International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 07 Jul-2026 | Impact Factor: 3.5

Smart Traffic Flow Prediction Using Deep Learning: A Systematic Review of Recent Advances, Challenges, and Future Research Directions

Dr. P. K. S. Bhadauria

Dr. B. R. Ambedkar College of Agricultural Technology and Engineering, Itawah, Uttar Pradesh, India

Email: pksbhaduria@rediffmail.com

How to Cite this Article:

Bhadauria, P. K. S. (2026). Smart Traffic Flow Prediction Using Deep Learning: A Systematic Review of Recent Advances, Challenges, and Future Research Directions. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(7), 1-9. https://doi.org/10.55041/ijcope.v2i7.140

https://doi.org/10.55041/ijcope.v2i7.140

Abstract

Rapid urbanization, population growth, and the increasing number of vehicles have significantly intensified traffic congestion across metropolitan regions worldwide. Conventional traffic management systems are often inadequate for addressing the dynamic and nonlinear nature of urban transportation networks. Consequently, artificial intelligence (AI), particularly deep learning (DL), has emerged as a transformative approach for intelligent traffic flow prediction. Accurate traffic forecasting enables proactive traffic management, optimized route planning, reduced travel time, lower fuel consumption, and improved road safety, thereby contributing to the development of smart and sustainable cities. This systematic review critically examines recent advancements in deep learning-based traffic flow prediction models, emphasizing studies published between 2018 and 2026. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, this review synthesizes findings from high-quality journal articles, conference proceedings, and technical reports indexed in Scopus and Web of Science. The paper evaluates major deep learning architectures, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), Graph Neural Networks (GNN), Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), Transformer-based architectures, and hybrid deep learning models. The review further analyzes their predictive performance, computational efficiency, scalability, interpretability, and real-world applicability in intelligent transportation systems. Existing challenges such as data heterogeneity, missing sensor data, privacy concerns, model explainability, computational cost, and deployment limitations are critically discussed. A conceptual research framework highlighting emerging technologies—including edge computing, Internet of Things (IoT), digital twins, federated learning, explainable AI, and large foundation models—is proposed to guide future research. The review contributes theoretically by synthesizing fragmented literature, technologically by identifying advanced predictive architectures, managerially by providing recommendations for transportation authorities, and sustainably by demonstrating how AI-driven traffic prediction supports greener and more efficient urban mobility. The findings indicate that although graph-based and transformer-based architectures currently achieve state-of-the-art predictive performance, integrating explainability, real-time adaptation, and privacy-preserving learning remains a significant research priority.

Keywords: Smart Traffic Prediction; Deep Learning; Intelligent Transportation Systems; Graph Neural Networks; Traffic Forecasting; Explainable Artificial Intelligence; Smart Cities

1. Introduction

The unprecedented pace of urbanization has fundamentally transformed transportation systems across the world. According to the United Nations, nearly 68% of the global population is expected to reside in urban areas by 2050, resulting in substantial increases in transportation demand and urban traffic congestion. Simultaneously, reports from the International Transport Forum estimate that the number of passenger vehicles worldwide will exceed two billion by 2050 if current trends continue. These developments have intensified the need for intelligent transportation systems (ITS) capable of efficiently managing increasingly complex traffic networks [1,2,3,4,5].

Traffic congestion has become one of the most pressing challenges confronting modern cities. Beyond increasing travel time, congestion contributes significantly to economic losses, environmental pollution, excessive fuel consumption, and public health concerns. The Texas A&M Transportation Institute has estimated that traffic congestion costs billions of dollars annually through lost productivity and wasted fuel. Similarly, the European Commission identifies transportation as one of the largest contributors to greenhouse gas emissions, with road transport accounting for approximately three-quarters of transport-related carbon emissions. Consequently, accurate traffic flow prediction has become an essential component of sustainable urban transportation planning.

Traffic flow prediction refers to forecasting future traffic conditions using historical and real-time transportation data. Typical prediction variables include traffic volume, vehicle speed, travel time, road occupancy, and congestion levels. Accurate predictions enable transportation authorities to implement proactive traffic signal control, dynamic route optimization, congestion mitigation strategies, emergency response planning, and intelligent navigation services [6,7,8,9,10].

Traditional traffic prediction methods primarily relied upon statistical and mathematical modeling approaches such as Historical Average (HA), Autoregressive Integrated Moving Average (ARIMA), Kalman Filters, Bayesian Networks, and Support Vector Regression (SVR). Although these methods demonstrate satisfactory performance under relatively stable traffic conditions, they struggle to capture the highly nonlinear, dynamic, and spatial-temporal relationships characteristic of modern urban traffic systems. Their predictive accuracy deteriorates considerably during abnormal events such as road accidents, adverse weather conditions, public gatherings, infrastructure failures, or sudden demand fluctuations [11,12,13,14,15].

The rapid development of artificial intelligence has dramatically altered this landscape. Deep learning has emerged as one of the most influential technologies in intelligent transportation systems due to its capability to automatically learn complex feature representations from massive datasets without requiring extensive manual feature engineering. Compared with conventional machine learning techniques, deep learning architectures effectively model nonlinear dependencies while simultaneously capturing temporal and spatial traffic dynamics.

Among the earliest deep learning models adopted for traffic prediction were Recurrent Neural Networks (RNNs), which were specifically designed for sequential data analysis. However, conventional RNNs suffered from gradient vanishing and exploding problems when modeling long temporal dependencies. To address these limitations, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures were introduced. These models significantly improved forecasting accuracy by effectively preserving long-term temporal information and became dominant approaches for traffic forecasting throughout the previous decade [16.17.18.19.20]

„As intelligent transportation systems evolved, researchers recognized that traffic data exhibit not only temporal dependencies but also strong spatial relationships between connected road segments. Consequently, Convolutional Neural Networks (CNNs) were introduced to extract localized spatial features from traffic maps and sensor grids. Although CNN-based methods improved spatial representation, they remained limited when modeling irregular road network structures because transportation networks do not conform to regular grid patterns.

The emergence of Graph Neural Networks (GNNs) marked a major breakthrough in traffic forecasting research. By representing road networks as graphs consisting of nodes and edges, GNN-based architectures effectively captured complex spatial dependencies among interconnected transportation infrastructure. Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), Diffusion Convolutional Recurrent Neural Networks (DCRNN), Spatio-Temporal Graph Convolutional Networks (STGCN), Adaptive Graph Convolutional Networks (AGCN), and Graph WaveNet significantly outperformed earlier deep learning architectures across numerous benchmark datasets such as METR-LA, PEMS-BAY, and PeMSD7 [21,22,23,24,25].

More recently, Transformer architectures have revolutionized sequence modeling by replacing recurrent mechanisms with self-attention. Originally developed for natural language processing, Transformers have demonstrated remarkable effectiveness in traffic prediction because self-attention enables simultaneous modeling of long-range temporal dependencies while reducing sequential computation. Hybrid Transformer-GNN architectures introduced after 2022 further improved prediction accuracy by combining graph-based spatial learning with attention-driven temporal modeling. Emerging studies published through 2026 additionally explore multimodal fusion using traffic sensors, GPS trajectories, weather information, satellite imagery, and Internet of Things (IoT) devices to enhance predictive performance under dynamic urban conditions.

The proliferation of IoT technologies has further accelerated the availability of large-scale traffic datasets. Modern smart cities deploy thousands of heterogeneous sensing devices, including inductive loop detectors, roadside cameras, radar systems, connected vehicles, GPS-enabled smartphones, drones, and vehicle-to-everything (V2X) communication infrastructure. These technologies generate massive streams of real-time traffic information characterized by high velocity, volume, and variety. Such data richness provides unprecedented opportunities for developing highly accurate predictive models while simultaneously introducing significant challenges associated with missing values, noisy observations, heterogeneous data integration, computational scalability, cybersecurity, and privacy protection [26,27,28,29,30].

Another significant development involves the integration of edge computing and cloud computing into intelligent transportation systems. Rather than transmitting all sensor data to centralized cloud servers, edge computing enables preliminary processing closer to data sources, reducing communication latency and supporting real-time traffic prediction. Furthermore, federated learning has emerged as a promising privacy-preserving paradigm that allows decentralized model training across distributed traffic sensors and connected vehicles without directly sharing sensitive data. These innovations are expected to play a crucial role in next-generation intelligent transportation ecosystems.

Despite substantial progress, several important research challenges remain unresolved. First, many state-of-the-art deep learning models operate as "black boxes," limiting interpretability and reducing trust among transportation authorities responsible for critical infrastructure decisions. Second, existing models frequently assume complete and high-quality sensor data despite real-world transportation systems often experiencing sensor failures, communication delays, and missing observations. Third, computational complexity continues to hinder large-scale deployment, particularly in resource-constrained environments requiring low-latency inference. Fourth, many studies evaluate algorithms using benchmark datasets under controlled experimental settings rather than validating performance in diverse real-world urban environments. Finally, the increasing reliance on personal mobility data raises critical concerns regarding cybersecurity, ethical AI, and data privacy [31,32,33,34,35].

These challenges indicate that achieving practical deployment requires more than incremental improvements in prediction accuracy. Future intelligent traffic forecasting systems must simultaneously address robustness, explainability, scalability, fairness, privacy preservation, computational efficiency, and sustainability. Integrating explainable artificial intelligence (XAI), digital twins, multimodal sensing, federated learning, and large-scale foundation models may substantially enhance the reliability and applicability of future traffic management systems.

Given the rapidly expanding literature in this field, there is a growing need for a comprehensive and up-to-date synthesis that critically evaluates recent developments rather than merely summarizing existing studies. Previous review articles have often focused exclusively on specific model categories, lacked systematic methodologies, or did not incorporate recent advances in graph learning, transformer architectures, edge intelligence, and foundation AI models emerging through 2026. Moreover, relatively few reviews comprehensively examine theoretical, technological, managerial, and sustainability implications within a unified framework.

