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Artificial intelligence in intelligent transportation systems

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Abstract

Purpose – This article examines the contribution of artificial intelligence to augmenting Intelligent Transportation Systems (ITS) to enhance traffic flow, safety, and sustainability.

Design/methodology/approach – The research investigates using AI technologies in ITS, including machine learning, computer vision, and deep learning. It analyzes case studies on ITS projects in Poznan, Mysore, Austin, New York City, and Beijing to identify essential components, advantages, and obstacles.

Findings – Using AI in Intelligent Transportation Systems has considerable opportunities for enhancing traffic efficiency, minimizing accidents, and fostering sustainable urban growth. Nonetheless, issues like data quality, real-time processing, security, public acceptability, and privacy concerns need resolution.

Originality/value – This article thoroughly examines AI-driven ITS, emphasizing successful applications and pinpointing significant difficulties. It underscores the need for a sustainable economic strategy for extensive adoption and enduring success.

Keywords ITS, AI technologies, Transportation system, Traffic management system

Paper type Literature review

1. Introduction

The growing demand for mobility has led to increased congestion, safety concerns, and environmental pollution in transportation infrastructure (Narayanaswami, 2023). Traditional systems needed more effective information management and real-time decision-making tools. The evolution of information and communication technology (ICT) and the Internet of Things (IoT) has enabled the development of Intelligent Transportation Systems (ITS), which integrate communication, sensing, and control technologies to improve efficiency and safety (Boukerche *et al.*, 2020). ITS uses technologies like sensors, cameras, GPS devices, and wireless communication networks to collect and analyze real-time traffic data, which is then used to optimize traffic flow and improve safety through applications like Advanced Traffic Management Systems (ATMS), Advanced Traveler Information Systems (ATIS), and Advanced Vehicle Control Systems (AVCS).

AI has been a transformative force in transportation systems, significantly enhancing efficiency. It has revolutionized transportation efficiency through data processing and analytics, predictive modeling, autonomous vehicles, traffic simulation and optimization, and personalized travel recommendations (Iyer, 2021). AI algorithms can analyze vast amounts of data from various sources, identify patterns, predict traffic flow, and optimize traffic management strategies. Autonomous vehicles, guided by AI algorithms, understand their surroundings, make decisions, and navigate efficiently. Traffic simulation models, a product of

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AI, accurately represent real-world traffic conditions, allowing testing and optimization of traffic management strategies. The role of AI in transforming transportation systems is significant, and its impact is felt across various aspects of the field (Nikitas *et al.*, 2020).

However, Intelligent Transportation Systems face challenges such as data quality, real-time processing requirements, complexity, computational costs, security vulnerabilities, public acceptance and privacy concerns, and data security (Oladimeji *et al.*, 2023). AI algorithms rely on high-quality data for accurate predictions, but inconsistency can hinder real-time bus arrival predictions. Real-time processing requires efficient algorithms, but computational resources can be limited in resource-constrained environments. Security vulnerabilities, public acceptance, and privacy concerns arise from AI's use, necessitating transparent data governance policies and robust security measures (Englund *et al.*, 2021; Lamssaggad *et al.*, 2021).

Previous studies on the role of Artificial Intelligence in transportation systems focus on specific AI technologies, such as computer vision (Dilek and Dener, 2023), Deep reinforcement learning (Haydari and Yılmaz, 2020), and natural language processing (Mehri, 2022), or a case study related to a country, such as (Greer *et al.*, 2018; John *et al.*, 2019; Domańska and Malik, 2024), or a category of countries, such as developing countries (Diderot *et al.*, 2023). This study attempts to cover the role of the most popular AI technologies in ITS and several case studies related to different backgrounds.

This paper aims to answer the following questions:

(1) How has AI transformed Intelligent Transportation Systems, and what are the key benefits and challenges?

(2) What are the key differences between ITS and traditional transportation systems?

(3) What are the main components of a typical ITS architecture, and how do they interact with each other?

(4) What are the key takeaways from the real-world case studies reported in the literature, particularly regarding the effectiveness and limitations of AI in ITS?

The paper explores the rise of Intelligent Transportation Systems as a solution to the increasing demand for mobility and the limitations of traditional transportation systems. It highlights the transformative role of AI in enhancing efficiency through data processing, predictive modeling, autonomous vehicles, and personalized recommendations. The study also discusses the use cases of non-AI and AI technologies in ITS, highlighting the data-driven, proactive, interconnected, and user-centric nature of ITS. It also discusses the typical architecture of ITS, including data collection, data analytics, and application layers.

The study presents five real-world implementations of ITS, focusing on AI algorithms for optimizing traffic flow, improving public transport efficiency, and improving safety and security. The study advocates for a multi-stakeholder approach, addressing data privacy concerns and proposing solutions such as investing in accurate sensors, developing robust AI algorithms, utilizing cloud-based solutions, enhancing cybersecurity, and promoting transparent data governance.

2. ITS technologies

Non-AI technologies in ITS are mainly collection and communication technologies, such as:

(1) Traffic Sensing Technologies include fixed sensor-based techniques (e.g. inductive loop detectors, video cameras) and probe vehicle-based techniques (e.g. GPS and accelerometers in vehicles). These technologies offer primary data regarding traffic conditions but do not necessarily incorporate AI for decision-making.

