

Large Language Model and AI Agent System for Smart City: A Systematic Literature Review

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Abstract

As smart cities rapidly develop, large language model (LLM) agent systems are playing an increasingly vital role in enhancing citizens' quality of life, particularly in traffic management. This study aims to explore the core technological architecture and current developments of LLM agent systems in smart city transportation through a systematic literature review of studies published between 2022 and 2024 in the Web of Science database. The findings reveal key trends, challenges, and opportunities in the application of LLM-based AI agents, with major application areas including traffic data processing and prediction, autonomous driving technology, generative AI for transportation systems, and traffic management. The research contributions of this study include synthesizing current knowledge on LLM-based AI agents in smart city transportation, addressing gaps in existing literature, and providing practical recommendations for improving urban traffic management efficiency. The practitioner implications of this study include insights for optimizing traffic management, enhancing autonomous driving technologies, and improving urban mobility through the implementation of LLM-based AI agents in smart city initiatives.

Keywords: Agent, Large Language Model, Generative AI, Smart City, Systematic Literature Review

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I. INTRODUCTION

As cities continue to grow in complexity, the integration of advanced AI technologies has become crucial for managing urban environments effectively. This paper explores the intersection of Large Language Models (LLMs) and AI agent systems, focusing on their applications in smart cities. The rapid development of LLMs, renowned for their language understanding and generation capabilities, has positioned them as foundational models for various applications (Huang and Chang 2022). In smart city contexts, these models hold the potential to revolutionize urban management, enhance efficiency, sustainability, and quality of life for citizens.

LLMs have emerged as one of the most influential technologies in the AI landscape, with notable advancements in human-like conversational abilities and multimodal capabilities. These models are renowned for their massive scale, powerful capabilities, and exceptional generalization abilities across various tasks (Touvron et al. 2023; Wang et al. 2024a).

LLM-based AI agents framework, consisting of modules such as Profile, Memory, Planning, and Action (Wang et al. 2024b), allows for personalized and dynamic interactions between users and intelligent agents (Cheng et al. 2024). As LLMs evolve, their integration with multimodal technologies has shown strong capabilities in cross-modal understanding and generation of text and images, enhancing their flexibility and task execution capabilities (Xu et al. 2024). Its development involves multiple domains, such as physical, social, and network domains, making agent-based simulation in urban environments more complex and challenging than in single environments (Chen 2012). The development of smart cities relies heavily on the integration of various high-tech methods and systems, aiming to improve urban operational efficiency and enhance citizens' quality of life.

Despite the advancements, there remain significant challenges in the deployment of LLM-based agent systems within smart cities. These challenges include issues related to data integration, privacy, real-time processing, and system transparency. While the current research highlights the potential of LLMs in various domains, there is a need for a comprehensive understanding of how these technologies can be effectively applied in the context of smart cities. This paper addresses this gap by conducting a systematic literature review to answer the research question: How do LLM-based agent systems contribute to the development and management of smart cities?

This paper seeks to answer the research question: How do LLM-based agent systems contribute to the development and management of smart cities? By systematically examining the current research, this study aims to identify key trends, challenges, and opportunities associated with the implementation of LLM-based agents in urban environments. The findings will provide a deeper understanding of how these technologies can drive innovation and improvement in smart city infrastructure.

The structure of this study is as follows. Section 2 provides a comprehensive literature review, covering the origins of common-sense reasoning and AI, the framework of LLM-based agents, multimodal approaches, the evolution of LLM-based AI agents, multi-agent systems, and their applications in smart cities. Section 3 outlines the research methodology, detailing the process of searching for and screening relevant papers, including the eligibility criteria, information sources, search strategy, study selection, and data extraction. Section 4 presents the search results and analyzes the relationships between the documents, including publication trends, types of publications, and a comprehensive analysis of the selected studies covering various AI techniques, their traffic-related focus, benefits, and challenges. Finally, Section 5 summarizes

the research findings, highlighting the implications of LLM-based agent systems for the future of smart cities and suggesting directions for future research.