Accordingly, this paper presents a systematic review of deep learning-based smart traffic flow prediction. The review aims to (i) critically examine recent deep learning architectures for traffic forecasting, (ii) compare their predictive strengths and limitations, (iii) identify persistent research gaps, (iv) propose a conceptual framework integrating emerging technologies, and (v) provide practical recommendations for researchers, policymakers, transportation agencies, and smart city practitioners. By synthesizing contemporary evidence across multiple disciplines, this study seeks to advance both academic understanding and real-world implementation of intelligent traffic prediction systems [36,37,38,39,40].

The remainder of this manuscript is organized as follows. Section 2 presents a comprehensive literature review of major deep learning approaches for traffic flow prediction. Section 3 identifies the research gap and formulates the problem statement. Section 4 describes the systematic review methodology based on the PRISMA framework. Section 5 discusses the synthesized findings and comparative analysis of existing approaches. Section 6 outlines future research directions. Section 7 discusses practical implications for academia, industry, and policymakers. Finally, Section 8 concludes the paper by summarizing key findings and contributions.

2. Literature Review

The evolution of traffic flow prediction has paralleled advancements in artificial intelligence, big data analytics, and intelligent transportation systems (ITS). Early traffic prediction relied primarily on statistical time-series techniques, whereas recent studies increasingly employ sophisticated deep learning architectures capable of modeling complex nonlinear spatial-temporal relationships. This section critically reviews approximately three decades of research, with particular emphasis on developments between 2018 and 2026. Rather than presenting studies chronologically, the literature is organized into thematic categories to highlight methodological evolution, comparative performance, strengths, and remaining research challenges.

2.1 Evolution from Statistical Models to Deep Learning

Initial traffic forecasting methods were based on statistical and mathematical models such as Historical Average (HA), Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Kalman Filters. These approaches assumed relatively stable temporal relationships and linear dependencies within traffic observations.

Ahmed and Cook (1979) introduced one of the earliest autoregressive traffic prediction models, demonstrating that historical observations could effectively estimate short-term traffic conditions. Subsequently, Williams and Hoel (2003) improved forecasting performance using seasonal ARIMA models for freeway traffic prediction.

Although these statistical methods required relatively low computational resources and were easily interpretable, their performance deteriorated significantly under highly dynamic traffic conditions. Incidents, weather changes, holidays, sporting events, and road construction frequently violated their underlying assumptions of stationarity and linearity.

Machine learning algorithms such as Support Vector Regression (SVR), Random Forests (RF), Gradient Boosting Machines (GBM), and Artificial Neural Networks (ANN) partially addressed these limitations by learning nonlinear relationships from historical data. However, these methods generally depended upon manually engineered features and exhibited limited capability for modeling long-term temporal dependencies.

The emergence of deep learning represented a paradigm shift by enabling automatic feature extraction from massive heterogeneous datasets without requiring handcrafted variables [41,42,43,44,45].

2.2 Recurrent Neural Networks for Temporal Traffic Prediction

Traffic flow is fundamentally sequential, making recurrent neural networks among the earliest deep learning models adopted for transportation forecasting.

Recurrent Neural Networks (RNNs) introduced hidden-state memory mechanisms capable of learning temporal dependencies across consecutive observations. However, traditional RNNs suffered from gradient vanishing and exploding problems when processing long sequences.

Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), addressed these limitations through memory cells and gating mechanisms. LSTM rapidly became the dominant architecture for traffic prediction because it effectively captured long-term traffic patterns.

Ma et al. (2015) demonstrated that LSTM substantially outperformed traditional neural networks and ARIMA models on freeway traffic datasets by reducing prediction errors during peak congestion periods.

Fu et al. (2016) extended LSTM by integrating stacked hidden layers, enabling more accurate multi-step traffic forecasting.

Similarly, Zhao et al. (2017) proposed deep LSTM architectures capable of simultaneously modeling traffic volume, vehicle speed, and occupancy. Their findings indicated improved robustness under fluctuating traffic demand.

Despite these advantages, researchers observed several limitations.

First, LSTM primarily captures temporal relationships while largely ignoring spatial interactions among neighboring road segments.

Second, training deep recurrent architectures remains computationally expensive for city-scale transportation networks.

Third, sequential processing restricts computational parallelism compared with attention-based architectures.

Consequently, researchers sought complementary approaches capable of integrating both spatial and temporal information [46,47,48,49,50].

2.3 Gated Recurrent Unit (GRU): Improving Computational Efficiency

The Gated Recurrent Unit (GRU) simplified LSTM by reducing the number of gating mechanisms while preserving comparable predictive performance.

Cho et al. (2014) originally proposed GRU to reduce computational complexity in sequential learning.

Subsequent transportation studies demonstrated that GRU often achieved similar prediction accuracy with fewer parameters and faster convergence.

Zhang et al. (2018) applied GRU for urban traffic forecasting using Beijing transportation data, reporting lower computational cost than LSTM while maintaining comparable forecasting accuracy.

Li et al. (2019) further integrated bidirectional GRU structures, enabling simultaneous learning from historical and future contextual information during training.

Although GRU offers computational advantages, it shares LSTM's primary limitation of insufficient spatial representation.

2.4 Convolutional Neural Networks for Spatial Traffic Modeling

Unlike recurrent architectures emphasizing temporal sequences, Convolutional Neural Networks (CNNs) effectively learn localized spatial features.

Initially developed for computer vision, CNNs were adapted to traffic forecasting by representing road networks as two-dimensional traffic images.

Zhang et al. (2017) introduced DeepST, which modeled citywide traffic inflow and outflow using convolutional neural networks.

Their study demonstrated that CNNs captured localized congestion propagation more effectively than traditional neural networks.

Yao et al. (2018) extended CNN-based forecasting by integrating external contextual variables including weather, holidays, and special events.

Experimental results showed significant improvements during abnormal traffic conditions.

Nevertheless, CNN-based approaches assume regular grid structures.

Real transportation networks consist of irregular road topologies where neighboring roads may not correspond to adjacent image pixels.

Consequently, CNN performance decreases when applied to complex urban road networks.

This limitation motivated the emergence of graph-based deep learning [51,52,53,54,55,56].

2.5 Graph Neural Networks: Modeling Road Networks as Graphs

Graph Neural Networks (GNNs) represent one of the most significant breakthroughs in intelligent transportation research.

Unlike CNNs, GNNs naturally represent road systems as graphs where intersections correspond to nodes and roads correspond to edges.

This representation enables effective modeling of non-Euclidean spatial relationships.

Graph Convolutional Networks (GCN)

Kipf and Welling (2017) introduced Graph Convolutional Networks (GCN), establishing the theoretical foundation for graph-based learning.

Yu et al. (2018) subsequently proposed Spatio-Temporal Graph Convolutional Networks (STGCN), integrating graph convolution with temporal convolution.

Their model achieved state-of-the-art performance on METR-LA and PeMS datasets while significantly reducing computational time compared with recurrent models.

Diffusion Convolutional Recurrent Neural Networks (DCRNN)

Li et al. (2018) introduced Diffusion Convolutional Recurrent Neural Networks (DCRNN), modeling traffic propagation through bidirectional diffusion processes.

Unlike standard graph convolution, DCRNN explicitly represented directional traffic flow, improving congestion forecasting during rush hours.

Numerous benchmark studies identified DCRNN as one of the highest-performing traffic prediction architectures.

Graph WaveNet

Wu et al. (2019) proposed Graph WaveNet by integrating adaptive graph learning with dilated causal convolutions.

Rather than relying solely on predefined road connectivity, Graph WaveNet dynamically learned hidden traffic relationships.

Experimental results demonstrated improvements exceeding several percentage points in MAE and RMSE compared with STGCN.

Adaptive Graph Learning

Bai et al. (2020) introduced Adaptive Graph Convolutional Recurrent Networks (AGCRN), automatically constructing graph structures during training.

This innovation eliminated dependence on manually defined adjacency matrices.

AGCRN demonstrated particularly strong performance in cities where transportation infrastructure changes dynamically.

Collectively, graph-based architectures significantly improved predictive accuracy while effectively modeling complex spatial dependencies.

However, graph models generally require substantial computational resources and remain difficult to interpret.

2.6 Attention Mechanisms and Transformer-Based Models

Transformer architectures represent the newest generation of deep learning models for traffic forecasting.

Originally developed for natural language processing, Transformers replace recurrent processing with self-attention mechanisms capable of learning long-range dependencies in parallel.

Xu et al. (2020) demonstrated that Transformer-based traffic prediction outperformed LSTM for long-term forecasting horizons exceeding one hour.

Zheng et al. (2022) integrated temporal attention with graph convolution, improving forecasting robustness during unexpected traffic events.

Several studies published after 2023 combined Graph Neural Networks with Transformers to jointly model spatial topology and temporal attention.

These hybrid architectures consistently ranked among the best-performing models on public benchmark datasets.

Their principal strengths include:

- Parallel computation
- Long-range dependency modeling
- Better scalability
- Higher prediction accuracy

Nevertheless, Transformer architectures often require considerably larger datasets, increased computational resources, and higher energy consumption than recurrent networks.

2.7 Hybrid Deep Learning Models

Recognizing that no individual architecture perfectly captures all traffic characteristics, researchers increasingly develop hybrid models.

Examples include:

- CNN-LSTM
- CNN-GRU
- GCN-LSTM
- GAT-LSTM
- Transformer-GNN
- CNN-BiLSTM
- Graph Transformer Networks

These hybrid systems simultaneously capture:

- Local spatial relationships
- Long-term temporal dependencies
- Dynamic graph interactions
- External contextual variables

Guo et al. (2019) combined graph convolution with gated recurrent networks, achieving improved robustness during congestion.

Chen et al. (2021) incorporated weather forecasts, GPS trajectories, and road network topology into hybrid architectures.

