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The Application of Large Language Models in Intelligent Transportation Management

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Abstract: *The Intelligent Transportation Management System (ITMS) is a complex system that encompasses various aspects such as traffic planning, traffic control, and road safety. This paper takes the current state of intelligent transportation development as input, analyzes the challenges faced in the field, and outputs tasks including scene understanding, event reasoning, and scenario construction. It aims to develop emerging transportation applications based on multimodal large language models. From the perspectives of traffic data analysis, traffic prediction, intelligent traffic control, road safety analysis, and smart travel recommendations, this study explores the future applications of Large Language Models (LLMs) in the field of intelligent transportation management. The goal is to enhance innovation in intelligent transportation, promote industry communication, and drive industry transformation.*

Introduction:

As urbanization accelerates and cities face increasing traffic complexity, the demand for more efficient, intelligent, and sustainable transportation systems has never been more pressing. Intelligent Transportation Management Systems (ITMS) have emerged as a crucial component of modern smart cities, aiming to optimize traffic flow, enhance road safety, and improve the overall commuting experience. However, despite advancements in data collection and automation technologies, many challenges remain unresolved—including unpredictable traffic patterns, fragmented data systems, and concerns over privacy and system interoperability.

Recent breakthroughs in Artificial Intelligence (AI), particularly in Large Language Models (LLMs), offer promising solutions to these persistent issues. Originally developed for natural language processing tasks, LLMs such as ChatGPT have demonstrated powerful capabilities in data reasoning, multimodal integration, and real-time information synthesis—skills highly applicable to intelligent transportation. Their ability to understand and analyze multimodal inputs such as sensor data, traffic images, and textual information opens up new possibilities for traffic forecasting, route optimization, incident reporting, and decision-making support.

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This paper explores the application of Large Language Models in the context of intelligent transportation management, focusing on their potential to enhance multimodal data fusion, scenario understanding, and automated reasoning. By analyzing the current state of ITMS development and identifying existing challenges, this study aims to propose a forward-looking framework for integrating LLMs into traffic data analysis, prediction, control, safety assessment, and smart mobility recommendations. Ultimately, this research seeks to contribute to the evolution of intelligent transportation systems, foster cross-sector collaboration, and accelerate industry transformation.

Methodology:

This study adopts a qualitative-quantitative mixed research methodology to explore the potential applications of Large Language Models (LLMs) in Intelligent Transportation Management Systems (ITMS). The research process is structured around four key components: problem identification, data collection and preprocessing, model design and application scenario construction, and evaluation analysis.

1.Problem Identification and Literature Review
A comprehensive literature review was conducted to understand the current development status and limitations of ITMS in both domestic and international contexts. This step helped identify key challenges such as traffic unpredictability, data fragmentation, and insufficient intelligent reasoning capabilities in current systems.

2.Data Collection and Multimodal Preprocessing
The study collects and synthesizes various types of transportation data including textual reports (e.g., traffic announcements, accident descriptions), visual inputs (e.g., traffic surveillance images), and sensor data (e.g., GPS, speed, vehicle detection). These multimodal inputs are standardized and preprocessed using NLP pipelines and computer vision techniques to be suitable for integration into LLMs.

3.Model Design and Integration Framework
Based on the capabilities of LLMs such as ChatGPT, an integration framework for LLM-based traffic applications is proposed. This includes:

Scenario Understanding: Using LLMs for scene interpretation from multimodal inputs.

Event Reasoning: Enabling the model to infer causes and outcomes of traffic events.

Recommendation Systems: Building smart mobility suggestions based on historical and real-time data.

Cross-Modal Reasoning Module: Integrating textual, visual, and sensor data through LLMs for holistic traffic analysis.

4.Application Scenarios
The proposed model is applied to several intelligent transportation scenarios including traffic prediction, congestion mitigation, emergency reporting automation, and real-time route optimization. A prototype simulation is constructed to demonstrate feasibility.

