Exploring the Roles of Large Language Models in Reshaping Transportation Systems: A Survey, Framework, and Roadmap

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Project page: https://github.com/tongnie/awesome-llm4tr

Abstract

Modern transportation systems face pressing challenges due to increasing demand, dynamic environments, and heterogeneous information integration. The rapid evolution of Large Language Models (LLMs) offers transformative potential to address these challenges. Extensive knowledge and high-level capabilities derived from pretraining evolve the default role of LLMs as text generators to become versatile, knowledge-driven task solvers for intelligent transportation systems. This survey first presents LLM4TR, a novel conceptual framework that systematically categorizes the roles of LLMs in transportation into four synergetic dimensions: information processors, knowledge encoders, component generators, and decision facilitators. Through a unified taxonomy, we systematically elucidate how LLMs bridge fragmented data pipelines, enhance predictive analytics, simulate human-like reasoning, and enable closed-loop interactions across sensing, learning, modeling, and managing tasks in transportation systems. For each role, our review spans diverse applications, from traffic prediction and autonomous driving to safety analytics and urban mobility optimization, highlighting how emergent capabilities of LLMs such as in-context learning and step-by-step reasoning can enhance the operation and management of transportation systems. We further curate practical guidance, including available resources and computational guidelines, to support real-world deployment. By identifying challenges in existing LLM-based solutions, this survey charts a roadmap for advancing LLM-driven transportation research, positioning LLMs as central actors in the next generation of cyber-physical-social mobility ecosystems. Online resources can be found in the project page: https://github.com/tongnie/awesome-llm4tr.

Keywords: Large Language Models, Vision-Language Models, Intelligent Transportation Systems, Transportation Management, Foundation Models, Generative AI, Survey

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1. Introduction

1.1. Motivation

Modern transportation systems, characterized by their cyber-physical-social complexity, face unprecedented challenges such as congestion, resilience, sustainability, and adaptability to dynamic urban environments (Dimitrakopoulos and Demestichas, 2010). Traditional transportation management methods, however, often struggle with complex real-world data, increasing demand, human factors, and interaction with infrastructures. With the advancement of deep learning and big data techniques, the integration of transportation systems with advanced artificial intelligence (AI) tools, known as intelligent transportation systems (ITS) (Zhang et al., 2011), has led to significant progress in both academia and industry. Within the ITS framework, current transportation management strategies can often be organized around the *sensing-learning-modeling-managing* paradigm. During the past decades, this data-centric paradigm has demonstrated promising results combined with machine learning and AI-driven solutions.

However, the fast emergence of multimodal mobility ecosystems presents unprecedented technical and operational challenges. The combination of emerging mobility solutions such as autonomous vehicles, cloud computing, drone logistics, human-robot interactions, shared mobility platforms, and AI-powered intersection control has exposed critical limitations in current ITS architectures (Guerrero-Ibanez et al., 2015). Traditional ITS rely heavily on static models and fragmented data pipelines. Thus key challenges may stem from the need to reconcile heterogeneous and large-scale data streams across collaborative cloud-edge-end interfaces, manage real-time decision conflicts between human and machine agents in mixed autonomy environments, ensure

secure interoperability among proprietary platforms with competing optimization objectives, and develop novel modeling approaches that are applicable to overlapping mobility networks (ground, aerial, shared) beyond conventional traffic flow theories.

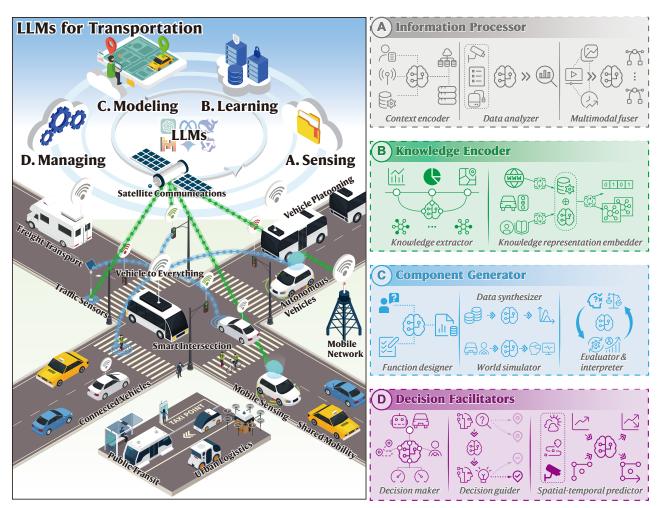


Figure 1: The LLM4TR framework proposed in this survey. We categorize main tasks in transportation systems as sensing, learning, modeling, and managing. The functionality of LLMs for each of them is structured as information processor, knowledge encoder, component generator, and decision facilitator. Based on this taxonomy, we provide a comprehensive review of existing literature.

The rapid evolution of Large Language Models (LLMs) offers a paradigm shift to overcome these inherent barriers. With emergent capabilities such as language understanding, in-context learning, multimodal reasoning, and human-like decision making, LLMs have evolved beyond their initial functionality as text generators, becoming versatile and general problem solvers (Zhao et al., 2023; Minaee et al., 2024; Shanahan, 2024). They have not only revolutionized the field of machine learning, but also demonstrated remarkable performances in application-oriented domains (Kaddour et al., 2023; Naveed et al., 2023). Their ability to process unstructured data, encode domain-agnostic knowledge, solve complex tasks, and generate context-aware solutions, aligns seamlessly with the demands of future ITS. In addition, natural language can serve as a universal interface for interpretable human-machine interaction in transportation systems.

Given these desirable properties of LLMs, the potential of LLMs to address the above challenges of modern ITS has recently gained great popularity. Far beyond conversational chatbots, LLMs can be a transformative force for transportation systems (Qu et al., 2023; Lv, 2023; Mahmud et al., 2025). For example, LLMs improve the accuracy of traffic prediction by integrating spatiotemporal patterns with semantic context (Ren et al., 2024), automate multimodal traffic scenario understanding (Zhou et al., 2023), optimize real-time traffic control through natural language interfaces (Lai et al., 2023), generate high-fidelity simulation environments (Zhao et al., 2024), facilitate communication between vehicles and users (Cui et al., 2024), and hence significantly improve the operational efficiency of ITS. These pioneering studies have suggested that LLMs can play a powerful role in shaping future transportation systems in various aspects and provide promising solutions to address the limitations of current ITS.

However, despite the early successes of pioneering studies in demonstrating the promise of integrating LLMs into transportation systems, they have explored isolated applications without articulating how the functionalities of LLMs interconnect throughout transportation systems. In addition, although these studies provide practical experiences for the utilization of LLMs, there is an absence of a principled framework to guide such integrations.

Therefore, there is a great need to build a unified and standard conceptual framework to guide future progress in this rapidly evolving area.

Table 1: Comparison wit	th existing reviews about	LLMs and generative AI	for transportation (up to the	date of this review).

Survey	Year	Venue	Taxonomy	Scope	Focus	
Zhou et al. (2023)	2023	IEEE TIV	Tasks	Perception, scene understanding, navigation, and decision making of autonomous driving	Applications of VLMs in main autonomous driving tasks	
Yan and Li (2023)	2023	ArXiv	Tasks	Traffic perception, traffic prediction, traffic simula- tion, and traffic decision- making	Applications of generative AI on different tasks in ITS	
Zhou et al. (2024a)	2024	TRANS. RES. E	Applications and ar- chitecture components	Transport plan, network de- sign, management, infras- tructure construction in ur- ban mobility systems	A conceptual framework that introduces a hierar- chically unified generative foundation model	
Zhang et al. (2024a)	2024	IJCRS	Applications and tasks	Traffic management, trans- portation safety, and au- tonomous driving	The potential of LLMs to in- crease forecasting accuracy, improve safety, and enhance decision making	
Wandelt et al. (2024)	2024	Appl. Sci.	Applications	Autonomous driving, safety, tourism, traffic, and others	Overview of current liter- ature, challenges and re- search recommendations	
Gan et al. (2024)	2024	Adv. Eng. Inform.	Tasks and deployment techniques	Perception, prediction, con- trol, and simulation for ITS; navigation, planning, and decision making for AV	Application and deployment of large models for ITS and AV	
Zhang et al. (2024g)	2024	ArXiv	Data processing pipelines and models	Traffic and demand forecast- ing	Tokenization, prompt, em- bedding and fine-tune tech- niques, zero-shot/few-shot prediction	
Choi et al. (2024)	2024	ArXiv	Models	Traffic data generation, traf- fic estimation and predic- tion, and unsupervised rep- resentation learning	Generative models in trans- portation, such as GAN, VAE, and diffusion models	
Mahmud et al. (2025)	2025	IEEE TITS	Applications	Traffic prediction, signal op- timization, traffic control, public transport, and V2X communication,	Potential of LLMs in opti- mizing ITS	
Thi	s survey	у	Roles of LLMs from a methodological per- spective	Sensing, learning, modeling, and managing of transporta- tion systems	Different roles of LLMs in integration with transporta- tion systems	

1.2. Scope and focus

Faced with both opportunities and challenges, a systematic survey and framework is urgently needed. Therefore, this survey seeks to fill the above knowledge gaps by presenting a comprehensive review of the latest literature, introducing a unified conceptual framework called *large language models for transportation* (*LLM4TR*), and structuring a corresponding taxonomy to elucidate the roles of LLMs in transportation (see Fig. 1). Specifically, this survey provides the first comprehensive methodological review of LLMs in transportation research, emphasizing their transformative roles rather than isolated applications. Our analysis spans diverse applications within the sensing-learning-modeling-managing paradigm, such as traffic prediction, autonomous driving, safety analytics, traffic control and operation, traffic simulation, and urban mobility optimization. To articulate the research scope and future directions, we propose LLM4TR, a conceptual framework that positions LLMs as a core that dynamically adapts its roles to synergize sensing, learning, modeling, and managing tasks. A structured taxonomy is followed to classify how these studies integrate LLMs into transportation systems and what enhancements LLMs can offer. Finally, we also provide an introductory review of key techniques about LLMs and an informative collection of available resources for real-world development of LLMs in transportation systems.

We are also aware of several related review articles on LLMs or generative AI techniques for transportation in Tab. 1. Our survey differentiates itself from others with a fresh perspective, novel taxonomy, broader coverage, and practical guidance. Furthermore, to support future development and encourage community engagement, we curate a GitHub repository at link: https://github.com/tongnie/awesome-llm4tr, with a supporting collection of datasets, benchmarks, and tools for LLM-driven transportation research. We will continue to update this online project so as to provide a platform for tracking the latested advances in the field. Finally, we hope that

this review will provide the research community with a broader perspective that will advance the application of LLMs in transportation research and practices.

1.3. Contribution

This survey makes four key contributions to the community:

- 1. *LLM4TR framework*: We provide the first comprehensive review on LLMs in transportation research from the methodological perspective, focusing on the four main categories of problems in transportation systems such as sensing, learning, modeling, and managing, and covering a broad spectrum of topics.
- 2. *Unified taxonomy*: A structured taxonomy is further developed to elucidate the roles of LLMs in transportation, including *information processor, knowledge encoder, component generator, and decision facilitator*. Based on this taxonomy, we clearly illustrate how to integrate LLMs to enhance current transportation systems.
- 3. *Research trend and outlook*: We present a visualization of the current research trend in the community and identify the current focus and existing challenges. Possible future directions are also discussed, focusing on both underexplored techniques and pathways for real-world deployment.
- 4. *Practical guidance*: We provide a collection of useful resources including datasets, literature, libraries, and hardware requirements, to support the grounding of LLMs in transportation domains. We also create an online platform for researchers and practitioners in the community to track the latest advances of LLMs in transportation and hope to provide a potential roadmap for advancing this emerging field.

1.4. Text organization

The remainder of this paper is structured as follows. Section 2 introduces foundational concepts and preliminaries, including tasks in transportation systems and background of LLMs. Section 3 introduces the LLM4TR framework and its taxonomy. Sections 4 to 7 detail specific roles of LLMs in transportation systems. Section 8 provides practical guidance for deploying LLMs, including datasets and resources. Section 9 discusses future opportunities and challenges. Section 10 concludes this survey.

2. Background and Overview

In this section, we first provide an overview of fundamental tasks in transportation systems. Then we briefly review the recent advances of LLMs by introducing the background, key findings, and mainstream techniques.

2.1. Overview of tasks in transportation systems

Modern transportation systems, characterized by their cyber-physical-social complexity, require innovative methods to address increasing challenges in congestion, sustainability, and resilience (Vahidi and Sciarretta, 2018; Ganin et al., 2019). Conventional methods, based on static models and fragmented data, struggle with the exponential growth of multimodal networks, human-centric mobility behaviors, and dynamic urban environments (Wang et al., 2019). To address these challenges, contemporary transportation research organizes methodological approaches around four fundamental tasks: *sensing, learning, modeling, and managing.* These interconnected domains form the backbone of modern ITS, allowing data-driven operation and management of transportation networks. This section briefly explores advances in each task, emphasizing their methods, synergetic relationships, and potential to shape the next generation of smart transportation systems.

2.1.1. Sensing

Sensing refers to the acquisition of traffic data and the environmental perception process. Sensing forms the foundation of modern ITS, and it focuses on data acquisition to capture real-time and historical traffic dynamics, environment conditions, and traveler behaviors (Gentili and Mirchandani, 2012). Traditional sensing methods rely on infrastructure-based sensors such as loop detectors, cameras, and radar systems, which provide aggregate traffic metrics such as volume, speed, and occupancy. However, emerging edge and mobile sensing technologies, including distributed IoT devices, GPS probes, smartphones, Wi-Fi sensors, and social media feeds, are improving data granularity by providing details of individual mobility patterns (Guerrero-Ibáñez et al., 2018; Kanarachos et al., 2018; Van Brummelen et al., 2018). The integration of these advanced sensing methods is crucial not only for traffic monitoring but also for enabling downstream applications in learning, modeling, and real-time management of transportation networks.

These sources, while rich in detail, are often accompanied with challenges such as noise, sparsity, and heterogeneity (Zhang et al., 2024f; Zheng et al., 2025). To address these issues, researchers employ advanced data enhancement techniques such as denoising, imputation, and super-resolution that can reconstruct high-resolution traffic states from sparse or low-quality inputs. In addition to industry-driven technology advances, academic studies have also focused on the challenges of heterogeneous data sources and privacy concerns (Fries et al., 2012; Zhu et al., 2018). Key innovations such as edge computing architectures that preprocess sensor data at the

source to reduce latency (Arthurs et al., 2021), and privacy-preserving sensing frameworks using distributed and federated learning to analyze mobility patterns without exposing individual trajectories (Zhou et al., 2015). Recent work also emphasizes integrating multi-source data (e.g., combining ride-hailing trajectories with loop detector counts) with data fusion strategies to enhance spatial-temporal coverage, thus enabling a more holistic view of urban mobility patterns (El Faouzi et al., 2011).

2.1.2. Learning

Learning refers to pattern recognition and predictive analytics of traffic data. Learning in transportation systems involves both machine learning and data-driven predictive learning approaches that extract actionable insights from large and heterogeneous datasets, bridging the gap between sensing and decision-making (Kumar and Raubal, 2021; Shaygan et al., 2022). Early work focused on statistical methods and shallow machine learning models to assist in pattern recognition and traffic data mining; however, the last decade has witnessed a surge in deep learning, reinforcement learning, and generative learning frameworks (Veres and Moussa, 2019; Haydari and Yılmaz, 2020; Lin et al., 2023). Many complex predictive tasks can be solved by end-to-end learning methods, such as dynamic routing, traffic prediction, anomaly detection, and safety-critical applications (Veres and Moussa, 2019). This shift is driven by the need to handle massive amounts of traffic big data generated by increasing traffic participants and infrastructures with scalability.

Deep learning transforms raw sensor data into actionable insights through three primary paradigms: supervised learning, unsupervised learning, and reinforcement learning (Veres and Moussa, 2019). A representative application in transportation lies in graph-based deep learning, where heterogeneous data (e.g., traffic flow, social media activity, traffic participants) are structured into spatio-temporal graphs to uncover latent correlations and interactions (Xue et al., 2025). Graph neural networks (GNNs) have proven effective for tasks such as traffic prediction and interaction modeling by encoding road network topology and traffic dynamics (Rahmani et al., 2023). In addition, unsupervised learning frameworks (e.g., deep generative models (Choi et al., 2024)) are used to learn the distribution of mobility patterns and generate simulated system states in large-scale networks. More recent advances include physics-informed neural networks that embed traffic flow equations into learning architectures (Shi et al., 2021), multi-agent RL frameworks coordinating connected vehicles or traffic controllers (Farazi et al., 2021), transfer learning techniques enable knowledge sharing across cities with diverse traffic patterns (Tang et al., 2022), and causal learning methods disentangle confounding factors in traffic analysis (Liu et al., 2024f).