Studies published between 2024 and 2026 increasingly employ multimodal fusion, integrating:

- CCTV imagery
- Drone surveillance
- Connected vehicle data
- Weather sensors
- Social media event detection
- Satellite imagery

These multimodal systems significantly improve prediction accuracy under abnormal traffic scenarios.

2.8 Explainable AI in Traffic Prediction

Despite impressive predictive performance, deep learning models remain largely "black boxes."

Transportation authorities require transparent reasoning before deploying AI systems in mission-critical infrastructure.

Recent studies therefore investigate Explainable Artificial Intelligence (XAI).

SHAP values, LIME explanations, Integrated Gradients, and attention visualization have become increasingly popular for interpreting traffic prediction models.

Researchers demonstrate that explainability improves stakeholder trust while facilitating regulatory compliance.

However, XAI integration remains limited in existing transportation literature, with relatively few studies quantitatively evaluating explanation quality.

2.9 Federated Learning and Privacy-Preserving Traffic Prediction

Traffic prediction increasingly depends on personal mobility data generated by connected vehicles and smartphones.

Consequently, privacy has become a major concern.

Federated Learning enables decentralized model training without transmitting raw data.

Instead, only model parameters are exchanged.

Studies after 2022 demonstrate that federated traffic prediction achieves prediction accuracy comparable to centralized learning while significantly improving privacy protection.

However, communication overhead, heterogeneous client devices, and non-independent data distributions remain unresolved challenges.

2.10 Edge Computing, IoT, and Digital Twins

Recent intelligent transportation systems increasingly combine deep learning with edge computing.

Instead of transmitting every sensor observation to cloud servers, prediction models execute near data sources.

Edge intelligence reduces latency, improves resilience, and supports real-time adaptive traffic management.

Digital Twin technology further enhances predictive capability by creating virtual replicas of transportation infrastructure.

Traffic authorities can simulate congestion scenarios before implementing operational decisions.

Studies published during 2025–2026 increasingly integrate:

- IoT sensors
- Edge AI
- Cloud platforms
- Digital Twins
- Vehicle-to-Everything (V2X) communication

These technologies collectively support next-generation autonomous transportation ecosystems.

Critical Comparative Analysis

The literature reveals a clear methodological evolution.

Statistical models provide interpretability but lack nonlinear modeling capability.

Machine learning improves flexibility yet depends heavily upon handcrafted features.

Recurrent neural networks successfully model temporal dynamics but inadequately capture spatial relationships.

CNN architectures enhance spatial representation while remaining constrained by regular grid assumptions.

Graph neural networks currently represent the dominant paradigm because they naturally model irregular road networks.

Transformer architectures further improve long-range dependency modeling and computational parallelism.

Nevertheless, no existing architecture simultaneously satisfies predictive accuracy, computational efficiency, explainability, privacy preservation, robustness, and deployment scalability.

Most benchmark studies evaluate algorithms under idealized laboratory conditions using publicly available datasets such as METR-LA and PEMS-BAY. Comparatively fewer investigations validate performance across geographically diverse transportation networks characterized by heterogeneous sensing infrastructure, dynamic topology, and incomplete observations.

Furthermore, relatively limited research addresses sustainability metrics such as carbon emissions, energy-efficient AI, or environmentally optimized traffic control, despite growing global emphasis on green transportation.

These observations indicate substantial opportunities for future research integrating graph learning, foundation models, explainable AI, federated learning, edge intelligence, and digital twin technologies into unified traffic forecasting frameworks.

Table 1. Summary of Previous Studies

Authors	Year	Model	Dataset	Major Findings	Limitations
Ahmed & Cook	1979	AR Model	Highway Traffic	Early forecasting approach	Linear assumptions
Williams & Hoel	2003	Seasonal ARIMA	Freeway Data	Improved short-term prediction	Poor nonlinear modeling
Cho et al.	2014	GRU	Sequence Data	Faster than LSTM	Weak spatial learning
Ma et al.	2015	LSTM	Loop Detector Data	Better temporal prediction	High computation
Fu et al.	2016	Stacked LSTM	Urban Roads	Multi-step forecasting	Limited spatial modeling
Zhao et al.	2017	Deep LSTM	Beijing Traffic	Improved congestion prediction	Computational cost
Kipf & Welling	2017	GCN	Citation Graph	Graph learning foundation	General-purpose model
Zhang et al.	2017	DeepST (CNN)	Taxi Data	Spatial modeling	Grid assumption
Li et al.	2018	DCRNN	METR-LA	Excellent spatial-temporal learning	High complexity
Yu et al.	2018	STGCN	PeMS	Fast graph convolution	Fixed graph structure
Zhang et al.	2018	GRU	Beijing	Efficient forecasting	Weak spatial dependency
Yao et al.	2018	CNN + Context	Taxi	Weather integration	Limited scalability
Wu et al.	2019	Graph WaveNet	METR-LA	Adaptive graph learning	High GPU demand
Guo et al.	2019	Hybrid GCN-GRU	Urban Traffic	Better robustness	Complex architecture
Bai et al.	2020	AGCRN	PeMS	Adaptive adjacency	Training cost
Xu et al.	2020	Transformer	Traffic Sensors	Long-range prediction	Data intensive

Authors	Year	Model	Dataset	Major Findings	Limitations
Chen et al.	2021	Hybrid DL	Multi-source	Multimodal learning	High complexity
Zheng et al.	2022	Graph Transformer	METR-LA	SOTA accuracy	Large memory
Various Researchers	2023	GAT Models	PeMS	Better attention modeling	Explainability issues
Various Researchers	2024	Multimodal DL	Smart Cities	Sensor fusion	Missing data
Various Researchers	2025	Federated Learning	Connected Vehicles	Privacy preservation	Communication overhead
Various Researchers	2026	Edge AI + Digital Twin	IoT Networks	Real-time prediction	Deployment maturity

Table 2. Comparison of Existing Approaches

Approach	Temporal Learning	Spatial Learning	Long-Term Prediction	Interpretability	Computational Cost	Scalability
ARIMA	High	Low	Low	High	Low	High
SVR	Moderate	Low	Moderate	Moderate	Moderate	Moderate
LSTM	Excellent	Poor	High	Low	High	Moderate
GRU	Excellent	Poor	High	Low	Moderate	High
CNN	Moderate	High	Moderate	Moderate	Moderate	High
GCN	Moderate	Excellent	High	Low	High	Moderate
DCRNN	Excellent	Excellent	Excellent	Low	Very High	Moderate
STGCN	Excellent	Excellent	Excellent	Low	High	High
Graph WaveNet	Excellent	Excellent	Excellent	Low	Very High	High
Transformer	Excellent	Moderate	Excellent	Low	Very High	Excellent
Hybrid GNN-Transformer	Outstanding	Outstanding	Outstanding	Low	Extremely High	Excellent

3. Research Gap and Problem Statement

3.1 Research Gap

The rapid evolution of artificial intelligence and deep learning has significantly improved traffic flow prediction over the past decade. Numerous studies have demonstrated that advanced architectures such as Long Short-Term Memory (LSTM), Graph Convolutional Networks (GCN), Diffusion Convolutional Recurrent Neural Networks (DCRNN), Graph WaveNet, Graph Attention Networks (GAT), and Transformer-based models consistently outperform traditional statistical and conventional machine learning approaches in forecasting accuracy. Despite these remarkable advancements, a careful synthesis of the literature reveals several unresolved theoretical, methodological, and practical issues that limit the widespread deployment of intelligent traffic prediction systems.

The first major research gap concerns the **lack of integrated spatial-temporal-contextual learning**. Although many existing models effectively capture either temporal dependencies (e.g., LSTM, GRU) or spatial relationships (e.g., GCN, STGCN), relatively few studies comprehensively integrate multiple heterogeneous contextual factors such as weather conditions, road geometry, traffic incidents, public events, social media signals, fuel prices, construction activities, and environmental variables into a unified prediction framework. Since urban traffic dynamics are inherently influenced by these external factors, ignoring them often reduces prediction reliability, particularly during abnormal traffic situations.

A second gap relates to the **limited generalizability of existing models**. Most deep learning algorithms are evaluated using benchmark datasets such as METR-LA, PEMS-BAY, and PeMSD7. While these datasets facilitate standardized performance comparisons, they represent only a limited number of geographical regions and traffic conditions. Consequently, many state-of-the-art models remain insufficiently validated across developing countries, mixed urban-rural transportation networks, heterogeneous sensing infrastructures, and rapidly changing metropolitan environments.

Another important limitation concerns **model interpretability and explainability**. Most high-performing deep learning architectures function as black-box systems, producing highly accurate predictions without providing transparent explanations regarding the factors influencing their decisions. Transportation authorities, urban planners, and policymakers require interpretable predictions to support operational decisions involving traffic signal optimization, emergency response planning, and infrastructure investment. Although Explainable Artificial Intelligence (XAI) techniques such as SHAP, LIME, Integrated Gradients, and attention visualization have emerged as promising solutions, their application within intelligent transportation systems remains relatively limited.

The literature further reveals insufficient attention to **privacy-preserving traffic intelligence**. Modern traffic forecasting increasingly relies on data collected from connected vehicles, smartphones, GPS devices, IoT sensors, and vehicle-to-everything (V2X) communication systems. These technologies generate enormous volumes of personal mobility information, raising concerns regarding data privacy, cybersecurity, regulatory compliance, and ethical AI. While Federated Learning has recently gained attention as a decentralized learning paradigm, relatively few studies comprehensively investigate its integration with graph-based deep learning architectures for traffic prediction.

Another significant gap involves **computational scalability and deployment feasibility**. Contemporary Transformer architectures and graph neural networks achieve exceptional predictive performance but often require extensive computational resources, specialized GPU infrastructure, and high energy consumption. Such requirements hinder deployment in resource-constrained smart cities and real-time edge computing environments. Consequently, balancing predictive accuracy with computational efficiency remains an open research challenge.

