Integration of Large Language Models with Transportation Systems: A Survey

Abstract

The integration of Large Language Models (LLMs) and Natural Language Processing (NLP) into transportation systems marks a significant advancement in operational efficiency, safety, and decision-making. This survey examines the transformative impact of these technologies across road, railway, and air traffic systems. LLMs enhance data analysis, communication, and decision-making processes, contributing to improved traffic management and forecasting. By leveraging advanced computational techniques, LLMs address limitations of traditional models, offering adaptive frameworks for traffic prediction, signal optimization, and incident detection. In railway systems, LLMs improve scheduling, predictive maintenance, and operational efficiency, while in air traffic management, they enhance communication systems and automate flight procedure design. The integration of NLP facilitates real-time traffic information extraction from social media, enhancing traffic management strategies. However, challenges such as data quality, computational constraints, and ethical considerations remain. Future research should focus on domain-specific adaptations, multimodal integration, and innovations in human-agent collaboration to fully realize the potential of LLMs in creating intelligent, adaptive, and sustainable transportation infrastructures.

1 Introduction

1.1 Conceptual Framework

The integration of Large Language Models (LLMs) into transportation systems is anchored in a conceptual framework that harnesses their computational prowess to tackle the complexities of modern transportation. This framework aims to enhance transportation efficiency, safety, and intelligence through components such as intelligent transportation systems (ITS), which utilize communication technologies and artificial intelligence to optimize urban planning, vehicle routing, crowd behavior analysis, and traffic condition prediction, addressing challenges from rapid urbanization and rising vehicle numbers. By leveraging multi-modal data and natural language processing, the framework facilitates traffic analysis, generates synthetic traffic scenarios, and provides actionable insights, promoting healthier and more sustainable urban mobility solutions [1, 2].

Central to this framework is the categorization of LLMs by scaling, emergent abilities, and unique characteristics, particularly their in-context learning and instruction-following capabilities [3]. This categorization is essential for understanding the effective application of LLMs in transportation systems.

Furthermore, the framework highlights the dual role of LLMs as planners and facilitators within the planning process, classifying existing research into LLM-assisted planning methods and frameworks [4]. This duality is vital for optimizing transportation operations and enhancing decision-making processes.

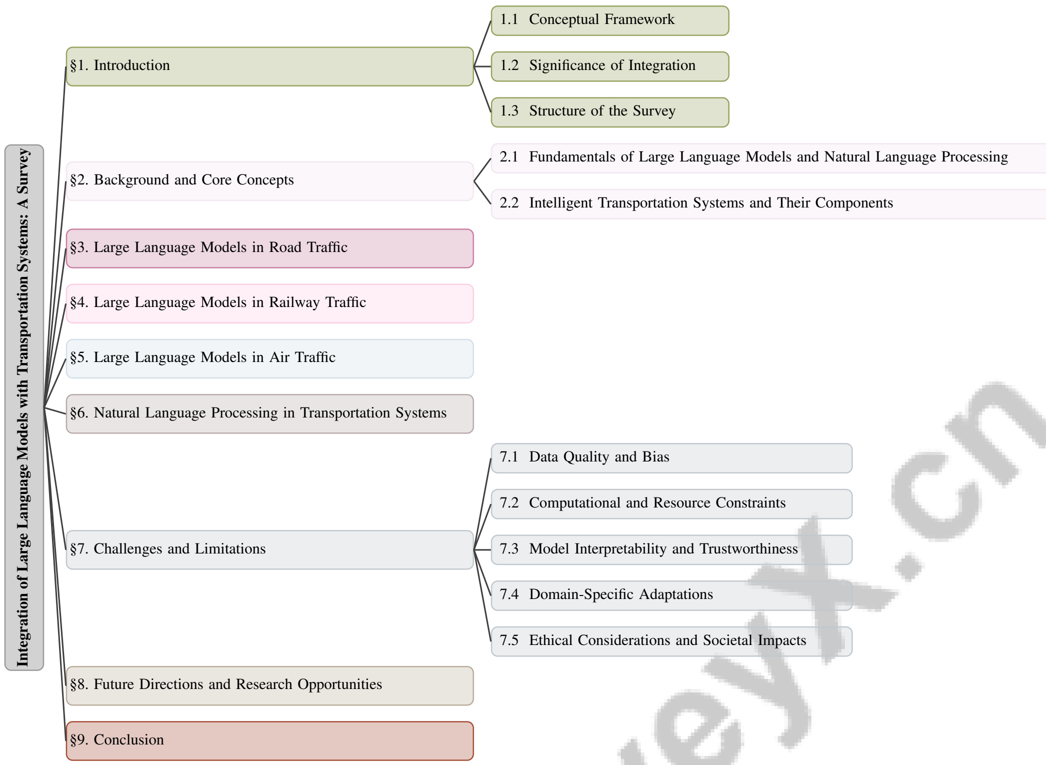

Figure 1: chapter structure

Additionally, an event detection model employing LLMs and clustering analysis is integrated to improve the identification of significant occurrences, which is crucial for transportation incident management [5]. This capability enhances incident detection and management responsiveness.

The framework also acknowledges the roles of dataset practitioners, emphasizing the dynamic nature of their tasks [6]. This understanding is critical for effective transportation data management and ensuring that LLMs are trained on high-quality, relevant data.

Moreover, a unified evaluation model is introduced, integrating people, processes, and technology domains for a holistic assessment of LLMs, surpassing previous benchmarks [7]. This comprehensive evaluation is crucial for assessing LLM performance and impact in transportation systems.

By incorporating advanced modeling techniques, contextual awareness, and optimized LLMs, the conceptual framework lays a robust foundation for effectively integrating LLMs into Intelligent Transportation Systems (ITS). This integration enhances traffic signal management, accident prediction, and object detection, fostering the development of safer, more efficient transportation solutions while leveraging the extensive data generated in modern transportation networks. This approach supports the evolution of traffic safety research and applications, addressing critical challenges and promoting methodological transparency and reliability in deploying AI-driven technologies [8, 9, 10].

1.2 Significance of Integration

The integration of Large Language Models (LLMs) and Natural Language Processing (NLP) in transportation systems marks a significant advancement in operational efficiency, safety, and decision-making. By combining LLMs with relational databases, these systems enhance factual accuracy and response relevance, addressing traditional LLM limitations [11]. This improvement is critical in transportation contexts where precise data interpretation and timely responses are essential.

LLMs in transportation facilitate the automation of complex tasks and bridge knowledge gaps, akin to their applications in telecommunications [12]. Models like TransGPT utilize domain-specific knowledge to optimize routing and scheduling processes, significantly enhancing performance in transportation-specific tasks [1]. The integration of knowledge graphs with LLMs further bolsters factual reasoning abilities, crucial for accurate traffic forecasting and management [13].

Safety remains a paramount concern in transportation, and LLMs enhance this by improving the understanding and automation of car accident reports [14]. The combination of Graph Neural Networks (GNNs) with LLMs improves predictive reliability, identifying high-quality data candidates vital for effective traffic management [15]. Additionally, self-service platforms empower stakeholders to securely select, train, and host customized LLMs, democratizing access to advanced AI tools and making sophisticated transportation solutions more accessible [16].

The application of LLMs in addressing traffic safety issues, exemplified by models like ChatGPT, reveals their potential to contribute to safer, more efficient transportation systems [10]. Integrating computational experiments with LLM-based agents enhances the modeling of complex social systems, providing deeper insights into transportation dynamics and supporting robust urban planning [17].

The potential of AI to enhance research processes underscores the importance of integrating LLMs across various domains, including transportation, to drive innovation and efficiency [9]. However, addressing safety and security concerns associated with LLM systems is crucial for their widespread application [18]. As LLMs become more integrated into society, establishing standardized methodologies and ethical guidelines is necessary to ensure responsible use [7].

