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Smart City Transportation Safety Using AI and Big Data Analytics: A Review

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Abstract: *Smart city transportation systems are increasingly adopting artificial intelligence (AI), Big Data analytics, Internet of Things (IoT), connected vehicles, and intelligent transportation technologies to address growing mobility and safety challenges. This review examines the role of AI and Big Data in strengthening transportation safety by analyzing transportation infrastructure, heterogeneous data sources, data characteristics, storage and processing architectures, data quality, integration, and intelligent safety applications. The reviewed literature demonstrates that combining diverse transportation data with advanced AI techniques provides substantial potential for proactive safety management, including accident detection, risk prediction, traffic anomaly identification, driver behavior analysis, hazard recognition, and real-time incident monitoring. Big Data technologies further support scalable data collection, multimodal integration, distributed processing, and timely decision-making, while edge computing and connected-vehicle technologies can improve responsiveness in safety-critical environments. The findings indicate that AI-driven analytics can transform conventional reactive safety practices into more predictive, adaptive, and data-driven approaches. However, challenges involving data heterogeneity, quality, privacy, cybersecurity, interoperability, scalability, environmental variability, real-time processing, and explainability remain important considerations for reliable smart-city transportation safety.*

Keywords: *Artificial Intelligence, Big Data Analytics, Transportation Safety, Smart Cities, Accident Detection, Connected Vehicles, IoT.*

I. INTRODUCTION

The growing pressure of rapid urbanization, population increase, increased mobility pressure, and environmental issues are posing complex urban challenges that demand for efficient, safe, sustainable, and connected mobility through smarter infrastructure and intelligent transportation systems [1][2]. Conventional transportation systems are becoming intelligent and data-driven environments with the expansion of connected infrastructure. With the increasingly ubiquitous integration of Internet of Things (IoT) devices, connected vehicles, communications networks, cloud platforms, and intelligent sensing, cities are now able to monitor and manage transportation conditions on a finer temporal and spatial scale. This transition is especially important in the context of complicated urban mobility caused by increased mobility demand, the diversity of road users, and the dynamic nature of traffic circumstances [3]. By 2050, the United Nations (UN) expects urban residents to make up some 68% of the global population, making scalable and intelligent transportation solutions increasingly necessary.

Road safety remains a critical challenge within this rapidly evolving urban environment [4]. The WHO reports approximately 1.16 million road traffic deaths annually, with 20–50 million additional people sustaining non-fatal injuries. Vulnerable road users, including walkers, cyclists, and motorcyclists, account for more than half of worldwide road traffic mortality, with about 92% of fatalities occurring in low- and middle-income nations [5]. These situations highlight the need to develop a different paradigm of safety by shifting from traditional, mostly reactive strategies to proactively monitor, detect, anticipate and intervene with safety measures [6].

Artificial intelligence (AI) and big data analytics are key capabilities that can help meet these requirements, as they convert heterogeneous transportation data into actionable safety intelligence [7][8]. Machine learning, deep learning, computer vision, and spatiotemporal analytics can be used to integrate and analyze data collected from GPS devices, CCTV cameras, connected vehicles, roadside sensors, V2X communication, public transportation systems and environmental monitoring systems [9]. These techniques are useful in predicting accidents, detecting anomalies in traffic, analyzing driver behavior, identifying road hazards, forecasting congestion, and recognizing incidents in real-time [10]. Moreover, big data platforms can support high-volume, high-velocity transportation information, which is extensively stored, processed and analyzed in a distributed manner and continuously [11].

Data-driven technologies are therefore increasingly part of smart transportation safety, linking data acquisition, intelligent analysis and action decisions to safety. They can be used to facilitate proactive safety management, adaptive traffic

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control, emergency response and better protection of vulnerable road users [12]. But to be effective, data quality, interoperability, privacy, cybersecurity, model reliability, computational requirements and real-time processing must be addressed. These dimensions are key in creating trustworthy and scalable intelligent transportation safety ecosystems.

A. Structure of the paper

The paper is organized as follows: Section II reviews existing studies, Section III discusses AI techniques for transportation safety, Section IV examines Big Data analytics, Section V presents major safety applications, Section VI discusses challenges and emerging research directions, and Section VII concludes and presents future work.