2.1.3. Modeling

Modeling refers to the formulation and simulation of transportation systems. Modeling in transportation research aims to replicate real-world traffic phenomena through the development of mathematical, simulation-based, and data-driven models that represent traffic dynamics, travel behaviors, and infrastructure interactions (Daganzo, 1997). These high-fidelity modeling techniques serve as a virtual testbed for scenario analysis. During the past decade, researchers have developed a spectrum of principled models from discrete choice and activity-based models for travel demand analysis to complex simulations using deep neural networks (Golob, 2003; Di and Liu, 2016; Chen and Cheng, 2010; Raadsen et al., 2020). These models represent system dynamics across multiple scales. Microscopic models such as car-following theory (e.g., Intelligent Driver Model) simulate individual vehicle interactions (Gipps, 1981), while macroscopic models use fluid dynamics analogues through the Lighthill-Whitham-Richards equations (Papageorgiou, 1998). Mesoscopic approaches balance computational efficiency and behavioral realism using queueing networks (Burghout et al., 2005).

Emerging approaches further couple analytical models with data-driven modeling techniques (Zhang et al., 2011; Chen et al., 2016). These implementations combine traditional paradigms with real-time data streams for virtual-physical synchronization (Zhang et al., 2025b). For instance, dynamic traffic assignment (DTA) models are widely used to simulate network-wide vehicle and passenger trajectories, incorporating behavioral factors like route choice and departure time decisions (Janson, 1991; Wang et al., 2018). However, traditional DTA struggles with scalability in large, multimodal networks (Pi et al., 2019). To address this, data-driven optimization frameworks such as simulation-based optimization integrate multi-source data to estimate demand-supply parameters iteratively (Osorio and Bierlaire, 2013; Osorio and Chong, 2015). This is achieved by minimizing discrepancies between simulated and observed traffic states by adjusting origin-destination matrices and network supply attributes (Zhou and List, 2010; Wu et al., 2018; Ma and Qian, 2018; Ma et al., 2020). Today, simulation frameworks have evolved from standalone tools (SUMO, VISSIM, MATSim, etc.) to holistic platforms enabling large-scale scenario testing (Li et al., 2023a). Both microscopic and macroscopic behaviors and multimodal data can be integrated into foundational neural networks to simulate network-scale mobility patterns (Chen et al., 2024a).

2.1.4. Managing

Managing refers to the optimization and control strategies for the operation of transportation systems. Transportation management leverages insights from sensing, learning, and modeling tasks with optimization theory and control systems to improve traffic operations and network performance (Papageorgiou et al., 2003). Management tasks leverage real-time data to dynamically adjust operational strategies, such as adaptive traffic signal control and real-time route guidance (Fu, 2001; Guo et al., 2019). For example, model predictive control enables real-time signal timing adjustments (Ye et al., 2019), mixed-integer programming optimizes fleet dispatching for shared mobility services (Mourad et al., 2019), and network-level coordination uses Nash bargaining solutions to balance stakeholder interests for congestion pricing schemes (De Palma and Lindsey, 2011).

Cutting-edge approaches exploit end-to-end learning, where control policies directly map sensor inputs to actionable signals. Deep reinforcement learning (DRL) has proven to be effective for adaptive control, where agents learn optimal policies by interacting with simulated or real-world environments and maximizing cumulative rewards (Farazi et al., 2021). DRL has been widely used in various traffic control applications, such as ramp metering control (Han et al., 2023), intersection signal control (Chu et al., 2019), perimeter control (Chen et al., 2022), and vehicle platooning control (Li et al., 2021). In addition, the rise of connected vehicles and edge computing has prompted the development of cloud-based management systems that can process vast amounts of vehicle trajectory data to optimize signal timings without additional infrastructure (Wang et al., 2024a).

2.2. Background of Large Language Models

Large language models (LLMs) refer to Transformer-based (Vaswani et al., 2017) language models that contain hundreds of billions (or more) of parameters being trained on massive text data (Zhao et al., 2023; Shanahan, 2024). The Internet-scale training data and extensive model parameters enable LLMs to have impressive capabilities, from a natural language modeler to a general problem solver. To have a quick understanding of modern LLMs, this section briefly introduces the backgrounds and preliminaries of LLMs.

2.2.1. Emergent capabilities of LLMs

The emergent abilities of LLMs are formally defined as "the abilities that are not present in small models but arise in large models (Wei et al., 2022a)", which is one of the most significant properties that distinguish LLMs from previous pretrained language models. These emergent abilities include *in-context learning, instruction following, and step-by-step reasoning,* which is the result of the *scaling laws*.

Scaling laws. The emergent capabilities of LLMs are fundamentally tied to scaling laws, which describe predictable performance improvements as models scale in size, training data, and computational resources. Empirical studies have shown that as these models grow, they exhibit enhanced capabilities in understanding and generating human-like text. Pioneering work by Kaplan et al. (2020) established that model loss decreases predictably with increases in model parameters, dataset size, and training computation, enabling systematic optimization of LLM architectures. Subsequent research by Hoffmann et al. (2022) refined these principles, suggesting that optimal performance arises from balancing model size and training data size, as exemplified by the compute-optimal Chinchilla model. Crucially, scaling laws stand the emergence of novel abilities of LLMs. Wei et al. (2022a) identified that performance rises abruptly once models surpass critical thresholds in scale.

In-context learning. A prominent feature of modern LLMs is in-context learning (ICL), the ability to adapt to new tasks dynamically through input contextual examples or related knowledge without re-training or gradient updates. Formally introduced by Brown et al. (2020), ICL enables few-shot or zero-shot generalization by inferring latent task structures from input prompts. Specifically, LLMs are provided with a natural language instruction and/or several task demonstrations, it can generate the expected output for the test task instances by completing the word sequence of input text. Formally, given a set of *k* paired natural language query-answer demonstrations $\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$, the task description *T*, and the target query x_{k+1} , LLMs generate the prediction of the \hat{y}_{k+1} by learning from the context:

$$LLMs(T, \mathcal{D}, (x_{k+1}, \underline{})) = \hat{y}_{k+1}, \tag{1}$$

where the ground truth answer is left as a blank to be predicted by the LLM. Eq. 1 requires no gradient steps. Empirical studies show that ICL performance scales with model size, which transforms LLMs into versatile, prompt-programmable systems (Wei et al., 2022a).

Instruction following. Instruction following reflects the capacity of LLMs to execute open (unseen) tasks by adhering to natural language descriptions. This ability is cultivated through instruction tuning, a process where models are fine-tuned on datasets pairing instructions with desired outputs (Sanh et al., 2021; Wei et al., 2021). Ouyang et al. (2022) suggested that reinforcement learning from human feedback (RLHF) (Christiano et al., 2017) aligns LLMs with user intent, enabling robust generalization to unseen instructions. Chung et al. (2024) further showed that multi-task instruction tuning can enhance cross-task transfer by teaching models to decode task semantics from prompts. Instruction following enables LLMs to follow the instructions to generalize new tasks, bridging the gap between human intent and model behavior.

Step-by-step reasoning. Advanced LLMs exhibit step-by-step reasoning, solving complex problems via intermediate logical chains or hierarchical steps akin to human cognition. Wei et al. (2022b) formalized this

Model	Release Date	Organization	Size (B)	Data (TB)	Hardware Cost	Public Access
T5 (Raffel et al., 2020)	2019.10	Google	11	750 GB of text	1024 TPU v3	Yes
GPT-3 (Brown et al., 2020)	2020.5	OpenAI	175	300 B tokens	-	No
PaLM (Chowdhery et al., 2023)	2022.4	Google	540	780 B tokens	6144 TPU v4	No
LLaMA (Touvron et al., 2023a)	2023.2	Meta	65	1.4 T tokens	2048 A100 GPU	Partial ¹
GPT-4 (Achiam et al., 2023)	2023.3	OpenAI	-	-	-	No
LLaMA-2 (Touvron et al., 2023b)	2023.7	Meta	70	2 T tokens	2000 A100 GPU	Yes
Mistral-7B (Jiang et al., 2023)	2023.9	Mistral AI	7	-	-	Yes
Qwen-72B (Bai et al., 2023)	2023.11	Alibaba	72	3 T tokens	-	Yes
Grok-1	2024.3	xAI	314	-	-	Yes
Claude 3	2024.3	Anthropic	-	-	-	No
GLM-4-9B (GLM et al., 2024)	2024.6	Zhipu AI	9	10 T tokens	-	Yes
LLaMA-3.1 (Dubey et al., 2024)	2024.7	Meta	405	15 T tokens	16 thousand H100 GPU	Yes
Gemma-2 (Team et al., 2024)	2024.6	Google	27	13 T tokens	6144 TPUv5p	Yes
DeepSeek-V3 (Liu et al., 2024a)	2024.12	DeepSeek	671 ²	14.8 T tokens	2048 H800 GPU	Yes

Table 2: Overview of mainstream LLMs.

1 Non-commercial research license.

2 MoE architecture, with 37B activated for each token.

as chain-of-thought (CoT) prompting, where models structure explicit reasoning traces before final answers, markedly improving performance on arithmetic, symbolic, and commonsense tasks. Kojima et al. (2022) found that even zero-shot CoT, triggered by phrases like "Let's think step by step," elicits coherent reasoning in sufficiently large models. This capacity transforms LLMs into interpretable problem solvers, enabling decision making in domains requiring structured logic, such as mathematics and program synthesis. Other advance prompting strategies include CoT with self-consistency (CoT-SC) (Wang et al., 2022a), tree of thought (ToT) (Yao et al., 2023), and graph of thought (GoT) (Besta et al., 2024).

2.2.2. Mainstream LLMs

The evolution of LLMs has been driven by advances in Transformer architectures (Vaswani et al., 2017), enabling unprecedented scalability and performance across natural language processing tasks. These models are pretrained on extensive text corpora, enabling them to understand and generate human-like text. Early foundational models like BERT (Devlin et al., 2019) introduced bidirectional context learning through masked language modeling. While GPT-3 (Brown et al., 2020) features autoregressive pretraining and few-shot learning via its 175 billion-parameter architecture. Subsequent innovations include T5 (Raffel et al., 2020), which unified NLP tasks under a text-to-text framework, and PaLM (Chowdhery et al., 2023), which demonstrated emergent reasoning capabilities at scale. Recent models prioritize efficiency and human alignment. For example, LLaMA (Touvron et al., 2023a,b) optimized training for smaller and open-access models. GPT-4 (Achiam et al., 2023) and Gemini (Team et al., 2024) enhanced multimodal and instruction-following abilities. A recent addition to this landscape is DeepSeek-R1 (Guo et al., 2025), an open-source LLM released in January 2025 by a Chinese startup. DeepSeek-R1 has garnered attention for its competitive performance in complex tasks such as mathematical reasoning and coding, achieved with significantly lower computational resources and cost compared to its counterparts. We summarize several representative LLMs from technical perspectives in Tab. 2.

2.3. Key techniques in LLMs

LLMs have revolutionized natural language processing (NLP) by achieving state-of-the-art performance across diverse tasks. This section systematically introduces the foundational techniques underpinning modern LLMs: pretraining, architecture design, post-training optimization, and utilization strategies. Each component is critical to the development, refinement, and application of these models, as evidenced by their widespread adoption in academia and industry.

2.3.1. Pretraining

Pretraining is the foundational phase where LLMs learn language representations from large-scale corpora. This process enables models to capture syntactic and semantic patterns, facilitating their application to various downstream tasks. Since the capacities of LLMs largely rely on the pretraining corpus, high-quality and carefully processed datasets are important. Common public sources for pretraining include general-purpose text from the Internet such as webpages, conversations, and online books. In addition, specialized and structured datasets are also used to improve the capabilities of LLMs in a wide range of tasks, such as multilingual text, scientific text, and code bases (Min et al., 2023; Naveed et al., 2023; Zhao et al., 2023). The scale of pretraining data and computational resources significantly influences the model's performance and generalization capabilities .

The pretraining objectives guide the model to learn robust representations which typically involve unsupervised or self-supervised learning objectives, such as predicting masked tokens or the next word in a sequence. For instance, models like BERT employ masked language modeling, while GPT models utilize autoregressive training. There are two dominant paradigms:

• Autoregressive pretraining: (e.g., GPT series (Brown et al., 2020)) trains models to predict the next token in a sequence, promoting coherent text generation capabilities (Radford et al., 2019). Given a token series $x = \{x_1, x_2, ..., x_n\}$, the language modeling (LM) task aims to autoregressively predict the target tokens x_i based on the preceding tokens $x_{<i}$ in this sequence:

$$\max \ell_{\rm LM} = \max \sum_{i=1}^{n} \log P(x_i | \boldsymbol{x}_{< i}), \tag{2}$$

• Autoencoding pretraining: (e.g., BERT (Devlin et al., 2019) and BART (Lewis et al., 2019)) masks or corrupts random tokens with replaced spans or masks and trains models to reconstruct them, enhancing bidirectional context understanding. Formally, the objective of autoencoding pretraining is denoted as:

$$\max \ell_{\rm AE} = \max \log P(\tilde{\boldsymbol{x}} | \boldsymbol{x}_{/\tilde{\boldsymbol{x}}}). \tag{3}$$

More advanced strategies can be developed by combining the two prototypes. Models like T5 (Raffel et al., 2020) unify tasks into text-to-text frameworks, while UL2 (also known as Mixture-of-Denoisers) (Tay et al., 2022) combines denoising autoencoding and autoregressive objectives.

After LLMs have been pre-trained, a decoding strategy is needed to generate desired textual output. Two prevailing methods include **search-based** and **sampling-based** strategies (Zhao et al., 2023). The greedy search predicts the most likely token at each step, conditioned on the previously generated context tokens. While the sampling-based method randomly selects the next token based on the probability distribution of contexts to enhance the diversity during generation. The mitigation of the selection of words with extremely low probabilities is crucial to improve the quality of the generation. To control the randomness of sampling, a practical method is to adjust the temperature coefficient of the softmax function to compute the probability of the *j*-th token over the vocabulary, called *temperature sampling* (Renze, 2024):

$$P(x_k | \boldsymbol{x}_{< i}) = \frac{\exp(l_k / \tau)}{\sum_{k'} \exp(l_{k'} / \tau)},$$
(4)

where l_k is the logits of each word and τ is the temperature coefficient. Reducing τ increases the chance of selecting words with high probabilities while decreases the chances of selecting words with low probabilities.

Training LLMs requires significant computational costs. Several optimization techniques are usually adopted to facilitate efficient training under a limited computational budget, such as distributed training (data, tensor and pipeline parallelism (Shoeybi et al., 2019)) and mixed precision training (Micikevicius et al., 2017).

2.3.2. Architecture

The Transformer architecture, introduced by Vaswani et al. (2017), serves as the cornerstone of modern LLMs. It employs self-attention mechanism enables dynamic weighting of input tokens, capturing long-range sequential dependencies without recurrence or convolution. The vanilla Transformer consists of an encoder-decoder structure, with each layer comprising multi-head self-attention and position-wise feed-forward networks. This design enables efficient computation and scalability, making it ideal for large-scale language modeling tasks. Key components include:

Multi-head self-attention. Central to the Transformer is the self-attention mechanism, which allows the model to weigh the importance of different parts of the input sequence when encoding each token. This mechanism computes attention scores in a pairwise way by comparing query, key, and value vectors derived from the input embeddings. The resulting weighted sum captures contextual relationships, enabling the model to understand the significance of each token in relation to others. Multi-head attention extends the self-attention mechanism by employing multiple attention heads, each learning different aspects of the input representation. The outputs of these heads are concatenated and linearly transformed, allowing the model to capture a diverse range of semantic features and relationships within the data. Formally, the input sequence *X* ∈ ℝ^{n×dmodel} is processed through *h* parallel attention heads, where each head *i* computes scaled dot-product attention as:

$$\begin{aligned} \boldsymbol{Q}_{i} &= \boldsymbol{X} \boldsymbol{W}_{i}^{Q}, \quad \boldsymbol{K}_{i} &= \boldsymbol{X} \boldsymbol{W}_{i}^{K}, \quad \boldsymbol{V}_{i} &= \boldsymbol{X} \boldsymbol{W}_{i}^{V} \quad (\boldsymbol{W}_{i}^{Q}, \boldsymbol{W}_{i}^{K} \in \mathbb{R}^{d_{\text{model}} \times d_{k}}, \ \boldsymbol{W}_{i}^{V} \in \mathbb{R}^{d_{\text{model}} \times d_{v}}), \\ \text{head}_{i} &= \text{softmax} \left(\frac{\boldsymbol{Q}_{i} \boldsymbol{K}_{i}^{\top}}{\sqrt{d_{k}}} \right) \boldsymbol{V}_{i}, \quad d_{k} &= d_{v} = d_{\text{model}} / h, \end{aligned}$$

followed by concatenation and linear projection:

 $MultiHead(\boldsymbol{X}) = Concat[head_1, \dots, head_h] \boldsymbol{W}^O \quad (\boldsymbol{W}^O \in \mathbb{R}^{hd_v \times d_{model}}).$

An issue of standard self-attention is the quadratic complexity, which becomes a bottleneck when dealing with long sequences. Various efficient attention variants are proposed to reduce the computational complexity, such as sparse attention (Child et al., 2019) and FlashAttention (Dao et al., 2022).