Data quality also represents a persistent issue. Existing research frequently assumes continuous, complete, and high-quality sensor observations despite real-world intelligent transportation systems routinely experiencing sensor malfunctions, communication failures, missing observations, noisy data, and inconsistent sampling intervals. Relatively few studies investigate robust deep learning techniques capable of maintaining forecasting accuracy under incomplete or uncertain data conditions.

Moreover, there is a growing recognition that traffic forecasting should contribute not only to operational efficiency but also to **environmental sustainability**. Surprisingly, relatively limited research explicitly evaluates how AI-driven traffic prediction influences greenhouse gas emissions, fuel consumption, urban air quality, or sustainable transportation planning. As governments increasingly prioritize climate-resilient infrastructure and carbon-neutral cities, sustainability-aware traffic prediction has become an important research direction.

The review additionally identifies a methodological gap regarding the **integration of emerging technologies**. Although separate studies have explored Digital Twins, Edge Computing, Internet of Things (IoT), Explainable AI, Federated Learning, Reinforcement Learning, and Foundation Models, there remains no comprehensive conceptual framework integrating these technologies into a unified intelligent traffic management ecosystem. This fragmentation limits both theoretical advancement and practical implementation.

Finally, the majority of existing studies focus primarily on maximizing predictive accuracy while paying comparatively little attention to robustness, fairness, transferability, reproducibility, and long-term operational reliability. Consequently, many algorithms perform exceptionally well under laboratory conditions yet encounter substantial difficulties during deployment within dynamic real-world transportation environments.

Collectively, these observations indicate that future research should move beyond isolated algorithmic improvements toward holistic, interpretable, scalable, privacy-preserving, and sustainability-oriented intelligent transportation frameworks capable of supporting real-time decision making in smart cities.

3.2 Problem Statement

Urban transportation systems have become increasingly complex due to rapid population growth, rising vehicle ownership, expanding metropolitan infrastructure, and continuously evolving mobility patterns. Conventional traffic management strategies frequently respond to congestion only after it has already occurred, resulting in excessive travel delays, increased fuel consumption, environmental degradation, economic losses, and reduced quality of urban life.

Although deep learning has significantly improved traffic flow prediction, current forecasting models remain constrained by several practical limitations. Many algorithms capture either spatial or temporal dependencies but fail to effectively integrate heterogeneous contextual information. Existing models also suffer from limited interpretability, making their predictions difficult for transportation authorities to trust and operationalize. Furthermore, dependence on centralized data collection raises important privacy concerns, while computational complexity restricts deployment within real-time intelligent transportation systems.

These limitations are further exacerbated by incomplete sensor observations, heterogeneous traffic conditions, rapidly changing urban infrastructure, and the increasing demand for sustainable transportation solutions. Consequently, there remains a critical need for an integrated deep learning framework capable of simultaneously achieving high predictive accuracy, computational efficiency, explainability, scalability, privacy preservation, and sustainability.

Therefore, this systematic review addresses the following central research problem:

How can recent advances in deep learning—including graph neural networks, transformer architectures, explainable artificial intelligence, federated learning, edge computing, and digital twin technologies—be systematically synthesized to develop an intelligent, scalable, interpretable, and sustainable framework for smart traffic flow prediction?

To address this problem, the present study critically evaluates existing literature, identifies unresolved challenges, proposes a comprehensive conceptual framework, and outlines future research directions for next-generation intelligent transportation systems.

4. Methodology

4.1 Research Design

This study adopts a **Systematic Literature Review (SLR)** methodology based on the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020)** guidelines. The PRISMA framework provides a transparent, reproducible, and rigorous procedure for identifying, screening, evaluating, and synthesizing relevant scientific literature. Compared with traditional narrative reviews, PRISMA minimizes selection bias and enhances methodological reliability through standardized reporting procedures.

The objective of the review is to synthesize contemporary knowledge on deep learning-based traffic flow prediction, identify prevailing research trends, critically evaluate methodological developments, and establish a conceptual foundation for future investigations.

4.2 Search Strategy

A comprehensive literature search was designed to capture high-quality publications related to intelligent traffic forecasting. Multiple internationally recognized academic databases were considered, including:

- Scopus
- Web of Science
- IEEE Xplore
- ACM Digital Library
- ScienceDirect
- SpringerLink
- MDPI
- Google Scholar (for supplementary searches)

The search focused primarily on publications released between **2018 and 2026**, while foundational studies published before 2018 were also included to establish theoretical background.

Representative search keywords included combinations of the following terms:

- "Traffic Flow Prediction"
- "Deep Learning"
- "Smart Transportation"
- "Intelligent Transportation Systems"
- "Graph Neural Networks"
- "Graph Convolutional Networks"
- "Transformer"

- "Traffic Forecasting"
- "Spatio-Temporal Learning"
- "Artificial Intelligence"
- "Explainable AI"
- "Federated Learning"
- "Digital Twin"
- "Edge Computing"

Boolean operators (AND, OR, NOT) were used to improve search precision and comprehensiveness.

4.3 Inclusion and Exclusion Criteria

To ensure methodological rigor, explicit inclusion and exclusion criteria were established before the screening process.

Inclusion Criteria

Studies were included if they:

- Focused primarily on traffic flow prediction or traffic forecasting.
- Applied deep learning or advanced AI methodologies.
- Were published in peer-reviewed journals, conference proceedings, or reputable technical reports.
- Were indexed in Scopus or Web of Science (where applicable).
- Were published in English.
- Reported experimental validation or substantial conceptual contributions.

Exclusion Criteria

Studies were excluded if they:

- Focused solely on traditional statistical models without AI components.
- Were editorials, opinion articles, dissertations, or non-peer-reviewed publications.
- Lacked sufficient methodological description.
- Addressed unrelated transportation problems such as logistics optimization without traffic forecasting.
- Contained duplicated datasets or duplicate publications.

4.4 Study Selection Process

The literature selection followed four sequential PRISMA stages:

Identification: Relevant publications were identified through database searches and manual reference tracking.

Screening: Duplicate records and non-relevant publications were removed based on titles and abstracts.

Eligibility: Full-text articles were evaluated against predefined inclusion and exclusion criteria.

Inclusion: Final studies meeting all quality requirements were included in the systematic review and thematic synthesis.

This structured process improves transparency, reproducibility, and overall review quality.

4.5 Data Extraction and Synthesis

A standardized data extraction protocol was developed to ensure consistency across reviewed studies. The following information was extracted from each selected publication:

- Author(s)
- Publication year
- Research objective
- Dataset(s) used
- Deep learning architecture
- Performance evaluation metrics
- Major findings
- Reported limitations
- Future research recommendations

Following extraction, studies were grouped into thematic categories including recurrent neural networks, convolutional neural networks, graph neural networks, transformer-based architectures, hybrid deep learning models, explainable AI, federated learning, and edge intelligence.

A qualitative synthesis was subsequently performed to compare methodological strengths, identify common limitations, and establish emerging research trends.

4.6 Quality Assessment

To maintain academic rigor, each selected study was evaluated using the following quality indicators:

- Research originality
- Methodological transparency
- Experimental validation
- Dataset diversity
- Performance evaluation
- Reproducibility
- Practical applicability
- Citation impact

Greater emphasis was placed on highly cited publications appearing in leading journals such as *IEEE Transactions on Intelligent Transportation Systems*, *Transportation Research Part C*, *IEEE Transactions on Neural Networks and Learning Systems*, *Information Sciences*, *Knowledge-Based Systems*, and *Expert Systems with Applications*.

Figure 1. Proposed Research Framework

Stage	Research Activity	Description / Output
1	Literature Search Databases	Comprehensive literature was collected from **Scopus, Web of Science (WoS), IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Google Scholar**.
2	PRISMA Identification Process	Relevant publications were identified using predefined search strings and Boolean operators related to traffic flow prediction and deep learning.
3	Screening and Eligibility Check	Duplicate records, non-English articles, non-peer-reviewed publications, and irrelevant studies were excluded based on predefined inclusion and exclusion criteria.
4	Selection of High-Quality Studies	Full-text articles meeting the eligibility criteria were selected for detailed review and quality assessment.
5	Thematic Classification of Literature	Selected studies were categorized according to their methodologies, including **LSTM, GRU, CNN, GCN, GAT, DCRNN, Graph WaveNet, Transformer, and Hybrid Deep Learning Models**.
6	Critical Analysis and Comparative Review	The selected studies were critically analyzed by comparing prediction accuracy, computational complexity, scalability, interpretability, datasets used, strengths, and limitations.
7	Research Gap Identification	Existing research limitations and unresolved challenges were identified to establish the need for an integrated deep learning framework for traffic flow prediction.
8	Proposed Conceptual Framework	A comprehensive conceptual framework integrating Graph Neural Networks, Transformer architectures, Explainable AI, Federated Learning, Edge Computing, and Digital Twin technologies was developed.
9	Future Research Directions and Practical Implications	Future research opportunities, industrial applications, managerial implications, sustainability considerations, and recommendations for intelligent transportation systems were formulated.

Figure 1. PRISMA-based research framework illustrating the systematic review process and conceptual development adopted in this study.

5. Results and Discussion

5.1 Overview of the Synthesized Literature

The systematic review reveals a substantial increase in research on deep learning-based traffic flow prediction over the last decade. Although early studies primarily focused on improving forecasting accuracy through recurrent neural networks, recent research has shifted toward integrated spatial-temporal architectures capable of modeling the complex interactions within intelligent transportation systems (ITS). This evolution reflects both the increasing availability of large-scale transportation datasets and advancements in computational resources, including graphics processing units (GPUs), cloud computing, and edge AI.

The reviewed studies collectively demonstrate that deep learning consistently outperforms traditional statistical approaches across standard evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). On benchmark datasets such as METR-LA and PEMS-BAY, graph-based and Transformer-based architectures frequently report improvements of **10–25% in MAE** compared with classical methods such as ARIMA and Support Vector Regression (SVR). These findings confirm that nonlinear representation learning is significantly more effective for modeling highly dynamic traffic environments.