II. SMART CITY TRANSPORTATION AND BIG DATA ECOSYSTEM

Urban transportation is evolving through interconnected infrastructure, intelligent systems, connected vehicles, and large-scale data ecosystems that enable real-time monitoring, efficient mobility management, enhanced safety, and sustainable urban development.

A. Smart City Transportation Infrastructure

Smart city transportation infrastructure is a system that encompasses roads, vehicles, travelers and the environment, and combines them with intelligent technologies in the form of sensing, communication, and control. It is different from conventional infrastructure in that it allows for the real-time exchange of information between vehicles, pedestrians, cyclists, road infrastructure systems, and transportation management systems [13]. The technologies driving the IoT have been adopted to monitor traffic, assess the condition of infrastructure, dynamically manage lane and signal use, and provide real-time safety warnings [14].

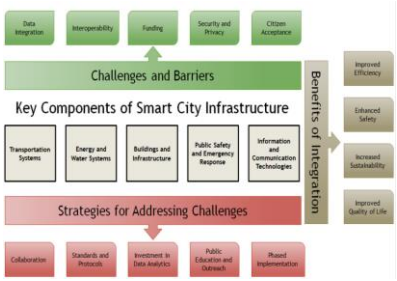


Figure 1: The Key Components of the Smart City Transportation Infrastructure [17]

This infrastructure can enhance vulnerable road user (VRU) safety, offer accessible and even personalized mobility services, streamline emergency response, and optimize vehicle trajectory and traffic flow [15]. Additional measures to improve energy efficiency and environmental monitoring also help in minimizing emissions, congestion, and energy use. In summary, physical infrastructure and the smart use of intelligent and connected technologies create a basis for safer and more efficient, inclusive and sustainable transport in smart cities [16]. The smart city infrastructure consists of several key components that form the foundation for integrating ITS illustrate in Fig. 1:

- Integrates transportation, energy and water, buildings, public safety, and ICT infrastructure.
- Faces barriers related to data integration, interoperability, funding, security, privacy, and citizen acceptance.
- Uses collaboration, standardization, data analytics, public education, and phased implementation to address these challenges.
- Supports improved efficiency, enhanced safety, increased sustainability, and better quality of life.

B. Intelligent Transportation Systems in Smart Cities

Smart city infrastructure, made possible by advances in intelligent transportation technology, is revolutionizing urban transit by facilitating more efficient, linked, and environmentally friendly systems. The rapid urbanization and the rising needs for travel have placed emphasis on the need for advanced traffic management, mobility services and transportation planning solutions [18]. To meet these challenges, ITS uses technologies like the IoTs, AI, communication networks and data analytics to gather, analyse and apply transportation data in real-time.

The capabilities enable features such as traffic monitoring, intelligent signal control, route optimization, public transportation management and connected mobility services. The synergy between ITS and other smart city infrastructure also facilitates the coordination between transport, energy, communication and public services, leading to better mobility, less congestion, safer cities and more sustainable urban development [19].

C. Connected Vehicles and IoT-Based Transportation

The integration of Internet of Things (IoT) technologies has enabled vehicles, roadside infrastructure, sensors, and communication networks to exchange transportation data in real time. These capabilities support intelligent transportation

systems (ITS) through applications such as traffic monitoring, congestion management, route optimization, incident detection, and road safety [20]. Communication between vehicles, infrastructure, and everything else is made possible by vehicle-to-everything (V2X) and vehicle-to-vehicle (V2V) protocols, which in turn allow for intelligent mobility and cooperative transportation services.

Technologies such as Dedicated Short-Range Communications (DSRC), Cellular Vehicle-to-Everything (C-V2X), and 5G, 6G-based networks provide communication support for safety and traffic-management applications [21]. But their widespread use brings up issues of interoperability, scalability, reliability, cybersecurity, privacy, and heterogeneous data integration. The developments have led to various research trends, which can be valuable for using bibliometric analysis to identify influential actors, new themes, technological advances, and research trends in the field of connected vehicles, IoT, V2X, DSRC, and C-V2X [22].