The integration of LLMs and NLP into transportation systems substantially enhances operational efficiency and safety through advanced traffic analysis, modeling, and decision-making. These technologies enable the generation of synthetic traffic scenarios, insightful traffic recommendations, and improved adaptability of transportation infrastructure, fostering a more intelligent and responsive traffic management environment. Multi-modal models like TransGPT address the unique challenges of the transportation domain, ensuring effective utilization of both textual and visual data to optimize traffic safety and operational performance [1, 10]. This transformation is vital for addressing the evolving challenges of modern transportation and fostering sustainable and resilient solutions.

1.3 Structure of the Survey

This survey is meticulously structured to provide an in-depth exploration of the integration of Large Language Models (LLMs) and Natural Language Processing (NLP) technologies into transportation systems, emphasizing recent advancements, practical applications, and challenges in leveraging these AI-driven tools to enhance operational efficiency and service quality [19, 20, 21, 9, 22]. It begins with an introduction that presents the overarching theme of integrating advanced computational techniques with transportation systems, highlighting the potential for enhanced efficiency, safety, and intelligence.

The first section, "Conceptual Framework," outlines the theoretical foundations of LLM integration, focusing on their computational capabilities and dual roles as planners and facilitators, drawing from existing research on LLM-assisted planning methods and event detection models.

Following this, the "Significance of Integration" section examines the transformative impact of LLMs and NLP on transportation systems, showcasing improvements in factual accuracy, safety, and decision-making.

Subsequent sections delve into specific modes of transportation, detailing LLM applications in road, railway, and air traffic systems, and addressing the unique challenges and opportunities in these domains, supported by relevant case studies and examples.

The survey also discusses "Challenges and Limitations," identifying critical issues such as variability in data quality standards among dataset practitioners, computational constraints in deploying LLMs, and ethical considerations regarding data usage and model outputs. These factors are essential for comprehensively understanding the broader implications of LLM integration, particularly in ensuring methodological transparency and reliability in academic research and practical applications [20, 6, 9].

Finally, the survey concludes with "Future Directions and Research Opportunities," providing insights into potential advancements and innovations in the field. This section emphasizes the need for ongoing research and development to fully leverage the benefits of LLMs and NLP in transforming transportation systems.

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This structured approach enables a comprehensive exploration of intelligent transportation systems (ITS), highlighting their potential to enhance traffic management and urban mobility through advanced technologies such as augmented reality, LLMs, and artificial intelligence. By examining the integration of real-time data collection, social media insights, and innovative control systems, the analysis offers critical insights for researchers, practitioners, and policymakers focused on optimizing urban planning, improving service quality, and ensuring the safety and efficiency of future transportation networks [22, 2, 23].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Fundamentals of Large Language Models and Natural Language Processing

Large Language Models (LLMs) are critical in advancing Natural Language Processing (NLP) for intelligent transportation systems, enhancing text generation and comprehension through neural networks and self-attention mechanisms based on the Transformer architecture [5]. These models facilitate complex text processing tasks but face challenges like ungrounded hallucinations that can cause inconsistencies [7]. In transportation, LLMs and NLP are vital for processing extensive data from Intelligent Transportation Systems (ITS), enabling the extraction and summarization of contextual information from diverse sources. They support keyword extraction, text embedding, and clustering, essential for real-time traffic analysis on platforms like Twitter [5], and their integration with knowledge graphs enhances factual reasoning for accurate traffic forecasting and management [13].

Despite their benefits, deploying LLMs in transportation systems presents challenges related to computational and memory demands, complicating scaling and resource management [6]. Optimizing computational resources is crucial for efficient LLM inference, particularly in cloud-based environments [7]. Moreover, combining Reinforcement Learning (RL) with LLMs for multimodal information processing highlights the need for effective reward function design and generalization in natural language understanding, essential for robust transportation applications [13].

LLMs and NLP significantly enhance data analysis, communication, and decision-making processes in transportation, improving traffic management and forecasting [24]. However, addressing limitations such as insufficient reasoning capabilities for complex tasks is crucial for advancing decision-making in transportation systems [25]. Overcoming these limitations allows LLMs to surpass the constraints of traditional rule-based approaches, fostering more intelligent and adaptive transportation infrastructures [5]. The variability in evaluation frameworks for LLMs underscores the need for robust, standardized benchmarks to effectively assess their performance across diverse linguistic tasks [7]. Addressing these challenges is essential for the effective utilization and comprehension of LLMs in NLP, given their complexity and the rapid advancements in the field [13].

2.2 Intelligent Transportation Systems and Their Components

Intelligent Transportation Systems (ITS) converge advanced technologies within transportation networks to enhance efficiency, safety, and sustainability across road, railway, and air traffic systems. Utilizing real-time data from vehicles and infrastructure, ITS facilitates intelligent traffic management, urban mobility optimization, and autonomous transportation through enhanced routing and traffic prediction. The integration of artificial intelligence and the Internet of Things (IoT) enables ITS to analyze large volumes of mobility data, addressing critical issues such as traffic congestion and accident prevention. Frameworks like SafeRNet leverage real-time analytics to recommend safer routes, contributing to more efficient transportation systems in rapidly urbanizing areas [23, 8, 1, 2, 26].

Road traffic systems within ITS employ technologies to manage congestion, enhance safety, and optimize traffic flow. The integration of LLMs with classical machine learning methods addresses limitations in existing techniques, particularly under distribution shifts in test data, improving predictive accuracy and responsiveness to traffic conditions [27]. LLM-based data agents facilitate real-time data processing and decision-making, leading to more responsive traffic management solutions [28].

Railway traffic systems benefit from ITS through improved scheduling, predictive maintenance, and safety enhancements. Multimodal models like AllSpark, which integrate diverse data modalities, support joint interpretation and reasoning necessary for efficient railway operations [29]. LLMs' ability to manage complex datasets, such as those utilized in CHATMAP for cartographic data, enhances geospatial information management critical for railway operations [30].

In air traffic systems, ITS plays a vital role in air traffic control and management. The integration of LLMs facilitates improved interaction with complex datasets, enhancing information retrieval and communication systems essential for maintaining safety and efficiency in air traffic management [31].

The incorporation of augmented reality (AR) within ITS further enhances vehicular communication, network resource management, and safety across all transportation modes [23]. AR applications provide real-time visualizations and data overlays, improving situational awareness and decision-making for operators and drivers.

Intelligent Transportation Systems leverage LLMs and other advanced computational models to transform transportation networks into more intelligent, adaptive, and efficient systems. By integrating these technologies, ITS components across road, railway, and air traffic systems can better tackle the complex challenges of modern transportation environments, ultimately contributing to more sustainable and resilient infrastructure [19].

3 Large Language Models in Road Traffic

The deployment of Large Language Models (LLMs) in transportation, particularly for traffic prediction and management, marks a significant advancement in the field. As traffic systems become more intricate, the need for sophisticated analytical tools becomes evident. LLMs address traditional models' limitations by employing advanced computational techniques, offering a more adaptive framework for understanding traffic dynamics crucial for effective transportation management. The following subsections delve into the specific applications of LLMs in traffic prediction, signal optimization, and real-time data analysis, demonstrating their role in enhancing accuracy and efficiency in real-time traffic scenarios.