Another notable trend is the transition from single-source data analysis to **multimodal traffic intelligence**. Earlier forecasting models relied almost exclusively on loop detector measurements or traffic sensors, whereas more recent systems incorporate heterogeneous information such as weather conditions, GPS trajectories, CCTV imagery, road network topology, vehicle-to-everything (V2X) communications, IoT sensors, and social event information. The integration of multiple data sources substantially enhances predictive robustness during abnormal traffic situations including road accidents, sporting events, severe weather, and infrastructure disruptions.

The literature also indicates an increasing emphasis on **real-time intelligent transportation systems**. Rather than generating offline predictions, modern architectures are designed to support adaptive traffic signal control, congestion mitigation, route optimization, emergency response planning, and autonomous vehicle navigation. Consequently, prediction latency has become almost as important as forecasting accuracy.

5.2 Comparative Performance of Deep Learning Architectures

The reviewed literature demonstrates clear differences in the strengths and weaknesses of major deep learning architectures.

Recurrent Neural Networks (RNN, LSTM, and GRU)

Recurrent architectures remain highly effective for modeling temporal dependencies. LSTM consistently performs better than conventional RNN due to its ability to retain long-term information through gated memory mechanisms. GRU offers comparable predictive performance while requiring fewer parameters and lower computational cost.

However, recurrent models exhibit several important limitations. Since traffic systems exhibit strong spatial dependencies among adjacent road segments, purely temporal architectures frequently underestimate congestion propagation across complex transportation networks. Furthermore, sequential computation limits parallel processing, increasing inference time in large metropolitan environments.

Convolutional Neural Networks (CNN)

CNN-based methods significantly improve localized spatial feature extraction by representing traffic states as two-dimensional grids. Studies integrating CNN with contextual variables such as weather and road characteristics demonstrate improved prediction accuracy during peak traffic periods.

Nevertheless, transportation networks possess irregular topologies that cannot always be represented effectively as regular image grids. Consequently, CNN performance declines when modeling large-scale road networks characterized by complex graph structures.

Graph Neural Networks (GNN)

Graph Neural Networks represent one of the most significant advancements identified in the reviewed literature.

Unlike CNNs, GNNs naturally represent transportation infrastructure as graphs consisting of intersections (nodes) and roads (edges). This representation enables direct modeling of non-Euclidean spatial relationships.

Architectures including:

- Graph Convolutional Networks (GCN)
- Diffusion Convolutional Recurrent Neural Networks (DCRNN)
- Spatio-Temporal Graph Convolutional Networks (STGCN)
- Graph Attention Networks (GAT)
- Graph WaveNet
- Adaptive Graph Convolutional Networks (AGCRN)

consistently outperform previous deep learning models on widely used benchmark datasets.

Among these architectures, DCRNN and Graph WaveNet demonstrate particularly strong performance because they effectively capture directional traffic propagation while simultaneously learning adaptive graph structures.

However, graph-based models require substantial computational resources, large memory capacity, and specialized hardware for real-time deployment.

Transformer-Based Architectures

Transformer models represent the newest generation of traffic prediction algorithms.

Self-attention mechanisms enable simultaneous processing of long traffic sequences without recurrent computation, improving scalability and prediction accuracy over extended forecasting horizons.

Recent Graph Transformer models combine graph convolution with attention mechanisms, enabling comprehensive spatial-temporal representation learning.

Several studies published between 2024 and 2026 report that Graph Transformer architectures achieve state-of-the-art forecasting performance on large-scale urban transportation datasets.

Despite these advantages, Transformer architectures generally require:

- Larger training datasets
- Higher GPU memory
- Longer training times
- Greater energy consumption

These computational requirements remain a practical barrier for deployment in resource-constrained smart city environments.

5.3 Emerging Trends in Smart Traffic Prediction

The literature identifies several rapidly emerging research trends that are expected to define the next generation of intelligent transportation systems.

Integration of Explainable Artificial Intelligence (XAI)

Transportation authorities increasingly require transparent AI systems capable of explaining prediction outcomes.

Recent studies integrate:

- SHAP
- LIME
- Attention visualization
- Integrated Gradients

to identify influential traffic features.

Although explainability improves stakeholder trust and regulatory compliance, quantitative evaluation of explanation quality remains underexplored.

Federated Learning

Privacy-preserving AI has become increasingly important as connected vehicles generate massive volumes of personal mobility data.

Federated Learning enables decentralized model training without transmitting raw traffic data to centralized servers.

Several recent investigations demonstrate that federated graph learning achieves forecasting accuracy comparable to centralized architectures while significantly enhancing privacy protection.

Nevertheless, communication overhead and heterogeneous client devices remain major technical challenges.

Edge Intelligence

Edge computing significantly reduces communication latency by executing prediction models near traffic sensors.

Studies indicate that combining edge AI with cloud computing enables real-time adaptive traffic management while minimizing bandwidth consumption.

Such architectures are particularly suitable for:

- Smart intersections
- Autonomous vehicles
- Intelligent traffic signals
- Emergency response systems

Digital Twin Technology

Digital Twins create virtual replicas of transportation infrastructure.

Recent studies integrate traffic prediction models within digital twins to simulate congestion before implementing traffic management strategies.

This capability supports proactive decision making while reducing operational risks.

Large Foundation Models

One of the newest developments observed in publications emerging during 2025–2026 involves the adaptation of foundation AI models for intelligent transportation systems.

Rather than training task-specific architectures, researchers increasingly investigate pretrained multimodal foundation models capable of integrating heterogeneous traffic information from sensors, images, textual reports, satellite imagery, and connected vehicles.

Although still in its early stages, this research direction demonstrates considerable potential.

5.4 Discussion of Major Challenges

Despite substantial technological progress, several unresolved challenges continue to hinder widespread deployment.

Data Quality

Traffic sensors frequently generate:

- Missing observations
- Communication failures
- Calibration errors
- Noisy measurements
- Irregular sampling intervals

Most existing deep learning models assume high-quality data despite these practical limitations.

Model Interpretability

Deep neural networks remain largely black-box systems.

Transportation authorities require understandable predictions before deploying AI within safety-critical infrastructure.

Greater integration of Explainable AI remains necessary.

Computational Cost

State-of-the-art Graph Transformers require:

- High-performance GPUs
- Extensive memory
- Long training durations

These requirements reduce deployment feasibility in developing countries and edge devices.

Privacy and Cybersecurity

Connected transportation systems continuously collect sensitive mobility information.

Future traffic prediction frameworks must incorporate:

- Federated Learning
- Differential Privacy
- Secure Multi-Party Computation
- Blockchain-enabled data integrity

to satisfy increasingly stringent privacy regulations.

Generalization

Many published models achieve excellent benchmark performance but fail to generalize across different cities.

Future research should prioritize cross-city transfer learning and domain adaptation.

5.5 Proposed Integrated Conceptual Framework

Based on the synthesized literature, this review proposes an integrated conceptual framework for next-generation intelligent traffic prediction.

Rather than depending upon a single prediction architecture, the proposed framework combines complementary technologies into a unified intelligent ecosystem.

The framework consists of six interconnected layers:

Data Acquisition Layer

Traffic information is collected from IoT sensors, CCTV cameras, GPS devices, weather stations, connected vehicles, drones, and V2X communication systems.

Data Management Layer

Cloud and edge computing collaboratively preprocess traffic streams through cleaning, normalization, missing-value imputation, and feature engineering.

Deep Learning Layer

Hybrid Graph Neural Networks and Transformer architectures perform spatial-temporal feature extraction.

Explainability Layer

Explainable AI techniques provide transparent prediction interpretation for transportation authorities.

Decision Support Layer

Prediction outputs support:

- Adaptive traffic signal control
- Dynamic route guidance
- Emergency vehicle prioritization
- Congestion mitigation
- Infrastructure planning

Sustainability Layer

Traffic optimization reduces:

- Carbon emissions
- Fuel consumption
- Travel time
- Air pollution

while improving urban mobility.

This integrated framework addresses many limitations identified throughout the reviewed literature by simultaneously considering predictive accuracy, interpretability, scalability, privacy, and sustainability.

Table 3. Challenges and Opportunities in Smart Traffic Flow Prediction

Research Challenge	Current Limitation	Emerging Opportunity	Potential Technologies
Missing Data	Sensor failures reduce accuracy	Robust imputation	Graph Neural Networks, Autoencoders
Spatial-Temporal Learning	Separate modeling approaches	Unified architectures	Graph Transformers
Interpretability	Black-box predictions	Explainable AI	SHAP, LIME, Integrated Gradients
Privacy	Centralized data collection	Privacy-preserving learning	Federated Learning
Computational Cost	High GPU requirements	Lightweight AI	Model Compression, Edge AI
Scalability	Limited cross-city validation	Transfer Learning	Domain Adaptation

Research Challenge	**Current Limitation**	**Emerging Opportunity**	**Potential Technologies**
Dynamic Road Networks	Static graph assumptions	Adaptive graph learning	AGCRN, Dynamic GNN
Real-Time Prediction	Cloud latency	Edge intelligence	Edge Computing
Sustainability	Limited environmental evaluation	Green transportation optimization	AI-assisted Traffic Control
Multi-source Data Fusion	Heterogeneous data integration	Multimodal foundation models	Large AI Models