D. Big Data Sources in Smart Transportation

Smart transportation systems depend on a variety of data streams that are continuously collected to track mobility, understand traffic conditions, optimize resource use and ensure transportation safety. The data sources include vehicle data, road infrastructure, traveler data, environmental information, and transportation service data, which can be used for data-driven decision-making and intelligent management of mobility:

- Traffic sensor data: Includes data from loop detectors, radar sensors, infrared sensors, and traffic counters, providing information on vehicle flow, speed, density, and congestion levels.
- Vehicle and GPS data: GPS devices and onboard vehicle systems generate location, speed, route, acceleration, and travel-time data that support mobility analysis and route optimization.
- CCTV and surveillance data: Camera systems provide visual information for traffic monitoring, incident detection, vehicle tracking, and identification of unsafe road conditions.
- Connected-vehicle and V2X data: Communication among vehicles, infrastructure, pedestrians, and networks provides real-time information about traffic conditions, hazards, road events, and vehicle behavior.
- Public transportation data: Bus, train, and metro systems generate data related to routes, schedules, passenger demand, vehicle locations, and service performance.
- Weather and environmental data: Weather stations and environmental sensors provide information on rainfall, temperature, visibility, air quality, and other conditions that can affect traffic and road safety [23].
- Data related to roads and infrastructure: Intersections, pavement conditions, building activities, traffic lights, digital maps, road sensors, infrastructure databases, and maintenance systems all contribute to a comprehensive picture of roads and infrastructure.
- Social media and crowdsourced data: User-generated reports, social media posts, navigation applications, and crowdsourced platforms contribute real-time information about traffic incidents, congestion, road closures, and mobility experiences.

Table 1: Big Data in Its

Source	Tools	Data
Smart Card	Smart Card	OD Flows, Travel Time
GPS	GPS	Vehicle Position, Vehicle Density, Vehicle Speed
Video	Video Camera	Vehicle Position, Vehicle Speed, Vehicle Density, Vehicle Classification
Road Site Sensor	Induction Loops, Road Tubes, Microwave Radar, LIDAR/Infrared Acoustic, Toll Plazas	Vehicle Position, Vehicle Speed, Vehicle Density, Vehicle Classification
Floating Car Sensor	License Plate Recognition, Transponders	Travel Time, OD Flows
Wide Area Sensor	GPS, Cell phone Tracking, Airborne Sensors	Travel Time, OD Flows
Connected and Autonomous Vehicles (CAVs)	Diverse Sensors	Coordinate, speed, acceleration, safety data,
Passive Collection	Social Media, Mobile Phone Data	Travel Time, OD Flows
Other Sources	Smart Grid, Smart Meters, Cellular Service, Dedicated Tests	Electric and Energy Consumption, Location, Channel Data

This Table I categorizes big data sources in smart transportation, detailing the associated collection tools and captured data types, including vehicle mobility metrics, travel times, traffic flows, and energy consumption [24].

E. Characteristics of Transportation Big Data

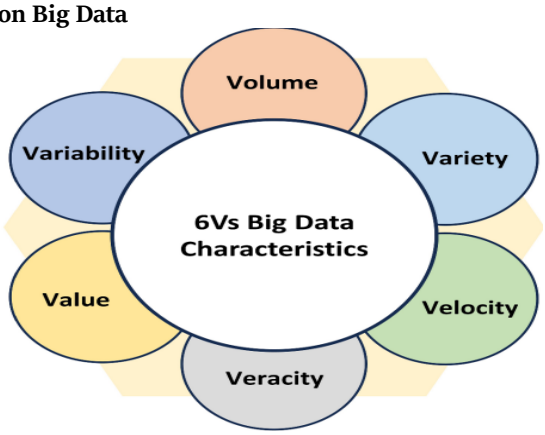


Figure 2: 6Vs Big Data Characteristics in Transportation [26]

Transportation big data is characterized by its large scale, rapid generation, heterogeneous formats, reliability, usefulness, and changing patterns [25]. These attributes shape the processes for collecting, processing, storing and analyzing transportation data, and affect the management of real-time traffic, mobility and safety applications. Fig. 2 shows the base multidimensional characteristics of big data generation, processing and analysis in modern intelligent transportation systems.

