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RESEARCH

Data Science in Transportation Networks with Graph Neural Networks: A Review and Outlook

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Abstract
Data science in transportation networks (DSTNs) refers to using diverse types of spatio-temporal data for various transportation tasks, including pattern analysis, traffic prediction, and traffic controls. Graph neural networks (GNNs) are essential in many DSTN problems due to their capability to represent spatial correlations between entities. Between 2016 and 2024, the notable applications of GNNs in DSTNs have extended to multiple fields, such as traffic prediction and operation. However, existing reviews have primarily focused on traffic prediction tasks. To fill this gap, this study provides a timely and insightful summary of GNNs in DSTNs, highlighting new progress in prediction and operation from academic and industry perspectives, which are missing in existing reviews. First, we present and analyze various DSTN problems, followed by classical and recent GNN models. Second, we delve into key works in three areas: (1) traffic prediction, (2) traffic operation, and (3) industry involvement, such as Google Maps, Amap, and Baidu Maps. Along these directions, we discuss new research opportunities based on the significance of transportation problems and data availability. Finally, we compile resources, such as data, code, and other learning materials to foster interdisciplinary communication. This review, driven by recent trends in GNNs in DSTN studies since 2023, could democratize abundant datasets and efficient GNN methods for various transportation problems including prediction and operation.

Keywords Data science · Transportation networks · Graph neural networks · Traffic prediction · Traffic operation

Introduction

In 2021, Google developed and globally deployed a graph neural network (GNN) model to predict estimated time of arrival (ETA) in transportation networks via Google Maps.[1] Here, the ETA prediction denotes predicting ongoing duration of a trip along a specified route based on current road traffic conditions. This model demonstrated superior prediction performance compared to baseline models, with case studies in Los Angeles, New York, Singapore, and Tokyo. Furthermore, it achieved a relative reduction of negative ETA predictions by 16–51% across 19 cities in America, Europe, and Asia (Derrow-Pinion et al. 2021). This project overcame research and production challenges, benefiting worldwide users in trip and route planning. As one of the most influential intelligent transportation applications in recent years, this project prompts three key questions that this review seeks to answer:

- *RQ1:* What are GNNs and what advantages do they offer in modeling graph-structured data?
- *RQ2:* What practical applications could GNNs provide in transportation networks?
- *RQ3*: What are the promising research directions for GNNs in transportation networks?

The ETA prediction is an instance of data science in transportation networks (DSTNs), which involves extracting and harnessing valuable information from massive amounts of data within transportation networks. DSTNs contain the collection, processing, fusion, prediction, and operation using various types of traffic data. Specific examples include congestion propagation characterization (Luan

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et al. 2022), standard traffic prediction tasks like traffic congestion prediction (Rahman and Hasan 2023b; Feng et al. 2023b; Bogaerts et al. 2020; Cui et al. 2020), prediction of ride-hailing (Ke et al. 2021a), and E-scooters demand (Song et al. 2023). Besides, DSTNs encompass traffic data imputation (Chen et al. 2020; Nie et al. 2024, 2025b), crash risk analysis (Zhao et al. 2024), system resilience evaluation (Wang et al. 2020), vehicle route optimization (Liu and Jiang 2022), etc. The DSTN tasks are essential for integrating the sensing and operation of transportation systems to enhance their utilities. For instance, through applications of traffic imputation and prediction techniques, online map navigation platforms can construct temporal traffic profiles, facilitating efficient traffic guidance for both private vehicles and public transit users. Despite its significance, many DSTN tasks can be difficult due to three primary factors: (1) the complexity of spatial traffic state relationships across distinct locations (Wu et al. 2020a, 2021; Lan et al. 2022), (2) the dependency of transportation networks on human activities such as sport events (Yao and Qian 2021), and (3) the large number of nodes and edges in transportation networks in metropolitan areas (Boeing 2020).

To address the above barriers, existing studies have utilized GNNs in various DSTN problems. Here, GNNs are advanced machine learning methods specifically designed for graph-structured data (Manessi et al. 2020; Veličković 2023; Corso et al. 2024). These models integrate graph convolution operations with neural architectures, capturing internodal relationships along graph edges (Scarselli et al. 2008; Kipf and Welling 2016; Veličković et al. 2017; Abu-El-Haija et al. 2019). This property aligns seamlessly with the need to describe numerous entity-entity relationships, such as user–item interactions in recommendation systems (Ying et al. 2018a; Chen et al. 2024b), protein–protein interactions in drug discovery (Jiménez-Luna et al. 2020), and atom–atom proximity in material exploration (Merchant et al. 2023). In transportation networks, GNNs have driven innovations in modeling complicated interconnections between various types of spatial entities in DSTN problems (Rahmani et al. 2023). These include vehicles for intelligent drivings (Chen et al. 2021), sensors for traffic speed prediction (Feng et al. 2023b), users for mobility action prediction (Xue et al. 2024b), road segments for travel time estimation (Fang et al. 2020), origin–destination pairs for ride-sourcing services (Ke et al. 2021b), and airspace sites for air traffic density prediction (Xu et al. 2023). The proliferation of seminal work on GNNs' applications in DSTNs calls for a systematic review and outlook in this domain.

Several reviews have summarized fundamental GNN architectures and their variations across various fields (Table 1). For example, Zhou et al. (2020) examined general GNN components, including graph convolutional networks (Kipf and Welling 2016) and gated GNNs (Li et al. 2015), as well as their variants. They also enumerated applications of these models in natural science, computer vision, and natural language processing up to 2020. Subsequent reviews on GNNs focused on specific domains, such as recommendation systems (Wu et al. 2022) and time-series analysis (Jin et al. 2023b). Additionally, Zhang et al. (2024a) examined the expressive power of GNNs, focusing on the influence of node indices on GNN outcomes. Focusing on industrial applications, Lu et al. (2024) concluded the utilization of GNNs across diverse industrial domains, including biology and finance. Note that these reviews did not specifically focus on transportation networks.

Table 1 Existing GNN reviews on general applications and specific areas

Review	Scope
Zhang et al. (2020), Zhou et al. (2020), Wu et al. (2020b)	General
Keramatfar et al. (2022), Corso et al. (2024)	
Wu et al. (2022), Gao et al. (2023)	Recommendation systems
Jin et al. (2023b)	Time series mining
Zhang et al. (2024a)	Expressive power
Lu et al. (2024)	Biology, finance, etc

Regarding GNNs in transportation networks, we listed existing literature reviews in Table 2. Specifically, Shaygan et al. (2022) discussed GNN methods for predicting traffic speed (Li et al. 2017; Guo et al. 2021), traffic flow (Song et al. 2020), and both (Zheng et al. 2020). Jiang and Luo (2022) enumerated studies on predicting traffic flow and demand for various transportation modes such as railway, taxi, and bicycle. Nevertheless, the two reviews have not included studies on traffic operations like traffic signal control (Devailly et al. 2021). Subsequent reviews filled this gap by expanding GNN applications to traffic operations in intelligent transportation tasks (Rahmani et al. 2023; Wei et al. 2023). However, they did not incorporate large-scale industry deployments of GNNs in transportation networks by digital services such as Google Maps (Derrow-Pinion et al. 2021), Amap (Dai et al. 2020), and Baidu Maps (Fang et al. 2020).