II. LITERATURE REVIEW

2.1 The Origin of Common-Sense Reasoning and The Origin of Artificial Intelligence

In 1959, McCarthy introduced the concept of common-sense reasoning as part of artificial intelligence (AI) in his seminal paper (McCarthy 1959). Today, Large Language Models (LLMs) have evolved into a cornerstone technology in AI. These models are capable of processing and generating natural language text, drawing from vast amounts of network knowledge (Wang et al. 2024b). Renowned for their scale and robust capabilities, LLMs exhibit exceptional generalization across various tasks (Touvron et al. 2023; Wang et al. 2024a) and demonstrate extraordinary potential in human-like conversational interfaces (Wang et al. 2024b; Xi et al. 2023). The language understanding and generation capabilities of LLMs position them as foundational models for a variety of applications (Huang and Chang 2022).

2.2 The Framework of LLM-Based Agents

LLMs operate within a framework consisting of four core modules: Profile, Memory, Planning, and Action (Wang et al. 2024b). The Profile module enables agents to grasp the role or context of a problem, while the Memory module allows them to recall past actions and navigate dynamic environments. The Planning module assists in breaking down instructions into manageable tasks, coordinating execution, evaluating outcomes, and refining actions to achieve goals with precision. Finally, the Action module empowers agents to select and utilize appropriate tools based on the planning results (Barua 2024). This structured interaction between users and intelligent agents personalizes and streamlines the dialogue process (Cheng et al. 2024).

2.3 Multimodal Approaches and LLM Advancements

Multimodal technology has demonstrated strong capabilities in cross-modal understanding and the generation of text and images (Xu et al. 2024). The release of ChatGPT, in particular, has spurred renewed interest in the transformative potential of LLMs and their ability to push the boundaries of AI development (Chen et al. 2024). Multimodality addresses the limitations of LLMs in task execution by promoting interaction and collective decision-making among agents. This approach integrates diverse data types, such as text, images, and audio, into the model, enhancing overall performance (Barua 2024).

While LLMs initially processed only text input, they have expanded to accommodate different input modalities. For example, Fuyu adapts image representation to fit the token space of LLMs, allowing decoder-only models to generate image captions. As models scale, next-GPT (Wu et al. 2023) emerges as an "any-to-any" model, capable of processing multiple modalities (text, audio, image, and video) via modality-specific encoders. These advancements highlight the role of multimodal approaches in enhancing the task execution capabilities and flexibility of LLMs.

2.4 Evolution of LLM-Based AI Agents

LLM-based AI agents rely on LLMs as their "brain," enabling human-like decision-making processes (Sumers et al. 2023). Supported by four key modules, these agents implement various critical functions that have been independently studied and refined over time (Zhao et al. 2023). The evolution of agent structures has progressed through four stages: reactive agents, deliberative agents, hybrid agents, and adaptive agents (Müller 1996).

The potential of autonomous agents based on LLMs spans numerous fields, with research on LLM-based agents rapidly expanding (Boiko et al. 2023; Gao et al. 2023a). These agents excel at decomposing complex tasks into smaller sub-goals (Khot et al. 2022), systematically

evaluating each part, and exploring multiple paths (Yao et al. 2024). Furthermore, tasks can be completed through the collaboration of multiple autonomous agents, which utilize external tools and resources to enhance their functionality, allowing them to operate more effectively in diverse and dynamic environments (Gao et al. 2023b; Li et al. 2023; Ruan et al. 2023).

Key features of these agents include autonomy, perception, intelligence, goal orientation, and social capabilities (Mele 1995). These characteristics enable agents to perceive their surroundings, make decisions, and take actions in response (Gao et al. 2024; Xi et al. 2023). Agents can also learn from past experiences, adjusting their behavior to make better decisions for future complex tasks (Shinn et al. 2024; Wang et al. 2024a). Through contextual learning (Dong et al. 2022), agents serve as both short-term memory or external vector databases (Lewis et al. 2020) and long-term memory systems, preserving and retrieving information over time (Wang et al. 2024b). This allows LLM-based agents to maintain contextual coherence and learn from interactions.

Additionally, agents can dynamically evolve through self-modification, such as adjusting initial goals, planning strategies, and self-training based on feedback or communication logs, without solely relying on stored historical records to inform subsequent actions (Guo et al. 2024).