- Volume: Refers to the large amount of transportation data generated from vehicles, sensors, cameras, GPS devices, and infrastructure. The number of data instances and features increases the computational and storage requirements.
- Velocity: Indicates the rate of data generation, transmission, and processing for transportation. For dynamic decision-making, incident detection, and real-time traffic monitoring, high-velocity data is crucial.
- Variety: Describes the different forms and formats of transportation data, including structured sensor records, semi-structured IoT data, and unstructured images, videos, and social media content.
- Veracity: Indicates the accuracy, reliability, completeness, and consistency of transportation data. Noise, missing values, errors, and conflicting information from heterogeneous sources can affect analytical results.
- Value: Represents the usefulness of data for extracting meaningful insights and supporting transportation decisions. Its value depends on the quality, relevance, and analytical techniques applied to the data.
- Variability: Reflects changes and fluctuations in transportation data over time and across different conditions. Traffic patterns, weather, demand, and road conditions can cause substantial variations in data distributions and behaviour.

F. Big Data Storage and Processing

Efficient storage and processing are essential for handling the scale, speed, and complexity of transportation big data [27]. Modern architectures combine cloud, edge, distributed, and real-time technologies to support scalable analysis and timely decision-making.

- Cloud-based platforms: Provide scalable storage and computing resources.
- Edge-based processing: Processes data closer to its source for faster responses.
- Distributed computing: Enables parallel processing of large datasets.
- Real-time stream processing: Analyzes continuous data streams for immediate insights.

G. Big Data Quality, Governance, and Accessibility

Ensuring high-quality, well-governed, and accessible data is essential for reliable smart transportation applications [25]. Data quality affects the accuracy of analytics and decision-making, while governance establishes appropriate standards for security, privacy, ownership, and responsible data use [28][29]. Effective accessibility ensures that authorized users and systems can efficiently obtain and utilize transportation data.

- Ensuring accuracy, completeness, consistency, and timeliness of transportation data.
- Establishing data governance policies for ownership, standards, security, and privacy.
- Maintaining interoperability among heterogeneous transportation data sources.
- Providing secure and controlled access to authorized users and systems.
- Addressing missing, noisy, duplicated, and inconsistent data through appropriate preprocessing.
- Supporting transparent and reliable data sharing among transportation stakeholders.

III. BIG DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE FOR TRANSPORTATION SAFETY

Big data analytics transforms large and diverse transportation datasets into meaningful insights for understanding current conditions, identifying problems [30], predicting future events [31][32], and supporting intelligent decision-making, with its analytics approaches as follows:

- Descriptive analytics: Summarizes historical and current transportation data to identify traffic patterns, congestion levels, travel behavior, and system performance.
- Diagnostic analytics: Analyzes transportation data to identify the root causes of congestion, accidents, delays and other transportation related issues.
- Predictive analytics: Applies statistical and machine learning methods to anticipate traffic conditions, accidents, travel demand and potential safety issues.
- Prescriptive analytics: Suggests appropriate action in response to analytical output, such as optimized route, signal timing, traffic control, resource allocation, etc.
- Real-time analytics: Used data generated in real time from sensors, vehicles, cameras, and IoT devices to enable real-time traffic monitoring and response.

A. Big Data-Driven Transportation Safety Applications

Big data analytics supports transportation safety by combining information from vehicles, infrastructure, sensors, cameras, and environmental sources to identify hazards, understand incidents, predict risks, and improve emergency responses [33].

- Accident analysis: Accident trends, causes, locations, severity, and contributing factors from past accidents.
- Accident-risk identification: Identifies locations and conditions with a higher risk of accident using traffic, vehicle, road, weather, and behavioral data.
- Traffic anomaly detection: Identifies abnormal traffic patterns, sudden speed changes, abnormal vehicle movements, unexpected traffic situations etc.
- Road hazard detection: Detects hazards including damaged roads, obstacles, unsafe intersections, poor visibility, and hazardous environmental conditions.
- Driver behaviour analysis: Examines behaviours such as speed and acceleration, braking, lane changing and more to detect unsafe or unusual driving.
- Traffic congestion and incident analysis: Identifies congestion, crashes, road closures, and other traffic disruptions using real-time and historical data.
- Emergency response management: Supports rapid incident detection, emergency vehicle routing, resource allocation, and coordinated responses using real-time transportation data.