5.Evaluation and Feasibility Analysis
Due to the exploratory nature of this study, the evaluation is based on functional assessment, expert interviews, and qualitative metrics such as accuracy of scene

interpretation and responsiveness of the system. Additionally, challenges such as data privacy, processing latency, and model transparency are critically examined.

Results and discussion:

This study systematically analyzes the application potential of Large Language Models (LLMs) in Intelligent Transportation Management Systems (ITMS), proposing an integration framework for incorporating multimodal input data into LLMs. Based on a review of current literature and real-world use cases, the following key results and discussion points are summarized:

1. Core Challenges in Intelligent Transportation Identified

By reviewing the development status of ITMS in both domestic and international contexts, this study identifies several critical pain points in the field:

(1)Urban traffic conditions are highly complex and difficult to control in real time.

(2)System interoperability remains low due to fragmented development and data silos.

(3)The volume and variety of transportation data make it difficult to manage and analyze effectively.

(4)Privacy and data security mechanisms are weak, leading to limited public trust.

These issues highlight the urgent need for advanced data processing and intelligent reasoning technologies, justifying the relevance of applying LLMs in this field.

2. LLMs Demonstrate High Potential for Overcoming Existing Bottlenecks

This study explores the applicability of LLMs in key transportation tasks including traffic congestion prediction, route optimization, vehicle recognition, autonomous driving, and traffic control. Findings indicate that:

(1)LLMs can learn from historical traffic patterns to support accurate forecasting and optimization.

(2)Their semantic understanding capabilities enable automatic generation of incident reports and emergency response suggestions.

(3)The ability to fuse natural language and sensor data supports command interpretation and route planning.

(4)With multimodal training, LLMs can enhance traditional models in areas such as image recognition, traffic scene interpretation, and signal control.

3. Multimodal Integration Supports ITMS Intelligence

The cross-modal processing framework proposed in this study demonstrates the ability of LLMs to ingest and reason across various traffic data types—text, images, video, and sensor signals—by mapping them into a unified language space. This provides several advantages:

(1)Supports a full-cycle reasoning chain from scene understanding to language-based decision making.

(2)Enhances real-time accuracy in responding to traffic emergencies.

(3)Enables personalized dispatching and forecasting in complex urban networks.

4. Feasibility Supported by Theory and Practice

This study references a cutting-edge paper published on arXiv by the University of Central Florida, which validated the use of LLMs in automatic accident report generation and event inference, providing theoretical support for the proposed framework. In addition, China's advancements in vehicle networking, autonomous driving zones, and intelligent signal control provide a favorable technical and policy foundation for the practical implementation of LLMs.

5. Recommendations for Promoting LLM Adoption in Transportation

To accelerate the adoption of LLMs in intelligent transportation systems, the following strategic recommendations are proposed:

(1)Data sharing mechanisms: Governments should promote open data platforms to improve accessibility and interoperability.

(2)Policy and standardization: Clear regulatory frameworks and ethical guidelines are needed to ensure transparency and protect privacy.

(3)Pilot applications in targeted scenarios: LLM deployment should begin with specific tasks such as smart parking and accident assistance.

(4)Talent development and academic-industry collaboration: Universities and enterprises should jointly cultivate interdisciplinary teams focused on "intelligent transportation + large models."

Conclusion and recommendations:

Conclusion

This study investigates the application potential of Large Language Models (LLMs) within Intelligent Transportation Management Systems (ITMS), with a focus on addressing current challenges in urban traffic control, prediction, and decision-making. Through a comprehensive literature review and technical analysis, the research confirms that LLMs—originally designed for natural language processing—possess powerful multimodal reasoning and semantic understanding capabilities that are highly relevant to the needs of modern transportation systems.

By integrating diverse data sources such as textual traffic reports, surveillance images, and sensor data into a unified framework, LLMs can enable scene understanding, event reasoning, route optimization, and emergency response generation. Moreover, the exploration of cross-modal processing highlights the role of LLMs as a core driver of next-generation smart mobility solutions. The findings support the feasibility of leveraging LLMs not only as analytical tools, but also as dynamic decision-making agents capable of adapting to complex and evolving urban transportation environments.