(2) Communication Technologies: This comprises various wired and wireless communication systems, including the internet, cellular networks (3 G/4 G/5G), and dedicated short-range communications (DSRC), which facilitate data transmission between traffic management centers, infrastructure, and vehicles. These technologies facilitate data transmission but do not inherently entail AI for data processing or decision-making (Zhang and Lu, 2020).

(3) Traffic Signal Controllers: These systems can optimize traffic flow but frequently depend on pre-programmed logic and timing plans rather than AI-based adaptive control.

(4) Traveler Information Systems, including dynamic message signs (DMS), in-vehicle navigation systems, and real-time traffic information accessible through websites or mobile applications, disseminate information to travelers. These systems may not necessarily employ AI for personalized recommendations or predictive analysis, but they disseminate information.

(5) Electronic toll collection systems are an application of pricing and revenue management in ITS. These systems collect tolls without necessitating that vehicles halt, utilizing RFID technology or other automated payment methods. Although efficient, they do not inherently involve AI in the decision-making process.

In contrast, AI technologies (see Table 1) are dedicated to data analysis, optimization, and prediction. They are increasingly used in intelligent transportation systems for various applications (Suryadithia *et al*., 2021). These include predictive analysis for traffic flow, which uses big data and machine learning models to predict future traffic patterns. AI can also be used for public transport optimization, optimizing bus routes, schedules, and frequencies based on real-time passenger demand and traffic conditions. AI-powered systems can also be used for predictive maintenance, refining maintenance schedules, and anticipating potential vehicle failures. Adaptive traffic signal control involves using AI algorithms to dynamically adjust traffic signal timings based on real-time traffic flow and congestion levels. AI algorithms can provide real-time navigation guidance to drivers, recommending optimal routes based on current traffic conditions and minimizing travel times. Finally, fully automated vehicles (AVs) are a potential application of Connected Vehicles (CV) technology, relying heavily on AI technologies for autonomous operation and perception of their environment (Boukerche *et al*., 2020; Haydari and Yılmaz, 2020).

It is crucial to acknowledge that the distinction between AI and non-AI technologies in ITS can be imprecise. Specific systems may combine components of both. As an illustration, a traffic signal control system may employ non-AI logic for its fundamental operation. Still, it may incorporate AI algorithms to facilitate adaptive optimization by analyzing real-time traffic data. As AI technologies continue to develop, we can anticipate a more comprehensive assimilation of AI into various facets of ITS, resulting in safer, more efficient, and intelligent transportation systems (Oladimeji *et al*., 2023).

3. Traditional transportation systems versus intelligent transportation systems

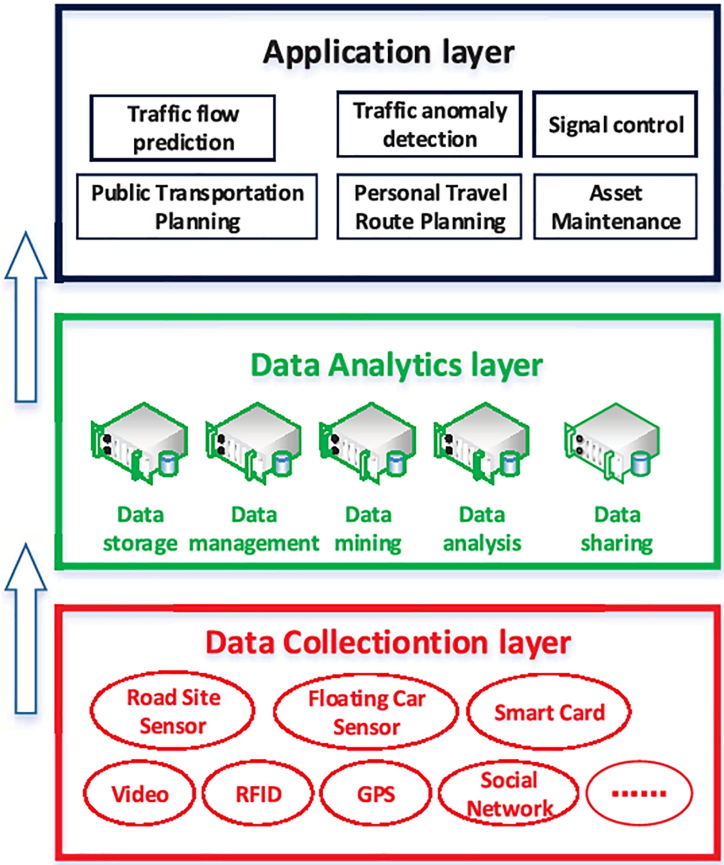
Traditional traffic management systems have limited sensors and data collection limitations, centralized control with fixed logic, static information dissemination through signage, printed maps, schedules, and radio broadcasts, limited communication between components, and often operating as stand-alone systems with limited data sharing and coordination.

These systems rely on basic sensors for traffic volume counts and limited CCTV camera deployments, relying on pre-programmed signals that do not adapt to real-time traffic conditions. Additionally, communication between components is primarily one-way, with limited connectivity between vehicles and infrastructure (Iyer, 2021; Chung, 2021).