A thorough review addressing these drawbacks enables us to identify new research directions in mining and managing transportation systems. This review presents a comprehensive, up-to-date summary of GNN approaches used in DSTN problems, relevant to both academia and industry (Fig. 1). First, we summarize critical DSTN problems including traffic prediction and operation. Second, we outline vanilla GNN models and their variants over time (You et al. 2020). Next, we analyze current applications and future opportunities of GNNs in DSTN problems. Finally, we highlight related online datasets, codes, and learning materials to

Table 2 Comparison between this review and existing reviews about GNNs in transportation networks

Review	Review of traffic prediction	Review of traffic operation	Details in industry practices	Outlook after 2023	Data and code
Ye et al. (2020)	√				
Jiang and Luo (2022)	√				√
Shaygan et al. (2022)	√				√
Jin et al. (2023a)	√				√
Rahmani et al. (2023)	√	√			√
Wei et al. (2023)	√	√			
This review	√	√	√	√	√

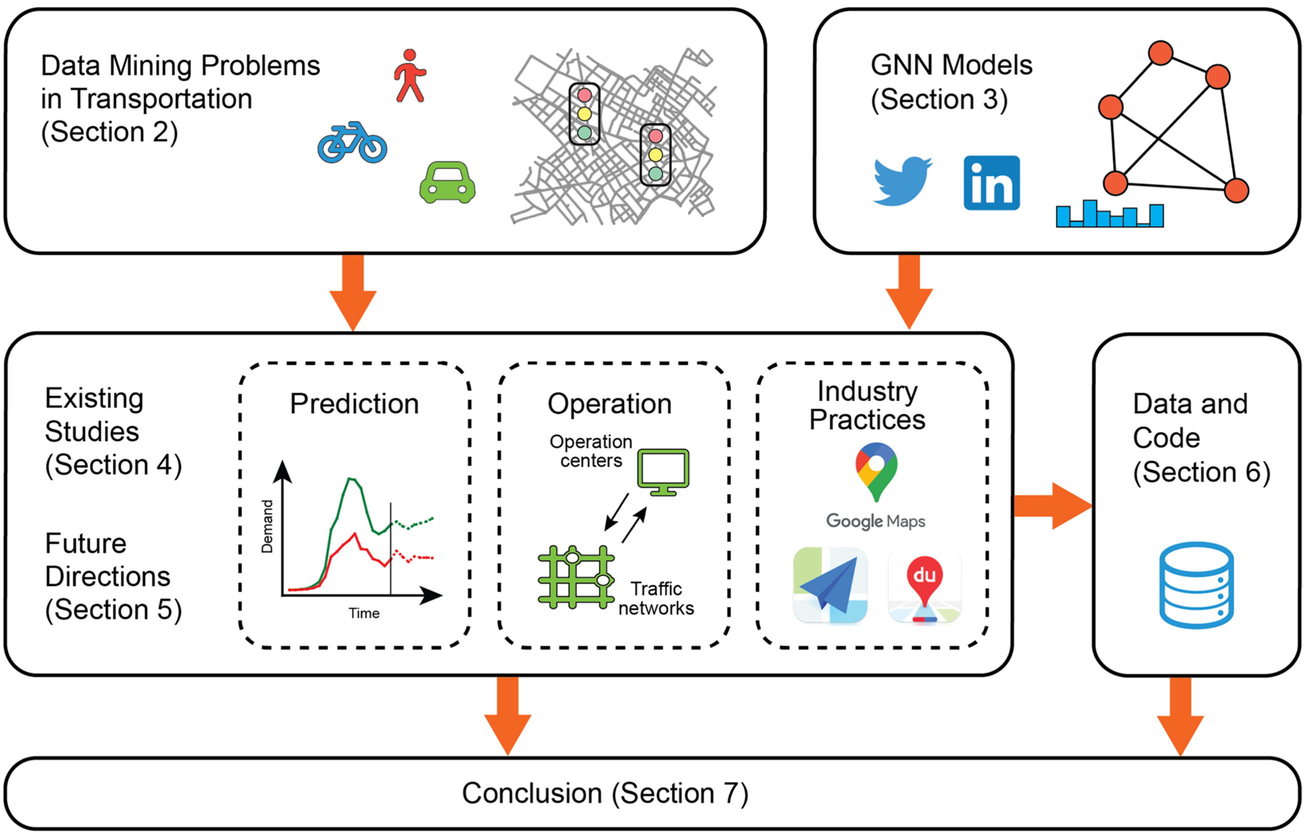

Fig. 1 The framework of this survey. The survey begins by presenting data science problems in transportation and various GNN models ("Prediction and Operation Problems in Transportation Networks" and "Graph Neural Networks" section). Subsequently, we delve into current and prospective research on traffic prediction, operations, and industry-driven applications ("Current Applications of GNNs in Transportation Problems" and "Future Opportunities of GNNs in Transportation Problems" sections). Finally, we discuss data and code collections, followed by a conclusion ("Collection of Data and Code" and "Conclusion" sections)

support future endeavors for academic and industry readers. Together, our contributions are as follows.

- We comprehensively analyze existing GNN studies in a wide spectrum of directions of traffic prediction and traffic operation across various transportation network components, including vehicles, sensor locations, road segments, and airspaces, from academic perspectives. Furthermore, we provide a detailed review of research progress and industry deployments by transportation services like Google Maps, highlighting their proprietary nature compared to academic approaches in problem definition and methodology development ("Current Applications of GNNs in Transportation Problems" section).
- We discuss future GNN research directions, such as interval prediction, model simplifications, combinato-

rial problems, and traffic safety management, considering data availability and the suitability of methods ("Future Opportunities of GNNs in Transportation Problems" section).
- We categorize resources such as open datasets, codes, and tutorials for GNN methods and their applications in transportation networks, with an emphasis on the years 2023 and 2024 ("Collection of Data and Code" section).

Note that our paper selection principle is the diversity of GNN applications and the breadth of coverage. We have particularly updated papers in 2023, 2024, and 2025. For traffic prediction, we primarily review papers published since 2023, as existing literature reviews such as Shaygan et al. (2022) have already provided comprehensive coverage of earlier work. For other domains, such as traffic operation and industry practices, we focus on publications from the last multiple years, as these areas have received limited attention in the existing literature.

The following sections are scheduled as follows (Fig. 1). "Prediction and Operation Problems in Transportation Networks" section outlines various DSTN problems, including traffic prediction and operation. Next, "Graph Neural Networks" section discusses fundamental GNN models and their evolutionary variants. "Current Applications of GNNs in Transportation Problems" section reviews current academic and industrial advances of GNNs in transportation networks. "Future Opportunities of GNNs in Transportation Problems" section outlines future directions on new applications. "Collection of Data and Code" section summarizes data, codes, and alternative resources to facilitate future study for readers. Finally, we conclude the review in the section "Conclusion".

Prediction and Operation Problems in Transportation Networks

This section provides an overview of key DSTN problems amenable to GNNs. In particular, we review general formulations of traffic prediction, traffic operation in academic research, as well as travel time estimation in industrial applications.

Traffic Prediction

Traffic prediction refers to forecasting traffic variable values within transportation networks (Wei et al. 2023; Fafoutellis and Vlahogianni 2023; Yan et al. 2024b). These networks can be modeled as graphs $G = (V, E)$, where V and E denote the sets of nodes and edges, respectively. In various transportation contexts, nodes and edges can represent different elements. In roadway networks with detected sensors, nodes represent sensor locations, while edges denote their proximities (Mallick et al. 2020; Ke et al. 2021a; Chen et al. 2024d). In taxi and aircraft traffic networks, nodes typically represent regions and edges indicate traffic flows between these regions (Yao et al. 2018; Xu et al. 2023). In bike-sharing networks, nodes represent the locations of bike-sharing stations (Cho et al. 2021). Together, graphs provide a simple data structure for spatially representing the states and interactions of transportation entities, thereby bringing a wide range of applications in transportation.

The general traffic prediction problem can be defined as follows: given a transportation system with multiple entities (e.g., traffic stations, sensor locations, and urban regions) and their traffic states by time t, predict these states after t. This formulation covers a wide variety of traffic prediction studies (Li et al. 2017; Yao et al. 2018; Choi et al. 2022; Rahman and Hasan 2023b). This task is crucial for providing future traffic conditions and demand estimations, which inform various traffic management policies. The key to an accurate traffic prediction model is to capture both the spatial and temporal dependencies inherent in traffic systems. Here, the temporal relationships can be appropriately modeled by time-series methods, such as Gated recurrent units (GRUs) (Chung et al. 2014) and Transformers (Wen et al. 2022). The spatial connections between traffic states at distinct locations can be effectively represented using GNNs. This is because GNNs can adaptively propagate information between nodes, which enables them to capture the complicated spatial traffic dependencies arising from traffic dynamics.