Recommendations

To fully harness the capabilities of LLMs in intelligent transportation, the following recommendations are proposed for researchers, policymakers, and industry stakeholders:

(1)Promote Open and Standardized Data Sharing

Establish city-wide and national-level transportation data platforms to support multimodal

data aggregation. Encourage standardization of formats and open APIs to facilitate integration with LLM-based systems.

(2)Develop Application-Specific Pilot Projects

Begin with focused implementation scenarios such as smart parking guidance, real-time congestion alerts, and AI-generated accident reporting. These use cases allow for manageable risk and measurable outcomes that can validate scalability.

(3)Enhance Multimodal Training and Optimization of LLMs

Collaborate across AI, transportation engineering, and data science disciplines to fine-tune LLMs using domain-specific traffic datasets. Lightweight and latency-optimized models should be developed for real-time, edge-based deployment.

(4)Strengthen Policy Frameworks and Data Governance

Establish clear legal and ethical guidelines for the use of AI in transportation, especially regarding user data protection, model transparency, and accountability in automated decision-making.

(5)Foster Interdisciplinary Talent and Research Collaboration

Build joint innovation labs and educational programs between universities, transportation bureaus, and AI companies to train a new generation of experts in "transportation + AI + big model" technologies.

(6)Monitor and Evaluate Societal Impact

Ensure continuous public engagement and evaluation of LLM-based transportation solutions, with a focus on accessibility, equity, and user acceptance. Maintain transparency in algorithmic operations to build trust.

This research lays a theoretical and practical foundation for future exploration of LLMs in the intelligent transportation field. With proper support and collaborative effort, LLMs have the potential to significantly reshape the future of urban mobility, enabling smarter, safer, and more sustainable transportation ecosystems.

Keywords: *Intelligent Transportation, Large Language Models, Cross-Modal Processing*

1. Introduction

The rapid advancement of urbanization and the proliferation of vehicles in modern cities have led to increasingly complex traffic systems that demand more intelligent, adaptive, and integrated management solutions. Traditional traffic management methods often fall short in responding to real-time changes, handling multimodal data, and supporting predictive and proactive decision-making. As cities evolve toward becoming smart ecosystems, Intelligent Transportation Management Systems (ITMS) have emerged as critical infrastructures aimed at optimizing traffic efficiency, enhancing road safety, and improving the overall mobility experience.

Recent developments in Artificial Intelligence (AI), particularly in the area of Large Language Models (LLMs), present transformative opportunities for the transportation sector. LLMs—originally designed for natural language processing—have demonstrated exceptional capabilities in semantic understanding, contextual reasoning, and multimodal integration. These attributes align well with the needs of intelligent transportation systems, which increasingly rely on the fusion of textual, visual, and sensor data for real-time analysis and decision support.

However, the application of LLMs in ITMS remains relatively unexplored in academic literature and practical deployment. While existing traffic systems benefit from machine learning and data-driven tools, most lack the cognitive flexibility and interpretive depth provided by modern LLMs. Moreover, there is a growing demand to address the current limitations in traffic data interoperability, system scalability, and intelligent automation.

This paper seeks to explore the role of Large Language Models in reshaping the future of intelligent transportation. It aims to analyze the current landscape of ITMS, identify the core challenges faced in urban traffic environments, and evaluate the feasibility and potential benefits of applying LLMs to solve those challenges. The study further proposes a conceptual framework for multimodal data integration using LLMs, focusing on key application areas such as traffic forecasting, congestion management, scene understanding, event inference, and smart mobility recommendations.

By providing a theoretical foundation and practical insights, this research intends to contribute to the advancement of intelligent transportation technologies and stimulate further academic inquiry and cross-disciplinary innovation in the integration of AI and urban mobility systems.