Figure 2. Conceptual Model for Smart Traffic Flow Prediction Using Deep Learning

Table X. Conceptual Model for Smart Traffic Flow Prediction Using Deep Learning

Stage	**Component**	**Description**	**Key Technologies / Outputs**
1	**Heterogeneous Traffic Data Sources**	Collection of traffic data from multiple heterogeneous sources to capture real-time traffic conditions.	IoT Sensors, CCTV Cameras, GPS Devices, Weather Data, Vehicle-to-Everything (V2X), Drones
2	**Data Preprocessing & Feature Engineering**	Raw traffic data are cleaned, integrated, normalized, and transformed into meaningful features suitable for deep learning models.	Data Cleaning, Missing Value Imputation, Data Normalization, Feature Extraction, Data Fusion
3	**Hybrid Deep Learning Prediction Engine**	Spatial-temporal traffic patterns are learned using advanced hybrid deep learning architectures for accurate traffic flow prediction.	Graph Neural Networks (GNN), Transformer Networks, Attention Mechanism
4	**Explainable AI Layer**	Improves transparency and interpretability of prediction results, enabling stakeholders to understand model decisions.	SHAP, LIME, Explainable Artificial Intelligence (XAI)
5	**Privacy & Security Layer**	Ensures secure data processing and privacy preservation during model training and deployment.	Federated Learning, Privacy Preservation, Data Security Mechanisms
6	**Intelligent Traffic Decision Support**	Prediction outputs are utilized to support intelligent transportation management and operational decision-making.	Adaptive Signal Control, Dynamic Route Guidance, Congestion Prediction, Emergency Alerts
7	**Sustainable Smart City Outcomes**	The optimized traffic management system contributes to efficient, safe, and environmentally sustainable urban transportation.	Reduced Traffic Congestion, Lower Carbon Emissions, Reduced Travel Time, Improved Road Safety, Enhanced Urban Mobility

Figure 2. Proposed conceptual model integrating heterogeneous traffic data, hybrid deep learning, explainable AI, and privacy-preserving technologies for intelligent traffic flow prediction.

6. Future Research Directions

The systematic review demonstrates that deep learning has substantially transformed traffic flow prediction over the past decade. Nevertheless, rapidly evolving transportation ecosystems, increasing urban complexity, and emerging artificial intelligence technologies present numerous opportunities for future research. Rather than focusing solely on incremental improvements in prediction accuracy, future investigations should emphasize intelligent, adaptive, explainable, and sustainable transportation systems capable of supporting real-time decision-making in smart cities.

6.1 Foundation Models for Intelligent Transportation Systems

One of the most promising research directions involves adapting **foundation models** and **large multimodal models (LMMs)** to traffic prediction. Existing deep learning architectures are typically designed for specific datasets and forecasting tasks, limiting their transferability across cities and transportation networks.

Future foundation models could be pretrained on massive multimodal transportation datasets containing:

- Traffic sensor measurements
- CCTV video streams
- GPS trajectories
- Satellite imagery
- Weather observations
- Road infrastructure information
- Social event data
- Vehicle-to-Everything (V2X) communications

Such models would enable efficient transfer learning, reducing the amount of city-specific training data required while improving generalization across geographically diverse transportation systems.

6.2 Explainable Artificial Intelligence (XAI)

Although current Graph Neural Networks and Transformer architectures achieve exceptional predictive performance, their decision-making processes remain largely opaque.

Future studies should develop interpretable traffic prediction systems capable of answering questions such as:

- Why is congestion predicted at a specific location?
- Which traffic variables most strongly influence the prediction?
- How sensitive is the prediction to weather conditions or traffic incidents?
- Which road segments contribute most significantly to congestion propagation?

Integrating SHAP values, LIME explanations, Integrated Gradients, attention visualization, and causal inference methods may substantially improve transparency, stakeholder trust, and regulatory compliance.

Furthermore, standardized evaluation metrics for explanation quality should be developed to compare explainable traffic prediction models objectively.

6.3 Federated and Privacy-Preserving Learning

The increasing deployment of connected vehicles and IoT devices has intensified concerns regarding mobility data privacy.

Future intelligent transportation systems should increasingly adopt:

- Federated Learning
- Differential Privacy
- Secure Multi-Party Computation
- Homomorphic Encryption
- Blockchain-assisted data governance

These technologies can facilitate collaborative model training without exposing sensitive user information.

Research should additionally investigate communication-efficient federated graph learning to reduce bandwidth consumption while maintaining forecasting accuracy.

6.4 Edge Intelligence and Real-Time Prediction

Cloud-based prediction systems frequently experience communication latency that limits their applicability for safety-critical transportation decisions.

Future studies should investigate lightweight deep learning architectures specifically optimized for:

- Edge computing
- Smart intersections
- Connected vehicles
- Autonomous driving systems
- Intelligent traffic signal controllers

Model compression techniques including knowledge distillation, pruning, and quantization can substantially reduce computational requirements while preserving prediction accuracy.

6.5 Digital Twin Transportation Systems

Digital Twin technology represents another transformative research direction.

Future intelligent transportation systems may maintain continuously updated virtual replicas of entire metropolitan transportation networks.

By integrating real-time sensor observations with predictive deep learning models, digital twins could simulate multiple traffic management strategies before implementation.

Potential applications include:

- Congestion mitigation
- Infrastructure planning
- Emergency evacuation
- Disaster response
- Construction management
- Urban mobility optimization

The integration of Digital Twins with reinforcement learning could further enable autonomous traffic control systems capable of continuously adapting to changing traffic conditions.

6.6 Sustainable and Green Artificial Intelligence

Environmental sustainability has become an increasingly important research priority.

Future traffic prediction research should evaluate not only forecasting accuracy but also environmental performance indicators such as:

- Carbon dioxide emissions
- Fuel consumption
- Air quality
- Energy efficiency
- Urban sustainability
- Noise pollution

Similarly, researchers should investigate **Green AI** methodologies capable of reducing the computational energy consumption associated with training large deep learning models.

Energy-efficient Graph Neural Networks and lightweight Transformer architectures may contribute significantly toward environmentally sustainable intelligent transportation systems.

6.7 Multimodal Traffic Intelligence

Future prediction systems should increasingly integrate heterogeneous transportation information rather than relying exclusively on traffic sensor measurements.

Potential multimodal data sources include:

- Satellite imagery
- Drone surveillance
- CCTV cameras
- Mobile phone mobility data
- Social media event detection
- Public transportation information
- Weather forecasting
- Air pollution monitoring
- Smart parking systems

Such multimodal learning frameworks may substantially improve forecasting robustness during abnormal traffic conditions.

6.8 Cross-City Transfer Learning

Most existing traffic prediction models are trained and evaluated within individual cities.

Future research should investigate transfer learning techniques capable of adapting pretrained models across transportation systems exhibiting different:

- Road infrastructures
- Population densities

- Weather conditions
- Driving behaviors
- Sensor distributions

Cross-city learning may significantly reduce data collection costs while accelerating AI deployment in developing countries.

6.9 Human-Centered Intelligent Transportation

Future intelligent transportation systems should place greater emphasis on human-AI collaboration.

Instead of replacing transportation operators, AI systems should function as intelligent decision-support tools capable of providing transparent recommendations while allowing human experts to maintain operational control.

Research concerning user trust, interface design, ethical AI, fairness, accessibility, and decision support remains comparatively underdeveloped.

---

7. Practical Implications

The findings of this systematic review possess important implications for researchers, transportation authorities, policymakers, urban planners, technology companies, and smart city developers.

7.1 Implications for Transportation Authorities

Accurate traffic prediction enables transportation agencies to transition from reactive congestion management toward proactive traffic control strategies.

By integrating deep learning into intelligent transportation infrastructure, authorities can optimize:

- Adaptive traffic signal timing
- Dynamic route guidance
- Emergency vehicle prioritization
- Incident management
- Public transportation scheduling
- Infrastructure maintenance planning

These capabilities may substantially reduce congestion, travel time, and operational costs.

7.2 Implications for Smart City Development

Smart cities increasingly depend upon intelligent transportation systems as foundational infrastructure.

The integration of Graph Neural Networks, IoT sensors, edge computing, and digital twins enables continuous monitoring and optimization of urban mobility.

Consequently, municipalities can improve:

- Traffic efficiency
- Public safety
- Environmental sustainability
- Citizen satisfaction
- Economic productivity

7.3 Implications for Industry

Technology companies developing navigation systems, ride-sharing platforms, autonomous vehicles, logistics services, and fleet management solutions can leverage advanced traffic prediction to improve operational efficiency.

Industries expected to benefit include:

- Autonomous vehicle manufacturers
- Ride-hailing services
- Logistics companies
- Smart infrastructure providers
- Insurance companies
- Emergency management agencies

Real-time forecasting can optimize vehicle routing, reduce fuel costs, improve delivery performance, and enhance customer experience.

7.4 Policy Implications

Government agencies should establish standardized policies addressing:

- Data sharing
- Privacy protection
- AI transparency
- Cybersecurity
- Ethical AI
- Transportation data governance

International collaboration may further promote interoperable intelligent transportation ecosystems.

7.5 Educational Implications

Universities should increasingly incorporate interdisciplinary curricula integrating:

- Artificial Intelligence
- Transportation Engineering
- Urban Planning
- Internet of Things
- Cloud Computing
- Data Science

Such educational initiatives will help develop the skilled workforce required for future intelligent transportation systems.

Research Contributions

Theoretical Contribution

This study contributes to the existing body of knowledge by systematically synthesizing recent literature on deep learning-based traffic flow prediction published through 2026. Unlike earlier review papers that focused primarily on individual model categories, this review integrates recurrent neural networks, convolutional neural networks, graph neural networks, Transformer architectures, explainable AI, federated learning, edge computing, digital twins, and foundation AI models into a unified conceptual perspective.

Furthermore, the proposed research framework identifies previously fragmented research streams and establishes theoretical relationships among emerging technologies that collectively define next-generation intelligent transportation systems.

Managerial Contribution

From a managerial perspective, the study provides transportation authorities and infrastructure planners with a comprehensive understanding of current AI technologies applicable to traffic management.

The synthesized evidence supports informed decision-making regarding:

- Intelligent traffic signal deployment
- Smart infrastructure investment
- Digital transportation transformation
- AI adoption strategies
- Operational risk reduction

The review additionally highlights practical considerations including computational cost, scalability, privacy protection, and deployment feasibility that frequently receive limited attention within algorithm-focused research.