- **Positional encoding.** Since Transformers process input sequences in parallel without inherent sequential order, positional encoding is introduced to inject information about the position of tokens within the sequence. This is typically achieved by adding sinusoidal functions of different frequencies or learned vectors to the input, allowing the model to distinguish between tokens based on their positions. Recent studies also developed more advanced positional embedding techniques to enable Transformers to generalize to sequences longer than those sequences for training, i.e., extrapolation, such as relative position embedding (Raffel et al., 2020), rotary position embedding (Su et al., 2024), and ALiBi (Press et al., 2021).
- Layer normalization. Training large-scale Transformers can be unstable due to factors such as gradient anomaly. Therefore, normalization is a widely adopted technique to stabilize the training process. Layer normalization (LN) (Ba et al., 2016) is applied in the vanilla Transformer, in which the mean and variance over all activations per layer are calculated to recenter and rescale the activations. Other techniques such as RMSNorm (Zhang and Sennrich, 2019) and DeepNorm (Wang et al., 2024b) are also widely employed in deep Transformers. In addition, recent studies have found that the position of normalization also has a notable impact on LLMs. There are generally three choices, i.e., post-LN, pre-LN, and sandwich-LN (Xiong et al., 2020; Ding et al., 2021).

Built on the above basic elements, modern LLMs (e.g., GPT-3 (Brown et al., 2020), PaLM (Chowdhery et al., 2023)) scale Transformers by increasing depth (layers) and width (hidden dimensions). In existing LLMs, the main architectural variants include encoder-decoder, causal decoder, and non-causal decoder Transformers:

- Encoder-decoder. Models like T5 (Raffel et al., 2020) and BART (Lewis et al., 2019) utilize both encoding and decoding mechanisms, enabling them to perform a wide range of tasks, including translation and summarization. The encoder applies stacked self-attention layers to encode the input sequence, and the decoder performs cross-attention on these representations and autoregressively generates the output.
- **Causal decoder.** As a representative *decoder-only* architecture, causal decoder models introduce the unidirectional attention mask to ensure that each input token can only attend to the past tokens and itself. This mechanism makes them suitable for text generation tasks. Prominent examples are the GPT-series models (Radford et al., 2018, 2019; Brown et al., 2020).
- Non-causal decoder. Another kind of decoder-only architecture is the non-casual structure. This architecture performs bidirectional attention on prefix tokens and unidirectional attention only on generated tokens. One representative prefix decoder LLMs is GLM (Zeng et al., 2022).

To scale the capacity of LLMs efficiently, the Mixture of Experts (MoE) technique can be exploited to combine the above architectures, such as in Swich Transformer (Fedus et al., 2022) and GLaM (Du et al., 2022). MoE involves sparsely activating a subset of model parameters (the "experts") for each input, allowing the model to handle a vast number of parameters without incurring prohibitive computational costs. This is achieved by employing a trainable gating mechanism to route each input token to the most relevant subset of experts.

Apart from the mainstream Transformer architecture, there are also emerging architectures proposed to alleviate the inherent issues of Transformers (e.g., the quadratic complexity) such as State-Space Models (SSMs) (Gu et al., 2021), Mamba (Gu and Dao, 2023), and RWKV (Peng et al., 2023).

2.3.3. Post-training

After pretraining on massive corpus, LLMs obtain the ability to serve as a general problem solver. To adapt them for domain-specific tasks, several post-training techniques can be applied to further refine their capabilities beyond initial pre-training. Three pivotal methodologies in this phase are instruction tuning, alignment tuning, and model adaptation (Zhao et al., 2023; Zhang et al., 2023; Wang et al., 2023f). These techniques enhance task generalization, align outputs with human preferences, and optimize models for domain-specific or resource-constrained settings, respectively. In the following, we briefly introduce their objectives, methods, and impacts based on contemporary research.

Instruction tuning. Instruction tuning refines LLMs to follow task-specific natural language instructions, enabling zero-shot or few-shot generalization to unseen tasks (Wei et al., 2021; Chung et al., 2024). Unlike conventional fine-tuning, which trains models on labeled examples for specific tasks, instruction tuning employs

datasets comprising task descriptions, input-output pairs, and diverse prompts (e.g., "Summarize this article: [text]"). This approach conditions models to infer task requirements from instructions, better comprehend tasks, and satisfy human expectations across diverse tasks. Representative models that perform instruction tuning include InstructGPT (Ouyang et al., 2022) and FLAN-T5 (Chung et al., 2024).

Instruction tuning is closed to supervised fine-tuning (SFT) (Ouyang et al., 2022) and prompt tuning (Liu et al., 2021). SFT performs full-parameter fine-tuning based on pre-trained models using task-specific labeled data (input-output pairs). Instruction tuning is a special form of SFT that fine-tunes a model using instructional task descriptions, with the goal of allowing the model to understand and generalize to unseen instructions. Prompt tuning is a parameter-efficient fine-tuning method (which will be discussed in the latter) that guides the model output by adjusting the prompts in the inputs, usually without updating the pre-trained model parameters, and optimizing only a small number of prompt-related parameters. The difference between the three concepts is relatively small. To help differentiate them, we compare different aspects of these techniques in Tab. 3. To summarize, SFT is the basic full-parameter fine-tuning method, instruction tuning is a variant of its instruction-oriented generalization, and prompt tuning is a parameter-efficient lightweight alternative.

Aspect	Supervised Fine-Tuning	Instruction Tuning	Prompt Tuning	
Objective	Adapt to a single task (e.g., classification, generation)	Enhance instruction under- standing and cross-task gen- eralization	Activate pretrained knowl- edge via prompts	
Training Data	Task-specific structured input-output pairs	Multi-task instruction- response pairs (with natural language instructions)	Minimal labeled/unlabeled data (reliant on prompt de- sign)	
Parameter Update	Full parameter fine-tuning	Full parameter fine-tuning	Optimize only prompt- related parameters (fixed backbone)	
Generalization	Task-specific optimization (risk of overfitting)	Strong cross-task generaliza- tion (requires diverse instruc- tions)	Depends on prompt design; effective for few/zero-shot learning	
Computation Cost	High (updates all parame- ters)	High (updates all parame- ters)	Very low (only prompts opti- mized)	
Typical Use Cases	Single-task models (e.g., text classifiers)	General-purpose models (e.g., ChatGPT prototypes)	Resource-constrained scenar- ios	

Table 3: Comparison between instruction tuning, supervised fine-tuning, and prompt tuning.

To perform instruction tuning, the first step is to collect instruction-formatted instances in natural language. Task descriptions are obtained either by crowd-sourced human experts or synthetic instances. Then, these formatted instances are employed to fine-tune LLMs in a supervised learning way. Recent studies (Wang et al., 2022a) have demonstrated that using instruction tuning on public instruction datasets such as Super-NaturalInstructions (Wang et al., 2022b) and PromptSource (Bach et al., 2022) can significantly improve performance on downstream tasks.

Alignment tuning. While pretrained LLMs have impressive generation ability, they may output harmful, biased, or misleading content. Thus, alignment tuning focuses on the adjustment of LLMs to comply with human values and preferences, ethical guidelines, and safety standards (Wang et al., 2023f). This is typically achieved by incorporating human feedback into training loops, often through reinforcement learning (RL) or contrastive learning techniques (Ouyang et al., 2022; Ziegler et al., 2019).

Different from the goals of pretraining and instruction tuning, alignment tuning highlights different aspects of the model output, such as honesty with correctness. These human-centric criteria can be obscure for LLMs to comprehend. Thus, the first step to align LLMs is to collect human evaluations and feedback from experts. In existing LLMs, one of the dominant method for generating human feedback is human annotation (Ziegler et al., 2019; Ouyang et al., 2022; Wang et al., 2023f). Since high-quality human feedback data is crucial for aligning LLMs, this process can be resource-consuming and requires careful treatment.

After collecting and constructing feedback datasets from human experts, a prevalent method for alignment is Reinforcement Learning from Human Feedback (RLHF) (Christiano et al., 2017; Ziegler et al., 2019), where models are fine-tuned using datasets of human preferences to guide their behavior. RLHF adapts LLMs to human feedback by learning a reward model, incorporating human in the training loop. It involves three stages:

 Collecting human rankings of SFT model output. The base model is first fine-tuned on high-quality human-generated responses to specific prompts. This step initially aligns the model's outputs with desired formats and tasks. Then the SFT model generates multiple responses to sampled prompts. Invited human annotators rank these outputs by quality, appropriateness, or alignment with goals. Comparative rankings (e.g., pairwise preferences) are often collected to reduce subjectivity and inconsistency.

- 2. **Training a reward model to predict preferences.** A separate reward model is trained to predict human preferences. It takes a prompt and response as input and outputs a scalar reward. It is trained using pairwise comparison data, optimizing for higher rewards for preferred outputs. The reward model can take on two forms: a fine-tuned language model or a model trained using human preference data, which has a parameter scale much smaller than that of the LLM to be aligned.
- 3. **Optimizing the LLM policy using RL to maximize rewards.** The SFT model is optimized using RL (e.g., Proximal Policy Optimization, PPO; (Schulman et al., 2017)) to maximize rewards from the reward model. The pretrained LLM acts as the policy that generates an output text, the action is the choice of vocabulary, and the state is the current token sequence. A KL divergence penalty can be added to prevent the model from deviating too far from the SFT model, balancing reward optimization with output coherence.

Pioneered by OpenAI's InstructGPT (Ouyang et al., 2022), RLHF reduced about 25% fewer toxic outputs than GPT-3 compared to GPT-3 while improving response quality. RLHF has been pivotal in enhancing the safety and reliability of LLMs in real-world applications, ensuring that LLMs produce outputs that are both accurate and ethically sound. Alternative approaches, such as direct preference optimization (DPO; (Rafailov et al., 2023)), bypass explicit reward modeling by directly aligning model likelihoods with human preferences, offering a simpler and RL-free alternative. Emerging study also explores constitutional AI (Bai et al., 2022), where models self-critique outputs against predefined rules using LLM agents. Very recently, a powerful open-source LLM called DeepSeek-R1 (Guo et al., 2025) is trained using group relative policy optimization (GRPO) without SFT, simplifying the training by evaluating actions relative to a group of samples (Shao et al., 2024).

Parameter-efficient fine-tuning. The discussed instruction tuning and alignment tuning methods typically require full-parameter tuning. Because LLMs are parameter-extensive, it is computationally prohibitive, memory intensive, and risks catastrophic forgetting. Parameter-efficient fine-tuning (PEFT) techniques address these limitations by updating only a small subset of parameters while preserving the model's inherent capabilities (Liu et al., 2022; Ding et al., 2023). These methods such as adapter tuning, prefix tuning, prompt tuning, and Low-Rank Adaptation (LoRA) strike a balance between task-specific performance and resource efficiency, enabling cost-effective deployment of LLMs across diverse applications. We briefly introduce these them as follows.

- Adapter tuning introduces lightweight neural adapters within Transformer layers while keeping the base model frozen. First proposed by (Houlsby et al., 2019), adapters are inserted between feed-forward layers or attention blocks and trained on task-specific data. These modules typically consist of down-projection and up-projection layers with a bottleneck architecture, reducing parameter overhead (e.g., <1% of total parameters). Subsequent work (Pfeiffer et al., 2020) optimized adapter placement and design. During fine-tuning, the adapters are optimized based on task-specific goals, while the parameters of the original LLMs are frozen.
- **Prefix tuning (Li and Liang, 2021)** prepends task-specific continuous vectors to each Transformer layer's key and value matrices. It avoids modifying the base model and enables context-aware adaptation of the attention computation. Since the number of parameters is determined only by the prefix length (typically 10-100 tokens) and the hidden layer dimension, prefix tuning is more scalable than adapter tuning.
- **Prompt tuning (Lester et al., 2021).** Different from prefix tuning, prompt tuning simplifies this approach by prepending trainable tokens only to the input layer, achieving competitive performance with extremely low parameter counts (e.g., 0.01% of base parameters). During training, only the virtual prompt embeddings would be learned according to task-specific supervisions.
- Low-Rank Adaptation (LoRA) (Hu et al., 2022). LoRA decomposes weight updates during fine-tuning into low-rank matrices, leveraging the hypothesis that task-specific adaptations reside in a low-dimensional subspace. By freezing pretrained weights and injecting trainable rank-decomposition matrices into dense layers, LoRA achieves parameter efficiency without inference overhead. LoRA has been widely adopted by open-source LLMs such as LLaMA (Touvron et al., 2023a).

PEFT techniques democratize access to LLMs by reducing computational barriers while retaining their internal knowledge. As LLMs grow in scale, these methods will remain critical for enabling scalable, sustainable, and versatile deployments across applications, especially in low-resource environments. In summary, post-training techniques such as instruction tuning, alignment tuning, and model adaptation collectively alleviate the limitations of raw pretrained LLMs, transforming them into controllable, safe, and adaptable systems.

2.3.4. Practical utilization

In addition to the above training and adaptation methods for developing powerful LLMs, there are emerging utilization techniques that unlocks the potential of LLMs in real-world applications. We briefly discuss them as these methods have been applied in transportation research by some pioneering work.

- **Prompt engineering.** Designing suitable prompts is crucial to guide LLMs to solve downstream tasks. Prompt engineering is the procedure to manually craft or automatically generate specific prompts that can elicit specific ability of LLMs to produce desired outputs (White et al., 2023). The standard template of a prompt contains four ingredients, they are task description, task input data, contextual information, and prompt style. There are several practical guidelines for users to design proper prompt contents (White et al., 2023; Giray, 2023; Ekin, 2023; Chen et al., 2023a). Generally, expressing the task description understandably, decomposing the task into sub-tasks, using CoT prompting, providing few-shot demonstrations, and adopting role-playing strategies can improve model performances.
- LLM-based agent. The context generation, strategic planning, and logical reasoning capabilities of LLMs enable them to solve complex tasks. Therefore, LLMs are integrated into autonomous agents capable of performing tasks involving multistep reasoning and decision making (Wang et al., 2024c). The LLM-based agent systems include three components: *memory, planning, and execution*. To solve a given task, the agent first gathers information from the environment and stores it in short-term memory. Then it processes these new data, potentially enhancing it with relevant details retrieved from long-term memory (Zhong et al., 2024). Using the processed information, the planning component formulates the next plan (Song et al., 2023). The execution component carries out this plan, possibly aided by external tools such as code (Gao et al., 2023a). By continuously repeating this cycle, the LLM-based agent automatically reflects and adjusts its behavior in response to environmental feedback (Shinn et al., 2023), ultimately achieving its goal.
- **Retrieval-augmented generation (RAG).** RAG enhances LLMs by integrating external knowledge retrieval mechanisms, addressing limitations in factual accuracy and domain specificity (Guu et al., 2020; Gao et al., 2023c). Similar to the workflow of LLMs, RAG consists of three steps, including context retrieval, prompt construction, and response generation (Lewis et al., 2020). The retriever uses a structured index representation such as dense vectors to search candidate documents. The selected retrieved documents are then integrated into the prompt along with instructions that guide LLMs to exploit the retrieved information to perform actions. Finally, LLMs synthesizes outputs conditioned on retrieved content.
- Tool manipulation. Fundamentally, LLMs are developed as text generators trained on extensive plain texts. This causes them to be less effective on tasks that aren't optimally represented in textual form, such as numerical computations. Additionally, their abilities are confined to the information available up to their last training update, limiting their access to the most recent data. To address these challenges, recent studies have proposed integrating external tools that can empower LLMs with capabilities that go beyond language modeling (Nakano et al., 2021; Schick et al., 2023). For example, LLMs can use the calculator for accurate computation (Nakano et al., 2021), employ search engines to retrieve unknown information (Schick et al., 2023), and adopt the compiler for programming (Gao et al., 2023a). Recetly, LLM-based Model Context Protocol (MCP) introduced by Anthropic provides a unified communication interface between LLMs and external data sources and tools. Through MCP, LLM applications can securely and efficiently access a variety of data resources such as files, databases, APIs, web pages, etc., and at the same time call external tools to perform specific tasks, thus breaking through the limitations of relying on pre-training data alone, and enhancing the LLM's context-awareness and real-world application capabilities.
- **Multimodal LLMs.** Recent advancements have introduced multimodal LLMs (MLLMs) capable of processing and generating not only text, but also images and other data types, thus broadening their applicability (Liang et al., 2024b). MLLMs adapt information from various modalities into the text modality to leverage the powerful capabilities of LLMs trained on textual data. An MLLM typically comprises an image encoder for processing images and a language model for text generation, connected via a module that aligns visual and linguistic representations, such as CLIP (Radford et al., 2021).