3.1 Traffic Prediction and Forecasting

Integrating LLMs into traffic prediction and forecasting systems transforms transportation data management, providing enhanced flexibility and robustness compared to traditional methods. Conventional models often rely on static approaches that fail to capture the dynamic nature of traffic flows. Recent methods leverage real-time data from social media platforms like Twitter to extract traffic-related information such as congestion and incidents from extensive datasets. These approaches utilize deep and unsupervised learning techniques to analyze traffic patterns, effectively capturing temporal and spatial dynamics. For instance, systems like TrafficGPT enhance prediction accuracy and provide interactive visualizations, offering a nuanced understanding of urban traffic conditions [32, 33, 34, 35].

As illustrated in Figure 2, the hierarchical structure of traffic prediction and forecasting highlights enhanced prediction methods, innovative techniques, and advanced applications. This figure emphasizes the integration of LLMs into traffic systems, showcasing key advancements and applications that further bolster the effectiveness of these predictive models.

Innovative techniques involve relational database-augmented frameworks that improve SQL query generation from natural language inputs, crucial for accurate data retrieval and processing, leading to improved predictive outcomes [11]. Leveraging LLMs' natural language understanding capabilities, transportation systems can achieve better factual accuracy and response relevance, essential for effective traffic management.

The SafeRNet framework illustrates the use of real-time and historical traffic data to determine the safest routes, enhancing traffic prediction capabilities [26]. By incorporating comprehensive data sources, LLMs facilitate informed decision-making, contributing to safer and more efficient transportation systems.

LLMs effectively address the challenge of accurately predicting traffic flow dynamics, as highlighted in studies on road traffic reservoir computing, by capturing the complex behavior of real-world traffic systems often overlooked by traditional models [36]. Thus, LLMs enhance forecasting accuracy by improving the understanding and anticipation of traffic patterns.

The application of LLMs in traffic prediction and forecasting not only enhances predictive accuracy but also improves the adaptability and responsiveness of transportation systems. By integrating advanced computational techniques, LLMs bolster the intelligence and efficiency of traffic management solutions, addressing critical issues such as accident prediction and traffic signal management. These advancements contribute to creating safer and more sustainable transportation infrastructures, enhancing decision-making processes and fostering innovative applications in traffic safety research [8, 37, 12, 10].

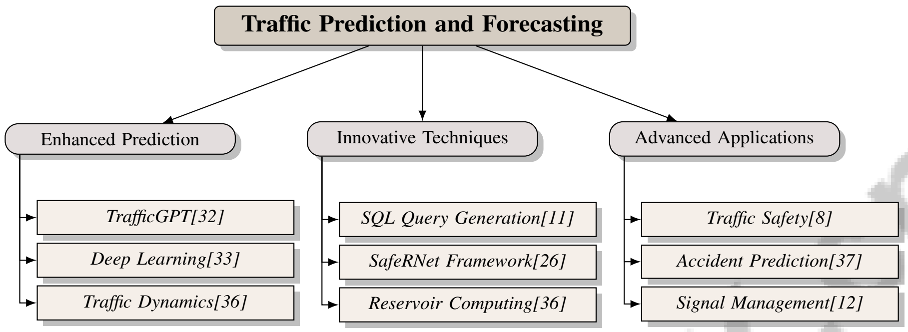

Figure 2: This figure illustrates the hierarchical structure of traffic prediction and forecasting, highlighting enhanced prediction methods, innovative techniques, and advanced applications. It emphasizes the integration of LLMs into traffic systems, showcasing key advancements and applications.

3.2 Signal Optimization and Traffic Management

Traffic signal optimization and flow management are critical components of intelligent transportation systems, with LLMs significantly enhancing these processes. Effective traffic signal control directly impacts vehicle waiting times and overall traffic efficiency, as demonstrated by studies on predicting waiting times at red signals [38].

Recent advancements in LLMs have introduced innovative approaches to traffic signal optimization. The Spatial-Temporal Large Language Model (ST-LLM) employs a fusion convolution layer to integrate spatial and temporal embeddings, followed by a partially frozen attention LLM to predict future traffic data [39]. This method enables accurate traffic condition predictions, facilitating better signal timing adjustments and reduced waiting times at intersections.

In cooperative driving scenarios, LLMs enhance decision-making through models like CoDrivingLLM, which improves interaction and learning capabilities for more efficient traffic management via synchronized vehicle behavior [40]. DriveGPT4 further advances autonomous driving systems by integrating multimodal LLMs that combine video and textual data to provide comprehensive explanations of vehicle actions [41], essential for optimizing vehicle interactions at traffic signals.

Moreover, blackbox optimization techniques exploring the hyperparameter space of LLMs enhance instruction-tuning results, leading to more effective signal optimization strategies [42]. Fine-tuning these models allows transportation systems to achieve precise control over traffic signals, adapting to real-time conditions.

The integration of law-adaptive backup policies ensures that reinforcement learning agents' actions comply with traffic laws, minimizing disruptions and enhancing signal management [43]. Hybrid models combining SARIMA with Bayesian learning algorithms further improve prediction accuracy across varying traffic conditions, supporting dynamic signal adjustments for responsive traffic management solutions [44].

TrafficGPT exemplifies the effectiveness of LLMs in dynamically fusing spatial and temporal features, allowing for accurate traffic predictions and improved user interaction [32], which is vital for optimizing traffic signals and ensuring efficient flow management.

3.3 Real-Time Data Analysis and Incident Detection

LLMs significantly enhance real-time data analysis and incident detection within transportation systems, leveraging advanced techniques such as spatial-temporal embeddings and sentiment analysis of social media data. This integration allows for accurate forecasting of traffic conditions and timely identification of emerging issues, ultimately improving the efficiency and safety of transit operations [22, 39, 10].

Social media data, particularly from platforms like Twitter, serves as a dynamic source of real-time traffic information, enriching traffic event detection by providing insights that complement traditional monitoring methods [34]. Equipped with Natural Language Processing (NLP) capabilities, LLMs effectively process and analyze large volumes of social media data, identifying traffic incidents and patterns not immediately visible through conventional systems.

The STLLM-DF model exemplifies the integration of LLMs with Denoising Diffusion Probabilistic Models, effectively managing missing data and complex relationships within traffic systems [45]. Similarly, the ST-LLM showcases superior performance in capturing spatial-temporal dependencies, demonstrating robust capabilities in few-shot and zero-shot prediction scenarios [39], crucial for real-time data analysis and incident detection.

The application of reservoir computing in road traffic, as explored in the Road Traffic Reservoir Computing (RTRC) study, utilizes the dynamic behavior of road traffic as a computational reservoir, mapping input signals into a high-dimensional space to enhance prediction accuracy [36]. By employing LLMs alongside such techniques, transportation systems can improve predictive capabilities, leading to more effective incident detection and management.

DriveGPT4 further enhances real-time data analysis by processing video frames and textual queries to predict vehicle control actions while providing natural language explanations [41]. This capability allows for informed decision-making and incident response, enabling operators to quickly understand and react to evolving traffic scenarios.

Overall, the integration of LLMs in real-time data analysis and incident detection enhances transportation systems' proactive management of traffic events. By leveraging extensive traffic-related information extracted from social media platforms, LLMs enable the identification of congestion, safety issues, and public sentiment in urban areas, facilitating actionable insights from over 120,000 geo-tagged traffic tweets. Furthermore, the use of Retrieval-Augmented Generation (RAG) enhances the model's ability to interpret nuanced sentiments and detect emerging issues, ultimately improving transit agencies' responsiveness and service quality [22, 35]. Through advanced computational techniques and real-time data processing, LLMs contribute to developing more intelligent and adaptive transportation infrastructures, enhancing safety and efficiency.