2.5 Multi-Agent Systems and Communication Paradigms

Current multi-agent systems primarily operate through three communication paradigms: cooperative, debate, and competitive (Guo et al. 2024). Each autonomous agent adopts unique strategies and behaviors, engaging in communication with others (Du et al. 2023; Guo et al. 2024; Hu et al. 2024). This approach, closely resembling real-world human dialogue, supports a broad range of tasks (Liu et al. 2024), including multi-robot systems (Mandi et al. 2024), social simulations (Dasgupta et al. 2023; Park et al. 2023), policy simulations (Xiao et al. 2023), game simulations (Gong et al. 2023; Mao et al. 2023; Xu et al. 2023c; Xu et al. 2023d), customer service, healthcare (Barua 2024), software development, scientific experiments, and smart cities.

2.6 Smart Cities and LLM-Based Agent Applications

The development of smart cities hinges on the integration of advanced technologies and systems, aiming to enhance urban operational efficiency and improve the quality of life for citizens. This development spans multiple domains—physical, social, and network—making agent-based simulations in urban environments significantly more complex and challenging than in isolated systems (Chen 2012). The core objective of smart cities is to achieve intelligent management and services through technologies such as the Internet of Things (IoT), big data, and AI.

Urban Generation Intelligence (UGI) is a real-world urban environment platform built using digital twin technology, offering various interfaces for physical agents to simulate diverse behaviors. The platform is underpinned by a foundational model called CityGPT, which is trained with city-specific multi-source data. Within the UGI platform, LLM-based agents can simulate human-like behaviors, including social interactions, economic activities, mobility, and street navigation, demonstrating strong city activity simulation capabilities (Xu et al. 2023a). To further enhance agent applications in smart cities, integrating Visual Language Models (VLM) with LLMs has become a growing trend. In intelligent transportation systems (ITS), this integration has already yielded positive results (Zhao et al. 2023; Zhou et al. 2023), improving application performance in smart cities.

2.7 Research Gaps and Focus

While existing literature has explored various aspects of AI in smart cities, there remains a significant gap in our understanding of the specific role and potential of LLM-based agent

technology in this context. This systematic review aims to address key research gaps, including the lack of a comprehensive overview of LLM-based agents in smart cities and the unexplored challenges and opportunities associated with integrating these agents into existing smart city infrastructures.

By addressing these gaps, this review aims to provide a foundation for future studies and practical implementations of LLM-based agents in smart cities, ultimately contributing to the advancement of urban management and citizen services. Through a focused examination of the current state, emerging trends, and integration issues of LLM-based agent technology in smart city environments, this study will offer synthesized knowledge and clear guidance for both researchers and practitioners in the field.

III. METHODOLOGY

In this systematic literature review, we adopted a four-stage process, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al. 2021) guidelines to ensure the rigor of the study. This approach played a crucial role in ensuring the comprehensiveness of the literature review and improving the methodological quality. By systematically conducting literature search, screening, and data extraction, this review contributes to enhancing the quality and reproducibility of systematic reviews, as well as increasing the transparency and credibility of the research.

3.1 Eligibility Criteria

This study was conducted based on the following criteria, which were established to enhance the relevance of the research papers and improve their quality.

1. Inclusion criteria

- (1) The research must include content related to smart cities based on large language models.
- (2) The research should focus on traffic-related topics.
- (3) The articles must be published in English.
- (4) The publication date should range from 2022 to August 2024.
- (5) The articles must be accessible.

2. Exclusion criteria

- (1) Articles not published in English
- (2) Articles that do not provide a detailed description of large language models
- (3) Studies where the application domain is unclear or irrelevant
- (4) Articles that are not accessible

3.2 Information Sources

This systematic literature review utilized the Web of Science database to search for research related to the intersection of large language model agents and smart city transportation. As one of the most authoritative academic resource platforms globally, Web of Science integrates top-tier academic journals, monographs, and conference papers from around the world, covering fields such as natural sciences, engineering, biomedicine, social sciences, arts, and humanities. It also offers powerful citation indexing and academic impact evaluation functions, providing researchers with a high-quality source of academic information.

