs of the infrastructure, enhance the performance of intersections, and decrease all the undue stoppage of vehicles. The 5G and 6G communication network is projected to introduce more of these technologies.

Autonomous Vehicles and Advanced Driver Assistance Systems

The applications of Artificial Intelligence in Intelligent Transportation Systems are the most transformative since the new technology can lead to a decrease in accidents, mobility enhances, and a higher transportation efficiency rate. Autonomous Vehicles and Advanced Driver Assistance Systems can be considered the most transformational because they will potentially reduce accidents, enhance mobility, and bring advantages in the field of transportation efficiency [6,82-85]. To sense the surrounding world, detect hazards, understand road signs and make timely driving decisions, Autonomous Vehicles rely on Artificial Intelligence, Deep Learning, Computer Vision, LiDAR, radar, and Vehicle-to-Everything Communication. The higher level of the assist systems enables cars to maintain some functions like a lane keeping, adaptive cruise, collision avoidance, automatic braking, and parking assist capability. These technologies are finding more and more relevance to Road Safety, Sustainable Mobility, and Smart Cities as they have minimized the element of human errors which have been one of the major factors that contribute to traffic accidents. The emerging trends in the self-driving systems suggest that autonomous mobility that is operated by Artificial Intelligence can cut down on the overall travel time by a large margin, improve travel throughput, and reduce the rate of collision as opposed to the traditional transport mechanisms. Alliances between automotive chipset vendors and Artificial Intelligence software firm are increasing the pace of self-driving tech introduction, as they enable an integrated platform bringing together safety systems, computer vision, as well as power-efficient processing. India Indigenous driverless vehicle projects indicate increased involvement of indigenous innovation in enhancing autonomous mobility technology to suit complex and uncontrollable road networks.

Public Transportation Optimization and Mobility-as-a-Service

Public Transportation systems are becoming more common in using Artificial Intelligence to enhance route planning, predict passenger demand, schedule, and operational efficiency. Machine Learning models and predictive analytics may help predict the number of passengers, define the bus, metro, rail schedules during specific time using the current demand. The applications are particularly relevant in Smart Cities as they assist the Mobility-as-a-Service, Shared Mobility, and Multi-Modal Transportation through the integration of various transportation services into one convenient, convenient-to-use mobility platform. MaaS platforms are designed to offer consumers personalized and sustainable types of transportation, where they have the chance to select the most efficient mix of public transit, ride-sharing, bicycle, walking, and Electric Vehicles. Public Transportation systems are also becoming more able to accommodate AI, particularly providing real-time information to passengers, predictive maintenance, and smart transportation organization. Artificial Intelligence can be applied by transportation agencies to optimize the frequency of buses, decrease waiting time, enhance the coverage of routes, and have speediness responding to service disruption. The capabilities are especially relevant to Sustainable Urban Development since these are expected to promote the increased usage of public transportation and decrease the reliance on vehicles. According to recent surveys, the Artificial Intelligence-based public transportation systems are growing to be more user-friendly, available, and responsive to the evolving travel demands.

Smart Parking and Intelligent Toll Collection Applications

A common and one of the most realistic and used applications of Artificial Intelligence in Intelligent Transportation Systems is Smart Parking as parking inefficiency is one of the major causes of congestion, wastage of fuel, and frustration among the drivers in the city. Smart Parking systems are the products of AI that allow recognizing available parking spots, navigating cars to the closest areas, and minimizing the amount of unnecessary traffic with the help of Computer Vision, IoT sensors, mobile apps, and Predictive Analytics [86-88]. In the Smart Cities, these systems enhance convenience to users, emit less carbon, and increased traffic flow. Artificial Intelligence will similarly be able to forecast parking demand across locations and day of the day to allow city planners to maximize parking amenities and pricing approaches. Another significant application is the Intelligent Toll Collection which avoiding congestion in the toll collection points and enhancing transportation efficiency. Computer Vision, license plate recognition, vehicle classification, and other automated payment technologies are used in artificial intelligence-based toll systems to facilitate contactless toll collection. Such systems decrease waiting time, consumption level of fuel, and road throughputs. Intelligent Toll Collection is being more and more merged with Connected Vehicles, Edge Computing, and Real-Time Monitoring systems to facilitate smooth transportation experience.