4 Large Language Models in Railway Traffic

4.1 Introduction to LLM Integration in Railway Systems

Large Language Models (LLMs) are transforming railway systems by enhancing operational efficiency and safety through advanced computational techniques. These models facilitate complex data processing, optimizing decision-making in railway traffic management. Key innovations include Language Adaptation strategies, such as LLaMA models, which employ parameter-efficient fine-tuning for effective adaptation to linguistic and operational contexts [9, 20, 6, 12, 46]. TransGPT, with its single-modal and multi-modal variants, exemplifies LLMs' potential to enhance scheduling and operational efficiency by accommodating diverse data inputs [1].

Figure 3 illustrates the integration of Large Language Models (LLMs) in railway systems, highlighting these key innovations, including Language Adaptation strategies and TransGPT models. Furthermore, the figure underscores the role of LLMs in addressing urban mobility challenges through intelligent infrastructures and real-time data analytics. These advancements contribute to intelligent and adaptive railway infrastructures, leveraging real-time data analytics and communication technologies to optimize traffic management and predict conditions, addressing urban mobility challenges [23, 2].

4.2 Enhancing Scheduling and Operations

LLMs significantly enhance railway scheduling and operational efficiency by analyzing large datasets, improving decision-making and strategic planning [20, 37, 27, 19]. These models process multi-modal data inputs, optimizing scheduling processes and ensuring efficient resource allocation [1]. LLMs enable dynamic schedule adjustments based on real-time data, enhancing operational resilience

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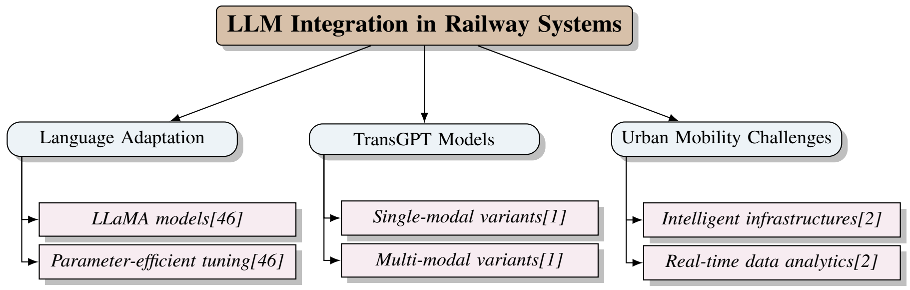

Figure 3: This figure illustrates the integration of Large Language Models (LLMs) in railway systems, highlighting key innovations such as Language Adaptation strategies and TransGPT models, alongside addressing urban mobility challenges through intelligent infrastructures and real-time data analytics.

and reliability [9, 22]. Predictive maintenance is facilitated through advanced data analysis, detecting patterns indicative of equipment failures, thereby improving operational efficiency [20, 5]. LLMs also optimize resource allocation, developing strategies that enhance capacity utilization while reducing operational costs [47].

4.3 Predictive Maintenance and Safety Improvements

Integrating LLMs into railway systems enhances predictive maintenance and safety by analyzing complex datasets to predict maintenance needs, reducing downtime and service disruptions [48]. GraphLLM improves graph reasoning, crucial for managing complex network structures in railway systems [49]. Knowledge graphs (KGs) enhance LLM performance in factual reasoning and knowledge retrieval, providing deeper insights into maintenance and safety protocols [13]. These advancements equip railway systems with enhanced capabilities for safety, reliability, and efficiency, supported by recent developments in LLM serving systems and fine-tuning methodologies [20, 9].

4.4 Communication Systems and Data Analysis

LLMs significantly enhance communication and data analysis in railway systems, improving operational efficiency and safety through advanced natural language processing capabilities [27, 19, 31, 18, 12]. Retrieval-augmented LLMs, such as Ret-LLM, improve interactions with complex datasets, providing accurate responses essential for railway operations [31]. Models like AllSpark demonstrate the integration of multimodal data inputs, enhancing data analysis accuracy and reliability [29]. LLMs optimize data analysis by processing large volumes of information, with knowledge graphs enhancing factual reasoning and knowledge retrieval [13]. These capabilities enable informed decision-making, supporting efficient and responsive railway operations [20, 37].

5 Large Language Models in Air Traffic

5.1 Conversational Agents in Air Traffic Management

Conversational agents powered by Large Language Models (LLMs) significantly enhance air traffic management by streamlining operations and improving decision-making. The CHATATC framework exemplifies this by effectively summarizing and retrieving data on Ground Delay Programs (GDPs), aiding Traffic Managers in daily operations [50]. These agents process complex datasets to manage delays and flight schedules more efficiently. TransGPT further demonstrates LLMs' potential by utilizing multi-modal data processing to anticipate operational challenges, leading to informed decisions and enhanced efficiency [1]. The AutoFPDesigner framework showcases multi-agent collaboration in automating flight procedure design using natural language inputs, reducing complexity and time [51].

Figure 4 illustrates the hierarchical structure of conversational agent frameworks in air traffic management, highlighting key frameworks such as CHATATC, TransGPT, and AutoFPDesigner, each contributing to different aspects like data summarization, multi-modal processing, and automated design. By leveraging sophisticated computational techniques, conversational agents like those in

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CHATATC enhance communication and strategic traffic flow management, improving operational responsiveness in complex environments [32, 17, 9, 50].

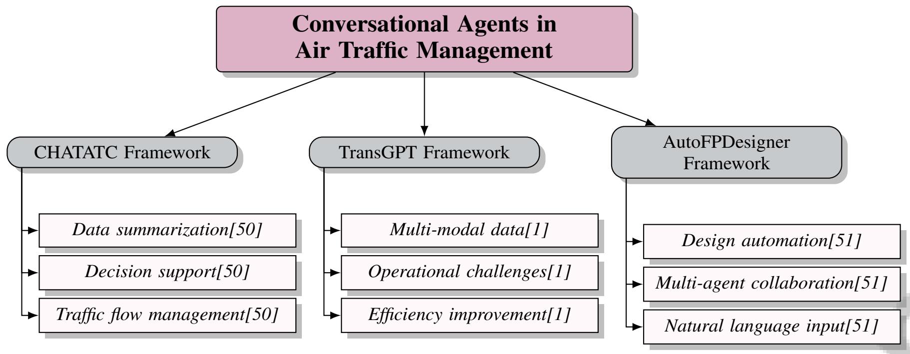

Figure 4: This figure illustrates the hierarchical structure of conversational agent frameworks in air traffic management, highlighting key frameworks such as CHATATC, TransGPT, and AutoFPDesigner, each contributing to different aspects like data summarization, multi-modal processing, and automated design.

5.2 Efficiency Improvements through Historical Data Analysis

LLMs enhance air traffic management efficiency by analyzing historical data to inform decision-making. The CHATATC framework synthesizes vast historical data, allowing Traffic Managers to focus on unique challenges [50]. Automating historical data analysis identifies patterns and trends for strategic planning and operational adjustments. LLMs improve forecasting and resource allocation by understanding past operational patterns, enabling systems to anticipate disruptions and optimize resources [9, 22, 50]. Fine-tuned LLMs automate systematic literature reviews, enhancing knowledge synthesis and providing insights into historical performance. The integration of retrieval-augmented LLMs enhances reliability across research domains [20, 31, 6, 9, 52]. This iterative learning process ensures that air traffic management systems remain responsive to evolving demands, contributing to safer and more efficient air transportation. The synergy of LLMs and optimization algorithms enables intelligent frameworks, enhancing decision-making in dynamic environments and optimizing air transportation operations [9, 37, 50].