3. The LLM4TR Framework

This section introduces the cornerstone of this survey. By identifying existing challenges of traditional transportation management frameworks, we propose a novel conceptual framework based on LLMs. Then we structure a systematic taxonomy to elucidate the roles of LLMs in this framework. Finally, to give an intuitive overview of the status of current studies, we visualize the research trend matrix based on our taxonomy.

3.1. Conceptual framework

Modern transportation systems are facing increasing challenges rooted in the limitations of conventional "four-step" management frameworks introduced in section 2.1. Traditional approaches to sensing, learning, modeling, and managing often operate in isolation and have three main dilemmas: (1) the rapid growth of multimodal and heterogeneous data versus the inefficiency of fragmented processing pipelines; (2) the demand for adaptive and human-centric decision making in dynamic environments versus the rigidity of static models

trained on historical patterns; (3) the need for scalable and generalizable AI tools for ITS versus the computational and interpretability constraints of conventional machine learning.

These barriers are exacerbated by the exponential growth of cyber-physical-social interactions in transportation systems. Traditional paradigms struggle to address these limitations. Sensing systems grapple with integrating multi-source, unstructured signals, and user queries into holistic representations. Learning frameworks often operate as black boxes, lacking mechanisms to embed domain knowledge or explain predictions. Modeling tools based on static or rigorous rules face a fidelity-efficiency trade-off, unable to adapt to changing environments and achieve self-refinement. Managing strategies are far from human-like reasoning about traffic semantics and contextual intentions.

The emergence of LLMs offers a new paradigm to overcome these barriers. Unlike conventional AI systems optimized for specific tasks, LLMs exhibit emergent properties such as few-shot learning, human-like reasoning, and cross-task generalization that align with the cyber-physical-social complexity of future transportation systems. Four intrinsic characteristics of LLMs position them as foundational enablers for next-generation "transportation intelligence":

- **Context understanding and world knowledge**: LLMs contain vast common sense and domain-agnostic knowledge through pretraining, allowing them to interpret traffic semantics from a comprehensive picture through the lens of urban geography, human behavior, and physical laws.
- Adeptness at sequence data processing: Traffic dynamics is inherently sequential, from vehicle trajectories to demand fluctuations. The backbone Transformer architecture of LLMs excel at modeling long-range spatiotemporal dependencies in sensor streams, travel behaviors, or driving interactions.
- Excellent reasoning and planning abilities: Chain-of-thought prompting and recursive self-improvement enable LLMs to decompose complex tasks into multi-step reasoning processes with verifiable intermediate states. In addition, LLMs can perform complex tasks by planning to use tools, integrate external knowledge, and learn from demonstrations.
- **Multi-modal information integration**: By aligning textual, visual, and geometric data into unified representations, MLLMs can fuse heterogeneous inputs such as LiDAR point clouds, driver voice commands, infrastructure sensor records for robust traffic environmental perception, bridging the digital-physical divide in transportation networks.

However, despite the early successes of pioneering studies in demonstrating the promise of integrating LLMs into transportation systems, they have explored isolated applications without articulating how the roles of LLMs interconnect throughout transportation systems. There lacks a unified framework and standard concept to guide systematic future progress in this area. Therefore, we address this knowledge gap by introducing *LLM4TR*, a conceptual framework where LLMs serve as polymorphic agents that dynamically adapt their roles to synergize sensing, learning, modeling, and managing tasks.

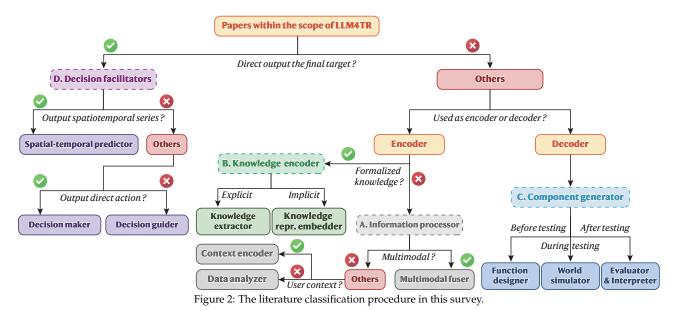
Definition: *LLM4TR* refers to the methodological paradigm that systematically harnesses emergent capabilities of LLMs to enhance transportation tasks through four synergistic roles: transforming raw data into understandable insights, distilling domain-specific knowledge into computable structures, synthesizing adaptive system components, and orchestrating optimal decisions.

As Figure 1 illustrates, the LLM4TR framework shapes the four-step transportation management cycle through an LLM-centric lens:

- **Processing information**: Beyond traditional sensor-based information collection, LLMs can serve as multimodal and comprehensive information processors that use natural language as interfaces.
- **Encoding knowledge**: As foundation models for general domains, LLMs shift data-centric solutions for specific traffic tasks to knowledge-driven encoders that can learn from the context.
- **Generating components**: Possessed with impressive generative power, LLMs automate the modeling and system design process by generating modular components following human-interpretable instructions.
- **Facilitating decision making**: LLMs facilitate transportation management by providing principled guidance or making human-like decisions after activating their task execution capabilities.

These four roles intersect in the "four-step" traffic management strategy (will be discussed in Fig. 3). Moreover, this framework transforms the conventional sequential pipeline by facilitating *closed-loop synergy* among stages. Processed information is transmitted to knowledge encoders with contextualized data, which in turn informs the generation of adaptive models. These models enhance the managing process, and the outputs from managing decisions facilitate actions that refine subsequent sensing processes. This creates a self-improving cycle through reflective feedback loops in which LLMs continuously align transportation operations with the evolving urban dynamics. Crucially, *LLM4TR* shifts the paradigm from *data-driven* to *knowledge-and-data-driven* intelligence,

3.2. Taxonomy



Under the above framework, this section develops a structured and unified taxonomy to elaborate recent advances of LLMs in transportation. Inspired by the taxonomy in Cao et al. (2024b), we survey the existing literature and summarize how LLMs are exploited to solve transportation problems from a methodological

perspective, i.e., the roles of LLMs in transportation systems. They generally include four aspects:

1. LLMs as information processors

- *Function:* LLMs process and fuse heterogeneous transportation data from multiple sources (text, sensor data, task description, and user feedback) through contextual encoding, analytical reasoning, and multimodal integration. They enable unified processing of complex traffic patterns, parsing and integrating multi-source information to assist in the managing and semantic understanding of traffic data, reducing the complexity of downstream tasks.
- *Example:* Using LLMs to analyze sensory traffic data (Zhang et al., 2024d), accident reports (Mumtarin et al., 2023), and convert user language queries to task-specific commands (Liao et al., 2024).

2. LLMs as knowledge encoders

- *Function:* LLMs extract and formalize transportation domain knowledge from unstructured data through explicit rule extraction and latent semantic embedding. This role bridges the gap between the unstructured domain knowledge inherent in the data and computable (or comprehensible) representations for downstream applications.
- *Example:* Building a knowledge base of traffic rules to assist traffic management (Wang et al., 2024e), formalizing traffic scenarios as knowledge graphs (Kuang et al., 2024), and generating representation vectors that are applicable for subsequent computing (He et al., 2024).

3. LLMs as component generators

- *Function:* LLMs create functional algorithms, synthetic environments, and evaluation frameworks through instruction-followed content generation. This role utilizes generative capabilities of LLMs to automate the design, testing, and refinement of components in intelligent transportation systems.
- *Example:* Designing reward functions for traffic control agents in reinforcement learning (Yu et al., 2024), assisting in synthesizing virtual driving environments (Zhao et al., 2024), and providing feedback for the refinement of model component (Tian et al., 2024).

4. LLMs as decision facilitators

• *Function:* LLMs predict traffic dynamics, optimize decisions, and simulate human-like reasoning, establishing new paradigms as generalized task solvers. This role employs LLMs as predictive engines and decision facilitators for both micro-level agent behaviors and macro-level system states.

• *Example:* Making control and planning decisions for autonomous driving (Sima et al., 2024), guiding safety-critical actions (Wang et al., 2023a), and forecasting traffic states (Ren et al., 2024).

Relationship and difference between the four roles of LLMs. This taxonomy reveals how LLMs go beyond traditional language processing to become versatile tools in transportation systems. For example, from raw data interpreters to central decision makers. Each role addresses different technical challenges while demonstrating synergetic effect when combined in integrated frameworks. *Information Processors* provide the fundamental data analysis that feeds *Knowledge Encoders*, which in turn structure domain-specific insights. These structured insights then enable *Component Generators* to produce context-aware simulations and algorithms, while *Decision Facilitators* utilize both raw data and encoded knowledge for decision optimization. They collaboratively enhance the sensing, learning, modeling, and managing of transportation systems.

The key difference lies in their methodological focus: *Information Processors* emphasize data transformation, *Knowledge Encoders* focus on knowledge formalization, *Component Generators* specialize in content synthesis, and *Decision Facilitators* prioritize outcome and action prediction. Generally, our taxonomy reflects the progress from data analytics (processing) to knowledge distillation (encoding), then to architecture design (generation), and finally to system implementation (decision).

Following this structured taxonomy, this survey classifies related literature using some principles shown in Fig. 2. Please note that in some studies the role of LLMs can be multifaceted. For example, they may serve simultaneously as both a context encoder and a decision maker. In our classification, we have identified and assigned each method to its primary role to ensure clarity and consistency.

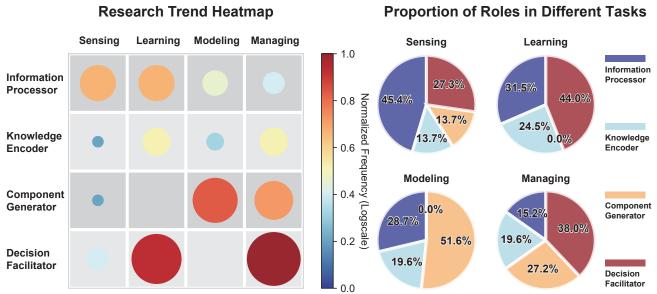


Figure 3: Heatmap of the current research trend and pie chart of the proportion of the four roles of LLMs in different tasks.

3.3. Research trend visualization

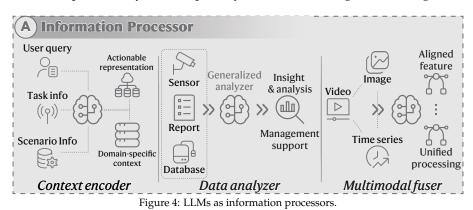
As an intuitive overview of the current research trend and focus, we visualize the statistics of selected papers according to our taxonomy in Fig. 3. Several key findings in these figures can be summarized as follows: (1) For the four roles defined in this paper, the "decision facilitator" attracts the most interest in existing studies, where most of them focus on managing and learning tasks such as traffic prediction, autonomous driving, and traffic signal control. This is also one of the most crowded tracks in transportation research. (2) The "component generator" is also a popular direction in which the generative capabilities of LLMs can assist in designing modules or systems. (3) Some areas are still unexplored. For example, adopt LLMs as decision makers in traffic modeling and designers for learning tasks. The former can automate the traffic simulation procedure by acting as a decision engine, while the latter can inspire the neural architecture design for spatial-temporal predictive learning. (4) From another facet, different tasks highlight different functionalities of LLMs. For example, the sensing task populates the integration of multimodal LLMs for information fusion; Among these four tasks, the application of the "knowledge encoder" accounts for the highest proportion in learning. These intuitive visual cues can guide future research choices and systematic overviews of this research field.

4. LLMs as Information Processors

Central to ITS are data collection and analysis methods that integrate information from various sources, including sensors, cameras, and vehicle communication systems (Zhang et al., 2011). Machine learning algorithms,

particularly deep learning models, are employed to process this data. However, this process may involve expert knowledge to develop problem-specific analytics methods.

Due to the in-context learning capability (Brown et al., 2020) and the multimodal extension, LLMs have emerged as versatile tools for processing heterogeneous transportation data, enabling efficient encoding, analysis, and fusion of multimodal information generated by traffic participants. This section explores three key methodological paradigms: (1) contextual encoding of traffic scenarios and task queries, (2) analytical reasoning over structured and unstructured traffic data, and (3) multimodal integration for holistic scenario understanding. These approaches collectively address challenges in handling heterogeneous information, multi-source data, and complex semantics in transportation systems, especially crucial for sensing and learning tasks.



4.1. Context encoder

A primary application of LLMs lies in encoding textual descriptions of dynamic traffic environments or task queries into machine-readable formats and task-specific patterns. This characteristic can facilitate the problem-solving process of ITS as LLMs can translate natural language instruction to domain-specific context that is compatible with other system components. Studies such as Keysan et al. (2023), Zhao et al. (2024), and Liao et al. (2024) demonstrate how LLMs transform free-form language descriptions of driving scenarios into encodings that can be directly consumed by downstream systems. Advanced implementations extend this capability to traffic simulation frameworks. TP-GPT (Wang et al., 2024a) generates accurate SQL queries for large-scale traffic databases and natural language interpretations by parsing user requests. It also employs a multi-agent collaboration strategy and few-shot learning to handle complex analytical tasks, such as traffic pattern recognition and privacy-preserving data interpretation. TP-GPT outperforms GPT-4 and PaLM 2 on a traffic analysis benchmark called TransQuery. ChatSUMO (Li et al., 2024a) integrates LLMs with the SUMO traffic simulator to democratize traffic simulation for non-experts. The LLM (e.g., Llama3.1) processes natural language inputs and converts them into keywords, which trigger Python scripts to fetch OpenStreetMap data, generate road networks, and configure traffic conditions. By automating code generation and data interpretation, ChatSUMO reduces scenario creation time from 15 minutes to 30 seconds while achieving 96% simulation accuracy.

Such context encoders also enable customized scenario synthesis, as evidenced by ChatScene (Zhang et al., 2024b) and Ruan et al. (2024), which decompose high-level user instructions into parameterized CARLA simulator configurations. Zhang et al. (2024b) introduce ChatScene, an agent that utilizes LLMs to generate safety-critical scenarios. By processing unstructured language instructions, ChatScene first creates textual descriptions of traffic scenarios. These descriptions are then decomposed into detailed sub-descriptions specifying vehicle behaviors and locations, enabling the generation of varied and safety-critical driving scenarios. Ruan et al. (2024) adopt LLMs to generate diverse traffic scenes in the CARLA simulator from natural language contexts. LLMs are used to decompose user prompts into road conditions, agent types, and actions, retrieve candidate roads from a structured database, and plan agent behaviors. The LLM-based parser addresses the limitations of predefined scenarios by dynamically generating customizable traffic scenes.

The contextual encoding paradigm also extends to real-time situational awareness through hybrid architectures. Xue et al. (2022) employs BERT as text encoder to generate feature embeddings for both contextual and numerical tokens. These embeddings are used to predict customer flows at Places-of-Interest (POIs). In (Abdelrahman et al., 2024), the authors combine computer vision techniques with LLMs to analyze pedestrian activities at intersections while preserving privacy. They convert raw video feeds into anonymized text descriptors using a vision encoder, then feed these descriptions into an LLM for contextual reasoning. This approach achieves real-time pedestrian behavior prediction without storing sensitive visual data.