Table 1. AI technologies and uses cases

AI technology	Use cases
Machine Learning (ML): Comprising diverse techniques that enable computers to learn from data. Supervised learning algorithms acquire knowledge from labeled data, demonstrating proficiency in forecasting traffic conditions and improving traffic light management. In contrast, unsupervised learning algorithms reveal hidden patterns in unlabeled data, facilitating the identification of traffic congestion hotspots and predicting possible incident sites. Notable applications include K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Linear Regression (LR), and Recurrent Neural Network (RNN) for supervised learning, with k-means clustering and principal component analysis (PCA) for unsupervised learning (Gangwani and Gangwani, 2021)	• Traffic Prediction: Analyzing historical and real-time data to forecast future traffic patterns • Incident Detection: Identifying anomalies in traffic patterns to detect accidents or road hazards • Adaptive Traffic Signal Control: Optimizing signal timings based on real-time traffic conditions
Computer vision employs artificial intelligence to allow computers to see and analyze images and videos. This facilitates the creation of advanced driver assistance systems (ADAS) that may aid in accident prevention. Computer vision can recognize pedestrians, bicycles, and other cars on the road. It may be used to assess the driver's attention and provide alerts if the driver is distracted. Computer vision may be used to create autonomous cars capable of operating independently without human involvement (Dilek and Dener, 2023)	• Vehicle Detection and Tracking: Video cameras identify and track vehicles in real time • License Plate Recognition: Automatically recognizing license plates for toll collection and law enforcement • Pedestrian Detection: Detecting pedestrians to improve safety, especially for autonomous vehicles
Natural Language Processing (NLP): NLP is a domain within artificial intelligence that facilitates computer comprehension and manipulation of human language. NLP may enhance communication between drivers and ITS, including voice-activated navigation systems and traffic information services. It may also examine social media data to identify traffic incidents and other transportation-related occurrences In the context of the Metaverse, a virtual world existing alongside the physical realm, NLP might facilitate the creation of virtual assistants to aid drivers in navigation, locating parking, and reserving transportation services (Mehri, 2022)	• Voice-Controlled Navigation: Allowing drivers to interact with navigation systems using voice commands • Real-time Traffic Information: Providing spoken updates on traffic conditions
Deep Learning (DL): Utilizing deep neural networks, deep learning is an advanced branch of machine learning that proficiently identifies complex patterns in data. In Intelligent Transportation Systems, Deep Learning techniques facilitate applications like object identification for autonomous driving, traffic flow prediction for congestion management, and real-time decision-making for traffic signal control. (Veres and Moussa, 2019)	• Autonomous Vehicles: Enabling self-driving cars to perceive their environment and make decisions • Advanced Driver Assistance Systems (ADAS): Enhancing safety features like lane departure warning and automatic emergency braking
Reinforcement Learning (RL): RL allows an agent to acquire optimum behaviors by engaging with an environment. In Intelligent Transportation Systems, Reinforcement Learning is essential for creating intelligent agents capable of adaptively managing traffic signals based on real-time traffic conditions or safely and effectively guiding autonomous cars (Haydari and Yılmaz, 2020)	• Optimal Traffic Signal Control: Learning optimal signal timings through trial and error and reinforcement • Autonomous Vehicle Control: Training autonomous vehicles to make decisions in complex traffic scenarios

Source(s): Author's own work



Source(s): Figure of Zhan *et al.* (2018)

Figure 1. ITS Architecture core layers

According to (Zhu *et al.*, 2018), the Core Components of ITS Architecture are (Figure 1):

(1) Data Collection Layer: This layer forms the foundation of ITS and is responsible for capturing real-time data from various sources using sensors and communication technologies.

- *Roadside Sensors:* Inductive loop detectors, video cameras, radar sensors, and weather sensors installed along roadways collect data on traffic volume, speed, density, incidents, and environmental conditions.
- *Floating Car Data:* GPS-enabled vehicle devices, including smartphones and dedicated navigation systems, provide data on vehicle location, speed, and travel time.
- *Other Sources:* Data from smart cards, RFID systems, social media, and other relevant platforms contribute to a comprehensive understanding of transportation dynamics.

(2) *Data Analytics Layer:* This layer processes the raw data collected from various sources, transforming it into meaningful information for analysis and decision-making.

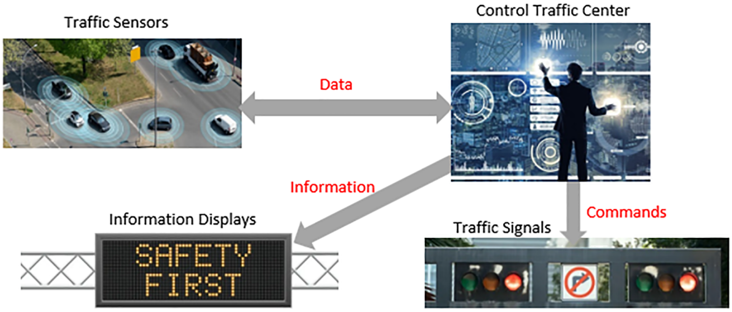
- *Data Storage and Management:* Efficient data storage and management systems are crucial for handling the vast amounts of ITS-generated data.
- *Data Mining and Analysis:* AI algorithms, particularly machine learning techniques, identify patterns, predict future traffic conditions, and optimize system performance.
- *Data Sharing and Dissemination:* Processed data is shared with relevant stakeholders, including transportation agencies, traffic managers, and travelers, through various communication channels.

(3) Application Layer: This layer leverages the processed data to provide various ITS applications and services, enhancing traffic management, traveler information, safety, and overall system efficiency.