5.3 Automated Flight Procedure Design

Automating flight procedure design through LLMs represents a significant advancement in air traffic management, streamlining the design process with advanced computational techniques. The AutoFPDesigner framework automates the design of performance-based navigation procedures using user-defined specifications in natural language [51]. This reduces complexity and time, enabling efficient and accurate development. LLMs leverage natural language inputs to create navigation procedures tailored to diverse airspace environments and operational requirements. Information retrieval systems enhance accuracy by providing contextually relevant responses, minimizing errors and ensuring adherence to aviation protocols [9, 31]. The CHATATC framework's ability to retrieve and summarize extensive historical data informs flight procedure design [50]. Utilizing historical insights enhances the accuracy and relevance of flight procedures, aligning them with current operational standards. Automation through LLMs, as demonstrated by AutoFPDesigner, significantly enhances efficiency, accuracy, and customization, achieving high safety and task completion rates. Advanced techniques mitigate LLM hallucination and improve factual accuracy, ensuring automation meets rigorous safety and methodological standards [9, 31, 51]. By harnessing computational techniques and natural language processing, LLMs foster the development of intelligent and adaptive air traffic management systems, contributing to safer and more reliable air transportation.

In recent years, the integration of Natural Language Processing (NLP) within transportation systems has garnered significant attention due to its potential to improve operational efficiency and customer satisfaction. As illustrated in Figure 5, this figure depicts the hierarchical structure of NLP applications in transportation, emphasizing key areas such as traffic information extraction from social media, customer feedback analysis in public transit, and NLP techniques for traffic event detection.

Each category is systematically divided into platforms and data sources, techniques and tools, and applications and benefits. This structured approach not only underscores the diverse applications of advanced NLP methods but also highlights their role in enhancing the responsiveness and service quality of transportation systems. By analyzing these components, we gain a comprehensive understanding of how NLP can transform the landscape of transportation services.

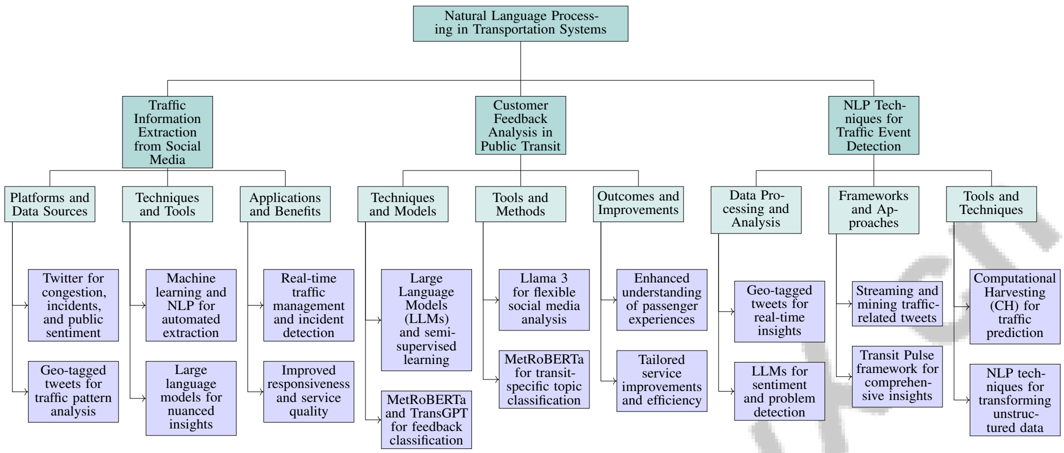

Figure 5: This figure illustrates the hierarchical structure of Natural Language Processing applications in transportation systems, focusing on traffic information extraction from social media, customer feedback analysis in public transit, and NLP techniques for traffic event detection. Each category is further divided into platforms and data sources, techniques and tools, and applications and benefits, highlighting the integration of advanced NLP methods to enhance transportation systems' responsiveness and service quality.

6 Natural Language Processing in Transportation Systems

6.1 Traffic Information Extraction from Social Media

Natural Language Processing (NLP) has become essential in extracting traffic information from social media, utilizing real-time user-generated data to enhance transportation systems. Platforms like Twitter provide insights into congestion, incidents, and public sentiment, enabling more effective traffic management and incident detection [47, 34, 1, 35, 22]. Automated models process vast amounts of geo-tagged tweets, achieving high accuracy in traffic pattern analysis across U.S. urban areas. Advanced NLP techniques, including large language models (LLMs), improve the extraction of nuanced insights, thereby enhancing transit agencies' responsiveness and service quality.

As illustrated in Figure 6, the hierarchical structure of traffic information extraction from social media emphasizes the integration of NLP techniques, social media platforms, and their applications in traffic management and service quality improvements. The framework by [35] employs machine learning and NLP to automate traffic information extraction from social media, turning unstructured data into actionable insights. This approach identifies relevant traffic events and trends, enhancing decision-making for transportation authorities. Similarly, [34] focuses on Twitter data to detect and categorize non-recurrent traffic events, such as accidents and road closures, crucial for real-time traffic management.

Social media data analysis extends beyond incident detection to include customer feedback in public transit systems [22]. By examining social media posts, transportation providers gain insights into passenger experiences, facilitating service quality improvements. Advanced NLP techniques transform unstructured social media data into actionable insights, bolstering transportation infrastructure. Integrating retrieval-augmented generation (RAG) with LLMs enables nuanced interpretations of user-generated content, allowing transportation agencies to swiftly identify emerging issues and improve service quality [14, 22, 1].

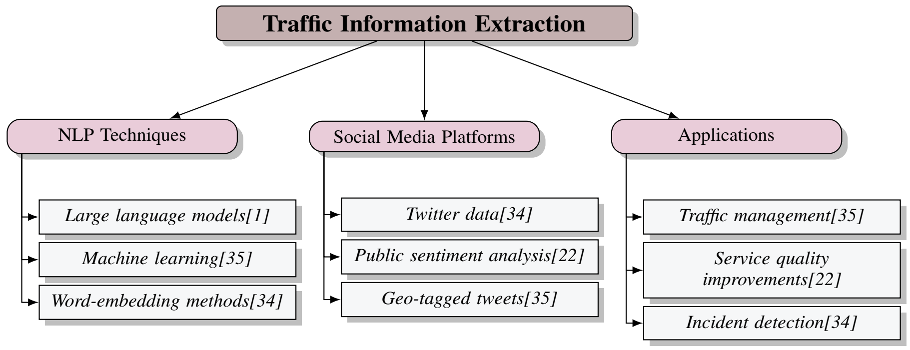

Figure 6: This figure illustrates the hierarchical structure of traffic information extraction from social media, emphasizing the use of NLP techniques, social media platforms, and their applications in traffic management and service quality improvements.

6.2 Customer Feedback Analysis in Public Transit

NLP integration in analyzing customer feedback within public transit systems significantly advances the understanding of passenger experiences and service quality enhancement. Utilizing techniques like Large Language Models (LLMs) and semi-supervised learning, transit agencies can efficiently parse unstructured data from diverse sources, identifying emerging issues and sentiment nuances. Models like MetRoBERTa and TransGPT exemplify automated, precise feedback classification, streamlining customer experience understanding [47, 14, 1, 22, 53].

Information extraction tools leveraging LLMs, such as Llama 3, allow for flexible analysis of transit-related social media posts, identifying emerging trends and issues in real-time [22]. The MetRoBERTa method uses semi-supervised learning to classify open-ended feedback into transit-specific topics, enhancing understanding and enabling tailored service improvements [47]. By converting unstructured feedback into actionable insights, NLP techniques support more responsive and customer-oriented services, improving public transportation systems' quality and efficiency [14, 22, 1, 47].

6.3 NLP Techniques for Traffic Event Detection

Method Name	Data Source Utilization	Machine Learning Integration	Sentiment Analysis
TIEF[35]	Geo-tagged Tweets	Machine Learning	Sentiment Analysis
TP[22]	Social Media Data	Llm-based Methods	Sentiment Classification
MRB[47]	Crm Feedback	Machine Learning	-
CH[54]	Real-time Traffic	-	-

Table 1: Comparison of various NLP-based methods for traffic event detection, highlighting their data source utilization, machine learning integration, and sentiment analysis capabilities. The table summarizes four distinct approaches, demonstrating the diversity in leveraging social media and real-time data for intelligent transportation systems.