Traffic Operation

Traffic operation includes a diverse range of management policies within transportation networks, like signal timing, vehicle operations, and transit management. In particular, we focus on two tasks where GNNs have been applied: vehicle routing (Zhang et al. 2023a) and vehicle relocation (Chang et al. 2022; Lei et al. 2020). Vehicle routing is defined as follows: given origins, destinations, and operational constraints, determine optimal routes with specific goals such as cost minimization. Analogously, vehicle relocation involves the strategic redistribution of vehicles within urban road networks by selecting suitable destinations. Both vehicle routing and relocation are fundamental problems faced by individual drivers, transportation network companies like Uber (Bertsimas et al. 2019), and logistics companies like FedEx (Kitjacharoenchai and Lee 2019).

Industry Practice

A notable industrial application of GNNs is travel time estimation (Derrow-Pinion et al. 2021; Dai et al. 2020; Fang et al. 2020). The goal is to predict the future vehicle travel time along a route between a specified origin and destination. Practically, the total travel time for a route can be calculated by aggregating the travel times of road segments that constitute the route. Hence, the estimation of route travel time can be converted to the calculation of travel times for individual road segments. Travel time estimation holds immense value for individual travelers in their daily commutes and public agencies in their operational management. Individual travelers can decide the trip departure time based on expected arrival time and estimated travel time outcomes. Concurrently, road segment travel time serves as crucial input for public agencies to provide advance notifications of vehicle arrival time to passengers. This can significantly reduce passenger waiting time and enhance the user experience for public transit (Li et al. 2024d).

Graph Neural Networks

Basic Ideas

Graph-structured data, comprising entities and their interconnections, are prevalent across various disciplines (Newman 2018; Hu et al. 2020). Mining patterns in such data can be challenging due to their complexity and the permutation-invariant property, meaning that the graph does not change after node reordering (Keriven and Peyré 2019). GNNs are specialized neural networks (NNs) designed to perform data mining by leveraging graph structure information (Kipf and Welling 2016; You et al. 2020). While classical NNs are composed of linear transformations and nonlinear activations (e.g., the sigmoid function, ReLU), GNNs employ a neighborhood aggregation mechanism to update node embeddings based on their neighborhoods (Fig. 2). This capability enables multiple tasks, such as node classification, link prediction, and graph summarization (Zhou et al. 2020).

Consider a graph with the node set V ($|V| = n$) and the adjacency matrix A. Each node is represented by a d-dimensional embedding, forming the embedding matrix $H \in \mathbb{R}^{n\times d}$. A k-layer GNN can be expressed as a sequence of transformations between node embeddings

$$H^{l+1} = f(H^l, A, W), 0 \le l \le k-1. \quad (1)$$

Here, H^l and H^{l+1} denote node embeddings at layers l and $(l+1)$. W is the learnable weight matrix, and $f(\cdot)$ represents the mapping function. Specifically, W, $f(\cdot)$, and A correspond to the linear transformation, nonlinear activation, and neighborhood aggregation modules, respectively. Note that Eq. 1 allows the final node embedding H^k to capture the graph structure through neighborhood-based information fusion over k iterations.

Generic GNN Models

As a specialized approach for processing graph-structured data, GNNs have undergone significant evolution, marked by numerous innovative architectures. This subsection provides a concise summary of the development of GNNs, highlighting key landmarks. The concept of GNNs was initially proposed by Scarselli et al. (2008). This groundbreaking work enabled the application of NNs to graph-structured data. The model achieved this by iteratively propagating information across nodes to reach a stable state.

Bruna et al. (2014) proposed the spectral approach, utilizing the spectral decomposition of the graph Laplacian to learn about graph data. This work represented a giant advance in the field of GNNs. Following this, Kipf and Welling (2016) introduced graph convolutional networks

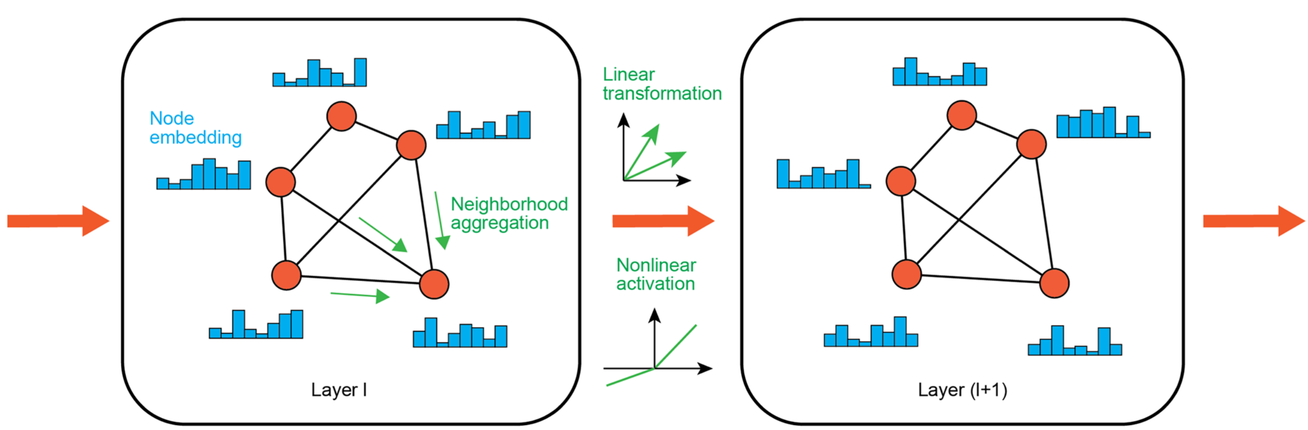

Fig. 2 Three mechanisms in GNN models: neighborhood aggregation, linear transformation, and nonlinear activation. These mechanisms collectively transform node embeddings, which are numerical vectors associated with the nodes, from layer l to layer $(l+1)$. Such information passing allows node embeddings to capture the graph's topology

(GCNs), which further streamlined the implementation of spectral graph convolution. This improvement enhanced the applicability of GNNs to large-scale graph data, particularly in node and graph classification tasks.

While GCNs require complete graph information simultaneously, graph attention networks (GATs) and GraphSAGE can aggregate neighborhood information locally. Here, GATs build attention mechanisms to dynamically determine the importance of information transfer between nodes, which is particularly effective in handling heterogeneous graph data (Veličković et al. 2017). GraphSAGE first fuses neighborhood representations and then concatenates them with the ego node's representation (Hamilton et al. 2017). In 2018, graph isomorphism networks (GINs) were proposed in the paper *How Powerful are GNNs* by Xu et al. (2018a). This work theoretically demonstrated the strong representation power of GNNs from the Weisfeiler–Lehman isomorphism test (Huang and Villar 2021), showing their ability to identify diverse graph structures.

Additionally, relational-GCN (R-GCN) accounts for the heterogeneity of edge types, supporting the modeling of graphs with diverse types of interactions (Schlichtkrull et al. 2018). Furthermore, DiffPool aggregates node representations for each node cluster in a hierarchical manner, which contributes to the learning of complicated hierarchical graph structures (Ying et al. 2018b). More recently, Kreuzer et al. (2021) introduced graph constraints into Transformer models (Vaswani et al. 2017), making another stride in the evolution of GNNs. This research employed learned positional encodings to capture node positional information and fed them into the Transformer structure.

GNN Variants

Following generic GNN models, the development of GNNs was driven by the universal properties of graph learning and a broad spectrum of applications (Fig. 3). To overcome the universal limitations of generic GNNs, researchers have developed the following models.