Road Safety, Accident Prediction, and Driver Behavior Analysis

Among the key application areas of Artificial Intelligence in Intelligent Transportation Systems is Road Safety since accidents on roads have remained one of the biggest social and economic burdens across the world. Computer Vision, Predictive Analytics, Driver Behavior Analysis, and Vehicle-to-Everything Communication usage by Artificial Intelligence systems are used to recognize hazardous driving behavior, prevent accidents and give early warning to drivers. These systems have the capability of identifying speeding, abrupt braking, distracted driving, lane leaveover, and fatigue in drivers. Artificial Intelligence can contribute greatly to Road Safety and save many lives by preventing accidents by detecting risky behavior. The modern trend of Artificial Intelligence based Road Safety systems has seen the addition of real time video surveillance, automatic detecting of accidents and projection of emergency response. Fully autonomous traffic monitoring is already deployed in some cities, which are able to notice traffic violations, recognize drivers with unsafe driving behavior and produce real-time alerts without human intervention. These are especially useful in Smart Governance since they enhance the efficiency of law enforcement, and transportation authorities can use them to get more data in the development of policies.

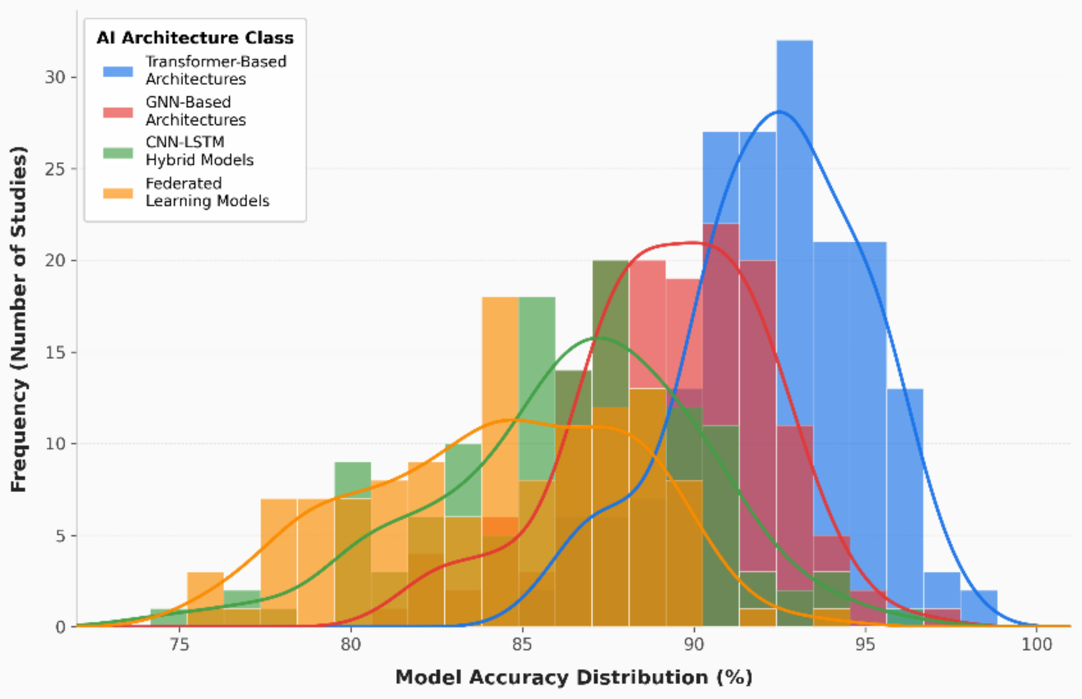

Fig. 6 Distribution of Model Accuracy Across AI Architecture Classes

Fig. 6 is a overlapping histogram with Kernel Density Estimation (KDE) curves illustrates the statistical distribution of reported model accuracy scores across four AI architecture classes: Transformer-based architectures, GNN-based architectures, CNN-LSTM hybrid models, and Federated Learning models, synthesized from 133 included studies. Transformer-based models exhibit a right-skewed, high-mean distribution (peaking near 91-94%), reflecting consistent high performance across diverse ITS datasets. GNN-based architectures show a slightly wider spread, indicative of their sensitivity to graph construction quality. CNN-LSTM hybrids display a bimodal tendency, possibly reflecting the heterogeneity of sequential versus spatial task types. Federated Learning models produce the widest and left-shifted distribution, capturing the accuracy trade-off inherent to privacy-preserving training constraints. The KDE overlays allow continuous density estimation beyond discrete bin boundaries, facilitating a nuanced reading of distribution shape. This histogram is ideally suited for identifying performance benchmarks, understanding variability, and framing reproducibility discussions in AI-for-ITS systematic reviews.

Connected Vehicles and Vehicle-to-Everything Communication Applications

Vehicle-to-Everything Communication and Connected Vehicles are becoming more popular applications in Intelligent Transportation Systems since vehicles are able to share their information with others vehicles, traffic infrastructure, pedestrians, and cloud platforms. These technologies facilitate Intelligent Routing, collision avoidance, cooperative driving and Traffic Prediction as they allow real-time communication between the transportation system components [2,89-91]. Vehicle-to-Everything Communication