3.3 Study Search Strategy Process

Due to the limited number of papers focused on smart cities with transportation themes that utilize large language models as the foundational technology, the search strategy was designed to separately search for large language models and smart cities. To ensure the quality of the search and comprehensiveness of the information, the strategy involved the following steps:

First, synonymous terms related to large language models (e.g., Language Generation Model) were included using the OR operator. Then, a search for "Agent" and its synonyms (e.g., Intelligent Agent) was conducted using the OR operator, followed by an AND operation to combine these results and obtain content that more closely aligns with the topic.

Second, in the topic and application domain, a topic search was conducted using "Traffic" and related terms (e.g., accident), which were then combined with the first stage criteria using the AND operator. The search strings and a list of publications are presented in Table 1.

Table 1. Keyword Strategies and Results via Web of Science Database

Set	Query String	Results
S1	ALL=(Agent OR AI Agent OR Artificial Intelligence Agent OR Intelligent Agent OR AI System OR Virtual Agent) AND ALL = (large language model OR llm-based OR Generative Model OR Language Generation Model)	6532
S2	[S1] AND (TS=(Traffic OR Circulation OR accident))	184

3.4 Study Selection and screening process

In this systematic literature review, the research selection process was conducted in two stages. First, based on the defined search strategy, all identified content was exported to EndNote, where duplicates were systematically removed. Second, through the application of custom exclusion and inclusion criteria, 8 articles were ultimately selected. Each article was assessed for its relevance and adherence to the established criteria. A comprehensive full-text review was then conducted on the final selection of articles.

At this stage, the structured search and selection process provided a solid foundation for this systematic literature review, thereby enhancing the relevance and quality of subsequent research on the topic. This method ensured methodological rigor and strengthened the reliability of our research findings, providing robust support for further analysis and discussion.

3.5 Data Extraction Process

In this systematic review, the data extraction process was carefully planned and executed to ensure that all extracted data was focused and thoroughly analyzed. This meticulous approach was crucial for maintaining the integrity and reliability of the review results. During this process, we identified the specific large language model techniques used in each study, examined the application areas within smart cities that focused on transportation and their development status, and carefully extracted and analyzed the relevant advantages and challenges in each study.

IV. RESULTS AND ANALYSIS

4.1 Systematic Search and Selection Process

Based on a systematic search and selection process, this flow chart (Figure 1) outlines the screening and selection process for the articles included in this study, based on the PRISMA methodology.

1. Identification: The initial search identified 184 records from the Web of Science database. No duplicate titles were found in this initial dataset.
2. Screening:

The first screening step involved filtering articles by publication year, focusing on studies published between 2020 and 2022. This criterion excluded 72 records, leaving 112 articles. A manual review was then conducted to remove unrelated articles, further reducing the dataset by 102 records, resulting in 10 articles deemed relevant to the study.
3. Inclusion:

Of the 10 related articles, 2 were excluded due to the unavailability of full-text versions.

The final selection consisted of 8 full-text studies included in the analysis.

This process highlights a systematic approach to identifying and selecting relevant studies, ensuring that only recent, accessible, and topic-relevant articles were included in the final analysis.