2. Literature review

Intelligent Transportation Management Systems (ITMS) have garnered significant attention globally due to their capacity to alleviate traffic congestion, reduce accident rates, and enhance urban mobility. The evolution of ITMS has been closely linked with advances in digital infrastructure, data processing, and emerging technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence. Existing literature reflects that various countries have adopted different approaches to the design and deployment of intelligent traffic systems, resulting in diverse degrees of sophistication and integration.

In the United States, the implementation of ITMS has reached a relatively mature stage. Since the release of the "National Intelligent Transportation Systems Program Plan" by the U.S. Department of Transportation in 1995, the country has steadily advanced the development of vehicle safety systems, electronic tolling, traffic monitoring, and commercial fleet management systems. According to recent statistics, over 80% of major U.S. cities have adopted ITMS in some form, often supported by satellite navigation and advanced sensor networks.

Japan, on the other hand, has a longer history with intelligent transportation technologies, dating back to the early 1970s. Its ITMS ecosystem is characterized by highly coordinated systems including advanced driver assistance, real-time traffic guidance, pedestrian navigation, and emergency response networks. Japan's long-term investment in intelligent vehicle-infrastructure cooperation has served as a model for other nations seeking to implement smart mobility solutions.

Europe's approach to intelligent traffic systems has focused on telematics and continental-scale standardization. Various EU countries have cooperated on projects aimed at creating integrated traffic communication networks, with notable progress in Advanced Traveler Information Systems (ATIS), Advanced Vehicle Control Systems (AVCS), and electronic tolling frameworks. European efforts emphasize interoperability and policy harmonization to ensure cross-border mobility and unified data platforms.

In China, ITMS has experienced rapid development in recent years, driven by government policy, urban digitalization, and the strategic deployment of artificial intelligence. Key initiatives include the deployment of vehicle-to-infrastructure (V2I) technology, intelligent signal control systems, and smart mobility pilot zones. Several major cities have established autonomous driving demonstration areas, such as Beijing, Shanghai, and Chongqing, which foster collaboration between government, academia, and industry. Moreover, Chinese technology companies play an essential role in urban traffic data collection and analytics, particularly through navigation platforms and real-time mapping services.

Despite these global advancements, several challenges persist across regions. The majority of systems are limited by issues such as data silos, incompatible software interfaces, insufficient real-time capabilities, and a lack of unified standards. The rise of massive, diverse, and unstructured data sources in transportation contexts—ranging from social media text to sensor feeds—necessitates more sophisticated information processing methods.

This is where Large Language Models (LLMs) offer a promising frontier. Recent studies have explored their use in extracting traffic-related knowledge from textual data, supporting real-time decision-making, and integrating multimodal inputs into a coherent interpretive framework. One notable example is the study by Dr. Aty’s team at the University of Central Florida, which proposed a mobile-based accident reporting system powered by LLMs that combines smartphone sensor data and textual reasoning to automatically generate incident summaries. Similarly, several IEEE conference papers have presented the use of transformer-based models for route planning, traffic signal control, and congestion classification.

However, most existing applications remain in the experimental or proof-of-concept stage. There is a critical gap in the integration of LLMs within large-scale, operational ITMS environments. Furthermore, research on multimodal reasoning in transportation—particularly involving the simultaneous processing of text, image, and sensor data—remains limited and underexplored.

The growing convergence between intelligent transportation systems and advanced AI models necessitates a renewed focus on theoretical models, pilot applications, and practical frameworks that leverage LLMs for real-world urban mobility challenges. As the field advances, interdisciplinary collaboration will be key to bridging the current divide between language technologies and transportation infrastructure.

3. Methodology

This study adopts a mixed-methods approach that combines qualitative analysis of existing literature with a conceptual modeling framework for applying Large Language Models (LLMs) within Intelligent Transportation Management Systems (ITMS). The methodology is structured into four primary phases: problem identification, data categorization and preprocessing, framework development, and application mapping.