- *Node positions*. Position-aware GNN (P-GNN) captures relative positions between an ego node and its neighborhood, thereby providing more rich node interconnection information (You et al. 2019).
- *Large graphs*. To mitigate the computational complexity in large-scale graphs (e.g., those containing over one million nodes), researchers created either macro-nodes by grouping original nodes (Chen et al. 2024b) or a series of multi-mesh nodes by summarizing multiple original nodes in local regions (Lam et al. 2023). In graph generation tasks, computation graph transformer (CGT) can capture the distribution of large-scale graphs while protecting user privacy (Yoon et al. 2022).
- *Robust learning*. Given that GNNs are threatened by adversarial attacks like node perturbations, Property GNN was proposed to learn clear graph representations from noisy observations (Jin et al. 2020), by exploiting the low rank and sparsity characteristics.
- *Out-of-distribution issues*. Out-of-distribution issues arise when a model deals with unobserved data that differs significantly from training data. In graph classification tasks, graph information bottleneck with explainability (GIBE) was developed to study the effect of regularization and its relationship with the out-of-distribution issues in GNNs (Fang et al. 2024).

Furthermore, the widespread deployments of GNNs led to the development of domain-specific models, facilitating both the prediction and generation capabilities across various domains.

- *Recommendation systems*. Recommendation systems provide suggestions of products, locations, and services to users based on behavioral data (Kang and McAuley 2018; Yan et al. 2024a). In user–item bipartite graphs, neural graph collaborative filtering (NGCF) propagates information between users and items along user–item edges (Wang et al. 2019). Later, researchers demonstrated the redundancy of linear transformations and nonlinear activation operations in NGCF (He et al. 2020).

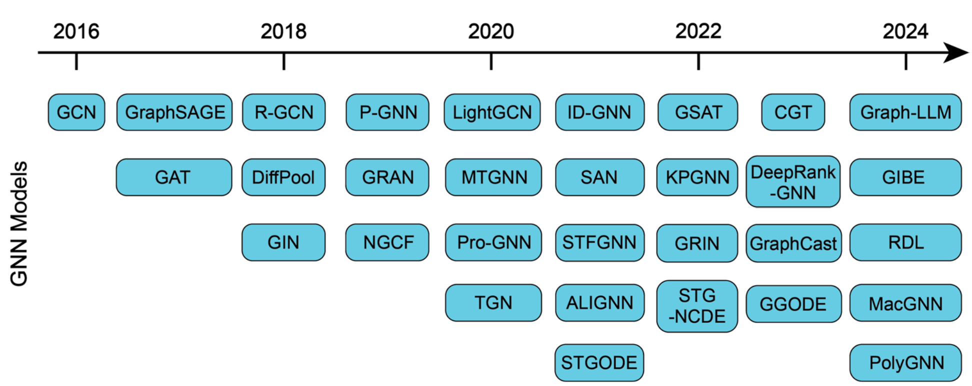

Fig. 3 Prominent GNN models from 2016 to 2024. For models in the same year, the vertical positionings do not adhere to explicit criteria. Readers can navigate research articles for each model by referring to their model abbreviations

They introduced LightGCN, a streamlined yet effective GNN model, to predict user–item interactions in user check-in and review data.

- *Social networks*. Researchers from Twitter developed temporal graph networks (TGNs), which learn node representations from dynamic networks, to perform link prediction tasks in social networks from the Twitter platform (Rossi et al. 2020). Another impactful deployment of GNNs in social networks was made by LinkedIn researchers (Borisyuk et al. 2024). They integrated multiple entities (e.g., users, companies) and relations (e.g., posts, notifications) into a LinkedIn Graph with a hundred billion nodes. GNNs on the graph resulted in a 2% online improvement in advertisement clicks and a 1% increase in job applications.
- *Protein–protein interactions*. DeepRank-GNN can effectively capture protein–protein interactions to learn task-specific protein structure patterns relevant to drug design (Réau et al. 2023). Here, GNNs are invariant to node ordering, making them well suited for modeling diverse interactions between proteins.
- *Integrated circuits*. In integrated circuit designs, a tree-based GNN model called SyncTREE facilitates timing prediction to support efficient timing updates throughout circuit design processes (Hu et al. 2024).

Readers can refer to alternative GNN models in reviews on recommendation systems (Wu et al. 2022), natural language processing (Wu et al. 2023a), electrical engineering (Chien et al. 2024), and materials' science (Reiser et al. 2022).

Integration with Large Language Models

GNNs are powerful for modeling graph-structured data but are vulnerable when node and edge information is incomplete. The recent proliferation of large language models (LLMs), including Llama 2 (Touvron et al. 2023), Llama 3 (Dubey et al. 2024), and GPT-4 (Achiam et al. 2023), offers immense potential for addressing this issue. In 2024, researchers have devised two primary approaches for integrating GNNs and LLMs (Fig. 4).

The first involves using GNNs to generate adjacency-aware node representations and tokens as inputs for downstream LLMs (Ren et al. 2024; Tsitsulin et al. 2024; Perozzi et al. 2024). This structure leverages GNNs' strength in encoding non-Euclidean graph data, as well as LLMs' rich semantic knowledge. The second approach utilizes LLMs to generate node representations in graphs with incomplete information, providing more comprehensive features for both nodes and edges to support aftermath graph learning process (Chen et al. 2024f). One typical application involves enhancing sparse user–item graphs in recommendation systems with LLMs (Wei et al. 2024). Pre-trained LLMs (e.g., GPT-4) could be utilized to generate user profiles or item attributes based on historical user–item interactions. By providing the LLMs with prompts such as "Generate user profiles using the following movies that the user has watched: (1) Titanic,

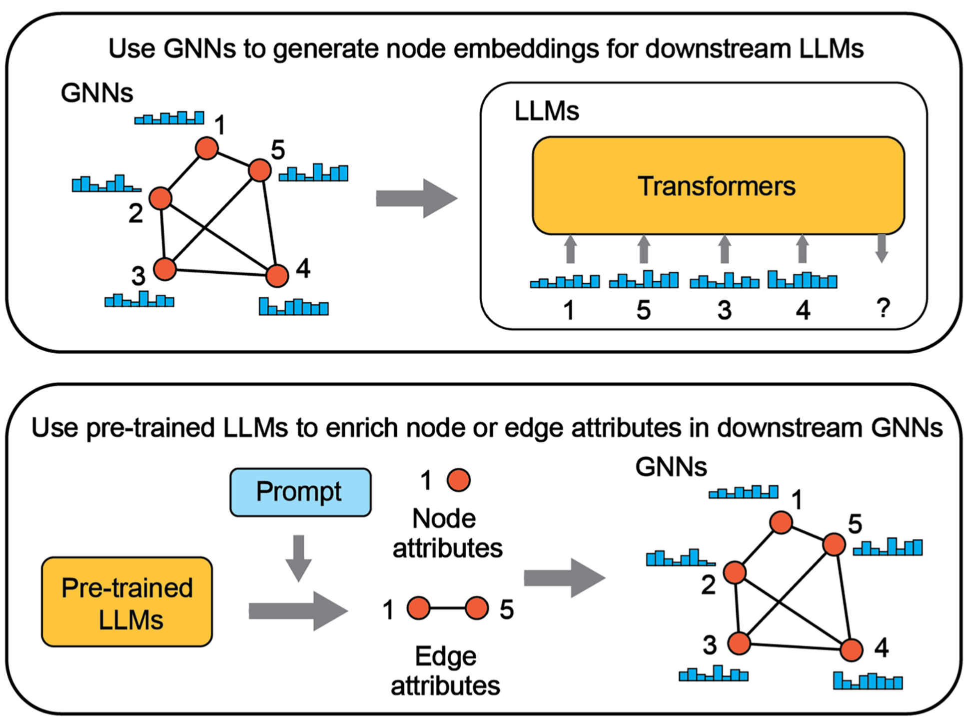

Fig. 4 Two approaches to integrate GNNs and LLMs. The first approach employs GNNs to produce network topology-aware node embeddings and feeds them into afterward LLMs (Perozzi et al. 2024). In contrast, the second approach leverages knowledge from pre-trained LLMs to enhance downstream GNNs (Wei et al. 2024), mitigating information deficiency during GNN training

(2) Forrest Gump, ...", we are able to obtain several potential user characteristics, including age, gender, and preferences. These generated attributes can then be incorporated as additional features to downstream GNN models, thereby achieving better prediction performance in recommendation systems. Readers can also refer to a recent study on LLM for GNN approaches in the context of delivery demand prediction (Nie et al. 2025a). Note that the improvement in prediction performance is attributed to the strong user profile inference capabilities of LLMs, which are trained on vast amounts of data. These combinations of GNNs can simultaneously preserve the advantages of GNNs in representing relational structures within data and LLMs in extracting semantic information from sequential data.