Table 1 provides a comparative overview of NLP techniques employed for traffic event detection, emphasizing their application in processing unstructured data to enhance intelligent transportation systems. NLP techniques for traffic event detection are increasingly vital in intelligent transportation systems, facilitating the extraction and analysis of unstructured social media data. Automated systems process extensive geo-tagged tweets, enabling real-time insights into traffic conditions and incidents [22, 5, 34, 35]. Advanced methodologies, including LLMs, enhance user-generated content analysis by detecting sentiment and unusual system problems, improving transit agency responsiveness.

The method of streaming and mining traffic-related tweets employs machine learning and NLP to extract valuable congestion and incident information, offering a dynamic traffic data source [35]. The Transit Pulse framework utilizes LLMs for sentiment analysis and problem identification, providing comprehensive insights into public transit conditions [22]. MetRoBERTa's effectiveness in classifying customer feedback highlights NLP's role in identifying traffic-related issues and enhancing transit quality [47].

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Computational Harvesting (CH) techniques illustrate NLP's potential in traffic event detection, predicting traffic volumes accurately with lower computational resources [54]. By leveraging diverse data sources like Twitter, NLP techniques transform unstructured information into actionable insights, contributing to more intelligent and adaptive transportation infrastructures [14, 34, 35].

7 Challenges and Limitations

The integration of Large Language Models (LLMs) into transportation systems presents significant challenges, primarily related to data quality and bias, which are pivotal for ensuring the reliability and accuracy of these models in practical applications. Addressing these issues is fundamental to developing effective mitigation strategies.

7.1 Data Quality and Bias

The performance of LLMs in transportation systems is heavily influenced by challenges related to data quality and inherent biases. The absence of standardized metrics for assessing data quality often leads to reliance on subjective measures, potentially compromising the robustness of LLM outputs [6]. This lack of standardized evaluation complicates the assurance of consistent, high-quality data inputs crucial for LLM effectiveness. Additionally, the quality and diversity of event logs used in LLM training can limit the generalizability of results across different transportation contexts [25], affecting precise modeling and data interpretation.

Biases in LLM outputs, reflecting societal stereotypes and discrimination, raise ethical concerns, particularly in academic research where the integrity of synthesized knowledge is paramount. Studies emphasize the importance of examining data quality in systematic literature reviews to mitigate biases and enhance methodological transparency [9, 6]. Such biases can result in skewed content, impacting equitable deployment in transportation systems. Addressing these biases is essential to prevent perpetuating existing inequalities.

The complexities of natural language, including ambiguously expressed goals and non-deterministic state transitions, further complicate planning and can lead to inaccuracies in LLM outputs. As urban populations grow, integrating advanced technologies like LLMs and real-time data extraction from social media becomes vital for generating actionable insights and optimizing urban planning [22, 1, 2, 35].

Improving data quality and addressing bias are crucial for enhancing the reliability of LLM applications in transportation, enabling more precise solutions to real-world challenges through methodologies like domain-specific fine-tuning and retrieval-augmented systems for enhanced accuracy [20, 31, 6, 9, 22].

Figure 7 illustrates the main challenges and solutions related to data quality and bias in the application of large language models (LLMs) within transportation systems. It categorizes the issues into data quality challenges, bias and ethical concerns, and methods for improving LLM reliability, highlighting key references in each area.

7.2 Computational and Resource Constraints

Deploying LLMs in transportation systems is constrained by significant computational and resource challenges. The substantial computational resources required for training LLMs, which demand extensive datasets and advanced hardware, create barriers for organizations with limited access to high-performance computing [52]. Existing methods for data mixture selection often require substantial computational resources, making them impractical for large-scale applications [55]. Current Graph Neural Network (GNN) algorithms, despite their competitive runtime, need improvements for efficiency without sacrificing accuracy [15]. Moreover, reliance on reinforcement learning for workflow optimization may not be the most efficient compared to other paradigms, indicating a need for more resource-effective approaches [56]. Modeling spatial and temporal dependencies in real-time applications, such as traffic prediction, presents challenges, as models like Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) often struggle with these complexities [29]. Integrating knowledge graphs into LLMs poses additional challenges, introducing potential noise during knowledge integration and limitations in the scope of included knowledge [13]. While

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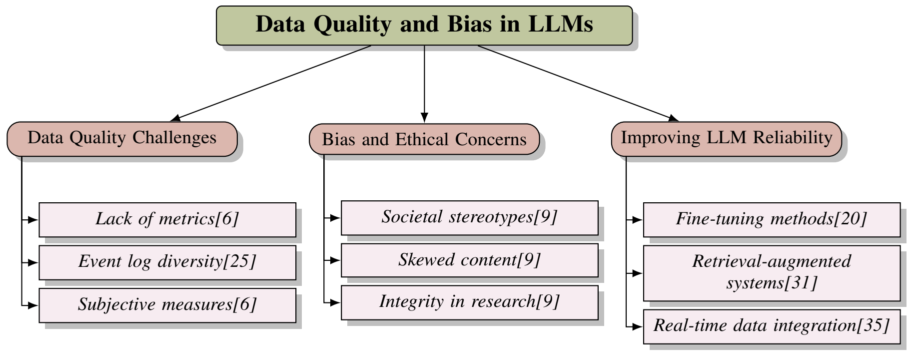

Figure 7: This figure illustrates the main challenges and solutions related to data quality and bias in the application of large language models (LLMs) within transportation systems. It categorizes the issues into data quality challenges, bias and ethical concerns, and methods for improving LLM reliability, highlighting key references in each area.

reservoir computing approaches offer lower computational costs and leverage real-world data for predictive modeling [54], their predictive performance may not always surpass that of more complex models. Addressing these computational and resource constraints is essential for the successful implementation of LLMs in transportation systems. Advancements in LLM serving systems and optimization algorithms can significantly enhance performance and scalability, facilitating intelligent modeling and strategic decision-making [20, 37, 9, 12].

7.3 Model Interpretability and Trustworthiness

The integration of LLMs into transportation systems presents challenges related to model interpretability and trustworthiness. The reliance on complex models can lead to overfitting, computational inefficiency, and a lack of interpretability [33]. The opacity of LLMs complicates understanding how these models make specific predictions, crucial for building stakeholder trust. Overfitting, where models excel on training datasets but fail to generalize effectively, limits their applicability in real-world scenarios. This issue necessitates robust training methodologies and fine-tuning strategies to enhance predictive capabilities across diverse contexts [9, 27, 19, 52]. The computational inefficiency associated with LLMs further complicates their scalability and practical deployment. The lack of interpretability in LLMs poses a barrier to acceptance and widespread use. Stakeholders require transparent models utilizing advanced data analysis techniques to ensure decisions are informed by reliable insights from diverse feedback sources, including social media and customer relationship management systems. This transparency enhances understanding of user experiences and supports the development of intelligent transportation systems that optimize urban planning and service quality [22, 2, 47]. To foster trust in LLMs, it is essential to develop robust methods that enhance interpretability while maintaining high performance. This includes fine-tuning techniques for factual accuracy, integrating information retrieval systems to minimize hallucinations, and establishing mechanisms for tracking LLM responses to sources. Addressing these challenges can ensure methodological transparency and reliability in applications like systematic literature reviews, setting new standards for AI use in academic research [9, 20, 6, 31]. Techniques such as model distillation and visualization tools can demystify LLM outputs, making them more accessible to non-experts. Effectively addressing model interpretability and trustworthiness challenges is crucial for the successful integration of LLMs into transportation systems, as these factors directly influence user confidence, safety, and the overall reliability of AI applications. Recent advancements in LLM safety underscore the importance of interpretability in mitigating risks such as value misalignment and adversarial attacks, ensuring compliance with ethical standards and governance frameworks [20, 9, 57]. Enhancing transparency and understanding can foster greater trust in these models, supporting the development of more intelligent and adaptive transportation infrastructures.