B. Artificial Intelligence Techniques for Transportation Safety

Artificial intelligence (AI) techniques provide assistance to transportation safety by processing a massive amount of data, which comes from various data sources such as vehicles, sensors, cameras, mobile devices and communication networks, to name a few [34]. Machine learning detects accident risk factors, forecasts accidents, and analyzes driver behavior, while deep learning captures complex patterns which are used for traffic forecasting, risk assessment, and predicting accidents. Adaptive traffic signals, dynamic routing, congestion management and collision-risk reduction with ongoing decision making all rely on reinforcement learning. Computer vision (CV) is a technology for analyzing images from CCTV and vehicle camera technologies in order to identify vehicles, pedestrians, road hazards, unsafe behavior and accidents. Natural Language Processing (NLP) used to extract safety-related information from incident reports, social media, emergency data, and other unstructured transportation data.

C. Spatiotemporal Big Data Analytics

Transportation data are strongly influenced by geographical location and time-dependent changes. By analyzing both the spatial and temporal dimensions, spatiotemporal analytics can detect hotspots, recurring congestion, traffic fluctuations and changing road conditions. Machine learning and artificial intelligence models may be trained using these patterns to predict traffic flow, identify dangerous spots, and detect emerging safety concerns.

D. Multimodal Data Fusion for Safety Intelligence

Integrating heterogeneous transportation data integration increases the “fidelity” and “meaning” of safety analysis. The information from GPS, CCTV, connected vehicles, road sensors, weather systems and V2X communications can be integrated to give a comprehensive picture of transportation conditions [35]. This integration enables the integration of accident detection, driver behavior analysis, road hazard detection and safety-risk assessment via fusion of data from multiple sources [36].

E. Predictive and Prescriptive Safety Analytics

Predictive analytics uses historical and real-time transportation data with statistical and AI techniques to estimate future traffic and safety conditions. These approaches can identify potential accident risks, forecast congestion, and determine high-risk locations or driving behaviors. Prescriptive analytics extends prediction by recommending appropriate actions for reducing identified risks.

- Accident and risk prediction: Estimates the likelihood and potential severity of safety incidents.
- Traffic forecasting: Predicts congestion, traffic flow, travel demand, and abnormal conditions.
- Risk-based decision-making: Identifies locations, vehicles, and conditions requiring safety interventions.
- Safety recommendations: Supports route adjustment, signal optimization, warnings, and emergency response planning.

F. Real-Time Big Data and AI Analytics

The constant feeds from the IoT, linked cars, CCTV cameras, GPS devices, and V2X networks allow transportation systems to assess situations in real time. AI-powered analytics can quickly identify accidents, unusual traffic, road hazards, and potential collisions. This capability enables immediate incident warning, dynamic traffic management, incident response, and emergency vehicle routing, while minimizing the delay between incident detection and action.

G. Edge AI and Cloud-Based Analytics

The edge-cloud computing paradigm is a powerful paradigm for transportation safety analytics. While cloud platforms allow for centralized processing, model training, historical analysis, and large-scale storage, Edge AI facilitates computational tasks and processes that are time-sensitive or complex, and require analysis to occur near the data sources. This hybrid method can reduce communication latency while ensuring scalability for large transportation datasets.

- Edge processing: Supports low-latency detection of accidents, pedestrians, obstacles, and unsafe driving.
- Cloud processing: Enables large-scale data storage, model training, and long-term transportation analysis.
- Hybrid analytics: Combines rapid local decisions with centralized computational resources.
- Efficient communication: Reduces unnecessary transmission by filtering and processing relevant data at the edge.

IV. INTEGRATED SMART CITY TRANSPORTATION SAFETY FRAMEWORK AND CHALLENGES

The integration of big data and AI into smart transportation faces technical, operational, and governance-related barriers that can affect data reliability, analytical performance, system scalability, and the safe deployment of intelligent transportation solutions.