- *Traffic Flow Prediction:* Predicting future traffic conditions based on historical data and real-time inputs allows for proactive traffic management strategies.
- *Traffic Guidance and Routing:* Providing travelers real-time traffic updates and personalized route guidance helps optimize travel time and reduce congestion.
- *Adaptive Traffic Signal Control:* Dynamically adjusting traffic signal timings based on real-time traffic flow improves traffic throughput and reduces delays.
- *Public Transport Planning:* Optimizing bus routes, schedules, and frequencies based on real-time passenger demand enhances the efficiency and reliability of public transportation.
- *Incident Management:* Rapidly detect and respond to incidents using real-time sensors and communication systems data, minimize disruptions, and improve safety.
- *Emergency Management Systems (EMS):* Real-time communication and coordination between emergency responders and traffic management centers facilitate faster response times and improve emergency safety.

Links and Interactions between layers are: (1) *Robust Communication Networks:* Communication technologies, including DSRC, cellular networks, and fiber optic cables, establish seamless connectivity between various components of ITS, facilitating real-time data flow and enabling intelligent interactions. (2) *Integration with Infrastructure:* ITS components are integrated with existing transportation infrastructure, such as traffic signals, variable message signs, and road sensors, to enable dynamic control and information dissemination. (3) *User Interfaces:* User-friendly interfaces, including in-vehicle navigation systems, mobile apps, and web portals, provide travelers with real-time information, personalized guidance, and other ITS services (Nikitas *et al.*, 2020).

Nevertheless, the effectiveness of AI in ITS relies on the quality and availability of data from non-AI technologies (as illustrated by Figure 2). AI algorithms in ITS rely on real-time traffic data to make accurate predictions and optimize signal timings. Integrating AI and non-AI technologies in ITS will lead to more sophisticated and efficient transportation systems as AI technologies advance (see Table 2).



Source(s): Author’s own work

Figure 2. ITS information exchange

The significant distinctions between traditional transportation systems and ITS are:

(1) ITS are data-driven: They optimize system performance by continuously collecting and analyzing enormous quantities of data.

(2) ITS are proactive: They employ AI and predictive analytics to forecast prospective issues and implement preemptive measures.

(3) Intelligent transportation systems are interconnected: They utilize communication technologies to facilitate the seamless data exchange between users, infrastructure, and vehicles.

(4) ITS are user-centric. They prioritize providing travelers personalized guidance and real-time information to improve their travel experience.

We can anticipate that ITS will play a more significant role in shaping the future of transportation as AI and other technologies continue to advance, resulting in safer, more efficient, and more sustainable mobility solutions (Englund *et al.*, 2021).

4. Case studies

This section presents real-world case studies describing the key components of implemented ITS and the reported benefits (Narayanaswami, 2023). The following section will discuss lessons learned from the case studies.

Case study 1: Poznan, Poland: The ITS Poznan project aimed to create an integrated intelligent traffic management system for the city. Key elements included:

(1) A “black box” device that enhanced traffic-responsive control, enabled central control, and allowed network optimization.

(2) Traffic light control systems were replaced and updated.

(3) The project also involved the implementation of an IT platform to facilitate data exchange and information sharing between system components.

(4) The system leverages real-time traffic data from measuring stations, allowing users to access information on traffic conditions and public transport arrival/departure times.

(5) Software was developed to enable buffer car park bookings and automatic incident detection.

Table 2. Highlights the key differences between ITS and Traditional Transportation Systems

Feature	ITS	Traditional transportation systems (without AI)
Data Collection	Employs various sensors (e.g. loop detectors, cameras, GPS, accelerometers), communication technologies (e.g. DSRC, cellular networks), and data collection systems (e.g. AVL, *APC*) to gather real-time data on traffic conditions, vehicle locationetc.	It relies primarily on manual data collection methods, periodic surveys, and limited sensor deployments, which results in less frequent and less comprehensive data on traffic conditions
Data Analysis	Utilizes AI technologies (e.g. machine learning, predictive analytics) to process and analyze real-time and historical data, extracting insights, predicting future traffic patterns, and optimizing system performance	Data analysis is often limited to basic statistical methods and historical trend analysis. Real-time data analysis and predictive capabilities are minimal
Traffic Management	Employs adaptive traffic signal control, dynamic vehicle routing, and other AI-powered strategies to optimize traffic flow, reduce congestion, and improve travel time reliability	Relies on fixed-time traffic signals, pre-determined routing plans, and manual traffic management interventions, leading to less responsive and inefficient traffic control
Traveler Information	Provides real-time traffic updates, personalized route guidance, and predictive information through various channels (e.g. DMS, in-vehicle navigation, mobile apps), enabling travelers to make informed decisions and optimize their journeys	Traveler information is typically limited to static signage, radio broadcasts, and pre-trip planning tools. Real-time information and personalized guidance are only sometimes readily available
Safety and Security	Incorporates advanced safety features (e.g. collision avoidance systems, lane departure warnings) and security measures (e.g. vehicle authentication, data encryption), leveraging AI and connectivity to enhance safety and prevent potential threats (Lv *et al*., 2020)	Safety features are primarily passive (e.g. seatbelts and airbags), and security measures are often reactive. Real-time threat detection and proactive safety interventions are limited
Efficiency and Sustainability	It aims to improve transportation efficiency and sustainability by optimizing traffic flow, reducing congestion and emissions, and promoting eco-friendly transportation modes. AI and connectivity play a key role in achieving these goals	Infrastructure expansion and traffic management strategies often address efficiency and sustainability. However, the integration of technology to optimize these aspects could be improved
Examples	Smart traffic signals, connected vehicles, real-time traffic monitoring and prediction systems, dynamic pricing and tolling, autonomous vehicles, public transport optimization systems	Fixed-time traffic signals, traditional road signage, manual toll collection booths, printed maps and schedules, and conventional public transport systems