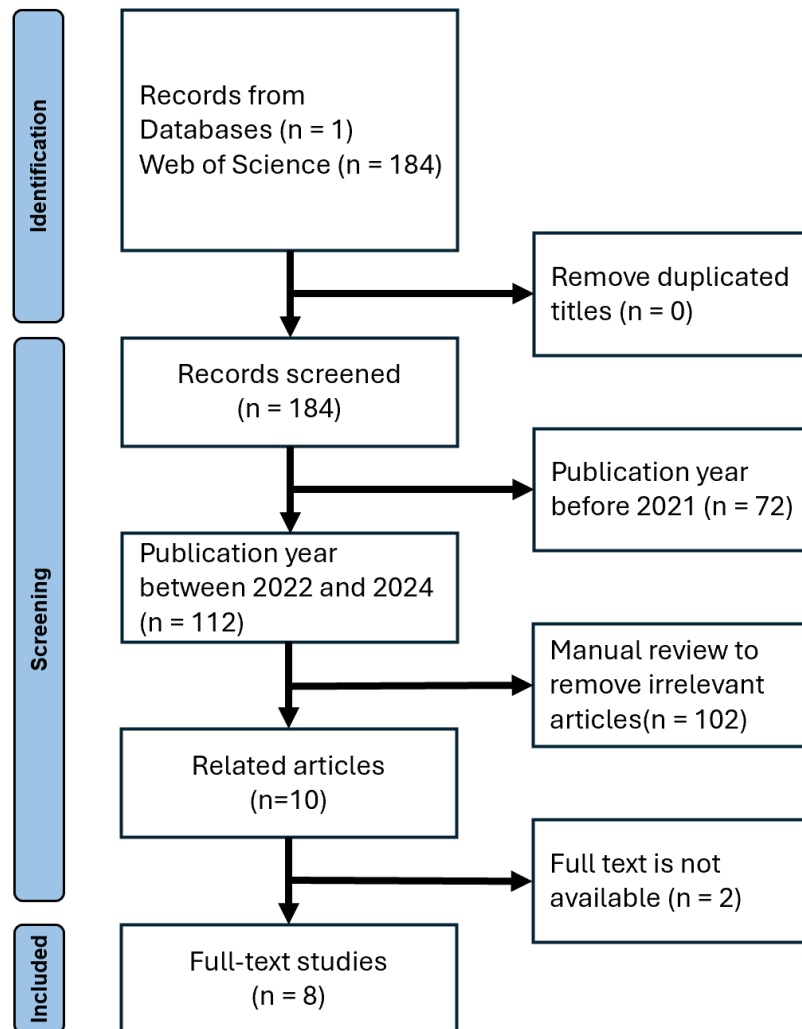


Figure 1. Flow chart for screening and selection of articles.

4.2 Emerging Trends in LLM Applications for Smart City Transportation

Figure 2. shows the growth trend in the number of relevant documents published from 2014 to 2024. The number of publications was relatively low before 2017, indicating that research in this area was in its early stages. After 2017, there was a significant and rapid increase in publication numbers, especially from 2021 onward. The rapid increase in research output over the last few years highlights the field's development potential and suggests that smart city and traffic management applications of AI, including generative AI and large language models, will likely continue to attract significant academic and industry interest moving forward.

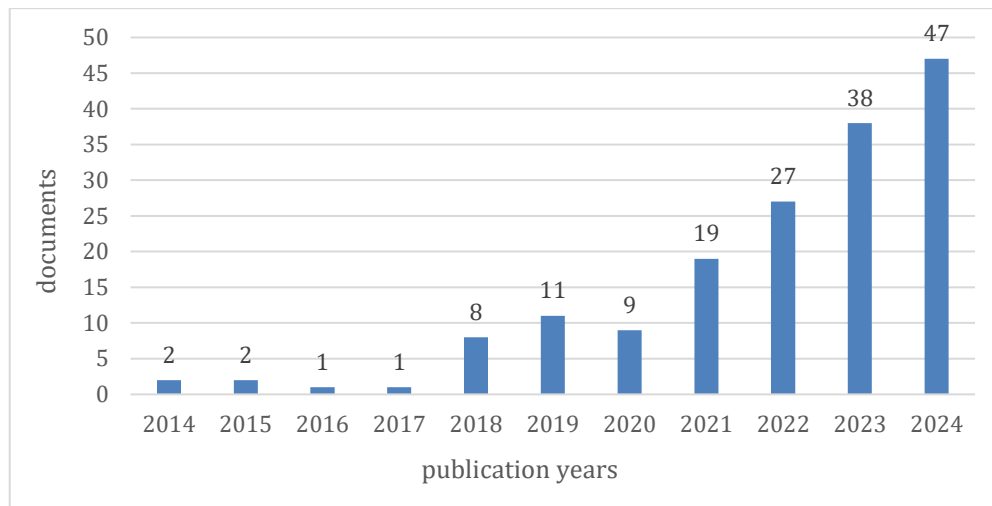


Figure 2. Growing trend analysis of AI and Smart City Traffic Management using Web of Science (2014-2024)

4.3 Keyword Co-occurrence Analysis

Figure 3. illustrates the main research themes and interconnections between keywords in the field of AI technologies applied to smart cities and traffic management. The primary clusters are centered around terms like "generative adversarial network (GAN)," "artificial intelligence," "deep learning," and "machine learning," indicating the significance of these technologies in areas such as traffic simulation, predictive modeling, and security applications. The prominent role of GANs and deep learning is particularly evident in applications related to autonomous driving, behavior prediction, and traffic flow management.