encompasses Vehicle-to-Vehicle, Vehicle-to-Infrastructure communication, Vehicle-to-Pedestrian, and Infrastructure-to-Pedestrian/Vehicle, which will make transportation networks safer and more efficient. Connected Vehicles AI uses are predictive route optimization, hazard detection, emergency braking coordination, and intelligent navigation. Autonomous Vehicles, in particular, would not be able to function without these systems since they are the means of communication infrastructure required to move vehicles safely and coordinatedly. Future Intelligent Transportation Systems will strongly depend on Vehicle-to-Everything Communication assisted by 5G and 6G networks to deliver mobility services that are seamless and of low latency.

Intelligent Logistics and Freight Transportation Applications

The Intelligent Logistics and freight transportation are becoming increasingly popular areas of artificial intelligence usage due to the increasing pressure on logistics systems to perform better in terms of the speed of delivery, lower operational costs, and decrease carbon emissions. Predictive analytics, Intelligent Routing, Demand Prediction and Real-Time Monitoring are AI-based logistics systems that are used to maximize freight movement, warehouse operations and delivery schedules. The applications are particularly useful to Smart Cities since they minimize congestion due to freight vehicles and enhance the performance of urban supply chains. The application of a machine learning model and Deep Learning models in logistics are becoming more popular in the optimization of routes, predictive maintenance, reduction of fuel consumption and fleet management. Artificial Intelligence may recognize the most effective routes of delivery, forecast any delays because of traffic, as well as dynamically adjust logistics processes due to variable weather parameters on the road. These abilities apply especially to e-commerce, food delivery, and other urban freight systems where speed and efficiency are of paramount importance.

Digital Twin and Predictive Maintenance Applications

Digital Twin technology is emerging as a significant use of Artificial Intelligence in Intelligent Transportation Systems since it enables transportation organizations to develop virtual models of roads, traffic networks, vehicles and infrastructure. These Digital Twins keep on communicating with real life data on Internet of Things sensors, Connected Vehicles, and Edge Computing [92-94]. Digital Twin models enable transportation planners to simulate traffic situations and assess the effectiveness of congestion management interventions, as well as test changes in infrastructure, before implementing it in the real world. The other application of importance is Predictive Maintenance as transportation infrastructure and vehicles need periodic maintenance to be safe and efficient. Artificial Intelligence can monitor the parts of the vehicle, the road, bridges, tunnels, and railway lines and anticipate failures to avoid them. This saves and decreases down-time, enhances Road Safety and minimizes maintenance expenses. Predictive Maintenance Integrating Predictive Maintenance, even more deeply with Digital Twin platforms and Big Data Analytics, is advancing to underpin more resilient, reliable transportation systems.