Source(s): Author's own work

The Poznan ITS Poznan project uses AI algorithms to optimize traffic flow based on real-time data from measuring stations. This involves reinforcement learning or evolutionary algorithms to dynamically adjust traffic light timings and network configurations. The project has been reported to reduce travel times, resulting in lower costs and shorter travel times for users. The system also improves traffic flow by providing real-time data from measuring stations, helping users plan journeys through the city. Measurable KPIs for this improvement include average vehicle speed, congestion reduction, and decreased travel time index. However, the success of the "black box" device depends on the quality and completeness of data received from measuring stations. If the data is noisy, incomplete, or delayed, the AI algorithms may make suboptimal decisions, decreasing efficiency (Domańska and Malik, 2024; Brzeziński and Koliński, 2023).

Case study 2: Mysore, India: The implementation of ITS in Mysore, India, focused on enhancing the efficiency and user experience of the bus transport system. The system includes:

(1) A vehicle tracking and real-time passenger information systems rely on GPS and a vehicle-mounted unit (VMU).

(2) The VMU transmits location data to a central server via GPRS.

(3) Electronic display systems at bus stops provide real-time arrival and departure information in both Kannada and English.

(4) A two-way voice communication facility connects bus drivers and the central control station.

(5) Other technologies employed include wireless communication, sensing technologies, inductive loop detection, video vehicle detection, and electronic toll collection.

The Mysore ITS project uses GPS data to provide real-time passenger information, which is then analyzed and predicted using AI algorithms. This technology can employ machine learning techniques like regression analysis or time series forecasting. The benefits of the Mysore ITS project include increased punctuality and reliability, reduced delays, and enhanced commuter satisfaction. The AI-driven prediction of arrival times and real-time passenger information helps manage transit variability and improve the reliability of vehicle arrival times. Key performance indicators (KPIs) include the percentage of buses arriving on time and the average deviation from scheduled arrival times. The project also enhances commuter satisfaction by minimizing delays and strengthening the system's reliability. However, the accuracy of bus arrival predictions in Mysore depends on the reliability of GPS data and the ability of AI algorithms to account for unpredictable factors like traffic congestion or delays. Inaccurate predictions could lead to frustration and decreased system reliability (John *et al.*, 2019; Chepuri *et al.*, 2019).

Case study 3: Austin, Texas: This case discusses how the Texas Department of Transportation (TxDOT) has used ITS to manage traffic congestion in Austin. The system includes:

(1) Traffic monitoring via an Operations Control Center that leverages loop detectors, surveillance cameras, and calibrated cameras.

(2) A coordinated signal system with semi-actuated control strategies on major roads.

(3) Proposed technologies include advanced traffic detection, coordinated signal control, dynamic vehicle routing, and traveler information dissemination systems.

(4) Dynamic message signs (DMS) and radio broadcasting systems to communicate traffic information to travelers.

The dynamic vehicle routing system proposed for Austin aims to optimize vehicle routes based on real-time traffic data analysis. Implementing this system would require sophisticated AI algorithms, possibly graph search algorithms like Dijkstra's algorithm or one of its variants, A* search (an informed best-first search algorithm that efficiently determines the lowest cost path between any two nodes in a directed weighted graph with non-negative edge weights), combined with predictive modeling based on real-time traffic conditions. The proposed benefits of implementing AI-powered technologies in Austin's ITS include reduced travel times, decreased fuel consumption, and reduced air pollution. The system would optimize routes based on real-time traffic conditions, minimizing idling and optimizing traffic flow. Key performance indicators (KPIs) could include average fuel consumption per vehicle or total fuel consumption across the transportation network. However, the system's effectiveness depends on its ability to adapt to rapidly changing traffic conditions (Salinas, 2019; Sepulveda, 2020).

Case study 4: New York City, New York: This case explains how ITS is being used to improve safety and security in New York City. Technologies mentioned include:

(1) Smart cards for public transportation payments.

(2) Biometrics include retinal or iris scanning, fingerprints, and facial recognition.

(3) Automatic vehicle identification.

(4) Map databases for traffic and incident analysis.

(5) Vehicle classification sensors.

(6) Security-focused technologies in bus transit systems, including two-way radios, video surveillance, cab enclosures, and security personnel.

(7) Weigh-in-motion technology to monitor truck weights.

(8) Spatial geo-location for vehicle tracking.

(9) Automated signal systems, signal priority systems, moveable lane barriers, variable message signs, automated incident detection systems, mayday systems, and public safety response systems.

(10) Automated vehicle location (AVL) systems.

(11) Advanced traffic management systems.

(12) Universal transponders on commercial vehicles.

(13) License plate-reading technologies.

(14) Wireless enhanced.

(15) Real-time interoperable communications links between transportation and public safety agencies.