In the left area, terms like "large language models" and "generative AI" appear more peripherally, suggesting that generative AI technologies, though relevant, are still emerging within this field and have yet to become a primary research focus. This observation reveals potential for further exploration, as LLM-based techniques could enhance natural language processing and decision-making in smart traffic systems, creating novel applications and challenges.

The map also highlights a strong emphasis on security-related applications, with terms such as "intrusion detection" and "network security," reflecting the critical need for data protection and cybersecurity in smart city traffic systems. Additionally, terms like "traffic control," "real-time systems," and "traffic congestion" underscore the importance of real-time traffic management and congestion control in this research area.

Overall, this map provides a comprehensive overview of trending AI technologies in smart city applications and identifies opportunities for leveraging LLMs in this domain. Future studies could explore how LLMs, with their enhanced language understanding and interaction capabilities, may improve the performance and responsiveness of smart city traffic management systems.



Figure 3. Keyword Co-Occurrence networks of AI and Smart City Traffic Management Literature (2022-2024)

4.3 Publication Types and Document Types Analysis

Table 2 categorizes the 112 documents analyzed by publisher type, highlighting the major organizations contributing to research in this field. IEEE leads with 43 publications, underscoring its prominent role in publishing work related to artificial intelligence, computing, and engineering. Elsevier follows with 16 publications, reflecting its broad range of scientific and technical journals. MDPI, with 14 publications, is a major open-access publisher frequently featured in research on emerging technologies. Springer, another well-known academic publisher, accounts for 11 publications. The Association for Computing Machinery (ACM) has 8 publications, focusing primarily on computing and information technology. The “Other” category, comprising 20 publications, includes smaller or specialized publishers that contribute to the diversity of research sources in this area.

This distribution shows the central role of a few large publishers, particularly IEEE, in disseminating knowledge in the fields of AI, computing, and smart city applications.

Publisher Type	Results
IEEE	43
Elsevier	16
MDPI	14
Springer	11
Association for Computing Machinery (ACM)	8
Other	20

Table 2. Publisher Types Based on the Application of AI and Smart City Traffic Management (2022-2024)

In this study, a total of 112 articles were identified, with the majority being "Journal Articles," as shown in Table 3. This indicates that research on this topic is primarily highly specialized, with in-depth exploration of specific issues. These articles have undergone rigorous peer-review processes, thus holding a high level of credibility and influence within the academic community and occupying an important position in the field. Additionally, there are 42 "Conference

Proceedings." Although conference proceedings are slightly fewer in number compared to journal articles, they still represent active academic exchange in this field, presenting cutting-edge research findings and facilitating knowledge sharing among peers.

Document Type	Results
Journal Article	70
Conference Proceedings	42

Table 3. Document Types of Literature Based on the Application of AI and Smart City Traffic Management (2022-2024)

4.4 Comprehensive analysis of LLM-based AI Agents for Smart City

After conducting a comprehensive analysis of these eight studies, as summarized in Table 4, it is clear that AI technologies have had a profound impact on the field of transportation. The areas of application include traffic data processing and prediction, the development of autonomous driving technology, the application of generative AI in transportation systems, and the role of large language models in traffic management.

Firstly, traffic data processing and prediction play a critical role in smart transportation systems. By applying deep learning, multimodal data processing, and generative AI technologies, the studies demonstrate how valuable information can be extracted from complex traffic data sets to forecast and analyze traffic conditions. Particularly, large language models have been effectively utilized to process images and text, not only predicting traffic accidents accurately but also enhancing the real-time responsiveness of autonomous driving systems through PCA loading and risk assessment (de Zarzà et al. 2023). These technologies have significantly improved the accuracy and efficiency of traffic accident prediction, trajectory prediction, and traffic signal control (Lee et al. 2023). However, challenges remain in addressing data asymmetry and handling high-noise data sets.

With the advancement of technology, autonomous driving is gradually coming into the public eye. Generative AI and deep reinforcement learning (Pan et al. 2023) have shown outstanding performance in enhancing the accuracy of autonomous driving. Digital twin technology (Xu et al. 2023b) further enhances the reliability of autonomous driving on the road. The integration of traffic data and AI technologies helps to improve the real-time decision-making capabilities and safety of autonomous driving. However, digital twin-assisted systems are still not fully capable of adapting to the dynamic vehicle states and environmental changes in autonomous driving, which remains a significant challenge in its development.