7.4 Domain-Specific Adaptations

Applying LLMs in transportation systems necessitates domain-specific adaptations to meet the unique challenges of various transportation modes. These adaptations enhance the performance of

LLMs across operational contexts. Fine-tuning methodologies and integrating information retrieval systems enable LLMs to process and interpret domain-specific data, improving factual accuracy and reducing hallucinations. This ensures that LLMs meet the demands of scholarly research, such as automating systematic literature reviews, while providing reliable responses to in-domain inquiries [9, 20, 6, 31]. Customizing LLMs to accommodate the linguistic and operational nuances of specific transportation systems is a primary consideration. For instance, LLaMA models utilize parameter-efficient fine-tuning techniques to adapt LLMs to specific linguistic contexts, enhancing their ability to process relevant data within railway systems [46]. Furthermore, integrating multi-modal data inputs, as demonstrated by models like TransGPT, is essential for managing diverse data sources in transportation systems [1]. By processing both single and multi-modal data, LLMs can enhance their ability to optimize scheduling processes and improve operational efficiency across transportation modes. Incorporating domain-specific knowledge into LLMs is vital for enhancing their factual reasoning capabilities. Utilizing knowledge graphs (KGs) enables LLMs to access structured information relevant to specific transportation domains, providing deeper insights into operational requirements and safety protocols [13]. The necessity for domain-specific adaptations in LLM applications is crucial for enhancing performance and relevance in transportation systems. Recent research highlights the effectiveness of fine-tuning LLMs for specific fields, integrating information retrieval systems to mitigate hallucinations, and optimizing decision-making processes through combining LLMs with traditional optimization algorithms. These adaptations streamline labor-intensive tasks, such as systematic literature reviews, ensuring LLMs provide accurate, in-domain responses by leveraging external knowledge sources, ultimately leading to more informed and efficient transportation management [9, 37, 31]. Customizing LLMs to meet the unique challenges of different transportation modes enhances their ability to process and interpret domain-specific data, contributing to the development of intelligent and adaptive transportation infrastructures.

7.5 Ethical Considerations and Societal Impacts

Deploying LLMs in transportation systems necessitates a thorough examination of ethical considerations and societal impacts to ensure responsible and equitable use. A primary concern is data privacy and security; the extensive data required for training and operating LLMs poses significant risks if not managed appropriately. Ensuring robust privacy-preserving techniques is crucial to maintaining public trust and safeguarding individual rights [18]. The computational resources required for deploying LLMs present ethical and environmental challenges. The substantial energy consumption associated with training and operating these models necessitates strategies to reduce resource usage, contributing positively to energy savings and sustainable service deployment [7]. The societal impact of biases inherent in LLMs remains a critical concern. The propagation of biases and potential for discriminatory outcomes highlight the need for comprehensive ethical oversight to ensure LLM applications do not perpetuate existing inequalities [18]. Evaluating LLMs emphasizes addressing biases and cultural sensitivities, ensuring ethical and responsible assessments [7]. The interpretation of social media language, characterized by complexity and informality, presents additional ethical challenges. Sarcasm, slang, and other informal expressions complicate accurate interpretation of user feedback, necessitating careful consideration of linguistic nuances in transportation applications [58]. Perceptions of hallucinations in LLMs raise ethical considerations, particularly in real-world applications like transportation, where inaccurate outputs can have significant consequences. Reevaluating the implications of these hallucinations is crucial for ensuring the reliability and trustworthiness of LLM-based systems [24]. Inclusivity in urban planning is another critical ethical consideration, as LLMs can enhance participatory processes by addressing diverse community needs. Ensuring these models promote inclusivity and equitable access to transportation services is essential for fostering just urban environments [59]. Examining the ethical and societal impacts of LLMs in transportation is crucial for responsible deployment. By addressing critical issues such as data privacy, resource consumption, biases, and inclusivity, we can leverage LLM capabilities to enhance transportation systems. These advancements aim to improve service quality and responsiveness through social media insights and customer feedback, prioritizing ethical outcomes for all stakeholders. Innovative approaches like the MetRoBERTa model demonstrate how LLMs can classify and analyze unstructured feedback, providing transit agencies with actionable insights to understand rider experiences and improve service delivery [20, 22, 47].

8 Future Directions and Research Opportunities

In exploring future directions and research opportunities within transportation systems, the pivotal role of Large Language Models (LLMs) in enhancing human-agent collaboration is paramount. The following subsection delves into specific innovations arising from this integration, emphasizing the transformative potential of LLMs in decision-making and operational efficiency in transportation contexts.

8.1 Innovations in Human-Agent Collaboration

Integrating LLMs into transportation systems fosters substantial advancements in human-agent collaboration, enhancing decision-making and operational efficiency. Future research should prioritize dynamic benchmarking systems that adapt to rapid AI advancements, incorporating real-time audits and frequent updates to ensure LLMs align with evolving transportation needs [7]. Expanding datasets and refining evaluation metrics are crucial for capturing the complexities of process mining tasks essential for optimizing transportation operations [25]. Improved data quality and scope enhance LLMs' support for complex decision-making processes in transportation environments.

Exploring methodologies that facilitate dynamic interactions between artificial and real-world systems is vital for advancing human-agent collaboration. Enhancing LLM capabilities for explainability and adaptability in real-world planning scenarios is essential. The development of Safe and Responsible Large Language Models (SRLLMs) that incorporate diverse datasets and AI safety protocols will further support effective collaboration [60].

Research should also focus on enhancing the robustness and adaptability of LLM-assisted planning systems by exploring frameworks that address real-world planning challenges. Integrating diverse data sources, such as social media and real-time traffic monitoring applications, alongside advanced classification algorithms like deep learning and unsupervised learning, can significantly improve traffic event detection accuracy. This multifaceted approach facilitates real-time traffic information extraction, including incidents and congestion levels, enabling comprehensive spatial and temporal analyses. Such improvements contribute to effective traffic management solutions, allowing urban areas to respond dynamically to unpredictable traffic events, thereby enhancing road safety and efficiency [10, 33, 34, 35].

Additionally, integrating Knowledge Graph-enhanced LLMs (KGLLMs) can be improved by merging various knowledge types, enhancing interpretability, and developing domain-specific models for specialized applications [13]. Longitudinal studies assessing the real-world impact of LLMs and further model customization will yield valuable insights into their collaborative potential in transportation systems.

By addressing critical challenges and seizing emerging opportunities, researchers can develop intelligent and adaptive transportation infrastructures that effectively integrate human and machine capabilities. Leveraging advanced technologies, such as intelligent transportation systems (ITS) and LLMs, will facilitate the analysis of mobility data, optimize urban planning, and enhance traffic management. As urban populations grow, leading to increased congestion and safety concerns, implementing AI-driven solutions is essential for creating sustainable and efficient transportation networks that improve safety, reduce congestion, and foster better communication between vehicles and infrastructure. Insights from social media can provide valuable feedback for transit agencies, enhancing their ability to respond to real-time challenges and improve service quality [10, 23, 1, 2, 22].

8.2 Advancements in Traffic Management and Urban Planning

Integrating LLMs into traffic management and urban planning presents significant opportunities for advancing these domains through enhanced communication and sense-making capabilities. LLMs' ability to generate coherent narratives can facilitate effective stakeholder communication, improving planning and management processes [61]. This narrative coherence is crucial for aligning diverse interests and ensuring comprehensive understanding and support for urban planning initiatives.