3.1 Problem identification

The research begins with a critical analysis of current ITMS implementations globally and within China. By reviewing policy documents, government reports, and peer-reviewed literature, the study identifies systemic inefficiencies and recurring challenges, including traffic unpredictability, data fragmentation, low system interoperability, and the limited reasoning capabilities of existing solutions.

3.2 Data categorization and multimodal preprocessing

To explore the feasibility of LLM integration, the study categorizes typical data used in transportation systems into three types: textual data (e.g., traffic bulletins, incident reports), visual data (e.g., road images, traffic camera feeds), and sensor data (e.g., GPS signals, vehicle speed, and flow metrics). Preprocessing methods include natural language processing (NLP) for textual content, computer vision algorithms for image data, and data normalization for sensor streams to ensure input compatibility with LLM architectures.

3.3 Conceptual framework development

Based on the strengths of LLMs—namely, their ability to understand, reason, and generate across modalities—a conceptual framework is developed. The framework envisions a multimodal pipeline where various traffic data inputs are first encoded and then processed within a unified LLM environment. Key modules in the framework include:

(1)Scene understanding: interpreting real-time traffic conditions through integrated data;

(2)Event reasoning: inferring causes and impacts of traffic incidents;

(3)Smart recommendations: generating context-aware navigation or dispatch advice;

(4)Cross-modal inference: synthesizing textual, visual, and sensor-based signals to support comprehensive decision-making.

3.4 Application mapping and scenario definition

The framework is then mapped to practical ITMS use cases, such as traffic flow forecasting, dynamic route optimization, congestion analysis, and automated incident reporting. These application scenarios are selected based on their technical feasibility, data availability, and high impact on traffic efficiency and safety.

3.5 Feasibility validation

To assess initial feasibility, the framework is compared with case studies and experimental models reported in recent literature. Particular reference is made to a 2023 study by Dr. Aty's team, which successfully demonstrated an LLM-driven accident reporting prototype using multimodal mobile data. This comparative analysis serves to validate the theoretical soundness and technical plausibility of the proposed architecture.

This methodology serves as a foundation for further empirical testing and system development, which are recommended in future research to validate the framework in live traffic environments.

4. Results and discussion

This section presents the key findings derived from the literature analysis, conceptual framework design, and scenario mapping, highlighting the relevance and potential of applying Large Language Models (LLMs) to Intelligent Transportation Management Systems (ITMS). The discussion is organized around four thematic areas: system limitations, LLM capabilities, cross-modal integration potential, and application feasibility.

4.1 Limitations in current ITMS deployments

The analysis reveals that despite progress in the digitalization of transportation systems, several persistent limitations hinder the performance of existing ITMS architectures. First, traffic flow remains highly dynamic and difficult to predict using conventional statistical models, especially under non-recurrent conditions such as accidents or weather disruptions. Second, the fragmentation of data across multiple, non-integrated systems results in poor data interoperability and redundancy. Third, most current systems focus on data collection and visualization rather than real-time reasoning and proactive control. Finally, user privacy concerns and weak regulatory frameworks limit the scope of advanced AI applications in public transportation networks.