- Data heterogeneity: Different formats, sources, sensors, and communication technologies complicate data integration and analysis.
- Data quality and incompleteness: Missing, noisy, inconsistent, and duplicated data can reduce analytical reliability.
- Large-scale data management: Increasing data volumes require scalable storage, processing, and efficient data-management architectures.
- Real-time processing and latency: Transportation data is regularly generated and has to be processed and responded to quickly for safety purposes.
- Privacy and cybersecurity: Location, vehicle, and behavioral data require strong protection against unauthorized access, attacks, and misuse.
- Infrastructure and computational requirements: AI and big data applications require substantial computing, storage, network capacity, and energy resources.
- Model generalization: AI models may perform poorly when applied to different cities, road environments, datasets, or traffic conditions.
- Interoperability: Heterogeneous transportation platforms and devices require standardized interfaces, protocols, and data formats.
- Regulatory and ethical issues: AI deployment must address accountability, fairness, transparency, data ownership, privacy regulations, and responsible data use.

A. AI–Big Data Architecture for Transportation Safety

AI–big data architecture for transportation safety connects various data sources (e.g., CCTV, RFID, GPS, IoT sensors) via a well-defined data collection, harmonization, ETL processing, storage, AI analytics, and decision-making pipeline [37]. Scalable NoSQL databases get their inputs from a number of sources, which are transformed into consistent data sets using harmonization and ETL tools. The data sets are then transferred across I/O bandwidth channels. This stored data is then used to generate insights through machine learning and AI analytics, accessible via reporting tools and real-time alerts, enabling proactive transportation safety management.

Fig. 3 illustrates the end-to-end data pipeline, tracking information flow from initial multi-source ingestion (CCTV, RFID, GPS, Sensors) through harmonization, ETL processing, and I/O bandwidth transfer into a centralized NoSQL database before final delivery to reporting and analytics tools.

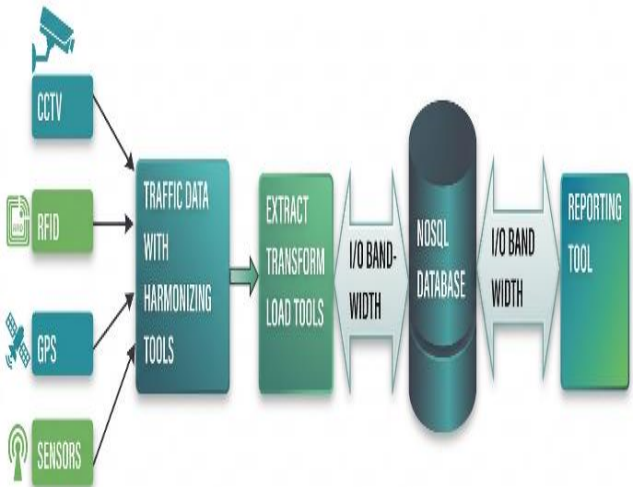


Figure 3: Big Data Architecture for Intelligent Transport System [38]

B. Data-to-Decision Pipeline for Smart Transportation Safety

Safety intelligence is about constantly changing raw transportation data into decisions that can be acted upon. Typical 6 stages of a pipeline are Data Collection, Pre-processing, Integration, Analytics, Prediction, Decision Making. In the pre-processing stage, the missing, noisy, duplicated and inconsistent records are detected and adjusted. Integrated datasets can then be analyzed statistically, with machine learning or deep learning methods, to provide safety indicators and predictions [39]. The data can be used to inform real-time alerts, adaptive traffic management, emergency response, and preventative safety action.

C. Intelligent Decision Support Systems

Advanced decision-support systems connect analytical outputs with transportation management operations, allowing authorities and automated systems to respond to changing safety conditions. These systems can combine real-time and historical data to rank risks, recommend actions, and prioritize incidents according to severity. Key functions include:

- Risk prioritization: Ranking accident-prone locations and high-risk events.
- Route recommendation: Selecting safer and more efficient routes according to current conditions.
- Traffic control: Supporting adaptive signal timing and congestion management.
- Emergency coordination: Assisting incident detection, emergency routing, and resource allocation.
- Safety alerts: Providing timely warnings to drivers, pedestrians, and transportation operators.