Generative Artificial Intelligence and Large Language Model Applications

Generative artificial intelligence and Large Language Models are becoming one of the most texturing applications on Intelligent Transportation Systems since they have the ability to produce synthetic traffic, summarize transportation reports, generate mobility predictions, and aid intelligent decision-making. The Generative Artificial Intelligence can be especially applied in cases where real transportation data has restrictions or is sensitive. Machine Learning and Deep Learning models that analyze Road Safety, Traffic Prediction, and the Autonomous Vehicles can be trained on synthetic datasets. Applications of LSPs in conversational travel agents, Intelligent Logistics, traffic incident reporting, and transportation planning systems are on the rise. These models are capable of processing a lot of transportation data, responding to user queries, congestion summaries, and personalized guidance. The recent studies emphasize that Large Language Models are becoming increasingly important in the field of traffic flow prediction, vehicle detection, and traffic sign recognition and pedestrian detection. The above capabilities imply that Generative Artificial Intelligence will mirror into an increasingly significant element of further Smart Cities and Sustainable Mobility systems.

4. Discussion

The literature shows that the prevailing trend of Intelligent Transportation Systems has occurred with the introduction of Artificial Intelligence, Machine Learning, and Deep Learning which have relegated transportation management to reactive and static systems, ultimately relegating them to predictive, adaptive, and data-driven mobility ecosystems. The old transport systems were set up to follow fixed timetables of traffic signals, past trends of demand, and remote-to-each other elements of infrastructure that tended to place them in a position where they could not respond swiftly to the urban environment [9,95-97]. Contastingly, modern Intelligent Transportation Systems that are enhanced by Artificial Intelligence can access extensive transportation information gained by Connected Vehicles, Internet of Things, surveillance cameras, roadside detectors, mobile apps, and vehicular networks to optimize the Traffic Prediction and Traffic Flow Optimization, Adaptive Traffic Control and Intelligent Routing. New trends indicate that Artificial Intelligence is steadily turning into the focal point of introspective intelligence in Smart Cities since it allows real-time mobility management, predictive maintenance, and planning of transportation dynamically across various transportation modes. New technologies like Graph Neural Networks, Federated Learning, Digital Twin, Urban Brain systems, Generative Artificial Intelligence, and Large Language Models are also gradually expanding the range of Intelligent Transportation Systems to the larger Sustainable Urban Development and Transportation Resilience programs. The development is offering possibilities of safer, greener, and more inclusive systems of mobility.

Table 1. Artificial Intelligence Applications, Techniques, and Challenges in Intelligent Transportation Systems

Sr. No.	Application	Techniques / Methods	Major Challenge
1	Traffic Prediction	Machine Learning, Long Short-Term Memory	Data sparsity
2	Traffic Congestion Management	Deep Learning, Predictive Analytics	Dynamic traffic variability
3	Intelligent Traffic Signal Control	Reinforcement Learning, Deep Reinforcement Learning	High computational complexity
4	Adaptive Traffic Control	Edge Artificial Intelligence, Real-Time Monitoring	Latency management
5	Autonomous Vehicles	Computer Vision, Sensor Fusion	Safety validation
6	Connected Vehicles	Vehicle-to-Everything Communication, 5G	Interoperability
7	Smart Parking	Predictive Analytics, Internet of Things	Sensor reliability
8	Accident Prediction	Convolutional Neural Networks, Driver Behavior Analysis	Imbalanced datasets
9	Road Safety Monitoring	Computer Vision, Object Detection	False positives
10	Public Transportation Optimization	Demand Prediction, Mobility-as-a-Service	Ridership uncertainty
11	Intelligent Logistics	Intelligent Routing, Big Data Analytics	Freight variability
12	Shared Mobility	Machine Learning, Multi-Modal Transportation	Demand uncertainty
13	Electric Vehicle Management	Predictive Charging Models, Edge Computing	Charging infrastructure gaps
14	Intelligent Toll Collection	License Plate Recognition, Computer Vision	Privacy concerns
15	Vehicle Trajectory Prediction	Graph Neural Networks, Long Short-Term Memory	Complex mobility patterns
16	Transportation Resilience	Digital Twin, Scenario-Based Simulation	Disaster unpredictability
17	Predictive Maintenance	Internet of Things, Artificial Intelligence	High implementation cost
18	Urban Analytics	Big Data Analytics, Cloud Computing	Data integration
19	Mobility-as-a-Service	Generative Artificial Intelligence, Mobility AI	Platform fragmentation
20	Sustainable Urban Development	Urban Brain, Digital Twin	Governance complexity
21	Carbon Emission Reduction	Intelligent Routing, Green Transportation	Behavioral resistance
22	Multi-Modal Transportation	Federated Learning, Real-Time Monitoring	System integration
23	Transportation Cybersecurity	Explainable Artificial Intelligence, Federated Learning	Security threats