The application of generative AI in transportation systems offers many innovative solutions, particularly in the areas of autonomous vehicle networks and traffic simulation. By combining generative AI with large language models (LLMs), the ability to generate data, simulate traffic, and optimize communication is further enhanced (Zhang et al. 2024a), thereby demonstrating great potential in improving the efficiency and safety of transportation systems (Xu et al. 2023b). However, the application of generative AI is still limited by the issue of data asymmetry, which is a key challenge that future research needs to address.

In traffic management, large language models have shown exceptional reasoning and planning abilities, demonstrating potential applications in traffic management. Nonetheless, due to LLMs' relatively limited expertise in the field of transportation, their efficiency in assisting traffic management is somewhat constrained, which also limits their effectiveness in the transportation domain. By integrating LLMs with Traffic Foundation Models (TFMs), this gap can be bridged, allowing LLMs to better understand their responsible domains, thereby providing comprehensive support for traffic management (Zhang et al. 2024b).

However, many challenges still exist in the application of traffic management. For example, different APIs may have different error rates, and Open-TI has been improved in this regard,

significantly reducing API error rates compared to other models, resulting in more stable task execution (Da et al. 2024). Additionally, balancing data rapid transformation with privacy and security issues to cope with rapidly changing environments remains a critical challenge for the future (Xu et al. 2023b).

Through the comprehensive analysis of these topics, it is evident that AI technology is transforming various aspects of transportation and demonstrating enormous application potential. Integrating large language models with other specialized domain technologies will further enhance user experience and service quality.

Table 4. Overview of the Selected Studies on LLM-based AI Agents for Smart City

Reference	AI Techniques	Traffic related Focus	Benefits	Challenges
TrafficGPT: Viewing, Processing and Interacting with Traffic Foundation Models(Zhang et al. 2024b)	Large Language Models (LLMs), Traffic Foundation Models (TFMs), Chain-of-Thought (CoT) Reasoning, ReAct Logic	Smart traffic management and control, traffic data analysis and decision support	Enhanced capability in processing and analyzing traffic data, improved precision in traffic control decisions, supports intelligent traffic system management, and improves efficiency and accuracy	Reliability in handling complex traffic datasets, human intervention needed to ensure output accuracy, challenges in dealing with ambiguous instructions and multi-turn dialogues
Generative AI Empowered Simulation for Autonomous Driving in Vehicular Mixed Reality Metaverses(Xu et al. 2023b)	Generative AI, Digital Twin (DT), Reinforcement Learning (RL), Deep Learning (DL)	Autonomous driving simulation, vehicular mixed reality, traffic data augmentation, safety enhancement	Improved driving safety, efficient traffic control, scalable simulations, and realistic data generation for autonomous vehicle testing	High computational cost, data privacy concerns, challenges in integrating physical and virtual environments, scalability in large-scale traffic networks
LLM Multimodal Traffic Accident Forecasting(de Zarzà et al. 2023)	Large Language Models (LLMs), Visual Language Models (VLMs), Multimodal Deep Learning, Transformer models	Traffic accident prediction, real-time traffic monitoring, autonomous driving assistance	Accurate accident forecasting, enhanced situational awareness for autonomous vehicles, improved traffic safety and decision-making	Data bias and privacy issues, high computational demands, integration complexity of multimodal data, ensuring real-time responsiveness
AI-Integrated Traffic Information System: A Synergistic Approach of Physics-Informed Neural Network and GPT-4 for Traffic Estimation and Real-Time Assistance(Gebre et al. 2024)	GPT-4, Physics-Informed Neural Networks (PINNs), Real-Time Data Analytics	Real-time traffic estimation, predictive analytics, intelligent traffic system assistance	Real-time and precise traffic information, enhanced prediction accuracy, improved traffic flow management, and decision support.	Integration with existing traffic infrastructure, computational resource intensity, handling dynamic traffic conditions, ensuring data consistency
Deep Learning-Based Multimodal Trajectory Prediction with Traffic Light(Lee et al. 2023)	Deep Learning, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Attention Mechanisms	Vehicle trajectory prediction, traffic signal interaction, collision avoidance	Improved vehicle path planning, better traffic light coordination, reduced collision risks, and enhanced traffic flow efficiency	Handling the variability of traffic conditions, model generalization across different environments, ensuring real-time prediction accuracy, and computational overhead
Generative AI-Enabled Vehicular Networks Fundamentals: Framework, and Case Study(Zhang et al. 2024a)	Generative AI, Deep Neural Networks (DNNs), Digital Twin (DT), Vehicle-to-Everything (V2X) communication	Vehicular network communication, traffic data generation, autonomous driving safety	Enhanced communication between vehicles, improved traffic safety, reliable data generation, and efficient traffic management	Data privacy and security concerns, integration with physical traffic infrastructure, high computational requirements, real-time data processing challenges