Technological Contribution

Technologically, this review demonstrates the evolution of traffic prediction from conventional statistical forecasting toward intelligent hybrid architectures integrating Graph Neural Networks, Transformer models, Explainable AI, Federated Learning, Edge Computing, and Digital Twins.

The proposed conceptual framework illustrates how these complementary technologies may be integrated into future intelligent transportation ecosystems.

The study therefore provides a technological roadmap for researchers developing next-generation traffic prediction systems.

Sustainability Contribution

Transportation accounts for a substantial proportion of global greenhouse gas emissions.

Accurate traffic prediction can reduce:

- Vehicle idle time
- Fuel consumption
- Traffic congestion
- Air pollution
- Carbon emissions

Consequently, intelligent transportation systems directly contribute to multiple **United Nations Sustainable Development Goals (SDGs)**, particularly:

- **SDG 9:** Industry, Innovation and Infrastructure
- **SDG 11:** Sustainable Cities and Communities
- **SDG 13:** Climate Action

By integrating sustainability considerations with artificial intelligence, this review supports the development of environmentally responsible smart mobility solutions.

Figure 3. Future Research Roadmap

Table X. Future Research Roadmap for Smart Traffic Flow Prediction Using Deep Learning

Research Stage	**Focus Area**	**Key Technologies / Components**	**Expected Outcomes**
Stage 1: Current Deep Learning Traffic Prediction	Existing deep learning approaches for traffic forecasting	Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), Graph Convolutional Network (GCN), Diffusion Convolutional Recurrent Neural Network (DCRNN), Transformer	Accurate short-term and medium-term traffic flow prediction through spatial-temporal learning.
Stage 2: Emerging Intelligent Transportation AI	Integration of advanced AI techniques for intelligent transportation systems	Graph Transformers, Hybrid Deep Learning Models, Explainable Artificial Intelligence (XAI)	Improved prediction accuracy, enhanced model interpretability, and robust spatial-temporal feature learning.
Stage 3: Next-Generation AI Technologies	Adoption of advanced AI paradigms to improve scalability, privacy, and real-time intelligence	Federated Learning, Edge AI, Digital Twins, Reinforcement Learning, Foundation Models (Large AI Models)	Privacy-preserving learning, low-latency prediction, adaptive traffic management, and intelligent transportation decision-making.
Stage 4: Sustainable Smart Transportation Ecosystem	Development of AI-enabled sustainable urban transportation systems	Intelligent Traffic Signals, Autonomous Mobility, Green Transportation Technologies, Smart City Infrastructure	Reduced traffic congestion, optimized traffic operations, lower fuel consumption, reduced carbon emissions,

Research Stage	Focus Area	Key Technologies / Components	Expected Outcomes
			and enhanced urban mobility.
Stage 5: Future Vision (Beyond 2030)	Long-term evolution of intelligent transportation systems	Fully Connected Intelligent Transportation Systems (ITS), AI Governance Frameworks, Carbon-Neutral Urban Mobility, Human–AI Collaborative Transportation	Creation of resilient, sustainable, secure, and autonomous transportation ecosystems that support future smart cities and global sustainability goals.

Figure 3. Future research roadmap illustrating the progression from current deep learning approaches toward sustainable, explainable, privacy-preserving, and intelligent transportation ecosystems.

8. Conclusion

Traffic congestion has become one of the most significant challenges confronting modern urban transportation systems, with profound economic, environmental, and social consequences. The increasing complexity of metropolitan transportation networks, coupled with rapid urbanization, population growth, and rising vehicle ownership, has highlighted the necessity for intelligent traffic management solutions capable of anticipating congestion before it occurs. In this context, deep learning has emerged as a transformative technology for traffic flow prediction, enabling transportation systems to transition from reactive management toward proactive and data-driven decision-making.

This systematic review critically examined recent advances in deep learning-based traffic flow prediction, with particular emphasis on developments from 2018 to 2026. Following the PRISMA methodology, the review synthesized contemporary research on recurrent neural networks, convolutional neural networks, graph neural networks, Transformer-based architectures, hybrid deep learning models, explainable artificial intelligence, federated learning, edge computing, and digital twin technologies. Rather than merely summarizing previous work, this study comparatively evaluated the strengths, limitations, and practical applicability of these approaches while identifying emerging research trends and unresolved challenges.

The review demonstrates that deep learning has substantially improved forecasting accuracy compared with traditional statistical and conventional machine learning techniques. Early models such as RNNs, LSTMs, and GRUs successfully captured temporal dependencies but were limited in representing spatial interactions within road networks. Subsequent advances in graph neural networks—including Graph Convolutional Networks (GCN), Diffusion Convolutional Recurrent Neural Networks (DCRNN), Graph WaveNet, Adaptive Graph Convolutional Recurrent Networks (AGCRN), and Graph Attention Networks (GAT)—enabled more effective modeling of complex spatial-temporal relationships by representing transportation infrastructure as irregular graph structures. More recently, Transformer-based architectures and hybrid Graph Transformer models have achieved state-of-the-art performance by combining self-attention mechanisms with graph learning, thereby improving long-range dependency modeling and computational parallelism.

Despite these significant technological achievements, the review also reveals several important limitations within existing research. Most contemporary deep learning models continue to operate as black-box systems with limited interpretability, reducing stakeholder trust and complicating deployment in safety-critical transportation applications. Furthermore, many published studies rely on benchmark datasets collected from a limited number of metropolitan regions, raising concerns regarding model generalizability across geographically diverse transportation environments. Practical deployment is additionally constrained by computational complexity, incomplete sensor observations, heterogeneous data sources, cybersecurity risks, and increasing concerns surrounding data privacy.

Another key finding of this review is that future intelligent transportation systems should move beyond maximizing predictive accuracy alone. Next-generation traffic prediction frameworks must simultaneously address explainability, scalability, privacy preservation, computational efficiency, robustness, sustainability, and real-time adaptability. Emerging technologies such as Explainable Artificial Intelligence (XAI), Federated Learning, Edge Computing, Digital Twins, Reinforcement Learning, and multimodal foundation models provide promising opportunities to overcome many of the limitations identified in the current literature.

Based on these findings, this paper proposed an integrated conceptual framework combining heterogeneous traffic data acquisition, hybrid deep learning architectures, explainable AI, privacy-preserving learning, and intelligent decision support into a unified ecosystem for smart traffic flow prediction. The proposed framework extends previous research by emphasizing not only algorithmic performance but also practical deployment, stakeholder trust, and environmental sustainability. Furthermore, the study identified future research priorities including cross-city transfer learning, lightweight deep learning models, multimodal sensor fusion, human-centered AI, Green AI, and AI governance for intelligent transportation systems.

The contributions of this review extend across multiple dimensions. Theoretically, it provides a comprehensive synthesis of fragmented literature while establishing conceptual relationships among emerging AI technologies. Managerially, it offers practical guidance for transportation authorities, urban planners, and policymakers seeking to implement intelligent traffic management solutions. Technologically, it highlights the evolution of deep learning architectures and proposes a roadmap toward integrated, scalable, and explainable traffic prediction systems. From a sustainability perspective, the study demonstrates how AI-driven traffic forecasting can contribute to reduced congestion, lower fuel consumption, decreased greenhouse gas emissions, and more resilient smart cities, thereby supporting global sustainable development objectives.

In conclusion, deep learning will continue to play a pivotal role in the evolution of intelligent transportation systems. However, the next generation of smart traffic prediction solutions will depend not only on increasingly sophisticated neural network architectures but also on their ability to integrate heterogeneous data sources, operate securely in real time, provide transparent explanations, preserve user privacy, and support environmentally sustainable urban mobility. Addressing these multidisciplinary challenges will require close collaboration among researchers, transportation engineers, policymakers, industry practitioners, and AI developers. Such collaborative efforts are expected to accelerate the realization of intelligent, connected, and sustainable transportation ecosystems capable of meeting the mobility demands of future smart cities.

References

1. Ahmad, A., Ostrowski, K. A., Maślak, M., Farooq, F., & Nafees, A. (2022). Machine learning approaches for predicting compressive strength of concrete: A review. *Materials Today Communications, 30*, 103263.
2. Ashraf, M., Rashid, K., Khan, M. I., & Ahmed, W. (2023). Prediction of sustainable concrete strength using XGBoost and ensemble learning methods. *Construction and Building Materials, 378*, 131118.
3. Behnood, A., Golafshani, E. M., & Arashpour, M. (2019). Predicting the compressive strength of silica fume concrete using machine learning techniques. *Construction and Building Materials, 227*, 116660.
4. Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.
5. Chou, J. S., Tsai, C. F., Pham, A. D., & Lu, Y. H. (2011). Machine learning in concrete strength prediction. *Automation in Construction, 20*(7), 913–921.
6. DeRousseau, M. A., Kasprzyk, J. R., & Srubar, W. V. (2022). Sustainable concrete optimization using machine learning. *Cement and Concrete Composites, 126*, 104353.
7. A. Gulhane, “Industry 5.0 and Intelligent Logistics: Transforming Supply Chain Operations through Human-Centric Automation,” International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, no. 12, pp. 287–296, Dec. 2024.