Interpretability of GNNs

The interpretability of GNNs focuses on understanding the reasoning behind prediction outcomes, which is essential for real-world decision-making processes (Ranu 2024; Chen et al. 2024a). Three key questions exist: given a trained GNN model, what features, subgraphs, and training samples significantly influence the prediction outcomes? These are categorized as feature-level, graph-level, and training data-level interpretation for GNNs, respectively.

First, multiple feature-level interpretation approaches have been introduced. For general NNs, SHapley Additive exPlanations (SHAP) assign each feature an importance value that satisfies desirable criteria (Lundberg 2017). For GNNs, GNNExplainer achieves feature-level interpretability by identifying a subset of node features that yield prediction results comparable to those obtained using all node features (Ying et al. 2019). To address the subset identification problem (equivalently, an integer program), the authors perform the relaxation using masked matrices with continuous values and optimize matrix values through backpropagation. Second, for graph-level interpretability, GNNExplainer identifies subgraphs that bring similar predictions for a given node to those of the complete graph. This is formulated as the maximization of mutual information which measures the predictive contribution of subgraphs. This technique has been employed to detect canner gene modules within biology research (Li et al. 2024c). Another graph-level interpretation method XGNN focuses on generating subgraphs via reinforcement learning (Yuan et al. 2020). Third, there is limited research focused on training data-level interpretation (Yuan et al. 2022), primarily due to the extensive search space of training data subsets with diverse graph structures. Note that training data-level interpretability is critical as it enables navigating crucial training samples and reducing overall training costs (Xie et al. 2023).

Current Applications of GNNs in Transportation Problems

Traffic Prediction

As mentioned in "Traffic Prediction" section, traffic prediction refers to forecasting traffic conditions (e.g., flow rate, traffic density, and average speed) within transportation networks. This process utilizes past traffic data and external factors, including weather (Shaygan et al. 2022) and special events (Yao and Qian 2021), as inputs and generates future traffic states as outputs. Initially, researchers applied standard feedforward NNs to traffic prediction tasks (Ma et al. 2015). Subsequently, seminal GNN models, like GCNs, GraphSAGE, and GATs (discussed in "Graph Neural Networks" section) catalyzed the development of various graph-based learning methods in traffic prediction, thanks to their advantages in capturing node relationships in networks (Chen et al. 2023b; Liang et al. 2023a). Notable models include DCRNN (Li et al. 2017), TGC-LSTM (Cui et al. 2019), and AGC-Seq2Seq (Zhang et al. 2019). The model proliferation led to comprehensive reviews by Jiang and Luo (2022) and Rahmani et al. (2023). While these studies and reviews predominantly focused on vehicular traffic speed and flow rate, recent research has expanded to cover other transportation modes, including bicycles (Liang et al. 2023b) and E-scooters (Song et al. 2023). The latest methodologies also advance to novel model architectures, such as the macro–micro-module, which unravels traffic patterns across multiple resolutions (Feng et al. 2023b). This trend has been particularly apparent since 2023. This subsection reviews novel studies to elucidate these emerging directions.

Prediction Targets

As listed in Table 3, GNNs have been continuously applied to predict traffic speed (Ouyang et al. 2024; Feng et al. 2023b) and flow (Zou et al. 2024; Lv et al. 2023). Recent studies have also employed GNNs for aviation traffic prediction. For instance, Xu et al. (2024b) modeled specific airspace sectors as nodes, used the numbers of planes flying between two nodes to define adjacency matrices, and finally utilized GNNs to predict future aircraft density near airports. Similarly, Li et al. (2024a) predicted airspace complexity, categorizing it into three levels (low, normal, and high) within different sector regions, to aid air traffic management. Here, airspace complexity was determined by factors, such as the sector volume, ground speed, and the number of planes. The applications of GNNs have

Table 3 Applications of GNNs in traffic prediction in 2023 and 2024

Target	Study	Model	Base module	Other modules	Data	Area	Contribution	Code
Traffic speed, travel time	Ouyang et al. (2024)	TPGraph	GCN	Transformer	Highway speed, travel time	California, Guizhou	Spatio-temporal	✓
Traffic speed	Jiang et al. (2023b)	MegaCRN	GCRN	Meta-graph learner	Highway speed	California, Tokyo	Spatio-temporal heterogeneity	✓
Traffic speed	Feng et al. (2023b)	MMSTNet	GCN	TCN, attention	Highway speed	California	Macro-micro	✓
Traffic speed	Wang et al. (2023a)	GSTAE	GCN	GRU	Highway speed	California	Handling missing values	
Traffic speed	Zhang et al. (2024c)	AIMST	GCN	TCN	Traffic speed	Xi'an, Jinan	Spatio-temporal, clustering	
Traffic speed	Zhang et al. (2024b)	CKG-GNN	GNN	Knowledge graphs	Traffic speed	Singapore	Contextual information	✓
Traffic speed and flow	Ju et al. (2024)	COOL	MPNN	Attention	Highway speed and flow	California	High-order relationships	
Traffic speed and flow	Rahman and Hasan (2023b)	DGCN-LSTM	GCN	LSTM	Highway speed and flow	Florida	Traffic during hurricane	
Traffic speed and flow	Ouyang et al. (2023)	DAGN	GCN	GRU	Traffic speed and flow	California, Shenzhen	Cross-city	
Transit flow	Zou et al. (2024)	OD-PF	GCN	Attention	Subway flow	Beijing	OD during incidents	
Traffic flow	Kong et al. (2024b)	STPGNN	Pivotal GCN	Node identification	Taxi GPS, highway flow	California, Beijing, England	Pivotal nodes	
Traffic flow	Chen et al. (2024c)	TFM-GCAM	GCN	Attention	Highway flow	California	Traffic flow matrix, Transformer	
Traffic flow	Li et al. (2023c)	STTGCN	GCN	Tensor, dilated conv	Highway flow	California	Binary adjacency matrix	
Traffic flow	Lv et al. (2023)	TS-STNN	Tree GCN	GRU	Highway flow	California	Hierarchical and directional	
Congestion level	Feng et al. (2023a)	F-GCN	GCN	Attention, LSTM	Taxi GPS	Beijing	Congestion between segments	
Multi-traffic mode	Yang et al. (2024)	M2-former	GCN	Attention	Subway, taxi, bus	Beijing	Multi-traffic	
Metro demand	Ding et al. (2024)	Metro-MGAT	GAT	Age-weighted loss	Metro ridership	Shanghai	Expanded demand	
Metro demand	Li et al. (2023a)	IG-Net	ChebNet	Multi-task learning	Metro ridership	Suzhou	Three interactions	
Traffic speed, taxi demand	Tygesen et al. (2023)	NRI-X	Graph Network	VAE	Highway speed, yellow taxi	NYC, California	Optimal graphs	✓
Charging demand	Wang et al. (2023b)	H-STGCN	GCN	GRU, clustering	EV trajectories	Beijing	Heterogeneous region scales	
Bike sharing demand	Liang et al. (2023b)	DA-MRGNN	GGCN	TCN	Bike, subway, ride-hailing	NYC	Interactions between modes	
E-scooter demand	Song et al. (2023)	SpDCGRU	Diffusion Conv	GRU	E-scooter OD trips, etc	Louisville	Spatio-temporal	
Taxi and bike demand	Chen et al. (2024d)	SFMGTL	ST-GNN	Clustering, etc	Taxi, bike	NYC, Chicago, Washington	Knowledge transfer	✓
Train delay	Huang et al. (2024)	GAT	GAT	Attention	Train, weather data	The Netherlands	Interpretability and accuracy	

Table 3 (continued)