4.2. Data analyzer

Beyond situational encoding, LLMs excel at extracting understandable patterns and insights from complex transportation datasets. Traditional methods of analyzing traffic data often involve domain-specific tools such

as statistical methods and expert knowledge (Zhu et al., 2018; Washington et al., 2020), making the insights dependent on specific problems. The generic pattern understanding ability of LLMs enables them to become generalized traffic data analyzer. TrafficGPT proposed by (Zhang et al., 2024d) demonstrates zero-shot analytical capabilities to analyze traffic data and provide insightful support for transportation management systems. CrashLLM (Fan et al., 2024) employs LLMs to analyze traffic crash data. By treating crash event feature learning as a text reasoning problem, CrashLLM fine-tunes various LLMs to predict fine-grained accident outcomes, such as crash types, severity, and injury numbers. It also enables nuanced analysis of contributing factors and supports what-if situational awareness traffic safety analyzes.

The natural language understanding capabilities of LLMs prove particularly valuable for mining unstructured data. They have potential for traffic safety analysis using textual materials such as accident report (Zheng et al., 2023b). In (Mumtarin et al., 2023), the authors query LLMs to extract related information and answer questions related to accidents from 100 crash narratives from Iowa and Kansas. In (Arteaga and Park, 2025), the authors use LLMs to identify underreported alcohol involvement in traffic crash narratives. Through iterative prompt engineering, the LLMs parse unstructured crash reports into binary classifications. The method achieves up to 1.0 recall and 0.93 precision, outperforming traditional text mining approaches.

Beyond text data, vision-language models (VLMs) and multimodal language models (MLMs) are also applied to understanding traffic scenarios from heterogeneous data sources (Wen et al., 2023); Qasemi et al., 2023; Zhou and Knoll, 2024; Lohner et al., 2024; You et al., 2024; Tong and Solmaz, 2024; Esteban et al., 2025). These models can also be integrated with external knowledge for better understanding. For example, recent studies address data scarcity through retrieval-augmented architectures. RAG-Driver (Yuan et al., 2024) integrates in-context learning with a retrieval-augmentation mechanism that dynamically retrieves expert demonstrations from a database of past driving scenarios. These retrieved examples, encoded as video control signal pairs with natural language explanations, are prefixed to the input query to guide the MLM in generating human-readable driving action descriptions and justifications. Evaluations on benchmarks like BDD-X underscore the potential of combining parametric memory with external knowledge bases for robust traffic analysis.

4.3. Multimodal fuser

MLLMs bridge the gap between heterogeneous data fusions in transportation systems. MLLMs can be incorporated into multimodal ITS by converting diverse types of data into aligned feature vectors or unified processing. This is often achieved by the cross-attention computation of the Transformer architecture (Vaswani et al., 2017). Zheng et al. (2023b) discuss how LLMs can address key traffic safety issues, such as automating accident report generation, augmenting traffic data, and analyzing multisensory data. To mitigate these challenges, the paper proposes the concept of multi-modality representation learning, which integrates data from various sources to improve traffic safety analytics. While Abu Tami et al. (2024) employs MLLMs such as Gemini-Pro-Vision and LLaVa to detect safety-critical events in driving videos. The framework fuses textual, visual, and audio inputs in a unified way through context-specific prompts to minimize hallucinations and improve reliability. A zero-shot learning approach is used to adapt the model to diverse scenarios without extensive retraining, addressing the limitations of traditional ML models that rely on annotated datasets. The SeeUnsafe framework (Zhang et al., 2025a) uses MLLMs to automate video-based traffic accident analysis. It replaces traditional "extract-then-explain" workflows with an interactive conversational approach, where the MLLM classifies accidents, grounds visual elements, and generates structured reports. Multimodal prompts are designed to align textual queries with visual data. Tested on the Toyota Woven Traffic Safety dataset, SeeUnsafe demonstrates improved processing throughput and adaptability.

4.4. Summary and outlook

As information processors, LLMs are revolutionizing transportation information systems through three interrelated capabilities: semantically rich context encoding, data-driven analytical reasoning, and robust multimodal fusion. From parsing scenario synthesis tasks in CARLA (Ruan et al., 2024) to predicting crash severity through narrative analysis (Fan et al., 2024), these approaches demonstrate remarkable adaptability across data modalities and application domains. While challenges persist in hallucination mitigation (Zheng et al. (2023b)) and cross-domain generalization (Yuan et al. (2024)), current studies establish a foundation for LLM-powered transportation information processing tools that balance automation with interpretability.

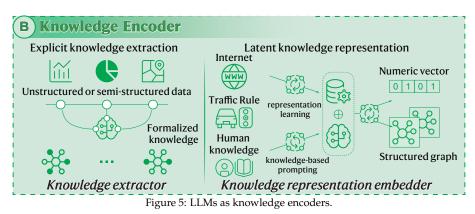
We list several potential directions for future explorations in the following:

- 1. Unified multi-source and cross-domain information fusion: Although the use of MLLMs has shown promise in dealing with data or user queries from different data modalities, most of existing studies only consider the integration of information for simple use cases. The power of cross-domain data fusion from diverse sources (e.g., geographic, traffic, social media, and environmental data) and modalities (e.g., spatio-temporal, visual, and textual modalities) has not yet been fully exploited (Zou et al., 2025).
- 2. Integrating external information for better response: Since the capabilities of LLMs largely depend on pretraining data, they may not have specific knowledge of complex transportation problems themselves.

Retrieval-augmented generation (RAG; (Guu et al., 2020)) provides a feasible approach for incorporating external knowledge or data base for more professional responses.

5. LLMs as Knowledge Encoders

LLMs can serve as repositories of implicit and explicit world knowledge (Jiang et al., 2020; Gurnee and Tegmark, 2023), enabling structured extraction, encoding, and application of domain-specific insights for transportation problems. This capability stems from their pretraining on vast corpora that contain traffic regulations, geographical semantics, and behavioral patterns. We categorize these studies of using LLMs to encode knowledge into: (1) explicit knowledge extraction for structured reasoning and (2) latent knowledge representation through embedding spaces. These studies demonstrate how to extract useful knowledge from the large parameter space of LLMs to facilitate the solving of traffic problems.



5.1. Knowledge extractor

In addition to analyzing the patterns underlying the data (i.e., data analyzer), methods in this category further manipulate LLMs to explicitly distill unstructured or semi-structured data into formalized and structured knowledge representations such as text and knowledge graphs that allow systematic reasoning about transportation domains. A pioneering approach by Kuang et al. (2024) introduced a framework that extracts common traffic knowledge from scene images using the Llava-7b vision-language model and generates visual traffic knowledge graphs by organizing the scene's information and reflecting relationships between traffic elements. This structured output enables downstream applications like conflict prediction.

Specialized LLMs further enhance domain-specific knowledge retention. TransGPT (Wang et al., 2024e) introduces a specialized LLM to serve as a transportation knowledge base, including two variants: TransGPT-SM for single-modal data and TransGPT-MM for multimodal data. TransGPT-SM is fine-tuned on textual transportation datasets to address tasks like traffic analysis and recommendation generation. TransGPT-MM extends this by incorporating both textual and visual data, handling tasks such as explaining traffic phenomena and answering traffic-related questions. Similarly, TrafficSafetyGPT (Zheng et al., 2023a) grounds LLMs in safety-critical contexts through supervised fine-tuning on the TrafficSafety-2K dataset, which is a curated corpus combining government-produced guidebooks and ChatGPT-generated instruction-output pairs. This alignment enables precise identification of regulatory violations in accident reports compared to general-purpose LLMs. These two methods explicitly convert LLMs to transportation knowledge bases.

Operational knowledge synthesis is exemplified by IncidentResponseGPT (Grigorev et al., 2024), which uses LLMs to create incident response plans based on traffic incident reports and regional response guidelines. It synthesizes these guidelines into a structured form using LLMs, and then combines them with real-time incident data to generate tailored, actionable traffic incident plans. Emerging frameworks such as TARGET (Deng et al., 2023) extend this paradigm by employing LLMs to automatically generate test scenarios by encoding traffic rules into a structured domain-specific language (DSL). In the TARGET framework, the LLM parses natural language traffic rules to extract key traffic components. By transforming unstructured rules into formal scenario representations, the LLM enables automated synthesis of executable test scripts in simulators like CARLA. This approach detected over 700 violations across four autonomous driving systems, demonstrating its effectiveness in translating regulatory knowledge into actionable testing scenarios while bypassing manual DSL coding.

5.2. Knowledge representation embedder

Beyond explicit knowledge extraction, LLMs encode transportation semantics into dense vector spaces that capture latent relationships between entities and scenarios. This is usually achieved by converting the contextual knowledge into computable format such as embedding vectors. In the embedding methodology,

LLMs are strategically employed as encoder architectures that transform input queries into semantically rich vector representations. Unlike conventional approaches generating textual or numerical output, this paradigm specifically produces high-dimensional embedding vectors, which subsequently serve as input features for subsequent computational processes.

Traditionally, language models such as BERT are used to extract representations from unstructured text input. For instance, Das et al. (2023) applies the BERT model to classify pedestrian maneuvers from unstructured police crash narratives. The authors fine-tuned BERT-base on Texas crash data for binary (intentionality) and multiclass (maneuver type) tasks. Text preprocessing included tokenization, lowercasing, and truncation to 512 tokens, with embeddings fed into a linear classification layer.

With the advent of LLMs, an emerging approach is to directly use pretrained LLMs to extract embeddings from the text prompt (He et al., 2024; Nie et al., 2025a). Specifically, He et al. (2024) attempt to elicit the inherent geospatial knowledge from pretrained LLaMA-3 model. A structured prompt that describes basic geolocation information of the POI is first derived by retrieving OpenStreetMap. Then the prompt is fed to LLMs to obtain a continuous vector. Such vectors are demonstrated to be effective in improving spatial-temporal forecasting models, including traffic prediction. Nie et al. (2025a) further extends this approach using a linear adapter and integrates it into an expert graph neural network predictor for city-wide traffic demand estimation. Evaluations also reveal the zero-shot transferability of such embeddings.

Similar principles of the LLM-based embedding approach have recently been explored in application domains. ALT-Pilot (Omama et al., 2023) uses LLMs for autonomous navigation. Using multimodal data from LiDAR and cameras onboard, combined with vision-language models (e.g., CLIP), the system enhances vehicle localization. LLMs are used to generate the embedding of language-based landmarks in the environment, enabling open-vocabulary navigation. By encoding environmental features into a shared embedding space, the system reduces localization errors in unmapped urban areas. Language-conditioned embedding techniques further enhance scenario generation and prediction tasks. LCTGen (Tan et al., 2023) utilizes LLMs to convert textual descriptions of an expected scenario into structured scene vectors that condition a Transformer model to produce realistic traffic behaviors. This alignment between language embeddings and spatiotemporal features allows generation of critical scenarios. Similarly, Zheng et al. (2024b) integrates GPT-4V-derived embeddings into motion forecasting through Transportation Context Maps (TC-Maps). By encoding global scene semantics as weighted one-hot vectors fused via cross-attention, their Motion Transformer model achieves a 0.95% mAP gain on the Waymo dataset, demonstrating that LLM-enhanced embeddings improve trajectory prediction by contextualizing local agent behaviors within holistic scene understanding.

5.3. Summary and outlook

As knowledge encoders, LLMs transform transportation data through dual mechanisms: structuring explicit domain knowledge (e.g., VTKGs in Kuang et al. (2024), protocol templates in Grigorev et al. (2024)) and encoding latent semantics into reusable embeddings (e.g., scenario vectors of LCTGen (Tan et al., 2023), LLM2Geovec in He et al. (2024)). Although specialized models such as TransGPT (Wang et al., 2024e) demonstrate the value of domain adaptation, challenges persist to maintain the freshness of knowledge. For example, incident response plans can become outdated as regulations evolve, and navigation embeddings like in ALT-Pilot (Omama et al., 2023) require continuous map updates. Nevertheless, the fusion of parametric knowledge (learned during pretraining or fine-tuning) and nonparametric representations suggests a path toward applying LLMs that dynamically internalize transportation knowledge while remaining grounded in real-world traffic problems.

We list several potential directions for future explorations in the following:

- Improving representation quality through alignment tuning: One of the limitations of using frozen
 pretrained LLMs to encoding knowledge is that the representation embedding is fixed and cannot be
 adaptively refined to tasks. A possible solution is to use supervised fine-tuning (Wang et al., 2023f) to
 improve the quality and specificity of the representations and further align them with human preference.
- 2. **Contrastive knowledge representation learning:** Most of the existing approaches obtain the knowledge embedding using pure text modality. As discussed in section 4.3, traffic data is usually multimodal and structured knowledge may exist beyond text. Contrastive language-image pretraining (CLIP) (Radford et al., 2021) provides a promising architecture for learning hybrid representations.
- 3. Up-to-date knowledge integration via online search: The inherent knowledge of LLMs is confined to the information available up to their last training update. This condition limits their access to the most recent data, e.g., real-time traffic condition. Integration of LLMs with web search tools such as WebGPT (Nakano et al., 2021) uses the search engine to find unknown knowledge, alleviating the limitation.

6. LLMs as Component Generators

One of the most impressive aspects of LLMs is their generative capability. They can generate high-quality content according to user instructions, which is skillful for solving transportation problems. In this context, LLMs

can emerge as powerful generative engines for components in ITS, enabling the automated creation of functional components, synthetic environments, and evaluative frameworks. As shown in Fig. 6, this section examines four critical generative paradigms: (1) algorithmic function design, (2) world simulation, (3) data synthesis, and (4) system evaluation. We systematically demonstrate how LLMs transcend traditional language modeling to become active creators of intelligent tools.

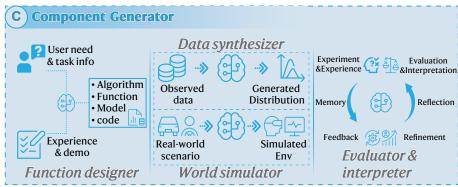


Figure 6: LLMs as component generators.

6.1. Function designer

Benefiting from pertained tasks such autoregressive language modeling in Eq. 2 and the in-context learning ability from textual demonstration, LLMs specialize in the design or refinement of code- or rule-based functions for traffic management. Such functions like the reward function in reinforcement learning (RL) are difficult to design manually and require expert guidance. LLMs revolutionize algorithmic design by translating natural language specifications into executable functions or codes.

A straightforward approach is to prompt LLMs directly and provide several examples of desirable properties and behaviors. InteractTraj (Xia et al., 2024) exemplifies this by interpreting natural language descriptions into interactive traffic trajectories. It employs a language-to-code encoder with an interaction-aware encoding strategy to process language descriptions into formatted numerical codes. A code-to-trajectory decoder with interaction-aware feature aggregation then maps these codes to final interactive trajectories, considering vehicle interactions, environmental maps, and vehicle movements. Zhong et al. (2023) introduce CTG++, a scene-level conditional diffusion model that leverages LLMs to convert natural language instructions into differentiable loss functions for traffic simulation. The LLM translates user queries like "simulate a traffic jam" into code-based differentiable loss functions that guide the diffusion process during denoising.

This paradigm extends to RL systems through innovative reward and policy engineering. LLMs can generate executable codes of reward function explicitly and specify the details of the computing process (Ma et al., 2023b). Autoreward proposed by Han et al. (2024) designs reward functions for RL-based autonomous driving. Instead of ambiguous desired goals, it employs concrete undesired linguistic goals to compute rewards. The agent's state and the undesired goal are embedded using pretrained models, and the cosine distance between these embeddings serves as the reward signal. Similarly, Yu et al. (2024) leverage LLMs to automate reward function design for RL-based bus holding strategies. Four LLM modules (reward initializer, modifier, analyzer, refiner) interact to generate dense rewards from sparse objectives. The LLM converts domain knowledge (e.g., headway balancing, passenger demand) into code-based reward functions, iteratively refining them using training performance feedback. A refiner module filters ineffective rewards to ensure stability. Villarreal et al. (2023) instead investigate the use of ChatGPT to help design RL policies for mixed traffic control. ChatGPT translates user prompts into RL-aligned metrics and suggests creative reward functions. Participants without RL expertise used ChatGPT to formulate Markov Decision Process (MDP) components for traffic scenarios. ChatGPT-assisted users achieved 150% and 136% increases in successful policies for intersection and bottleneck environments compared to non-assisted novices, even outperforming experts in some cases.