24	Digital Twin Networks	Reinforcement Learning, Graph Transformers	Scalability
25	Generative Mobility Simulation	Large Language Models, Scenario-Based Simulation	Explainability

A key discovery of the literature is that Deep Learning systems like Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Graph Neural Network have shown to deliver high-dimensional transportation performance significantly better than traditional statistical and Machine Learning algorithms. Graph Neural Networks have become especially promising due to the rail nature of transportation systems being intertwined into the form of a graph (roughened by roads, intersections, transit lines and flows of mobility). Their capability to obtain the spatio-temporal relationship enables them to provide extremely precise Traffic Prediction, Traffic State Estimation, Demand Prediction, Smart Parking optimization, and Intelligent Traffic Signal Control. Nevertheless, today, the attention was still being overwhelmingly paid to traffic forecasting whereas other essential aspects of Autonomous Vehicles, Shared Mobility, parking management, transportation safety, and demand-responsive transportation are rather under-explored. This imbalance allows concluding that future research has to broaden the scope of Graph Neural Networks and Graph Transformers to a larger scope of transportation applications. Equally, Reinforcement Learning as well as Deep Reinforcement Learning has proven to have a high potential with regards to Adaptive Traffic Control, autonomous navigation, although implementation of these systems is still largely hampered by high level of computational complexity, simulation, and the lack of real-world application.

The increased importance of Digital Twin and Urban Digital Twin technologies as an emerging platform in Intelligent Transportation System is also mentioned in the literature. Digital Twins are not perceived as solely digital models of roads and infrastructure, but dynamic and intelligent environments that can combine live transportation data, Artificial Intelligence models, predictive analytics, and scenarios simulations [98-101]. This intersection helps the transportation agencies to experiment with traffic policies, assessing congestion management approaches, anticipating infrastructure failures, and streamlining mobility systems preceding any alteration in the real world. Recent literature indicates that Digital Twin systems are developing into highly ambitious architectures like Twin-of-Twins systems, Network Digital Twins, and AI-powered Digital Twin Networks which can aid in real-time monitoring, simulation, optimization and autonomous decision-making. The Digital Twin-Edges Computing Majority of such research directions are expected to encompass the integration of Digital Twin with Edge Computing, Federated Learning, Explainable Artificial Intelligence, and Reinforcement Learning due to the necessity to create a more resilient, adaptive, and sustainable transportation system.

The other significant theme that is revealed through the literature is the increasing role of the Generative Artificial Intelligence, Large Language Models, and Mobility AI in Intelligent Transportation Systems. Although more recent studies note that Generative Artificial Intelligence can assist in transportation planning, policy evaluation, infrastructure design, traffic simulation, and mobility scenario generation this was not the primary emphasized task of earlier Artificial Intelligence research, that is, their focus was on predictive tasks instead of planning. Large Language Models are being applied to conversational mobility assistants, transportation reporting and Intelligent Logistics, and travel demand forecasting. The advent of Mobility AI systems integrated in the decision-support through measurement, simulation, and optimization shows that transportation systems also shift towards more autonomous and integrated decision support. Nevertheless, certain issues associated with explainability, risks of hallucination, regulatory compliance, and alignment with transportation-specific limitations remain a major concern of these technologies, as indicated in the literature. Consequently, intelligent transportation systems will probably have to bring in domain-related Large Language Models, retrieval-based generation models and multi-agent transport systems that can coordinate on infrastructure, vehicle, and policy environments.