Target	Study	Model	Base module	Other modules	Data	Area	Contribution	Code
Ship trajectory	Zhang et al. (2023b)	G-STGAN	GCN	Transformer, etc	Ship	Hong Kong, Weihai, Zhoushan	Integrates GCN and Transformer	
Air traffic	Xu et al. (2024b)	BEGAN	GAT	LSTM, Bayesian	Flights, etc	Georgia, Flordia	Knowledge-based	
Airspace complexity	Li et al. (2024a)	MAST-GNN	GCN	TCN-Att	Air traffic	China	Spatio-temporal	✓
Pavement performance	Cai et al. (2023)	CTGCN	GCN	LSTM	Pavement images, etc	Shanghai	Causal graphs	
Truck loan	Chen et al. (2024e)	SGTD	Gated GNN	LSTM	Truck GPS, loan records	China	Spatio-temporal	

MPNN Message Passing Neural Network, *NYC* New York City, *EV* Electric vehicle. For studies conducted before 2023, readers can consult the existing reviews, including Shaygan et al. (2022) and Rahmani et al. (2023)

expanded to forecasting traffic demand, including taxi traffic (Tygesen et al. 2023), metro passenger flow (Li et al. 2023b), and bike-sharing demand (Liang et al. 2023b). These studies primarily focus on forecasting demand for the existing infrastructure during its operation phase. In contrast, Metro-MGAT addresses the station ridership prediction problem for new metro stations during the planning phase (Ding et al. 2024).

Besides, Cai et al. (2023) constructed causal graphs for pavement systems, and applied GNNs to these causal graphs to forecast pavement performance across the city. Together, the spatial modeling capability of GNNs facilitates the understanding of relationships between entities within networks, enabling a wide variety of traffic prediction tasks.

Spatial Modules: GNNs

We now summarize GNN variants used in traffic prediction in Table 3. Over half of the listed studies (15 out of 29) developed their models using GCNs as foundation architectures. Recall from "Graph Neural Networks" section that GCNs employ matrix convolutional operations for information propagation, generally providing higher computational efficiency than the neighborhood aggregation in GraphSAGE (Liu et al. 2020) and the edge-by-edge attention computation in GATs. By combining graph convolution operations in GCNs and recurrent units, MegaCRN captures traffic variability across sensors and periods, as well as irregular disruptions caused by accidents (Jiang et al. 2023b).

Alternatively, the NRI local, NRI unif, and NRI DTW models, designed for traffic speed and taxi demand prediction (Tygesen et al. 2023), were built on the Graph Network (Battaglia et al. 2018). Note that the Graph Network updates information directly utilizing nodes, edges, and global graph characteristics, thereby constituting a generalized extension of GCNs.

Temporal Modules

GNNs can effectively capture spatial dependencies in traffic prediction tasks. However, additional components are still necessary to model temporal relationships. Table 3 indicates that temporal modeling techniques, including the Long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997), GRUs, and Transformers with attention mechanisms (Vaswani et al. 2017), were frequently integrated with GNNs. These temporal modules maintain strong capabilities to propagate information along the temporal axis.

Datasets

Many GNN-based traffic prediction studies predominantly used traffic speed and flow rate data from highway traffic datasets from California, such as PEMS-BAY, METR-LA (Li et al. 2017), PeMSD4, and PeMSD8 (Guo et al. 2019). These datasets consist of real-time traffic variable measurements collected from detector sensors, typically recorded at 5-min intervals. Recent research, however, has started to include various new data sources like taxis, trucks, accidents, electric vehicles, E-scooters, and flights (Table 3). Besides, case studies have broadened to countries such as China (Feng et al. 2023a). These studies demonstrate GNNs' effectiveness in spatial modeling for diverse DSTN problems globally. Despite these advancements, the direct application in many developing countries remains limited. Their traffic data might have high variations due to mixed vehicle and pedestrian environments, which poses challenges for diverse traffic prediction tasks.

Interpretability

Existing interpretation techniques for GNNs in traffic prediction originate from general approaches summarized in

"Interpretability of GNNs" section. In particular, Huang et al. (2024) built GNN models that account for delay propagation patterns in railway systems. This study, which falls within the feature-level category, identifies train headway as the critical factor for train delay propagation. Furthermore, Tygesen et al. (2023) conducted interoperability analysis by examining learnable adjacency matrices that reflect internodal interdependencies. Similarly, the collaborative prediction unit methods proposed by Li et al. (2022) explained GNNs from an edge perspective. Accordingly, the above two studies are graph level. Inspired by the GNNExplainer (Ying et al. 2019), Traffexplainer unveils critical spatial and temporal elements in traffic prediction through iterative updates of masked spatial and temporal matrices. Consequently, Traffexplainer belongs to both the feature-level and graph-level interpretation methods (Kong et al. 2024a). Note that the interpretation approaches for GNNs are closely associated with adversarial attacks on GNNs, which involve modifying a subset of nodes within transportation networks to harm traffic prediction performance (Zhu et al. 2023). Such analyses can contribute to developing robust GNN prediction models that maintain high performance across diverse contexts.

In summary, the applications of GNNs in traffic prediction exhibit three key trends: (1) from roadway traffic to multiple transportation modalities, (2) from standard GNN architectures to customized modules designed to capture stochastic, human-centric, and multi-resolution facets of traffic dynamics, and (3) from limited data sources to diverse, multinational datasets.

Traffic Operation

GNNs are capable of learning informative representations for nodes and edges that encode graph structures. These learned representations can be utilized to derive solutions for graph-based operation problems. For instance, computational scientists have utilized GNNs to address combinatorial optimization problems, such as general mixed-integer linear programs (Lee and Kim 2024), the Maximum Cut (Heydaribeni et al. 2024), the Maximum Independent Set (Schuetz et al. 2022), and the Traveling Salesperson Problem (TSP) (Min et al. 2024) (Fig. 5a). In particular, they first employed GNNs to obtain continuous node representations based on the operation problem. After that, they either mapped continuous node variable values to integers (Schuetz et al. 2022) or used tree search methods to derive discrete solutions (Min et al. 2024). Overall, GNNs can assist in addressing optimization problems by providing superior feasible solutions or evaluating the optimality of solutions (Cappart et al. 2023). Alternatively, the spatial learning capabilities of GNNs enable their potential for