Collaborative design frameworks combined with more general design targets push these boundaries further. In LearningFlow (Peng et al., 2025), multiple LLM agents collaborate to automate curriculum learning and reward design. The framework employs a curriculum analysis agent to evaluate training progress and a generation agent to iteratively produce tailored training curricula and reward functions. The LLMs are prompted with contextual descriptors of driving tasks and historical training data stored in a memory module, enabling dynamic adaptation. OminiTester introduced by Lu et al. (2024b) uses MLLMs to generate realistic and diverse corner cases to test autonomous vehicles. The approach integrates tools from SUMO to simplify the complexity of code generation by LLMs. Additionally, RAG is used to enhance scenario realism by grounding LLM outputs in crash reports or historical data. A self-improvement mechanism iteratively refines scenarios based on simulation feedback. Mei et al. (2025) introduces a closed-loop framework where LLMs identify adversarial vehicles and optimize their trajectories to test autonomous driving systems. Three LLM modules, including Initialization,

Reflection, and Modification, collaborate to generate executable code for attacker identification. The LLM iteratively refines attack strategies using feedback from simulation results and employs techniques like CoT prompting and Best-of-N sampling to enhance code quality. The generated adversarial scenarios are used to train RL-based policies, forming a feedback loop to improve robustness.

In addition to the explicit design of the reward code, LLMs / VLMs are themselves the reward model (Huang et al., 2024b; Gao et al., 2024b), which is studied as an *implicit reward model* (Kwon et al., 2023; Rafailov et al., 2023). They can provide an overall reward value based on the understanding of tasks and environments or score the alignment between feature embeddings of visual observations and language instructions. By integrating LLMs into the RL loop, the method reduces reliance on manual reward engineering and improves sample efficiency.

6.2. World simulator

LLMs are equipped with extensive common sense and world knowledge. They are assumed to have a basic understanding of the regularity of the world, such as space and time (Gurnee and Tegmark, 2023). This makes LLMs possible for assisting in simulating the environmental dynamics of real-world driving scenarios. Such generalized simulators are termed *world models* (Ding et al., 2024) that can learn to predict the future state of the environment with high fidelity, especially crucial for the evaluation of end-to-end autonomous driving systems (Feng et al., 2025).

In autonomous driving, large-scale pretrained generative models are increasingly utilized as world models to generate realistic images and video sequences of driving scenarios, thus enhancing training and evaluation of autonomous systems (Guan et al., 2024; Feng et al., 2025). These world models offer detailed representations of the driving environment by combining data from multiple sensors, semantic information, and temporal dynamics. Theys can learn world model dynamics for autonomous driving systems from action-free video demonstrations and additional conditions. By integrating perception, prediction, and planning, world models allow autonomous systems to respond quickly and intelligently to complex and often unpredictable situations in a closed-loop manner (Gao et al., 2023b; Hu et al., 2023; Wang et al., 2024g,i; Gao et al., 2024b; Yang et al., 2024b; Zheng et al., 2024a; Fu et al., 2024b).

As synthetic environment generators, pioneering methods apply vision generative models to create photorealistic driving scenarios with precise controllability. MagicDrive (Gao et al., 2023b) pioneers this by generating high-fidelity streetview images and videos with precise 3D geometry control. It integrates various control signals such as camera poses, road maps, 3D geometry, and textual descriptions to generate diverse and realistic scenarios. The consistency across different camera perspectives is achieved through a cross-view attention module. Drive-WM (Wang et al., 2024i) advances this by introducing a multiview world model features joint spatial-temporal view factorization. It is capable of generating high-quality, controllable, and consistent multiview videos in driving scenes. WoVoGen (Lu et al., 2024a) addresses the challenge of generating multi-camera street-view videos by incorporating a world volume-aware diffusion model. This approach ensures that the generated videos maintain both intra-world consistency and inter-sensor coherence.

The integration of LLMs with physics engines (world models) yields unprecedented scenario customization. For example, DriveDreamer-2 (Zhao et al., 2024) employs an LLM interface to convert user queries into agent trajectories, which are then used to generate high-definition maps adhering to traffic regulations. The versatility of LLMs enable the world model to generate customized driving videos from user's textual prompt, including uncommon scenarios like vehicles abruptly cutting in. DriveMM (Huang et al., 2024a) integrates LLMs into world models by developing a large multimodal model that synthesizes heterogeneous inputs to simulate dynamic driving environments and generate actionable outputs. It demonstrates that combining LLMs with multimodal data and structured training pipelines can produce world simulators for context-aware driving.

6.3. Data synthesizer

High-quality and meaningful data are valuable for the applications of data-centric ITS. Since the backbone Transformer architecture enables deep data interaction through the self-attention mechanism, LLMs can address data scarcity through generative synthesis of system parameters and data engineering.

The first use case is to synthesize system parameters or parameterized traffic scenarios. Chang et al. (2024) proposed a framework that leverages LLMs to generate parameters for safety-critical traffic scenarios, particularly rare corner cases, called LLMScenario. LLMScenario involves three stages: scenario prompt engineering, LLM-driven parameter generation, and evaluation feedback tuning. The LLM translates textual descriptions into actionable parameters for traffic simulations, addressing the challenge of generating diverse and realistic rare cases efficiently. SeGPT (Li et al., 2024b) leverages ChatGPT to parse user queries and synthesize parameterized scenarios, including vehicle trajectories and environmental conditions. By combining CoT prompting with domain-specific templates, SeGPT produces complex interactions that improve the robustness of prediction algorithms. This method addresses the data scarcity issue in autonomous vehicle testing by automating scenario creation without manual annotation. Beyond scenario generation, LLMs optimize system dynamics modeling by generating new parameters. Da et al. (2024a) leverage the knowledge of LLMs to understand and profile the system dynamics by a prompt-based grounded action transform in traffic control systems. They exploit LLMs to

infer how traffic dynamics change with weather conditions, traffic states, and road types. LLMs then synthesize new parameters for system dynamics. The policies' action is taken and grounded based on generated dynamics, thus helping the agent learn a more realistic policy.

For the role in traffic data engineering, TransCompressor (Yang et al., 2024a) demonstrates LLMs' dual role in traffic data synthesis. It employs GPT-4 for zero-shot compression and reconstruction of multimodal transportation sensor data. The LLM reconstructs data via minimalist prompts, eliminating the need for fine-tuning. Evaluated on bus, taxi, and MTR scenarios, it achieves high reconstruction accuracy, addressing storage and transmission inefficiencies. LLMs can also be applied to synthesize features in latent spaces. For example, Wang et al. (2024f) integrates multi-modal foundation models to address the challenges of open-set generalization in autonomous driving. The model employs latent space simulation for data augmentation, where text-based prompts dynamically adjust the policy's response to rare or unseen driving conditions. This approach enhancing robustness to out-of-distribution environments.

6.4. Evaluator and interpreter

After adopting LLMs as generators for functions or systems, the quality of the generation result needs to be evaluated before it is brought into service. This process typically requires human evaluations and explainable AI (XAI) techniques (Dwivedi et al., 2023). Fortunately, LLMs can bring human-like reasoning to system evaluation and decision self-refinement, simplifying the traditional procedure.

LLMs can be prompted to generate human-readable language interpretations and evaluations of current results directly. The evaluations based on the decision trajectory or performance record can further improve the quality of the generator. CRITICAL (Tian et al., 2024) is a framework designed to improve the training of autonomous vehicles by generating critical driving scenarios for RL agents. CRITICAL uses LLMs to interpret RL training episodes to evaluate failure patterns, suggesting modifications based on analysis of traffic dynamics and risk metrics. This closed-loop system refines AV behavior by continuously feeding back critical scenarios, improving training performance and safety resilience. In (Lin et al., 2024b), LLMs were leveraged to provide feedback for current driving policies based on performance on the leaderboard. LLMs provide refinement suggestions for both rule- and optimization-based policies by regenerating objective or heuristic functions. Similarly, Chen et al. (2023b) use ChatGPT to provide feedback on architectural choices for driving agents.

This paradigm also extends to other tasks such as traffic control. Pang et al. (2024a) introduced iLLM-TSC, a hybrid framework integrating RL and LLMs to enhance traffic signal control. The proposed method employs a two-step process: (1) An RL agent first generates preliminary signal control decisions based on real-time traffic observations. (2) An LLM then evaluates these decisions for reasonableness, refining them using contextual knowledge and compensating for gaps in state information. The LLM acts as a corrective layer, dynamically adjusting actions through prompt engineering to align with real-world constraints and safety priorities.

6.5. Summary and outlook

As generators, LLMs transform transportation systems through three key capabilities: 1) translating abstract requirements into functional algorithms (Xia et al., 2024; Han et al., 2024), 2) synchronizing photorealistic environments with controllable dynamics (Zhao et al., 2024; Gao et al., 2023b), and 3) providing interpretable system evaluations for self-refinement (Tian et al., 2024; Pang et al., 2024a). Persistent challenges include maintaining physical fidelity in the generated results. For example, while the generative world models are impressive in simulating traffic scenarios, they still trail real-world data distributions. However, the integration of LLMs with simulation engines and self-refinement mechanisms points to a future where ITS can self-generate their training ecosystems while maintaining alignment with physical and regulatory constraints.

We list several potential directions for future explorations in the following:

- 1. **Inspiring novel neural architecture designs**: Adopting appropriate neural network architectures often requires a lot of empirical experience. However, practitioners in traffic engineering often lack sufficient practice of deep learning projects, especially as current models become increasingly complex. The automatic architecture search and design utility of LLMs (Nasir et al., 2024) can facilitate this process.
- 2. Large-scale simulation with LLM-based agents: Large-scale LLM-based agent simulation harnesses the context-aware behavioral plasticity of LLMs to simulate complex behaviors in human-centric systems (Li et al., 2023b; Gao et al., 2024a). This offers great potential in large-scale traffic simulation, automated testing, and the development of traffic digital twins. For example, using LLMs for interaction modeling through latent social psychology simulation can enable naturalistic representation of crowd dynamics in multimodal hubs and self-organized traffic patterns during infrastructure failures.
- 3. **Identifying and alleviating inherent bias of LLMs**: The inherent bias of LLMs can be converted to the generated functions or data (Yu et al., 2023), which can be harmful for safety-critical applications such as autonomous driving. Human alignment techniques such as RLHF (Ziegler et al., 2019) can adjust LLMs to comply with human preferences, ethical guidelines, and safety standards.

7. LLMs as Decision Facilitators

Beyond the language modeling abilities, LLMs can serve as generalized problem solvers by step-by-step reasoning, task planning, and tool manipulation. Recent advances have positioned LLMs as powerful decision facilitators in transportation systems, capable of simulating human-like reasoning to forecast outcomes, optimize decisions, and adapt to unseen scenarios. As shown in Fig. 7, this section examines their predictive roles across decision-making, guidance, and spatial-temporal forecasting tasks, highlighting their ability to tackle complex tasks in transportation systems and generalize across domains.

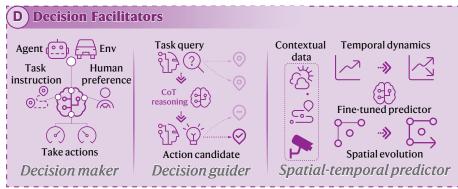


Figure 7: LLMs as decision facilitators.

7.1. Decision maker

Traffic signal control (TSC) represents a critical application in which LLMs exhibit human-like adaptability (Lai et al., 2023; Tang et al., 2024a; Da et al., 2024a; Movahedi and Choi, 2025; Pang et al., 2024a; Wang et al., 2024d; Masri et al., 2025) . Lai et al. (2023) pioneered this direction with LLMLight, which employs GPT-3.5/4 as intuitive decision makers for traffic light optimization. By prompting LLMs with real-time traffic conditions, the framework mimics human operators' contextual reasoning. Additionally, the authors developed LightGPT, an cost-efficient backbone LLM pretrained on traffic patterns tailored for TSC tasks. The framework outperforms RL-based methods in reducing waiting times and generalizes across diverse traffic datasets without retraining. Subsequent studies such as LA-Light (Wang et al., 2024d) integrates LLMs with perception tools to process static and dynamic data and hybridizes LLM reasoning with RL outputs, demonstrating superior fault tolerance during sensor outages. For complex intersections that encounter unpredictable traffic patterns, Movahedi and Choi (2025) advances closed-loop adaptation through their Generally Capable Agent (GCA) framework, where an actor-critic architecture enables iterative refinement of phase plans based on simulated outcomes. In SUMO simulations, the GCA-based controller outperformed conventional methods, reducing halted vehicles by 48.03% and increasing average speeds by 25.29%. These frameworks collectively address the limitations of static rule-based systems and data-hungry RL approaches through explainable, transferable decision-making.

In travel behavior modeling, LLMs bypass the traditional data-driven parameter calibration parameter calibration by leveraging semantic reasoning. Mo et al. (2023) demonstrates that structured prompts enable GPT-family models to match supervised models like multinomial logit models and neural networks in mode choice accuracy. However, the study notes occasional "hallucinations" in explanations where outputs lack logical consistency. Liu et al. (2024e) further evaluate the ability of LLMs to simulate human decision making in mode choice using a stated preference dataset. They first test zero-shot LLMs, finding significant behavioral misalignment due to discrepancies between LLM reasoning and real traveler preferences. To address this, they introduce persona-based few-shot learning, effectively bridging the gap between LLM reasoning patterns and empirical traveler preferences. Beyond discrete choices, Tang et al. (2024b) employs LLMs for personalized itinerary generation. LLMs generate human-readable itineraries by integrating optimized POI sequences and contextual descriptions. This hybrid method overcomes the limitations of spatial unawareness and static knowledge of standalone LLMs, ensuring both personalization and geographic feasibility. The LLM-based decision making process can also be integrated with behavior theory. In (Chen et al., 2025), the authors synthesize behavioral theory (Protective Action Decision Model), contextual cues, and a memory-based RL to enhance wildfire evacuation decision prediction. LLMs are prompted to simulate human cognitive processes, structured into threat assessment and risk perception stages. The memory module refines decisions by storing and retrieving past errors and self-reflections.

Autonomous driving systems increasingly integrate LLMs as cognitive engines and central decision makers (Jin et al., 2023c; Cui et al., 2023; Liu et al., 2023b; Wang et al., 2023c; Jiang et al., 2024; Zhou et al., 2024b; Fang et al., 2024b; Chen et al., 2024c; Pang et al., 2024b; Chen et al., 2024d; Zhou et al., 2025b). The direct utilization of their reasoning capabilities is to interpret dynamic environments and generate explainable actions. Specifically, Cui et al. (2024) integrate LLMs with voice interfaces to enable natural language interaction in autonomous vehicles.

They employ a two-stage architecture in which an LLM processes driver/passenger verbal commands and translates them into structured vehicle control signals. Similarly, Chen et al. (2024b) aligns vectorized object-level data with LLM representations using pretraining on "vector captioning" datasets, allowing the model to answer driving-related questions and generate contextualized control commands. VLMs like DriveLM (Sima et al., 2024) extend this paradigm further by structuring scene understanding as Graph Visual Question Answering (GVQA), enabling multistep reasoning about object interactions through perception-prediction-planning QA pairs. Complementing these multimodal approaches, DriveGPT4 (Xu et al., 2024b) processes temporal video sequences and textual queries in an end-to-end framework, directly predicting low-level control signals while providing human-interpretable action rationale.

Another line of work focuses on enhancing decision-making through memory-augmented reasoning and experience-based reflection. Fu et al. (2024a) addresses long-tail corner cases by deploying LLMs in a closed-loop simulator, where tools like trajectory planning and environmental memory enable continuous adaptation to unseen scenarios. Agent-Driver (Mao et al., 2023b) formalizes this concept with a cognitive architecture featuring a tool library, experiential memory of common sense and knowledge, and a reasoning engine capable of CoT planning and self-correction. DiLu (Wen et al., 2023a) further improves generalization by decoupling reasoning (applying common-sense knowledge) and reflection (learning from past decisions), outperforming traditional RL methods. Building upon these frameworks, recent studies directly reformulate core autonomous driving tasks through the lens of language modeling. GPT-Driver (Mao et al., 2023a) reformulates motion planning as a language modeling problem, representing planner inputs and outputs as language tokens. They introduce a prompting-reasoning-finetuning strategy to stimulate the LLM's numerical reasoning potential, enabling it to describe precise trajectory coordinates and its internal decision-making process in natural language. DrivingGPT (Chen et al., 2024d) proposes to unify both driving simulation and trajectory planning into a single sequence modeling problem. They introduce a multimodal driving language based on image and action tokens and train the model through standard next-token prediction. Together, these approaches collectively shift autonomous driving from modular pipelines to flexible and language-grounded systems.