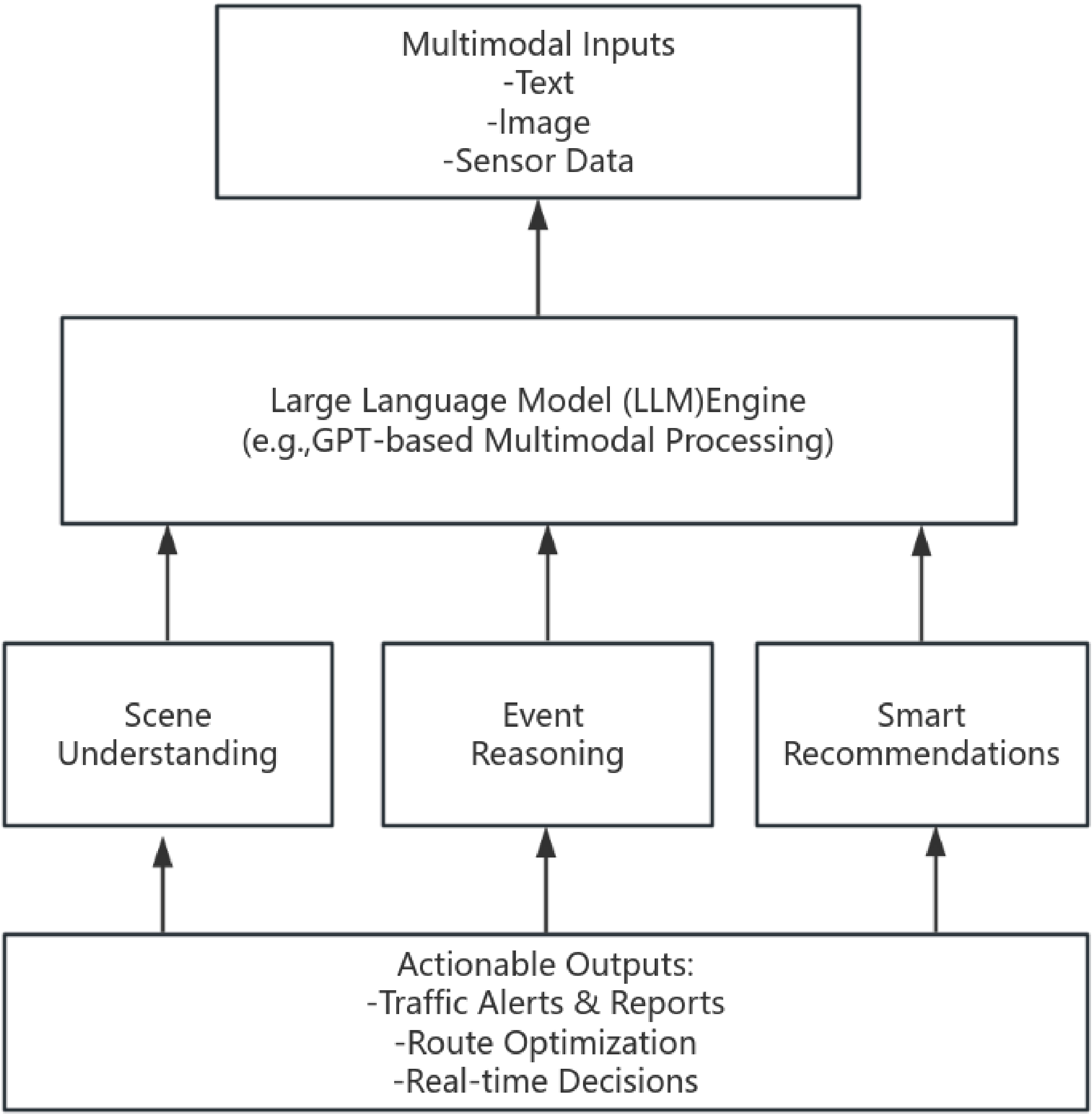
4.2 LLMs as enablers of semantic and contextual intelligence

Large Language Models demonstrate significant promise in addressing many of these limitations. With their ability to understand context, perform logical reasoning, and generate human-like language, LLMs can enhance the intelligence layer of ITMS. For instance, an LLM can be trained to process a stream of heterogeneous traffic data and convert it into actionable insights, such as summarizing real-time road conditions, classifying incident severity, or suggesting detours based on predictive congestion estimates. Furthermore, their generative capabilities make them suitable for producing natural language alerts, travel guidance, and even automated incident reports without human intervention.