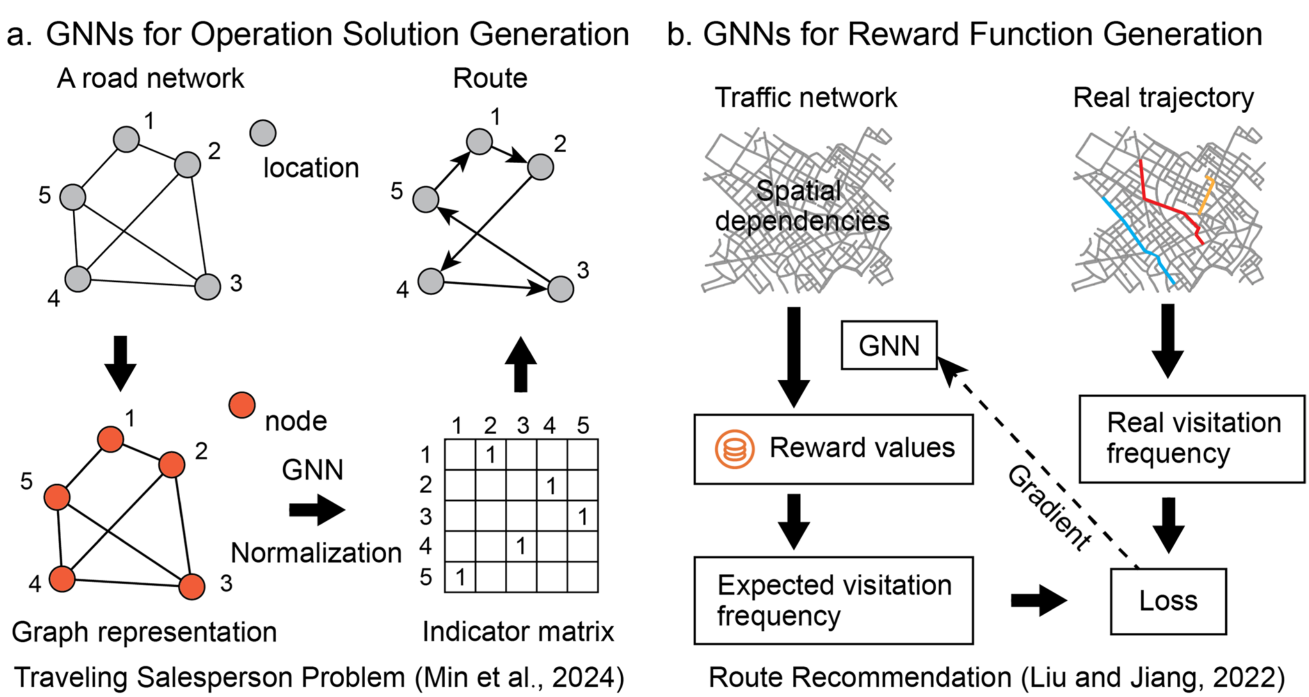

Fig. 5 Applications of GNNs in traffic operation. **a** GNNs can generate route solutions by incorporating road network topology. The outputs of GNNs are utilized to construct an indicator matrix, which represents a route traversing all nodes within the network (Min et al. 2024). **b** GNNs serve as reward function generators for route optimization. The parameters of the GNN are updated by minimizing the gap between the expected and actual visitation frequencies of the routes (Liu and Jiang 2022)

addressing resource allocation problems, which determines the optimal distribution of limited resources within interconnected systems. For instance, Wang et al. (2022b) proposed Aggregation GNNs to utilize asynchronous and delayed signal information to optimize decentralized resource allocation in wireless networks.

In transportation networks, researchers have applied GNNs to address various traffic operation problems, including vehicle repositioning (Chang et al. 2022), vehicle routing (Liu and Jiang 2022), railcar itinerary optimization (Zhang et al. 2025), and the control of connected autonomous traffic (Zhou et al. 2024). For example, an attention-enhanced GCN was developed to predict spatial travel demand for carsharing systems (Chang et al. 2022). The prediction outcomes acted as the input for downstream vehicle location optimization for profit maximization in carsharing companies. Besides, GNNs have been used in route recommendations (Liu and Jiang 2022) (Fig. 5b) and the routing of unmanned aerial vehicles (Fang et al. 2023). In these applications, GNNs provide reward function values or new information during the interactive optimization process, leveraging their capability to capture the spatial–temporal correlations of traffic features within networks. For delivery service route planning, researchers used GNNs and Transformers to generate waypoints along the route and employed a divide-and-conquer method to determine detailed routes (Zhang et al. 2023a).

Notably, GNNs have been leveraged to address the traffic assignment problem (TAP): given traffic demand in a road network, determine how traffic flows through the network (Nguyen 1974; Daganzo and Sheffi 1977). In particular, Rahman and Hasan (2023a) solved the TAP by learning a mapping from the demand matrix and the network structure to the link flow matrix using GNNs. They employed synthetic traffic data in the Sioux Falls network and a road network in Massachusetts from user equilibrium to train the GNN model, demonstrating that the GNN model was able to generate link flows with less than 2% errors. Besides, Liu et al. (2023b) created both real links and virtual links (which connect origin and destination nodes) in GNNs for solving the TAP. For model training, the authors customized a total loss function (i.e., L) as the weighted sum of three components: the link-level flow-capacity ratio error (i.e., L_{f-c}), the link flow error (i.e., L_f), and the node-based flow conservation error (i.e., L_c)

$$L = \alpha L_{f-c} + \beta L_f + \gamma L_c. \tag{2}$$

It is worth mentioning that the applications of GNNs in traffic operation problems are still in their early stages. The circumstances under which GNN solutions surpass the existing methods in terms of running time and solution quality, for both large- and small-scale networks, remain an open question (Boettcher 2023). Current experiments of GNNs on the TAP are limited by networks with at most hundreds of nodes (Rahman and Hasan 2023a; Liu et al. 2023b). It is unclear whether the successful online deployments of GNNs in large social networks, such as LinkedIn Graph with billion-level nodes (Borisyuk et al. 2024) ("GNN Variants" section), can be effectively transferred to road traffic networks. Future research can explore this area further.

Accident Prediction

GNNs serve as novel approaches for traffic accident prediction, which plays a central role in traffic safety management (Mannering et al. 2020). Two primary factors contribute to these applications. First, the robust learning capabilities of GNN neurons guarantee the extraction of complex relationships between traffic accident occurrences, road network profiles, and external factors from large-scale datasets, surpassing the limitations of traditional statistical methods and causal inference models in prediction accuracy. Second, the internode message-passing mechanism inherent in GNNs seamlessly fits the spatial interconnectedness of traffic accident events, which arise from traffic dynamics and naturalistic driving behaviors (Sae-ngow and Kulpanich 2023).

In particular, Yu et al. (2021) developed a deep spatio-temporal GCN using diverse data sources (including traffic speed data, road network data, and weather data) for accident prediction, and obtained superior prediction performance over previous methods. Besides, Trirat et al. (2023) proposed GNN models based on GCNs to predict accident risks in South Korea. Similarly, Tran et al. (2023) extended ChebyGIN, which considers multi-hop neighborhoods within one interaction, with a clustering method to forecast vehicle crashes in Australia. Recently, transportation researchers applied GCNs and Latent Dirichlet Allocation (Porteous et al. 2008) to examine traffic accident-related factors, such as daily vehicle kilometers traveled and residential activities using floating vehicle trajectory data in San Francisco (Zhao et al. 2024). Crucially, traffic accidents display zero-inflated properties, meaning that many road segments report no accidents (Dong et al. 2014). To address this, researchers developed probabilistic GNN models to forecast accident risk distributions in London, which is particularly useful for road segments with varying risk levels (Gao et al. 2024).

Industry Practice

Many technology companies have created specialized GNN models in online transportation services. A key application is the travel time estimation on road networks, which predicts arrival time based on departure time and routes (Table 5). This serves as a fundamental functionality form in digital maps like Google Maps. We now compare industry approaches with academic GNN research, looking at how they build graphs, design model architectures, and apply the technology.

Graph construction differs between academic research (Table 4) and industry applications (Table 5). Influential academic studies, such as DCRNN (Li et al. 2017) and Graph WaveNet (Wu et al. 2019), define nodes as stationary traffic sensors. Besides, academic studies set intersections (Jin et al. 2024), road segments (Mashurov et al. 2024; Wang et al. 2024a), or vehicles (Vankdoth and Arock 2023) as nodes and node connectivity as edges. In contrast, technology companies represent road segments as nodes (Fang et al. 2020; Derrow-Pinion et al. 2021). Here, a road segment is a contiguous section of roadway, typically ranging from tens to hundreds of meters in length (Dai et al. 2020). This distinction leads to divergent prediction targets: academic studies focus on predicting speed and volume on sensor locations or travel time along vehicle trajectories (Mashurov et al. 2024), while industry models aim to predict road segment-level travel time. Two major factors drive this distinction:

- Industry goals prioritize user-centric travel time estimation, which is more directly derived from road segment-based other than sensor-based predictions.
- Road segment-level travel time prediction requires traffic data on every road within road networks, which is generally accessible to technology companies, not academic researchers.

Industrial GNN applications in transportation were generally built upon established GNN architectures (Table 5). For instance, Google's ETA prediction utilized the Graph Network (Battaglia et al. 2018), which incorporated convolutions on nodes, edges, and the entire graph. Alternatively, Alibaba resorted to Chebyshev polynomials of graph Laplacian for graph convolution operations (Defferrard et al. 2016). Notably, Baidu's approach, while not explicitly using adjacency matrices for representation updates, integrated network structure information via tensors and applied three-dimensional attention mechanisms from Transformer architectures. To meet low-latency requirements in service, they created look-up tables for swift prediction outcome retrieval. Similarly, academic research on travel time estimation are primarily based on classical GNN models, such as GCNs and GraphSAGE (Table 4).