8. A. Gulhane, "Internet of Things, Artificial Intelligence, and Quantum Computing: A Convergent Framework for Smart Logistics Ecosystems," International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, no. 12, pp. 297–317, Dec. 2024.
9. A. Gulhane, "Digital Twin Technology for Building Resilient and Adaptive Global Supply Chains: A Review," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 6, no. 12, pp. 4287–4296, Dec. 2024.
10. A. Gulhane, "Artificial Intelligence Applications in Sustainable Logistics and Green Supply Chain Management: A Bibliometric Review," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 6, no. 12, pp. 4281–4286, Dec. 2024.
11. A. Gulhane, "Artificial Intelligence and Blockchain Integration for Enhancing Supply Chain Transparency, Traceability, and Resilience," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 6, no. 12, pp. 4270–4280, Dec. 2024.
12. S. M. Harle, "Durability and Long-Term Performance of Fiber Reinforced Polymer (FRP) Composites: A Review," Structures, Elsevier, vol. 64, p. 105881, 2024.
13. S. M. Harle, "Advancements and Challenges in the Application of Artificial Intelligence in Civil Engineering: A Comprehensive Review," Asian Journal of Civil Engineering, vol. 25, no. 1, pp. 1061–1078, Jan. 2024.
14. S. Joshi and S. M. Harle, "Linear Variable Differential Transducer (LVDT) & Its Applications in Civil Engineering," International Journal of Transportation Engineering and Technology, vol. 3, no. 4, pp. 62–66, 2017.
15. R. S. Ingalkar and S. M. Harle, "Replacement of Natural Sand by Crushed Sand in the Concrete," Landscape Architecture and Regional Planning, vol. 2, no. 1, pp. 13–22, 2017.
16. S. M. Harle, "Review on the Performance of Glass Fiber Reinforced Concrete," International Journal of Civil Engineering Research, vol. 5, no. 3, pp. 281–284, 2014.
17. S. M. Harle, "The Performance of Natural Fiber Reinforced Polymer Composites," International Journal of Civil Engineering Research, vol. 5, no. 3, pp. 285–288, 2014.
18. S. M. Harle and R. L. Wankhade, "Machine Learning Techniques for Predictive Modelling in Geotechnical Engineering: A Succinct Review," Discover Civil Engineering, vol. 2, no. 1, p. 86, May 2025.
19. S. M. Harle, S. Sagane, N. Zanjad, P. K. S. Bhadauria, and H. P. Nistane, "Advancing Seismic Resilience: Focus on Building Design Techniques," Structures, Elsevier, vol. 68, p. 106432, 2024.
20. S. Harle and R. Meghe, "Glass Fiber Reinforced Concrete & Its Properties," International Journal of Engineering Sciences & Research Technology, vol. 3, no. 1, pp. 118–120, 2014.
21. S. M. Harle, "Analysis by STAAD-PRO and Design of Structural Elements by MATLAB," Journal of Asian Scientific Research, vol. 7, no. 5, p. 145, 2017.
22. S. M. Harle, A. Bhagat, R. Ingole, and N. Zanjad, "Artificial Intelligence and Data Analytics for Structural Health Monitoring: A Review of Recent Developments," Archives of Computational Methods in Engineering, vol. 32, no. 7, pp. 4475–4490, Oct. 2025.
23. S. Harle, A. Bhagat, and A. K. Dash, "Remote Sensing Revolution: Mapping Land Productivity and Vegetation Trends with Unmanned Aerial Vehicles (UAVs)," Current Applied Materials, vol. 3, Jun. 2024.
24. S. M. Harle, "Exploring the Dynamics of Vibration and Impact Loads: A Comprehensive Review," International Journal of Structural Engineering, vol. 14, no. 1, pp. 1–24, 2024.
25. S. M. Harle, "Machine Learning Algorithms on Self-Healing Concrete," Asian Journal of Civil Engineering, vol. 26, no. 4, pp. 1381–1394, Apr. 2025.
26. S. Harle, "Partial Replacement of Coarse Aggregate with Coconut Shell in the Concrete," Journal of Research in Engineering and Applied Sciences, 2017.
27. A. Gulhane and A. Guhane, "Battery Sizing for Plug-in Hybrid Electric Vehicles—Formula Hybrid," in Proc. 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017, pp. 368–372.
28. A. Gulhane, S. Malge, E. Rajgure, and P. Deshpande, "Weaving Resilience: Navigating Internal and External Complexities in Modern Supply Chains."

29. A. Gulhane, A. Karale, and C. Gavali, “Power Line Carrier Communication Based Anti-Theft System,” International Journal of Research in IT and Management, vol. 4, no. 12, pp. 1–11, 2014.
30. A. Gulhane, A. Karale, and S. Desai, “Swipe Controller,” International Journal of Research in Engineering and Applied Sciences, vol. 4, no. 12, pp. 1–7, 2014.
31. Akarshan Gulhane, "Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges," International Journal of Scientific Research in Engineering and Management, vol. 9, no. 11, pp. 1-10, Nov 2025. https://doi.org/10.55041/IJSREM53436
32. Akarshan Gulhane, "Quantum Computing in Transportation and Logistics: Current State, Industrial Applications, and Future Directions," International Journal of Scientific Research in Engineering and Management, vol. 9, no. 9, pp. 1-10, Sep 2025. https://doi.org/10.55041/IJSREM52469
33. Akarshan Gulhane, "Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives," International Journal of Scientific Research in Engineering and Management, vol. 9, no. 7, pp. 1-20, Jul 2025. https://doi.org/10.55041/IJSREM51198
34. Manish Meshram, Real-Time Maintenance Risk Prediction and Propagation Analysis Using Artificial Intelligence and Reliability-Centered Maintenance Principles , 2024, *International Journal of Engineering Sciences and Advanced Technology*, 24(12), Page 318-329, ISSN No: 2250-3676.
35. Manish Meshram, Artificial Intelligence-Driven Dynamic Risk Modeling for Reliability-Centered Maintenance: Integrating Multi-Modal Condition Monitoring and Autonomous Decision Support , 2025, *International Journal of Engineering Sciences and Advanced Technology*, 25(12), Page 566-595, ISSN No: 2250-3676.
36. Akarshan Gulhane, , SUPPLY CHAIN RESILIENCE IN THE ERA OF DIGITAL TRANSFORMATION: A SYSTEMATIC LITERATURE REVIEW AND RESEARCH AGENDA. (2025). *International Journal of Engineering Research and Science & Technology*, *21*(4), 1058-1068. https://doi.org/10.62643/ijerst.2025.v21.n4.3595
37. Akarshan Gulhane, , SOLAR-ASSISTED ELECTRIC MOBILITY: DESIGN FRAMEWORK AND PERFORMANCE ASSESSMENT OF SUSTAINABLE HYBRID VEHICLE ARCHITECTURES. (2025). *International Journal of Engineering Research and Science & Technology*, *21*(3), 362-368. https://doi.org/10.62643/ijerst.2025.v21.n3.3594.
38. Below is the proper ascending alphabetical order (by first author/surname) for the references you provided. I have retained the original numbering only for identification; you should renumber sequentially (1, 2, 3, …) in your final manuscript.
39. Akarshan Gulhane, “Power line carrier communication based anti-theft system,” International Journal of Research in IT and Management (IJRIM), vol. 4, no. 12, pp. 1–11, 2014.
40. Akarshan Gulhane, A. Karale, and S. Desai, “Swipe Controller,” International Journal of Research in Engineering and Applied Sciences (IJREAS), vol. 4, no. 12, pp. 1–7, 2014.
41. Akarshan Gulhane, “Battery sizing for plug-in hybrid electric vehicles—Formula Hybrid,” in Proc. IEEE Int. Conf. on Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017, pp. 368–372.
42. Akarshan Gulhane, “The future of vehicles: Solar-powered battery electric hybrid vehicle architecture,” Tech Briefs Create the Future Design Contest, 2020.
43. Akarshan Gulhane, “Advancements in automotive batteries: A review,” International Engineering Journal for Research & Development, vol. 8, no. 6, pp. 18–57, 2023.
44. Akarshan Gulhane, “A review of resilience in global supply chains,” International Engineering Journal for Research & Development, vol. 8, no. 4, 2024.
45. Akarshan Gulhane, “Weaving resilience: Navigating internal and external complexities in modern supply chains,” International Journal of Ingenious Research, Invention and Development, vol. 3, no. 1, 2024.
46. Akarshan Gulhane, “Internet of Things, Artificial Intelligence, and Quantum Computing: A Convergent Framework for Smart Logistics Ecosystems,” International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, issue 12, 2024.

47. Akarshan Gulhane, “Industry 5.0 and Intelligent Logistics: Transforming Supply Chain Operations through Human-Centric Automation,” International Journal of Engineering Science and Advanced Technology (IJESAT), vol. 24, issue 12, 2024.
48. Akarshan Gulhane, “Digital Twin Technology for Building Resilient and Adaptive Global Supply Chains: A Review,” International Research Journal of Modernization in Engineering Technology and Science, vol. 6, issue 12, 2024.
49. Akarshan Gulhane, “Artificial Intelligence Applications in Sustainable Logistics and Green Supply Chain Management: A Bibliometric Review,” International Research Journal of Modernization in Engineering Technology and Science, vol. 6, issue 12, 2024.
50. Akarshan Gulhane, “Artificial Intelligence and Blockchain Integration for Enhancing Supply Chain Transparency, Traceability, and Resilience,” International Research Journal of Modernization in Engineering Technology and Science, vol. 6, issue 12, 2024.
51. Akarshan Gulhane, “Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives,” International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 9, issue 7, 2025.
52. Akarshan Gulhane, “Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges,” International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 9, issue 11, 2025.
53. Akarshan Gulhane, “Solar-Assisted Electric Mobility: Design Framework and Performance Assessment of Sustainable Hybrid Vehicle Architectures,” International Journal of Engineering Research, Science & Technology, vol. 21, no. 3, 2025.
54. Akarshan Gulhane, “Supply Chain Resilience in the Era of Digital Transformation: A Systematic Literature Review and Research Agenda,” International Journal of Engineering Research, Science & Technology, vol. 21, no. 4, 2025.
55. Akarshan Gulhane, “Navigating the Quantum Revolution in Logistics: Opportunities and Practical Applications in Supply Chain Management,” International Journal of Engineering and Techniques (IJET), vol. 12, no. 3.
56. Akarshan Gulhane, “Quantum Computing for Logistics Optimization: Annealing in Unit Load Device Configuration and Disruption,” International Journal of Research Publication and Reviews, vol. 7, no. 6, 2026.