D. Privacy and Security of Transportation Big Data

The continuous collection of location, vehicle, behavioral, and communication data creates significant privacy and cybersecurity risks. Transportation data should therefore be protected across 3 key stages:

- Data Collection: Protects GPS, CCTV, vehicle, sensor, and V2X information through data minimization, anonymization, and privacy-aware collection practices.
- Data Transmission: Secures information exchanged between vehicles, infrastructure, edge devices, and cloud platforms using encryption, authentication, and secure communication protocols.
- Data Storage and Access: Protects stored transportation datasets through access control, encryption, authorization, monitoring, and intrusion detection to prevent unauthorized access and data misuse.

E. Data Governance and Ethical Considerations

Effective transportation analytics requires well-defined policy on data collection, sharing, processing, and storage. Governance arrangements should establish the ownership, access to data, quality requirements, retention, security protocols and accountability of transportation agencies, technology vendors and stakeholders. Fairness, transparency and informed data use, algorithmic bias and protection against discriminatory decision-making are also ethical issues. Having audit trails and human oversight can enhance accountability in AI-driven safety-critical transportation decisions.

V. LITERATURE REVIEW

This section reviews recent advancements in intelligent transportation, emphasizing AI, Big Data, IoT, edge computing, and advanced analytics for improving traffic management, accident detection, safety, and sustainable smart-city mobility.

I. Pathak and S. Chatterjee (2026) The goal of this study is to provide a critical analysis of the current state of smart city and sustainable mobility-related intelligent transportation technology trends, applications, problems, and potential solutions. The review was oriented towards emerging themes such as traffic prediction and traffic flow optimization, intelligent traffic signal control, connected vehicles, autonomous vehicles, vehicle-to-everything communication, smart parking, accident prediction, driver behavior analysis, public transportation optimization, intelligent logistics and carbon emission reduction. In addition, the incorporation of the Internet of Things, Edge Computing, Big Data Analytics, Digital Twin technologies, Explainable Artificial Intelligence, Federated Learning, and Generative Artificial Intelligence is broadening the horizons of smart transportation and sustainable urban development [40].

Table 2: Summary of The Study on Smart City Transportation Safety Using AI and Big Data Analytics

Reference	Research Focus	Approach	Key Findings	Challenges and limitations	Future Directions
Pathak and Chatterjee (2026)	Intelligent transportation and sustainable smart-city mobility	Review of AI, IoT, Big Data, Edge Computing, Digital Twins, FL, and GenAI	Identified major applications in traffic management, connected vehicles, accident prediction, and sustainable mobility	Broad coverage with limited focus on integrated transportation safety	Develop integrated, explainable, and adaptive AI-based safety systems
Rathore et al. (2026)	Real-time traffic management using Big Data	Big Data mining, ML, predictive analytics, GPS, surveillance, social media, and sensors	Supports congestion prediction, incident detection, and dynamic traffic control	Heterogeneous data and real-time processing remain challenging	Improve real-time multimodal analytics and predictive incident management
Khanderi et al. (2025)	Real-time data processing for smart cities	ML, Edge Computing, and distributed data storage	Reported improvements in traffic speed, incident response, energy, and public safety	General smart-city focus with limited transportation-safety specialization	Develop scalable edge-AI frameworks for safety-critical applications
Adewopo et al. (2024)	Traffic accident detection using computer vision	Action recognition and integrated multi-source accident dataset	Supports improved accident detection under diverse road and environmental conditions	Limited datasets, weather, illumination, occlusion, and rapid actions affect recognition	Expand diverse datasets and robust real-time accident detection
Zhang et al. (2023)	Big-data-driven public transportation management	Cloud, Big Data, IoT, edge devices, FlinkSQL, and data lineage	Enables large-scale data processing, travel-behavior analysis, and secure data management	Data volume, variety, real-time processing, and data security issues	Improve scalable, secure, and intelligent transportation data platforms
Ang et al. (2022)	Data-driven smart-city transportation	Review of geoinformation, Big Data, ML, DL, and AI approaches	Highlighted the growing role of data analytics and AI in smart transportation	Limited emphasis on integrated accident safety and real-time risk prediction	Combine AI, Big Data, connected data, and real-time safety analytics

R. Rathore et al. (2026) Real-time traffic management using big data mining can address urban challenges such as congestion, road accidents, and environmental degradation. Big data mining enables the processing of large-scale, heterogeneous data from GPS systems, surveillance systems, social media, and sensor networks. Machine learning, predictive modeling, and advanced analytics help identify traffic patterns, predict congestion, and detect potential incidents, supporting real-time signal optimization, dynamic route guidance, and effective incident management [41].