Table 2. Artificial Intelligence Technologies, Opportunities, and Future Directions in Intelligent Transportation Systems

Sr. No.	Technology / Model	Opportunity	Future Direction
1	Artificial Neural Networks	Traffic forecasting	Hybrid neural architectures
2	Convolutional Neural Networks	Road safety enhancement	Low-light perception systems
3	Recurrent Neural Networks	Sequential traffic analysis	Multi-source time series integration
4	Long Short-Term Memory	Traffic demand prediction	Edge-based deployment
5	Graph Neural Networks	Spatio-temporal traffic modeling	Graph Transformers
6	Graph Transformers	Large-scale network optimization	Real-time graph intelligence
7	Reinforcement Learning	Adaptive traffic control	Multi-agent coordination
8	Deep Reinforcement Learning	Autonomous vehicle navigation	Urban-scale deployment
9	Federated Learning	Privacy-preserving intelligence	Distributed edge ecosystems
10	Explainable Artificial Intelligence	Transparent decision-making	Regulation-aware models
11	Generative Artificial Intelligence	Synthetic traffic generation	Autonomous transportation planning
12	Large Language Models	Conversational mobility services	Domain-specific transportation agents
13	Digital Twin	Scenario testing	Twin-of-Twins architecture
14	Urban Digital Twin	Sustainable mobility planning	Autonomous city-scale optimization
15	Edge Computing	Real-time responsiveness	On-device generative AI
16	Cloud Computing	Large-scale analytics	Hybrid cloud-edge systems
17	Internet of Things	Continuous data collection	Self-organizing sensor ecosystems
18	Vehicle-to-Everything Communication	Cooperative mobility	6G-enabled transportation
19	Connected Vehicles	Coordinated traffic systems	Fully autonomous fleets
20	Autonomous Vehicles	Reduced human error	Mobility Foundation Models
21	Smart Infrastructure	Real-time system monitoring	Self-healing transportation networks
22	Predictive Analytics	Proactive planning	Carbon-aware mobility optimization
23	Mobility AI	Transportation policy support	Human-AI collaborative governance
24	Digital Twin Networks	Infrastructure resilience	Autonomous optimization
25	Sustainable Artificial Intelligence	Green transportation systems	Energy-efficient model design

Even as Artificial Intelligence advances at a very fast pace in transportation, the literature has continued to point out critical impediments that could impede the widespread implementation of Intelligent Transportation Systems. Some of the most important challenges have been cybersecurity, Data Privacy, interoperability, infrastructure preparedness, cost of computation, and absence of standardized governance frameworks [6,102-105]. Connected Vehicles, Internet of Things (IoT), cloud, and Edge Computing infrastructure are susceptible to cybercrimes, data breach, and malicious interference due to reliance on continuous data transfers among Intelligent Transportation Systems. Moreover, the growing application of Generative Artificial Intelligence and autonomous systems begs the question of ethical decision making, the biases of the algorithm, the understandability of the model and responsibility. Explainable Artificial Intelligence and Federated Learning are thus becoming more significant as they have the ability to enhance transparency, privacy, and trust. The transport system of the future should be with more robust policy frameworks, moral Artificial Intelligence standards and intersectoral cooperation of governments, industry, and academic institutions to make Intelligent Transportation Systems secure, fair and socially acceptable.