LLMs can revolutionize traffic management by enabling highly accurate traffic predictions and real-time decision-making through advanced spatial-temporal analysis. Recent developments, such as Spatial-Temporal Large Language Models (ST-LLMs), have demonstrated effectiveness in capturing

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global spatial-temporal dependencies, thereby improving predictive accuracy for traffic patterns. This capability enhances intelligent transportation systems' efficiency and supports the automation of complex decision-making processes in dynamic traffic environments [20, 12, 9, 39]. By analyzing historical and real-time data, LLMs can optimize traffic flow, reduce congestion, and enhance safety across urban environments.

The integration of LLMs into urban planning processes can significantly enhance the development of sustainable and resilient cities through participatory planning. This approach leverages LLMs to effectively engage diverse stakeholders, addressing traditional challenges related to time and manpower. Empirical research shows that LLMs can generate inclusive solutions tailored to community needs, outperforming human experts in satisfaction and engagement metrics. By providing a natural language interface to geospatial data, LLMs assist in assessing urban attributes and potential business opportunities, fostering informed decision-making that promotes ecological sustainability and social inclusion [31, 18, 30, 9, 62]. This integration ensures that urban development aligns with environmental and social objectives, enhancing participatory planning processes and promoting equitable urban development.

Advancements facilitated by LLMs in traffic management and urban planning promise the creation of intelligent, adaptive, and sustainable urban environments. By leveraging LLM capabilities, planners and policymakers can effectively tackle multifaceted challenges posed by contemporary urbanization. This innovative approach enhances participatory urban planning, integrating LLMs into decision-making processes for greater stakeholder engagement and tailored, inclusive solutions. Empirical studies demonstrate LLMs' superiority over traditional methods in user satisfaction and inclusivity while optimizing urban mobility and addressing delivery demand through data-driven insights, ultimately contributing to smarter, more sustainable, and livable cities that accommodate diverse community needs [48, 2, 30, 4, 62].

8.3 Complementary Technologies and Multimodal Integration

Integrating complementary technologies and multimodal approaches presents a promising avenue for future research in enhancing LLM capabilities within transportation systems. As LLMs evolve, developing benchmarks that incorporate noisy data and realistic interaction scenarios is essential for accurately evaluating their performance in complex environments [63]. This approach ensures LLMs are robust enough to handle the intricacies of real-world applications, particularly in transportation contexts where data variability is common.

The potential for integrating LLMs with Evolutionary Algorithms (EAs) highlights opportunities for unlocking new optimization strategies and applications [64]. By combining LLMs' strengths in processing complex data with EAs' adaptive capabilities, researchers can develop more efficient solutions for transportation challenges, potentially discovering novel optimization techniques that enhance traffic management, resource allocation, and operational efficiency.

Future research should also focus on exploring additional hyperparameters and evaluating other inference engines to optimize LLM performance [65]. Incorporating resource utilization metrics into the optimization framework will enhance LLM deployment, ensuring efficient operation within transportation systems' constraints. Moreover, integrating external knowledge sources can improve factual accuracy and address biases in LLM outputs, contributing to more reliable and equitable transportation solutions [66].

Acquiring reliable, high-quality datasets in diverse languages, such as Italian, is crucial for enhancing LLM performance and reducing biases from dominant languages like English [46]. By refining vocabulary trimming methods and integrating efficiency techniques, researchers can accommodate a broader range of languages and contexts, improving LLM adaptability in multilingual transportation environments [67].

Developing lightweight models and exploring multimodal integration are essential for enhancing LLM deployment in advanced networks, such as 6G [68]. Focusing on these areas ensures LLMs can support the high-speed, high-capacity demands of future transportation infrastructures. Additionally, exploring alternative learning methods and paradigms, like teacher-student or adversarial learning frameworks, can enhance collaborative learning between workflow generators and interpreter LLMs, leading to more efficient transportation systems [56].

As illustrated in Figure 8, the integration of complementary technologies and language adaptation strategies plays a critical role in enhancing LLMs for transportation systems. This figure highlights the significance of evolutionary algorithms, hyperparameter optimization, and external knowledge sources in optimizing LLM performance. Furthermore, it emphasizes the importance of language adaptation techniques, such as vocabulary trimming and multimodal integration, in managing diverse languages and contexts. The figure also outlines workflow optimization through automated workflows, data analysis tools, and evaluation frameworks.

Finally, developing flexible tools for data analysis and formalizing evaluation frameworks are critical for accommodating dataset practitioners' diverse needs [6]. Addressing these research opportunities will significantly advance LLM capabilities in transportation systems, contributing to more intelligent, adaptive, and efficient infrastructures.

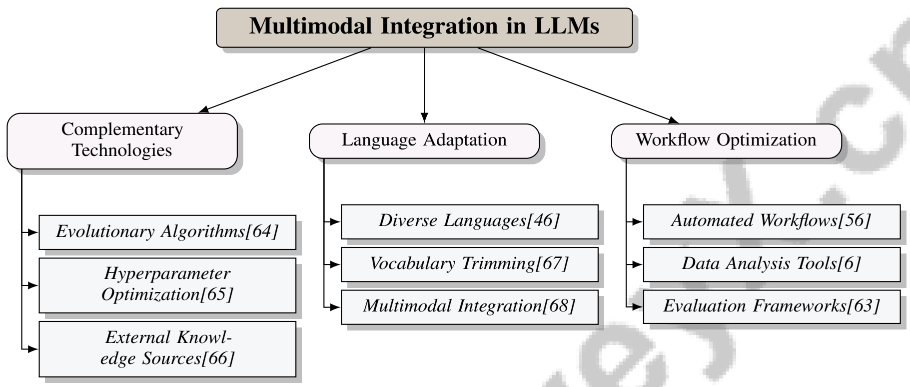

Figure 8: This figure shows the integration of complementary technologies and language adaptation strategies in enhancing Large Language Models (LLMs) for transportation systems. It highlights the role of evolutionary algorithms, hyperparameter optimization, and external knowledge sources in optimizing LLM performance. Additionally, it emphasizes the importance of language adaptation techniques such as vocabulary trimming and multimodal integration in managing diverse languages and contexts. The figure also outlines workflow optimization through automated workflows, data analysis tools, and evaluation frameworks.

9 Conclusion

The integration of Large Language Models (LLMs) into transportation systems represents a pivotal advancement in optimizing operational processes and enhancing efficiency. This survey highlights the transformative potential of LLMs in improving traffic prediction accuracy, algorithm design, and resource management. The automation capabilities of LLMs, exemplified by frameworks like AutoFlow, demonstrate their proficiency in generating workflows that are both readable and reliable, surpassing traditional manual approaches.

In the realm of air traffic management, tools such as AutoFPDesigner have effectively automated flight procedure design, achieving high standards of safety and task completion. Additionally, language-conditioned traffic scenario generation models have set new benchmarks for realism in traffic simulations, advancing beyond previous methodologies.

The survey underscores the importance of continuous research into LLM applications within transportation, particularly in refining event detection frameworks to enhance news analysis and reporting accuracy. Furthermore, the ability of LLMs to automate the knowledge synthesis phase of systematic literature reviews showcases their potential for achieving high factual accuracy and reliability, indicating their broader applicability across diverse research domains.

Incorporating LLMs into transportation systems offers numerous benefits, including increased efficiency, safety, and improved decision-making capabilities. Ongoing research and development in this area are crucial for unlocking the full potential of LLMs, ultimately leading to more intelligent, adaptive, and sustainable transportation infrastructures.

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