Operational traffic optimization also benefits from multi-agent coordination capabilities of LLMs. CoMAL (Yao et al., 2024) integrates multiple LLM agents to tackle mixed-autonomy traffic problems by optimizing traffic flow. It employs a collaboration module where autonomous vehicles communicate using LLMs to allocate roles and discuss strategies in real-time. It demonstrates superior performance in optimizing mixed-autonomy traffic compared to RL-based models. Meanwhile, Orfanoudakis et al. (2025) combines the Decision Transformer (DT) (Chen et al., 2021) with GNNs to optimize the charging schedules of electric vehicles. GPT-2-based DT is trained to predict actions by modeling sequences of states, actions, and rewards. This hybrid approach outperforms the heuristic baselines and RL methods in the EV2Gym simulator. These works illustrate LLMs' roles as both collaborative planners and sequential action learners in infrastructure-scale optimization.

7.2. Decision guider

In addition to serving as the central decision maker, LLMs can also be employed to guide decision making by generating action candidates or language instructions. Benefiting from extensive prior knowledge, LLMs can even provide guidance for unseen tasks, thus improving the sample efficiency of the control subsystem in ITS. LLMs increasingly guide safety-critical decisions through interpretable intermediate representations. AccidentGPT (Wang et al., 2023a) establishes a multimodal safety advisor that converts multi-sensor data to anticipate accidents, issue long-range safety warnings and dialogue-based contextualized recommendations, bridging perception with human-understandable guidance. For control systems, LLMs act as high-level planners whose predictions guide low-level controllers. Sha et al. (2023) propose LanguageMPC, where LLMs reason about traffic scenarios to adjust the priorities of a Model Predictive Control (MPC) system. For example, reweighting cost functions for safety or efficiency and focusing observation matrices on critical vehicles. Similarly, Long et al. (2024a) integrates VLMs with MPC in VLM-MPC. The VLM as a high-level planner processes camera inputs and driving histories to predict trajectory parameters, while MPC handles dynamic execution, addressing real-world delays. These approaches demonstrate how LLMs can inject semantic reasoning into traditional control paradigms without compromising operational safety. LLMs further predict user intent to align machine actions with human goals. Wang et al. (2023b) embeds ChatGPT as a vehicle "Co-Pilot" that translates natural language commands (e.g., "overtake the truck ahead") into domain-specific actions. By encoding user instructions alongside contextual memory, the model generates controller selections or trajectory plans.

7.3. Spatial-temporal predictor

As Transformers naturally excel at handling sequential data, LLMs have shown outstanding performance in time series analysis (Jin et al., 2023a; Gruver et al., 2023) as well as in spatial-temporal data mining (Jin et al., 2023b; Li et al., 2024c). One of the most fundamental macroscopic quantities in transportation systems is the traffic flow, usually structured as spatial-temporal data. Traffic flow forecasting is one of the fundamental tasks in data-centric transportation systems. Traditional methods include using convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) to model graph-based traffic time series

(Tedjopurnomo et al., 2020; Yin et al., 2021; Xue et al., 2025). MLP-based (Shao et al., 2022; Qin et al., 2023; Nie et al., 2025b) and Transformer-based (Xu et al., 2020; Yan et al., 2021; Liu et al., 2023a) architectures have emerged as new alternatives.

LLMs are revolutionizing traffic flow prediction through novel spatiotemporal tokenization strategies (de Zarzà et al., 2023; Zhang et al., 2024g). Early efforts draw inspiration from language models and train forecasters using traffic data such as TrafficBERT (Jin et al., 2021) and Transportation Foundation Model (TFM) (Wang et al., 2023e). TrafficBERT is pre-trained on traffic flow datasets to capture time-series information through self-attention mechanisms, outperforming models trained on specific roads. TFM integrates traffic simulation principles into traffic prediction. Using graph structures and dynamic graph generation algorithms, it is able to model interactions within the transportation system. Both studies demonstrate the potential of language models in enhancing traffic forecasting by effectively capturing spatiotemporal semantics.

More recently, GPT-like architectures have been adopted as backbone forecasters for traffic flow. ST-LLM (Liu et al., 2024b) introduces an embedding module to create a unified spatial-temporal representation and feeds the embeddings to LLMs to predict future traffic time series. To adapt the LLM to traffic prediction tasks, ST-LLM employs a partially frozen attention mechanism, where the frozen layers preserve foundational knowledge, and unfrozen attention layers focus on capturing the specific dependencies. To bridge the gap between sequential text and traffic data, STG-LLM (Liu et al., 2024d) introduces a spatial-temporal graph tokenizer that transforms traffic data into tokens. This transformation reduces the complexity of the graph-structured data, making it more accessible for LLMs. For explainability, xTP-LLM (Guo et al., 2024) transforms multimodal traffic information into natural language descriptions. CoT prompts are used to guide LLMs in identifying relevant factors from the given information. Then LLaMA-2 is fine-tuned using language-based instructions to align with the specific requirements of traffic prediction. Empirical evaluations show that xTP-LLM not only achieves competitive accuracy, but also provides intuitive explanations for its predictions. Both of the above methods utilize the fine-tuning technique to adapt LLMs to the traffic domain. To improve efficiency and reduce computational demands, TPLLM (Ren et al., 2024) further introduces a low-rank adaptation (LoRA) fine-tuning approach for GPT-2, allowing effective learning with fewer parameters. These architectures are also applied to traffic data imputation tasks (Chen et al., 2023c; Zhang et al., 2024c; Nie et al., 2024a; Fang et al., 2025).

Moreover, LLMs have also been used as backbone predictors for trajectory prediction by decoding mobility patterns across scales (Wang et al., 2023d; Xue et al., 2024; Liang et al., 2024a; Haydari et al., 2024; Long et al., 2024b; Zhu et al., 2024; Zhang et al., 2024g). This can be categorized as vehicle trajectory modeling from a micro-perspective and mobility prediction from a macro-perspective. For microscopic trajectory modeling, existing studies explore different trajectory encoding strategies for LLMs. Specifically, LMTraj (Bae et al., 2024) transforms trajectory prediction into a QA problem. They convert pedestrian trajectory coordinates and scene images into textual prompts using numerical tokenizers, and integrate them into a QA template for LLMs. Chib and Singh (2024) presents LG-Traj, a method that uses an LLM-based architecture with a motion encoder to capture motion patterns and a social decoder to capture social interactions among pedestrians. In (Lan et al., 2024), Traj-LLM is proposed to leverage pretrained LLMs without explicit prompt engineering. The approach begins with sparse context joint encoding to process agent and scene features into a form comprehensible by LLMs. In addition, LC-LLM (Peng et al., 2024) reformulates lane change prediction as a language modeling problem. It processes heterogeneous driving scenario information in natural language prompts for LLMs and employs supervised fine-tuning to tailor the LLM for lane change prediction tasks.

For macroscopic mobility prediction, LLMs are applied to decode complex spatial-temporal dependencies, contextual cues, and behavioral trends embedded in diverse datasets such as GPS trajectories, transit schedules, social media activity, and traffic reports (Liu et al., 2024g). Unlike traditional machine learning approaches, LLMs excel at synthesizing unstructured text with structured mobility data based on their fundamental knowledge, allowing them to model nuanced interactions between infrastructure, environment, and user behavior. To help LLMs analyze human mobility data, LLM-Mob introduced by Wang et al. (2023d) presents concepts of historical stays and context stays to capture both long-term and short-term dependencies in human movement. Additionally, context-inclusive prompts are designed to improve the accuracy of LLMs in generating time-aware predictions. Similarly, prompt-based prediction is also explored in LLM-MPE (Liang et al., 2024a). LLM-MPE pompts LLMs to process textual descriptions of public events and historical mobility data to predict human mobility during such events. It converts raw, unstructured event descriptions into a standardized format and segments historical mobility data into regular and event-related components in the prompt. Training foundation models using pure mobility data also demonstrates great potentials. In (Haydari et al., 2024), MobilityGPT is introduced as a geospatially-aware generative model that formulates human mobility modeling as an autoregressive generation task using the GPT architecture. They fine-tune MobilityGPT using a Reinforcement Learning from Trajectory Feedback (RLTF) mechanism, minimizing the travel distance between training and synthetically generated trajectories. UniMob (Long et al., 2024b) extents this paradigm and endeavors to unify individual trajectory and crowd flow predictions. UniMob employs a multi-view mobility tokenizer to transform both trajectory and flow data into spatiotemporal tokens, facilitating unified sequential modeling through a diffusion Transformer architecture. Finally, LLMs are also integrated into multimodal demand prediction by

fusing heterogeneous data sources and reformulating time series forecasting, such as electric vehicles charging demand (Qu et al., 2024), taxi and bike usage demand (Liu et al., 2024b), and package delivery demand (Nie et al., 2025a).

7.4. Summary and outlook

The integration of LLMs as decision facilitators has introduced remarkable capabilities in transportation systems, spanning decision-making, action guidance, and spatial-temporal forecasting. As decision makers, LLMs demonstrate human-like adaptability in traffic signal control, autonomous driving, and route optimization, outperforming traditional methods while offering explainable reasoning. In guiding decisions, LLMs bridge high-level reasoning with low-level control systems through interpretable instructions, enhancing safety and efficiency in complex scenarios. For spatial-temporal forecasting, LLMs decode intricate mobility patterns by unifying multimodal data representations, achieving competitive performance in traffic flow and trajectory prediction through tokenization and fine-tuning strategies. As LLMs evolve from auxiliary tools to central predictors, their integration with ITS techniques such as digital twin platforms and IoT ecosystems will likely promote predictive intelligence in smart transportation applications.

We list several potential directions for future explorations in the following:

- Data representation and computation: LLMs' text-centric training limits their effectiveness in processing numerical and geometric data inherent to transportation systems. Although tokenization methods such as spatial-temporal graph tokenizers (Liu et al., 2024d) and vector captioning (Chen et al., 2024b) show promise, fundamental gaps persist in representing continuous physical spaces and performing precise numerical computations. It remains an open question how to develop a customized data representation method that is suitable for multiscale traffic data (Nie et al., 2024b) and adaptable to LLMs.
- Safety and alignment: Critical applications like autonomous driving require rigorous safety guarantees. Current frameworks address this through simulation sandboxes (Fu et al., 2024a) and safety alignment techniques (Yang et al., 2024c; Xie et al., 2025), but real-world deployment demands formal verification methods and enhanced robustness against adversarial inputs (Liu et al., 2024c). Equipping LLMs with safety evaluation modules is a crucial step before practical implementation.
- Efficient domain-specific adaptation: While fine-tuning approaches like LoRA (Hu et al., 2022) improve the efficiency of adapting LLMs, the scalability of LLMs for infrastructure-scale optimization and real-time decision-making remains computationally intensive. Hybrid architectures such as MoE that combine general LLMs with lightweight domain-specific models (Fedus et al., 2022) could balance adaptability with operational efficiency. This suggests pathways towards resource-efficient LLM predictors.
- **Standardized evaluation:** Currently, the research community lacks standardized benchmarks to assess the predictive capabilities of LLMs in transportation tasks. Emerging datasets such as DriveLM (Sima et al., 2024) and evaluation frameworks (Fan et al., 2024) represent initial steps towards unified evaluation protocols. Future efforts are needed to establish benchmarks for reproducible and open-source studies.

8. Practical Guidance

In this section, we provide a review of publicly available resources that can facilitate the deployment of LLMs in transportation domains and help solve practical problems. As a practical guidance, we focus on related datasets, collection of literature, available software libraries, and hardware requirements.

8.1. Language-enhanced datasets

Adapting and applying LLMs in transportation requires customized datasets. A natural customization is language-enhanced datasets, i.e., the raw traffic data is coupled with language descriptions or language labels. Such datasets are necessary for grounding LLMs in transportation domains. To this end, we summarize several emerging language-enhanced ITS and autonomous driving datasets for LLM development, which are synthesized from the provided research papers. Tab. 4 demonstrates the rapid evolution of LLM applications in transportation systems, particularly in bridging the gap between raw sensor data and human-understandable decision processes. However, due to the rapid development of this field, we list only a few emerging datasets and benchmarks. These resources will be updated frequently on our online project page. We welcome researchers to contribute their related work, datasets, and benchmarks to our collections via GitHub.

Dataset	Year	Venue	Task	Use Case in LLM Develop- ment
BDD-X (Kim et al., 2018)	2018	ECCV	Action interpretation and con- trol signal prediction	Explainable end-to-end driv- ing through visual question answering.
SUTD-TrafficQA (Xu et al., 2021)	2021	CVPR	Video causal reasoning over traffic events	Evaluating the reasoning capa- bility over 6 tasks.
TrafficSafety-2K Zheng et al.	2023	arXiv	Annotated traffic incident and crash report analysis	GPT fine-tuning for safety situ- ational awareness.
NuPrompt (Wu et al., 2023)	2023	AAAI	Object-centric language prompt set for 3D driving scenes	Prompt-based driving task to predict the described object trajectory.
LaMPilot (Ma et al., 2024)	2024	CVPR	Code generation for autonomous driving decisions	CoT reasoning and instruction following for lane changes and speed adaptation.
CoVLA (Arai et al., 2024)	2024	arXiv	Vision-Language-Action align- ment (80+ hrs driving videos)	Trajectory planning with natu- ral language maneuver descrip- tions.
VLAAD (Park et al., 2024)	2024	WACV	Natural language description of driving scenarios	QA systems for driving situa- tion understanding.
CrashLLM (Fan et al., 2024)	2024	arXiv	Crash outcome prediction (severity, injuries)	What-if causal analysis for traf- fic safety using 19k crash re- ports.
TransportBench (Syed et al., 2024)	2024	arXiv	Answering undergraduate- level transportation engineering problem	Benchmarking LLMs on plan- ning, design, management, and control questions.
Driving QA (Chen et al., 2024b)	2024	ICRA	160k driving QA pairs with control commands	Interpreting scenarios, answer- ing questions, and decision- making.
MAPLM (Cao et al., 2024a)	2024	CVPR	Multimodal traffic scene dataset including context, image, point cloud, and HD map	Visual instruction-tuning LLMs and VLMs and vision QA tasks.
DrivingDojo (Wang et al., 2024h)	2024	NeurIPS	Video clips with maneuvers, multi-agent interplay, and driv- ing knowledge	Training and action instruction following benchmark for driv- ing world models.
TransportationGames (Zhang et al., 2024e)	2024	arXiv	Benchmarks of LLMs in mem- orizing, understanding, and applying transportation knowl- edge on 10 tasks	Grounding (M)LLMs in transportation-related tasks.
NuScenes-QA (Qian et al., 2024)	2024	AAAI	Benchmark for vision QA in autonomous driving, including 34K visual scenes and 460K QA pairs	Developing 3D detection and VQA techniques for end-to- end autonomous driving sys- tems.
TUMTraffic-VideoQA (Zhou et al., 2025a)	2025	aXiv	Temporal traffic video under- standing	Benchmarking video reasoning for multiple-choice video ques- tion answering.
V2V-QA (Chiu et al., 2025)	2025	arXiv	Cooperative perception via V2V communication	Fuse perception information from multiple CAVs and an- swer driving-related questions.
DriveBench (Xie et al., 2025)	2025	arXiv	A comprehensive benchmark of VLMs for perception, predic- tion, planning, and explanation	Visual grounding and multi- modal understanding for au- tonomous driving.

Table 4: Summary of language-enhanced ITS and autonomous driving datasets for LLM development and evaluation benchmarks.

8.2. Available resources

The rapid progress of LLMs has catalyzed extensive research and tool development, shaping a dynamic ecosystem of academic surveys and software libraries in the AI community. To help make it easier to access these open-source resources, we briefly summarize several critical surveys on LLMs and catalog representative open-source frameworks, providing researchers with accessible resources about foundational studies and practical tools for developing LLM applications in transportation.

Tab. 5 organizes influential surveys that systematically discuss the evolution, development, advancements, techniques, and challenges of LLMs. Tab. 6 outlines widely adopted libraries that involve application development, deployment, evaluation, and experimentation of LLMs.

Table 5: Representative surveys on LLMs and related techniques. Note that many of these surveys are still being updated.