New York City's map databases for traffic and incident analysis likely use AI techniques to identify traffic patterns and anomalies, potentially indicating security threats. These technologies, including clustering and anomaly detection algorithms, enhance safety and security, particularly in response to the 9/11 attacks. Measurable KPIs for these benefits include the number of accidents or security incidents, response times, and the effectiveness of security measures. Improved traffic flow is another area where AI-related technologies, including advanced traffic management and automated signal systems, are used. KPIs for improved traffic flow include the average speed of vehicles, traffic volume through specific corridors, and congestion reduction. However, using AI in security applications raises concerns about potential algorithm biases and the risk of false positives or negatives. If AI systems are not carefully designed and tested, they may disproportionately target specific groups or fail to identify legitimate security threats, undermining their effectiveness and potentially eroding public trust.

Case study 5: Chinese cities like Beijing and Shenzhen are at the forefront of Intelligent Transportation Systems development. Beijing has identified experimental routes for testing autonomous cars, while Shenzhen has initiated driverless bus trials. Worldwide, enterprises such as Didi Chuxing in China are creating intelligent commuting platforms that use big data and artificial intelligence to enhance ride-hailing services. ITS are made up of several interconnected components:

(1) Smart cars equipped with sensors and communication capabilities to enable features like autonomous driving and real-time traffic information. Unmanned aerial vehicles can be used for traffic monitoring and delivery services.

(2) Smart infrastructure includes sensors embedded in roads and traffic signals to collect data on traffic flow.

(3) Smart base stations facilitate communication between the various components of the system.

(4) Information and Communications Technology includes IoT, big data, cloud computing, mobile internet, and AI.

(5) Developmental Mechanisms, rules, regulations, and policies governing ITS operations, such as traffic regulations for autonomous vehicles, data privacy policies, and the operation of sharing economy platforms

ITS can reduce traffic congestion by optimizing flow and providing real-time information, improving safety through collision avoidance systems, and promoting sustainable transportation through public transport, electric vehicles, and ride-sharing services, reducing emissions and energy consumption.

However, ITS implementation faces challenges such as underdevelopment, a need for comprehensive regulations for autonomous vehicles and data privacy, and public acceptance of technologies like autonomous vehicles. Further research and innovation are needed to improve reliability and safety, while clear legal frameworks are needed to ensure citizen safety (Huang *et al*., 2017; Yan *et al*., 2020).

The case studies propose several key performance indicators (KPIs) to assess the effectiveness of ITS in improving traffic flow, reducing congestion, and ensuring reliability and efficiency. These KPIs include Average Vehicle Speed, Congestion Reduction, Travel Time Index, Percentage of Buses Arriving On Time, Average Deviation From Scheduled Arrival Times, Fuel Consumption per Vehicle, Number of Accidents or Security Incidents, Response Times, and Traffic Volume Through Specific Corridors. The sources also emphasize the importance of considering societal benefits alongside quantifiable metrics, such as reduced congestion, improved safety, and environmental benefits, and addressing data privacy, security, and transparency concerns to build relationship capital and user trust.

From the case studies, we can deduce that ITS can improve travel times, traffic flow, and safety but faces challenges like data quality, real-time processing requirements, complexity, and computational costs. Security vulnerabilities arise from reliance on AI and interconnected systems, and transparency is crucial for responsible AI implementation. To overcome these challenges, a multifaceted approach includes investing in data collection technologies, developing efficient AI algorithms, prioritizing cybersecurity, and fostering transparent data governance policies (Ganin *et al*., 2019; Greer *et al*., 2018).

5. Discussion

ITS requires significant upfront investment for infrastructure development, technology deployment, and system integration. Its long returns period, including reduced congestion, improved safety, and environmental benefits, makes it challenging to demonstrate immediate financial returns. Additionally, quantifying societal benefits financially takes more work for institutions and companies. For this, it is crucial to establish a sustainable business model for ITS to ensure widespread adoption and long-term success. Relying solely on public funding is not feasible and advocates for a multi-stakeholder approach involving public and private sector entities. The case studies recommend a shift from public funding to a multi-stakeholder approach, emphasizing the importance of creating value for all stakeholders, including users, service providers, technology companies, government agencies, and society. It also emphasizes relationship capital and user trust by addressing data privacy, security, and transparency concerns. The model also explores dynamic pricing and revenue management strategies, such as congestion charging and electronic toll collection.

Diderot *et al*. (2023) emphasize the obstacles developing countries encounter when implementing ITS, including the absence of preexisting infrastructure and distinctive local contexts. Nevertheless, despite these obstacles, there are opportunities to customize sophisticated technologies from developed nations to meet specific requirements. More specifically, addressing local context requires using edge computing and fog computing technologies to process data locally and train AI models tailored to local contexts. Leveraging the Metaverse for training and simulation can accelerate the development and implementation of ITS solutions while reducing dependence on expensive physical infrastructure. The key is prioritizing solutions by leveraging existing resources, utilizing readily available technologies, and incorporating local knowledge to customize solutions effectively.

Implementing ITS faces several challenges, including data quality and consistency, real-time processing requirements, complexity, and computational costs, security vulnerabilities, public acceptance and privacy concerns, and data security. AI algorithms heavily rely on high-quality, consistent data for accurate predictions and effective decision-making, which can be inconsistent or incomplete in ITS applications. This can pose a significant challenge where real-time bus arrival predictions depend on GPS data accuracy.