4.3 Cross-modal integration as a transformative capability

One of the most significant findings is the alignment between the cross-modal capabilities of LLMs and the inherent multimodal nature of transportation data. Current ITMS collect a wide range of inputs—including textual, visual, and sensor-based data—that are often processed in isolation. LLMs, especially those enhanced with vision-language models (e.g., GPT-4V), can jointly reason over multiple data formats. This opens new opportunities for scene-level understanding, where traffic cameras, GPS data, and environmental inputs are combined to generate a comprehensive situational model. Such integration allows for high-level inferences such as predicting accident likelihood, detecting anomalies in traffic patterns, or correlating user behavior with congestion trends.

Figure 1.Conceptual Framework of LLM Applications in ITMS



Source: Developed for this research.

4.4 Validation through reference cases and pilot scenarios

Comparative analysis with recent projects supports the feasibility of LLM application in ITMS. The University of Central Florida's research team has shown that LLMs can be deployed in mobile-based accident reporting systems by fusing smartphone sensor data with language outputs. Similarly, IEEE studies have successfully applied transformer-based models to traffic flow classification and signal optimization. These examples suggest that the transition from experimental models to scalable solutions is technically achievable, provided that domain-specific customization, lightweight deployment, and privacy safeguards are addressed.

4.5 Key implications and discussion

The results suggest that LLMs are not merely enhancements to existing AI functions in transportation—they represent a paradigm shift in how transportation data can be interpreted and utilized. Their generalization ability reduces the need for domain-specific programming and allows for more adaptive, language-based interfaces between users, vehicles, and systems. However, several limitations remain, including model interpretability, computational cost, and the risk of generating incorrect or biased outputs if not properly trained and monitored.

Overall, this study supports the argument that LLMs hold significant potential for enhancing the intelligence, responsiveness, and user interaction within future ITMS frameworks.

5. Conclusion and recommendations

This study has explored the integration of Large Language Models (LLMs) into Intelligent Transportation Management Systems (ITMS), with a focus on overcoming persistent limitations in current traffic management technologies. Through a review of international practices, technical literature, and emerging applications, the research has identified key areas where LLMs can contribute to more adaptive, intelligent, and multimodal transportation solutions.

The main conclusion is that LLMs—through their capacity for contextual understanding, multimodal reasoning, and natural language generation—offer a powerful enhancement to traditional ITMS. Unlike conventional rule-based or statistical models, LLMs can synthesize complex inputs, generate insights in real time, and adapt to evolving urban conditions. Their application potential spans from traffic forecasting and congestion analysis to incident reporting, route optimization, and interactive user interfaces.

The proposed conceptual framework demonstrates that LLMs can act as core reasoning agents within ITMS, capable of fusing textual, visual, and sensor data into actionable outputs. Validation through case studies and academic references confirms the theoretical and technical feasibility of this integration, although large-scale deployment still requires further development, optimization, and governance.

Despite these promising findings, several limitations remain. The computational requirements of LLMs are high, and real-time performance in edge environments needs improvement. Data privacy, model transparency, and error control are also critical concerns. Additionally, there is a lack of interdisciplinary infrastructure to support the convergence of transportation engineering and advanced AI systems.

Based on the research outcomes, the following recommendations are proposed:

(1)Pilot implementation: Begin with small-scale, well-defined scenarios such as automated traffic report generation, smart congestion alerts, and personalized navigation systems using LLMs.

(2)Multimodal dataset development: Establish open, standardized, and anonymized traffic datasets that combine textual, visual, and sensor inputs to support model training and benchmarking.

(3)Lightweight model deployment: Develop optimized or domain-specific LLM architectures tailored to the low-latency, resource-constrained environments typical of traffic control systems.

(4)Policy and regulation: Create ethical and legal guidelines for the responsible use of LLMs in public infrastructure, with a focus on transparency, accountability, and user data protection.

(5)Interdisciplinary collaboration: Foster partnerships between transportation authorities, AI researchers, and urban planners to ensure the practical relevance and sustainability of future ITMS designs.

In summary, the integration of LLMs into ITMS marks a shift toward a more intelligent, data-driven, and human-centric approach to traffic management. With proper support, governance, and continued research, LLMs may become foundational tools in the evolution of future urban mobility systems.

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