A. Khanderi et al. (2025) A real-time data processing framework was proposed for smart cities using machine learning, edge computing, and distributed data storage to process large-scale data streams. The evaluation reported a 60% increase in

average traffic speed, along with 40% and 53% reductions in congestion and incident response time, respectively. The framework also reduced peak energy load by 16%, waste by 50%, and costs by 25%, while improving crime detection time by 60%, disaster resource efficiency by 28.6%, and public satisfaction by 25.7% [42].

V. Adewopo et al. (2024) The application of advanced technologies in smart cities can improve public safety through effective traffic accident detection. Action recognition supports visual data interpretation and object motion tracking, but its performance is affected by rapid actions, limited datasets, weather, illumination, and occlusions. The study presents a comprehensive traffic accident detection dataset integrating diverse data sources, road networks, weather conditions, and regions worldwide to support computer vision and action recognition systems for accident prediction and detection [43].

T. Zhang et al. (2023), Public transportation's adoption of cloud computing, big data, the IoT, and mobile apps produces massive amounts of complicated data, making efficient real-time data sensing and processing a formidable problem. A data perception platform integrates multiple data systems and edge intelligent devices to collect passenger travel and smart-card transaction data. An efficient field-level data lineage method and row-level fine-grained permission control enable efficient processing, flexible data management, comprehensive data analysis, and secure utilization of large-scale data [44].

K. L.-M. Ang, et al. (2022) The state-of-the-art for SC transportation techniques and approaches. The paper gives a comprehensive review and discussion with a focus on emerging technologies from several information and data-driven perspectives including (1) geoinformation approaches; (2) data analytics approaches; (3) machine learning approaches; (4) integrated deep learning approaches; (5) artificial intelligence (AI) approaches. The paper contains core discussions on the impacts of geo-information on SC transportation, data-driven transportation and big data technology, machine learning approaches for SC transportation, innovative artificial intelligence (AI) approaches for SC transportation, and recent trends revealed by using integrated deep learning towards SC transportation [45].

Based on the reviewed studies, a research gap is that existing approaches largely focus on specific transportation applications such as traffic management, congestion prediction, accident detection, data processing, or public transportation optimization. Limited attention has been given to developing a unified AI- and Big Data-driven framework that integrates heterogeneous traffic, environmental, vehicle, and infrastructure data for real-time accident detection and risk prediction. Furthermore, challenges related to data heterogeneity, limited datasets, real-time processing, scalability, environmental variability, security, and explainability remain insufficiently addressed. These gaps highlight the need for robust and integrated transportation safety solutions for smart cities. Table II summarizes the reviewed studies, approaches, findings, limitations, and future research directions.

VI. CONCLUSION AND FUTURE WORK

A growing number of smart city transportation initiatives are seeing more support from AI, Big Data analytics, the IoT, linked cars, and intelligent transportation systems, all of which present new possibilities to improve the security of urban transportation. In order to provide data-based proactive safety management, the analysis demonstrates that sophisticated analytical techniques in conjunction with heterogeneous transportation data integration might be very promising. AI-based methods assist in accident detection, risk prediction, traffic anomaly identification, driver behavior analysis and real-time safety monitoring, whereas Big Data technologies provide the ability to collect, integrate, store and process a wide range of transportation data at large scale. Edge computing, computer vision, predictive analytics and connected-vehicle technologies were also identified as effective solutions for the reviewed studies to enhance incident response and transportation decision-making. These findings show that smart cities can get a lot out of using AI and Big Data to make their transportation systems safer, more responsive, scalable, and long-lasting.

Future work should emphasize multimodal data fusion, larger and diverse datasets, explainable AI, privacy-preserving analytics, and scalable edge-cloud architectures. Further research should address real-time deployment, cybersecurity, interoperability, environmental robustness, and validation across diverse urban transportation environments.

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