Research on Automatic Pilot Repetition Generation Method Based on Deep Reinforcement Learning(Pan et al. 2023)	Deep Reinforcement Learning (DRL), Markov Decision Processes (MDP), Simulation-based Learning	Autonomous vehicle navigation, adaptive driving strategy, path repetition learning	Improved autonomous driving performance, optimized driving paths, enhanced learning efficiency, and reduced computational costs.	Complexity in real-world implementation, model robustness in dynamic environments, scalability issues, and computational demands
Open-TI: Open Traffic Intelligence with Augmented Language Model(Da et al. 2024)	Large Language Models (LLMs), Open Traffic Intelligence (OTI), Augmented Reality (AR)	Traffic data analysis, real-time traffic monitoring, augmented reality in traffic management	Enhanced traffic data interpretation, real-time traffic insights, improved decision-making, and user engagement.	Data accuracy, integration with existing traffic systems, real-time processing constraints, and ensuring user privacy

V. CONCLUSION

Recent advancements in artificial intelligence, particularly in AI agent, have brought transformative changes to smart city transportation systems. This research aimed to clarify the role and impact of LLMs in smart city transportation through a systematic review of the literature. From an initial pool of 92 articles identified in the Web of Science database, eight studies met the inclusion criteria and were analyzed in depth.

Our findings reveal that LLM-based AI agents are being increasingly applied across various domains of smart city transportation. The most prevalent applications include traffic data processing and prediction, autonomous driving technology, generative AI for transportation systems, and traffic management. LLMs have shown exceptional capabilities in processing complex multimodal traffic data, improving the accuracy and efficiency of traffic predictions, and enhancing the real-time responsiveness of autonomous driving systems. The integration of LLMs with generative AI techniques has also demonstrated significant potential for optimizing autonomous vehicle networks and traffic simulations. However, challenges such as data asymmetry, high-noise data sets, and the adaptability of digital twin systems to dynamic environments remain critical hurdles that need to be addressed.

This study contributes to the growing body of research on AI applications in smart city transportation by providing a systematic review of LLM-based AI agents. It highlights the significant advancements and potential applications of LLMs in this field, offering valuable insights for both academic research and practical implementation. Specifically, the paper underscores the transformative impact of LLMs on transportation systems, particularly in enhancing the accuracy of traffic predictions, optimizing autonomous driving technologies, and improving overall traffic management.

The practical implications of this research are extensive, particularly for urban planners, transportation engineers, and policymakers. Integrating AI agents into smart city transportation systems can lead to more efficient, safe, and intelligent urban mobility solutions. For instance, LLMs in traffic management can help cities respond more effectively to real-time traffic conditions, reducing congestion and improving overall transportation efficiency. Additionally, the application of generative AI and digital twin technologies in autonomous driving systems can significantly enhance the safety and reliability of these systems, paving the way for the broader adoption of autonomous vehicles in urban environments.

While the applications of AI agents in smart city transportation are promising, several areas require further investigation. Future research should focus on addressing the challenges of data asymmetry and high-noise data in traffic predictions, improving the adaptability of digital twin systems to dynamic vehicle states and environmental changes, and enhancing the integration of LLMs with Traffic Foundation Models (TFMs). Additionally, exploring the use of LLMs in more complex and diverse urban environments, as well as their potential in other domains of smart city management could provide valuable insights for the future development of smart cities.

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