Real-time processing is crucial for ITS applications, particularly dynamic vehicle routing and traffic flow optimization. AI algorithms dealing with complex computations and large datasets must be optimized for speed and efficiency to meet these demands. Implementing sophisticated AI algorithms for ITS can require significant computational resources and expertise, which can be challenging in resource-constrained environments or agencies with limited budgets.

Security vulnerabilities are another significant concern in ITS, as AI systems are susceptible to security breaches and malicious attacks. Ensuring the security and integrity of AI-powered ITS is crucial for maintaining safety and public trust.

Public acceptance and privacy concerns arise from using AI in ITS, as it often involves collecting and analyzing personal data, such as location information and travel patterns. Addressing these concerns through transparent data governance policies and robust security measures is crucial for successful AI implementation in ITS.

Investing in accurate and reliable sensors for ITS projects to address data quality issues is crucial. Advanced sensors, such as GNSS (Global Navigation Satellite System receivers) receivers, IMUs (Inertial Measurement Units), cameras, RADAR, and LiDAR (Light Detection and Ranging), contribute to a richer and more reliable dataset, which can significantly improve the accuracy and completeness of ITS data.

Data validation and cleaning techniques are crucial for ensuring the quality of collected data. These techniques include data preprocessing, validation, cleaning, and developing robust AI algorithms. Data preprocessing involves cleaning duplicated data, removing unnecessary parts from images, and applying data augmentation techniques to increase the size and diversity of the dataset. Data validation helps identify and flag inconsistencies, errors, and outliers in the dataset, preventing erroneous data from entering the ITS system. Data cleaning techniques focus on rectifying identified errors and inconsistencies, including removing duplicate records, correcting data entry mistakes, and handling missing values. Data imputation techniques replace missing values with estimated values based on statistical methods or machine learning algorithms, ensuring the completeness of the dataset.

Robust AI algorithms are designed to handle imperfections in data without significantly compromising the accuracy of their predictions or decisions. These algorithms employ techniques to identify and mitigate the impact of the dataset's noise, outliers, and missing values. Standard techniques include data imputation, outlier detection, regularization, ensemble methods, and cloud and fog computing.

Data imputation techniques fill in missing values using various statistical or machine learning methods, while outlier detection algorithms identify data points that deviate significantly from the expected pattern. Regularization techniques prevent overfitting, a phenomenon where the model becomes too sensitive to noise in the training data and performs poorly on unseen data. Ensemble methods combine multiple AI models to improve prediction accuracy and robustness by averaging the predictions of different models, leading to more stable and reliable predictions.

It is crucial to emphasize the importance of real-time processing in ITS and how optimizing AI algorithms, edge computing, and data prioritization can improve response times and system safety. Proactive methods, such as AI-based traffic flow prediction, prevent congestion and improve overall efficiency. However, these methods require real-time data analysis and decision-making capabilities.

Model compression techniques reduce the size and complexity of AI models without significant loss of accuracy, making them suitable for real-time applications on devices with limited processing power. Parallel processing divides computational tasks into smaller units that can be executed simultaneously on multiple processing cores, significantly reducing computation time. Techniques like multi-threading and distributed computing are employed for parallel processing.

Edge computing can enhance real-time reliability in ITS by processing data from vehicles at the network's edge, reducing transmission and communication costs and allowing for quicker decision-making. This localized processing is particularly beneficial for applications that require immediate responses, like autonomous driving, where delays can pose safety risks. An edge node with an AI model can process data from a vehicle's sensors to detect potential collisions and trigger safety mechanisms in real-time.

Prioritizing key data for real-time processing ensures that the most critical information is processed quickly, enabling timely responses. For example, data from sensors detecting obstacles near the vehicle in autonomous driving should be prioritized for processing. Prioritization can be achieved through various mechanisms, such as assigning different priority levels to data streams, using queuing systems that prioritize high-priority tasks, or employing algorithms that focus on processing the most relevant data first.

Data freshness is another crucial factor to consider for real-time processing in ITS. Real-time data loses its value quickly as the traffic situation evolves, so it is essential to have mechanisms that ensure the data used for decision-making is up-to-date. By combining these techniques, ITS can leverage real-time data and AI capabilities to enhance traffic flow, improve safety, and optimize transportation systems for a smarter, more efficient future.

Cloud computing is a promising solution for ITS that provides a scalable, flexible, and cost-effective platform for data management, AI development, and resource sharing. It offers numerous benefits, including reduced hardware investment, simplified AI model deployment, enhanced scalability and flexibility, secure and scalable data storage and management, collaboration and resource sharing among stakeholders, and integration of fog computing. It eliminates the need for organizations to invest in expensive hardware infrastructure, making it ideal for applications that require significant computational power, such as real-time traffic simulation, large-scale data analysis, and training complex AI models. Cloud platforms facilitate the development and deployment of simplified AI models tailored for specific tasks in ITS, reducing computational costs and enabling more efficient utilization of available resources. Moreover, cloud computing offers scalability, allowing ITS systems to adapt to fluctuating demands during peak traffic hours or special events. This scalability ensures smooth operation and avoids performance bottlenecks. Fog computing complements cloud computing by extending computing capabilities to the network's edge, enabling real-time data processing and decision-making closer to the data source. In ITS, fog nodes can be deployed at traffic intersections, roadside units, or within vehicles to process data locally and reduce the latency associated with sending data to the cloud (Suryadithia *et al.*, 2021).