Paper Title	Year	Venue	Scope and Focus
A survey of Large Language Models (Zhao et al., 2023)	2023	arXiv	Reviews the evolution of LLMs, pretraining, adaptation, post-training, evaluation, and benchmarks.
Large Language Models: A Survey (Minaee et al., 2024)	2024	arXiv	Reviews LLM families (GPT, LLaMA, PaLM), training techniques, datasets, and benchmark performance.
Retrieval-Augmented Generation for Large Language Models: A Survey (Gao et al., 2023c)	2023	arXiv	Introduces the progress of RAG paradigms, including the naive RAG, the advanced RAG, and the modular RAG.
A Survey on In-context Learning: (Dong et al., 2022)	2022	arXiv	Summarizes training strategies, prompt de- signing strategies, and various ICL applica- tion scenarios, such as data engineering and knowledge updating.
Instruction Tuning for Large Language Mod- els: A Survey (Zhang et al., 2023)	2023	arXiv	Reviews methodology of SFT, SFT datasets, applications to different modalities, and influence factors.
Towards Reasoning in Large Language Models: A Survey (Huang and Chang, 2022)	2022	ACL	Examines techniques for improving and eliciting reasoning in LLMs, methods and benchmarks for evaluating reasoning abili- ties.
A Survey of LLM Surveys: https://github. com/NiuTrans/ABigSurveyOfLLMs	2024	GitHub	Compiles 150+ surveys across subfields like alignment, safety, and multimodal LLMs.

Table 6: Popular open-source libraries for LLM development.

Library Name	Basic Functions	Use Cases	URL
Hugging Face	Pretrained models (NLP, vision) and	Model deployment,	https://huggingface.
Transformers	fine-tuning pipelines	adapt tuning	co/docs/transformers
DeepEval	Framework for evaluating LLM out-	Educational applications,	https://github.com/
	puts using metrics like groundedness	hallucination detection	confident-ai/deepeval
	and bias		
RAGAS	Quantifies RAG pipeline	Context relevance scor-	https://github.com/
	performance	ing, answer quality	explodinggradients/
			ragas
Sentence	Generates dense text embeddings for	Survey item correlation	https://www.sbert.net/
Transformers	semantic similarity tasks	analysis, retrieval	
LangChain	Chains LLM calls with external tools	RAG, agentic reasoning,	https://www.langchain.
	for multi-step workflows	data preprocessing	com/
DeepSpeed	A deep learning optimization library	Distributed training,	https://www.
	developed by Microsoft, which has	memory optimization,	deepspeed.ai/
	been used to train LLMs	pipeline parallelism	
FastMoE	A specialized training library for MoE	Transfer Transformer	https://fastmoe.ai/
	models based on PyTorch	models to MoE models,	
		data parallelism, model	
		parallelism	
Ollama	Local LLM serving with support for	Offline inference,	https://ollama.ai
	models like Llama and Mistral	privacy-sensitive apps	
OpenLLM	Optimizes LLM deployment as pro-	Scalable model serving,	https://github.com/
	duction APIs compatible with Ope-	cloud/on-prem hosting	bentoml/OpenLLM
	nAI standards		

8.3. Computational requirement

Pretraining a foundational LLM in vertical domain such as transportation can be infeasible due to extremely high resource consumption. However, recent advances in parameter-efficient fine-tuning methods such as LoRA (Hu et al., 2022) and QLoRA (Dettmers et al., 2023) have made customization of LLMs widely accessible, allowing mid-range hardware to handle models previously restricted to enterprise-grade infrastructure.

To help the researcher have a basic understanding of the hardware requirements to adapt LLMs, we collect and organize data from peer-reviewed studies, community benchmarks, and industry experiments to provide a preliminary analysis of hardware requirements. Tab. 7 is a summary of approximate hardware requirements and performance statistics for fine-tuning LLaMA models across sizes. Note that these numbers vary widely depending on the exact training setup, precision (FP16, 8-bit, 4-bit quantization), and optimization strategies used. As can be seen, the full-parameter fine-tuning method requires significantly more GPU memory and typically a distributed training setup, while PEFT methods like LoRA dramatically reduce the number of trainable parameters and memory usage so that even a single high-VRAM consumer GPU (or a small GPU cluster) can be used.

Table 7: Hardware requirements for fine-tuning and inference across LLaMA model sizes. BS = Batch Size. Estimated values marked "(est.)" derive from scaling laws. Inference rates measured at batch size 1 unless noted. The numbers below are rough estimates aggregated from various community benchmarks and articles. Actual requirements and performance may differ for specific configurations.

Model Size	Full Tuning GPUs	LoRA Tuning GPUs	Full Tuning BS/GPU	LoRA BS/GPU	Tuning Time (Hours)	Inference Rate (Tokens/s)
7B	2×A100 80GB	1×RTX 4090 24GB	1-2	4-8	3-5	27-30
13B	4×A100 80GB (est.)	2×A100 40GB	1	2-4	8-12	18-22
70B	8×H200 80GB	4×H200 80GB	1	1-2	24-36	12-15
405B	64×H200 80GB (est.)	16×H200 80GB (est.)	1 (est.)	1 (est.)	72-96 (est.)	5-8

Please note that these statistics provide a rough guide for planning hardware budget for fine-tuning LLaMA models with different methods. For more detailed and up-to-date benchmarks, reviewing community resources and vendor documentation is recommended. For more concise measures derived from field experiments, see Zhao et al. (2023).

9. Discussion

9.1. Future opportunities of LLM4TR

While previous sections have discussed possible future directions for LLM-driven transportation research from a methodological perspective, this section provides a broader view of opportunities for future studies, particularly focusing on the deployment of LLMs in real-world transportation systems. In the following, we highlight five potential directions that can address current gaps and shape the evolution of our research field.

- 1. Bridging the industry-academia deployment gap in LLM-driven solutions: Despite advances in LLMdriven smart traffic analysis tools (e.g., Open-TI (Da et al., 2024b) and GenAI-ITS (Xu et al., 2024a)), a persistent gap exists between experimental prototypes and real-world deployment. For example, Open-TI shows progress by combining conversational interfaces (via GPT-3.5) with domain tools (SUMO, CityFlow) to automate multistep workflows, from parsing user queries (e.g., "Optimize bike lanes") to executing simulations. However, challenges remain in standardizing tool integration, ensuring computational scalability, and adapting LLMs to mainstream industry software. Future work should prioritize collaborative frameworks where academia co-designs LLM agents with transportation agencies, enhancing technical interoperability with existing infrastructure (e.g., traffic signal controllers, data management APIs). Additionally, "LLM-as-a-service" platforms could facilitate access to advanced tools, enabling entities with limited resources to get access to AI-driven ITS tools through natural language interfaces.
- 2. Situational awareness through hybrid knowledge grounding: LLMs risk generating plausible but ruleviolating solutions without robust domain grounding in transportation scenarios. Approaches such as the RAG-enhanced multi-agent system in Xu et al. (2024a) represent a promising solution by fusing realtime IoT data, traffic theory, and policy documents. Future systems could adopt hierarchical grounding strategies to better adapt LLMs to traffic problems: (1) *spatiotemporal grounding* via live sensor streams and vehicle-to-everything (V2X) communications for context-aware responses; (2) *theoretical grounding*

through explicitly encoding knowledge about transportation principles (e.g., traffic flow theory, traffic rules); and (3) *political grounding* using municipal regulations to ensure legal compliance. For instance, an LLM congestion pricing recommendation scheme should refer to emission models, equilibrium analysis, and local legislation. Achieving this requires hybrid architectures that closely couple LLMs with traffic models, enabling decisions that are both data-driven and knowledge-consistent.

- 3. Eliciting latent problem-solving abilities for emergent challenges: After being pre-trained on large-scale corpora, LLMs are possessed with potential abilities as general-purpose task solvers. These abilities might not be explicitly exhibited when LLMs perform some specific traffic problems. Therefore, it is useful to design suitable task instructions or specific in-context learning strategies to elicit such underexplored abilities (Shin et al., 2020; Wei et al., 2022b). Strategic ability elicitation could unlock these capacities. For example, *role-playing or persona adoption* strategy instructs the model to adopt the persona of a domain expert (e.g., an experienced traveler (Liu et al., 2024e)). This approach leverages the latent knowledge by framing responses in the voice and reasoning style of an expert, which can yield more domain-appropriate answers. The *problem decomposition* strategy breaks a complex domain-specific problem into a series of simpler sub-problems. Then the compositional tasks can be solved by meta agents. Finally, using *domain-contextualized instruction tuning* to guide LLMs to focus on relevant domain aspects and follow a structured approach to the problem.
- 4. **Model compression for real-time decision-making:** Deploying LLMs on resource-constrained edge devices (e.g., onboard vehicle computers, roadside units) necessitates lightweight yet capable models (Liu and Zhao, 2024). Recent advances in model compression suggests a promising pathway. By dynamically *pruning non-critical parameters*, e.g., tailoring sparsification to preserve traffic-related knowledge such as route optimization while compressing unrelated linguistic knowledge, models can be significantly reduced in size without undermining task-specific performance (Ma et al., 2023a). Furthermore, *hardware-aware quantization* methods (Lin et al., 2024a), such as mixed-precision and adaptive quantization schemes, are emerging to exploit the computational strengths of modern GPUs/TPUs. They can reduce memory footprint and inference latency in a way that is sensitive to the unique requirements of transportation applications, without reliance on cloud APIs.
- 5. Toward interpretable and trustworthy transportation AI: Traditional learning-based decision-making tools such as RL can be a black-box system, which is difficult for transportation agencies to understand and evaluate. LLMs can elucidate the design logic and action-making trajectory of themselves through CoT reasoning (Wei et al., 2022b). This property can be used for the interpretation of the results. While the CoT reasoning offers some transparency benefits, transportation agencies require stricter interpretability. Future frameworks can explore: *implementing formal verification* to verify safety-critical outputs; *developing hybrid interpretability tools* by merging CoT with simulation-based "digital twins" to test proposals of LLM in virtual environments before deployment. Crucially, building public traffic participants' trust in LLMs also requires calling on more people to participate in the development, use, and validation of LLM applications in transportation systems.
- 6. LLMs for social good in transportation systems: AI for social good initiatives harness AI technologies to empower communities, drive equitable decision-making, and tackle complex social and environmental challenges (Tomašev et al., 2020; Cowls et al., 2021). The potential of LLMs to address societal inequities and promote inclusive transportation ecosystems expands significantly. Future research should prioritize harnessing LLMs as equity amplifiers that identify and mitigate systemic biases in transportation infrastructure, policies, and services. By analyzing diverse data from socioeconomic demographics and mobility patterns to public feedback, LLMs can optimize transit routes for underserved communities and adjust ride-sharing subsidies dynamically based on real-time equity metrics. Moreover, LLM-driven participatory frameworks (Zhou et al., 2024c) can offer an opportunity for marginalized groups to co-design transportation solutions through natural language interactions. Additionally, by personalizing eco-routing suggestions and gamifying carbon footprint reduction through conversational agents, LLMs could navigate travel behaviors toward environmentally conscious choices.

These opportunities stress the need for interdisciplinary collaboration. LLMs for transportation must evolve beyond conversation interfaces into cyber-physical-social systems that harmonize sensing, learning, modeling, and managing traffic. Realizing this vision will depend on tackling shared technical challenges: curating highquality multimodal traffic corpora, establishing standardized evaluation pipeline, and fostering open ecosystems where modular LLM tools can be safely composed by diverse stakeholders. In the following section, we discuss the potential challenges and concerns of integrating LLMs into transportation systems.

9.2. Challenges and concerns

Despite the impressive advances in LLMs and their potential to transform transportation systems, the integration and deployment of LLMs into the safety-critical, ethically sensitive and computationally constrained domains raises several challenges that need careful attention. Below, we discuss these concerns related to model biases, domain limitations, computational requirements, data privacy, and ethical implications in depth.

- Bias and hallucinations inherent in LLMs: LLMs are typically trained on massive, heterogeneous datasets collected from the internet. Consequently, they may inherit and even amplify biases present in the training data. In transportation contexts, such biases can lead to erroneous predictions or inappropriate recommendations. In addition, the presence of hallucinations, which can cause LLMs to generate factually incorrect information, poses significant risks. In safety-critical systems like autonomous vehicles or traffic control centers, even minor hallucinations can have severe real-world consequences.
- 2. Ensuring rigor and controllability in LLM-driven solutions: While LLMs offer great potential, their integration into transportation systems requires rigor in performance guarantees. A core challenge lies in reconciling the probabilistic, opaque nature of LLMs with the deterministic nature of traffic rules and reliability required for real-time traffic management. Researchers need to develop certifiable validation frameworks that quantify uncertainty bounds, enforce context consistency in model outputs, and rigorously test LLM-based solutions against adversarial scenarios. To maintain human supervision, explainability tools like counterfactual reasoning interfaces should be mandated, allowing operators to monitor how LLM-derived recommendations align with controllability and operational constraints.
- 3. **Domain-specific problem-solving and numeric computing limitations:** While LLMs excel at processing and generating natural language, their capabilities in precise numerical computing and domain-specific problem solving remain limited. Transportation problems often include precise and quantitative analysis that depend on accurate numerical computations or mathematical optimization, such as real-time traffic prediction, equilibrium analysis, and dynamic routing. Standard LLMs are not inherently designed for these tasks, which can lead to suboptimal performance when used in isolation.
- 4. Computational demand for adapting LLMs: The impressive performance of LLMs comes at a high computational cost. Even fine-tuning and adapting these models on user-defined datasets necessitates prohibitive computational resources. Previous data-driven transportation modeling typically required only moderate or small computational overhead. Thus, computation in the era of LLMs becomes a technical bottleneck for transportation researchers and practitioners with limited hardware computing capacity. In addition, while API-based solutions offer an accessible approach to using pre-trained LLMs provided by third-part companies, the limited access and model agnosticism largely limits the ways in which capabilities of LLMs can be explored and applied.
- 5. **Privacy and security concerns:** LLMs require large amounts of data, some of which may be sensitive or personal such as real-time location data, travel patterns, or driver behavior information. This raises significant privacy concerns when LLMs memorize and leak personal information. In addition to privacy issues, there are also security risks related with deploying LLMs as decision makers in critical infrastructure. For instance, cyberattacks using adversarial prompts can manipulate LLM-based traffic controller. Such adversarial vulnerabilities of LLMs are adverse for user's security and system's functionality.
- 6. Ethical, legal, and equitable concerns: Finally, the integration of LLMs in transportation systems raises several ethical, legal, and equitable issues. The black-box nature of many LLMs complicates interpretability, making it difficult to trace decisions or explain errors when they occur. This opacity is problematic in scenarios where transparency is required for public safety and trust, such as autonomous vehicles. Furthermore, there are concerns about equitable access. Biased outputs of LLMs may disproportionately affect underrepresented or vulnerable groups. For example, route optimization models may prioritize routes through lower-income neighborhoods as "acceptable" congestion zones. While the high cost of deploying and maintaining advanced LLMs may also widen the gap between well-funded urban centers and less affluent regions. Lastly, legal liability in the event of system failures remains largely undefined. If an LLM-recommended merging strategy causes a collision of autonomous vehicles, is the responsibility with the model developer, traffic agency, or vehicle original equipment manufacturer?

10. Conclusion

The integration of LLMs into transportation systems marks a pivotal shift from traditional, data-centric approaches to a unified, language-driven paradigm. Through this survey, we have demonstrated that LLMs are not merely tools for natural language processing but foundational enablers of cyber-physical-social intelligence in transportation systems. By systematically categorizing their roles as information processors, knowledge encoders, component generators, and decision facilitators, the proposed LLM4TR framework redefines how transportation systems sense, learn, model, and manage complex urban dynamics. As information processors, they harmonize multimodal data streams; as knowledge encoders, they distill domain expertise into actionable insights; as component generators, they automate system design; and as decision facilitators, they orchestrate human-like reasoning for real-time control. This synergy fosters a self-improving cycle in which LLM enhances operational efficiency, interpretability, and adaptability in ITS.

In conclusion, this survey underscores that LLMs are not just incremental advancements but paradigmshifting technologies for transportation. By unifying language, knowledge, and generative intelligence, they pave the way for transportation systems that are not only smarter and more efficient but also inherently human-centric. As we stand at the intersection of AI and urban mobility, the LLM4TR framework provides both a roadmap and a call to action, to reshape transportation as a collaborative, adaptive, and sustainable ecosystem powered by the language interface. Despite early successes, challenges persist in ensuring safety, mitigating biases, and scaling deployments. Future research in this fresh field needs to prioritize hybrid architectures that embed LLMs within physics-aware simulations, foster industry-academia collaboration for real-world validation, and address ethical concerns in equitable access.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used DeepSeek (an AI-assisted tool) to improve language clarity and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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