One key conclusion of the literature revised is that Sustainable Mobility will be more and more relying on the combination of Artificial Intelligence, Edge Artificial Intelligence, 5G, 6G, Electric Fleece, Shared Mobility, and Mobility-as-a-Service. The future of Intelligent Transportation Systems is likely to transition out of vehicle-centric applications, to built-in urban mobility system systems with transportation, energy, communication, and governance systems interacting with one another. The importance of Edge Artificial Intelligence is especially critical since it allows low-latency decision-making to be made in Autonomous Vehicles, Connected Vehicles, and Intelligent Traffic Signal Control systems. Likewise, 5G and 6G networks will increase Vehicle-to-Everything Communication and offer very responsive, real-time transportation services. Sustainable Artificial Intelligence is becoming an influential research topic, too, though, as transportation agencies must find a balance between the advantages of Artificial Intelligence and its energy consumption, carbon footprint, and infrastructure costs all more frequently. Low-energy Artificial Intelligences models, green data centers, carbon-conscience traffic optimization, and fair transportation systems to serve both developed and developing urban settings should therefore be the focus of further research.

5. Conclusions

This review illustrates that Artificial Intelligence, Machine Learning, and Deep Learning are now considered to be at the center of Intelligent Transportation Systems, in smart cities and sustainable mobility environments. The literature shows that smart traffic technologies are quickly transforming out of fixed systems of traffic management into dynamic, data-driven, and predictive urban mobility systems. Traffic prediction, traffic flow optimization, intelligent traffic signal control, accident prediction, smart parking, intelligent routing, driver behavior analysis and road safety are all growing with the use of Machine Learning algorithms, Deep Learning architectures, Computer Vision, Reinforcement Learning, Convolutional Neural Networks, Recurrent Neural Networks and Long Short-Term Memory models. The technologies can be used to transport systems to handle large amounts of real-time data and enhance the efficiency of operations, the reliability of travel times, and passenger comfort, as well as urban sustainability.

The review further identifies the increased role of Connected Vehicles, Autonomous Vehicles, Vehicular Networks, Vehicle-to-Everything Communication, Internet of Things, Edge Computing, Cloud Computing, and Big Data Analytics in next-generation Intelligent Transportation Systems. These technologies contribute to real-time monitoring, predictive analytics, multi-modal transportation integration, and Mobility-as-a-Service models, all of which are critical to smart cities. Besides, the rising applications of Electric Vehicles, shared mobility, and intelligent public transportation networks, help reduce carbon emissions and achieve green transportation and sustainable urban development. The use of emerging technologies like Digital Twin, Generative Artificial Intelligence, Explainable Artificial Intelligence and Federated Learning are likely to augment the ability to adjust, enhance the level of transparency, security and personalization of intelligent transportation services.In spite of these developments, the literature continues to underscore significant issues that have the potential to hamper widespread implementation of Artificial Intelligence-based transportation systems. Issues relating to cybersecurity, data privacy, interoperability, infrastructure preparedness, data quality, algorithmic bias, model understandability, and regulatory uncertainty are still critical impediments. Cities, especially the developing ones, continue to be constrained with respect to digital infrastructure, sensor deployment, and investment by the government, availability of skilled workforce and policy support. Moreover, the absence of standard models of data exchange, ethical regulation of Artificial Intelligence, and the cooperation of different spheres might be an obstacle in the implementation of fully combined smart transportation systems.

Future studies must be put on more explainable AI models, more secure, energy-efficient and scalable Artificial Intellects to be used in Intelligent Transportation Systems. There is need to focus more on Federated Learning, Explainable Artificial Intelligence, real-time Edge Computing, transportation resilience, and cybersecurity-conscious traffic management systems. The introduction of intelligent transportation technologies to smart governance, urban analytics, climate adaptation plans and sets of frameworks of the circular economy to foster sustainable mobility should also be considered in future studies. Further empirical research and large-scale pilot efforts should also be done to assess the actual performance, societal adoption, and the sustainability of the Artificial Intelligence-driven transportation ecosystem in a wide range of urban settings. The synergy between Artificial Intelligence, Machine Learning, Deep Learning, Internet of Things, and sustainable mobility can transform the future of smart cities by establishing safer, less toxic and less wasteful, and inclusive transportation systems.

Conflict of interest

The authors declare no conflicts of interest.

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