Security vulnerabilities in ITS include implementing robust cybersecurity measures, developing secure AI algorithms, regularly updating and patching systems, and addressing public acceptance and privacy concerns. Transparency and public engagement are essential to address privacy concerns. ITS agencies should proactively communicate with the public about how AI is used, what data is collected, and how privacy is protected.

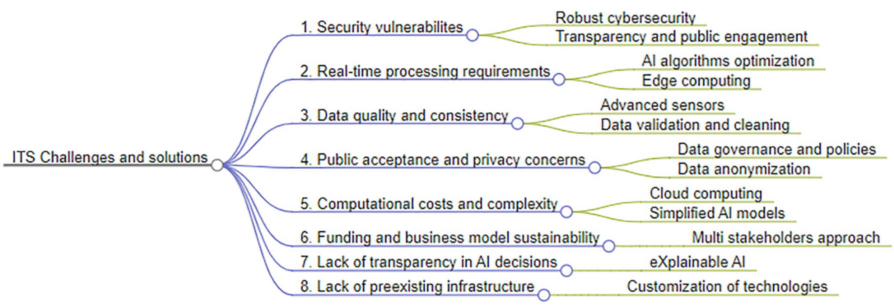
Data anonymization and privacy-preserving techniques can be implemented to enhance privacy. Pseudonym-based privacy schemes in VANETs can protect personal information. Privacy-preserving AI algorithms could be developed to analyze data without compromising individual privacy.

Establishing clear data governance policies is also essential for ITS projects. Comprehensive data governance policies should outline how data is collected, stored, used, and shared, prioritizing privacy protection and complying with relevant regulations. By addressing these challenges effectively, ITS projects can harness the power of AI to improve safety, efficiency, and sustainability in transportation systems while maintaining public trust and protecting privacy.

Advancements in AI, communication technologies, and sensor capabilities drive the development of ITS. These technologies will lead to increased automation in traffic management systems, including intelligent traffic control systems and self-driving vehicles. ITS will also offer personalized services, optimize payment options, and improve safety and security by integrating advanced features. Additionally, ITS will promote sustainable transportation by optimizing traffic flow, reducing emissions, and promoting eco-friendly modes. These advancements aim to enhance the overall efficiency and safety of transportation.

Due to the increasing complexity of AI systems, intense learning models, and the need for transparency and accountability in critical applications, eXplainable AI (XAI) has emerged (Xu *et al.*, 2019); it refers to the development of AI systems that can provide clear and understandable explanations for their decisions and actions.

The authors (Gaur and Sahoo, 2022) argue that XAI can significantly improve the development and deployment of ITS by improving transparency, trust, and performance. Benefits include enhanced safety and reliability, improved system performance, optimized traffic flow and resource allocation, and personalized services. However, challenges include the complexity of transportation systems, real-time requirements, data privacy, security concerns, and the need for standardized metrics and evaluation methods. XAI can help understand the reasoning behind AI models, leading to better debugging, model improvement, and reduced congestion. Additionally, XAI can provide insights into user preferences, enabling the development of personalized mobility services and demand-responsive transportation options. Despite these challenges, XAI has the potential to enhance ITS



Source(s): Author's own work

Figure 3. ITS main challenges and solutions

development and deployment significantly. For example, XAI can be used in autonomous vehicle development and deployment, explaining decisions made by autonomous driving systems. It can also help improve public transportation planning and optimization by analyzing data from smart cards, AVL systems, and passenger behavior.

We conclude this section with Figure 3, which summarizes the main challenges discussed and possible solutions (the challenges are ordered according to the frequency of their mention in the literature).

6. Conclusion

Intelligent Transportation Systems face challenges such as data quality, real-time processing requirements, complexity, computational costs, security vulnerabilities, public acceptance and privacy concerns, and data security. AI algorithms rely on high-quality data for accurate predictions, but inconsistency can hinder real-time bus arrival predictions. Real-time processing requires efficient algorithms, but computational resources can be limited in resource-constrained environments. Security vulnerabilities, public acceptance, and privacy concerns arise from AI's use, necessitating transparent data governance policies and robust security measures. Investing in accurate sensors is crucial for improving data quality in ITS projects. Advanced sensors like GNSS receivers, IMUs, cameras, RADAR, and LiDAR contribute to a richer dataset, while data validation and cleaning techniques ensure data quality. Robust AI algorithms handle data imperfections without compromising accuracy, using techniques like data imputation, outlier detection, regularization, ensemble methods, and cloud and fog computing. Real-time processing is essential for improving response times and system safety. Model compression techniques and parallel processing reduce model size and complexity without losing accuracy. Edge computing enhances real-time reliability by processing data from vehicles at the network's edge, reducing transmission and communication costs. Cloud computing offers a scalable, flexible, cost-effective platform for data management, AI development, and resource sharing.

In addition, ITS technological potential must be translated into tangible benefits for all stakeholders by developing an innovative and resilient business model. The proposed framework should offer a roadmap for developing a sustainable and value-driven ITS system.

XAI is also emerging as a solution to the increasing complexity of AI systems, intense learning models, and the need for transparency and accountability. It can significantly improve ITS by improving transparency, trust, and performance. Despite challenges like real-time requirements, data privacy, and lack of standardized metrics, XAI can enhance ITS development and deployment, such as in autonomous vehicle development and public transportation planning.

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