GNN models for travel time estimation from industry have been applied to diverse cities globally (Table 5). Google conducted offline case studies using traffic data

Table 4 GNNs in travel time estimation from academics

Study	Model	Node	Edge	Base module	Area
Jin et al. (2024)	STDGNN	Intersection	Road segment	GCN	Beijing, Chengdu, Porto
Mashurov et al. (2024)	GCT-TTE	Road segment	Adjacent	GCN	Abakan, Omsk
Vankdoth and Arock (2023)	U-Net + GNN	Vehicle	Vehicle connection	GCN	Beijing, Chengdu
Wang et al. (2024a)	DLSF-GR	Road segment	Adjacent	GraphSAGE	Not mentioned

Table 5 GNNs in travel time estimation from industry

Study	Derrow-Pinion et al. (2021)	Dai et al. (2020)	Fang et al. (2020)
Model	GN	H-STGCN	ConSTGAT
Company	Google	Amap	Baidu
Target	Supersegment	Road segment	Road segment
Node	Road segment	Road segment	Road segment
Edge	Adjacent	Any two	Adjacent
Base module	Graph Network (Battaglia et al. 2018)	GCN (Defferrard et al. 2016)	3D-attention on graphs
Other modules	MetaGradient (Xu et al. 2018b)	Temporal gated convolution (Yu et al. 2017)	Segment-based methods
Loss function	Huber loss	L1 loss	Huber loss, APE
Area	New York, Los Angeles, Tokyo, Singapore	Beijing	Taiyuan, Hefei, Huizhou
Performance	RMSE	MAE, RMSE, MAPE	MAE, RMSE, MAPE
Deployment	Yes	Not mentioned	Yes

Target the entities for which travel time predictions are being performed, *APE* absolute percentage error, *MAE* mean absolute error, *MAPE* mean absolute percentage error, *RMSE* root-mean-squared error from New York, Los Angeles, Tokyo, and Singapore, and online evaluations in over ten countries from North America, Europe, Asia, and the Pacific region (Derrow-Pinion et al. 2021). Besides, Amap and Baidu implemented their methods using crowdsourcing data from their applications in various Chinese cities (Dai et al. 2020; Fang et al. 2020). However, the study areas in current academic research are restricted to a limited number of countries (i.e., China, Russia, and Portugal) due to the scarcity of available data (Table 4). While academic research employed MAE, RMSE, and MAPE to evaluate model prediction accuracy, industry practitioners have also incorporated negative ETA outcomes, which measure the events when the ETA errors exceed specified thresholds (Derrow-Pinion et al. 2021). It prioritizes large prediction errors and ignores minor gaps, potentially contributing to improved user satisfaction ratings for their services.

Together, the implementations of GNNs in transportation networks by technology companies are sometimes grounded in academic research and address various deployment challenges. Many industrial travel time estimation products are fundamentally based on GCNs from academic studies. While academic experiments are constrained by limited open datasets and less practical sensor-level predictions, industry applications have expanded to road segment-level prediction across global cities. This process involves advanced training approaches such as MetaGradient (Xu et al. 2018b) and computational methods such as parallel computing to enhance user experience. However, due to privacy concerns, industry studies have not disclosed their codes and data, creating obstacles for academic researchers to further refine their methodologies.

Evaluation Metrics

We summarize the evaluation metrics employed across various types of GNN applications in transportation in Table 6. As shown, MAE, RMSE, and MAPE are extensively utilized in traffic prediction and demand prediction studies. For uncertainty-aware prediction, Wang et al. (2024b) used metrics such as Negative Log-Likelihood (NLL) to measure the distance between data and distributions. In accident

Table 6 Evaluation metrics in GNN-based transportation studies

Evaluation metric	Study
MAE, RMSE	**2024**: Huang et al. (2024), Liang et al. (2024), Ding et al. (2024), Borisyuk et al. (2024), Gao et al. (2024), Jin et al. (2024), Ju et al. (2024), Kong et al. (2024a), Kong et al. (2024b), Ouyang et al. (2024), Wang et al. (2024a), Zhang et al. (2024b), **2023**: Feng et al. (2023a), Feng et al. (2023b), Jiang et al. (2023b), Li et al. (2023a), Li et al. (2023b), Li et al. (2023c), Liang et al. (2023a), Liang et al. (2023b), Rahman and Hasan (2023a), Song et al. (2023), **2022**: Shao et al. (2022), Lan et al. (2022), Choi et al. (2022), Huang et al. (2022), Li et al. (2022), Luan et al. (2022), **2021**: Guo et al. (2021), Ke et al. (2021a), Ke et al. (2021b), **2020**: Cui et al. (2020), Liu et al. (2020), Wang et al. (2020), **2019**: Cui et al. (2019), Guo et al. (2019), **2017**: Yu et al. (2017)
MAPE	**2024**: Huang et al. (2024), Liang et al. (2024), Wang et al. (2024b), Ding et al. (2024), Borisyuk et al. (2024), Gao et al. (2024), Jin et al. (2024), Ju et al. (2024), Kong et al. (2024a), Kong et al. (2024b), Mashurov et al. (2024), Ouyang et al. (2024), Wang et al. (2024a), Zhang et al. (2024b), **2023**: Feng et al. (2023a), Feng et al. (2023b), Jiang et al. (2023b), Li et al. (2023a), Li et al. (2023b), Li et al. (2023c), **2022**: Shao et al. (2022), Choi et al. (2022), Huang et al. (2022), Li et al. (2022), Zhu et al. (2022), Lan et al. (2022), Luan et al. (2022),**2021**: Ke et al. (2021b), Guo et al. (2021), Ke et al. (2021a), **2020**: Cui et al. (2020), Wang et al. (2020), **2019**: Cui et al. (2019), **2018**: Yao et al. (2018), **2017**: Yu et al. (2017)
R^2	Ding et al. (2024), Li et al. (2023b), Liang et al. (2023a), Liang et al. (2023b), Rahman and Hasan (2023a), Zhu et al. (2022)
Accuracy	Defferrard et al. (2016), Fang et al. (2024), Feng et al. (2023a), Gao et al. (2024), Jin et al. (2020), Kipf and Welling (2016), Kreuzer et al. (2021), Li et al. (2024a), Tran et al. (2023)
AUC	Borisyuk et al. (2024), Fang et al. (2024), Kreuzer et al. (2021), Liu et al. (2023a), Nippani et al. (2024), Song et al. (2023), Tran et al. (2023), Yu et al. (2021)
F1 score	Guo et al. (2019), Li et al. (2024a), Liu et al. (2023a), Song et al. (2023), Tran et al. (2023), Yu et al. (2021)
Training time	Huang et al. (2024), Guo et al. (2021), Jin et al. (2024), Liu et al. (2020), Luan et al. (2022), Mallick et al. (2020), Zheng et al. (2020)
MedAE	Wang et al. (2024b)
PICP	Wang et al. (2024b)
MPIW	Liang et al. (2024), Wang et al. (2024b)
NLL	Wang et al. (2024b)
Recall	He et al. (2020), Liu et al. (2023a), Trirat et al. (2023), Yu et al. (2021)
PCC	Yao et al. (2018)
VAR	Zhu et al. (2022)

RMSE root-mean-squared error, *MAE* mean absolute error, *MAPE* mean absolute percentage error, *MedAE* median absolute error. PICP: prediction interval coverage probability, *MPIW* mean prediction interval width, *NLL* negative log-likelihood, *PCC* Pearson's correlation coefficient prediction, Yu et al. (2021) employed classification metrics, including Recall and F1 score.

Future Opportunities of GNNs in Transportation Problems

This section provides an overview of future directions of GNNs in various transportation problems (Fig. 6). The deployment of GNNs in transportation can become more robust, interpretable, and efficient across a wider range of transportation problems. This trend will be propelled by key factors, such as (1) increasingly accessible traffic datasets, (2) advancements in fundamental neural network architectures, and (3) extensive interactions between GNNs and related fields such as operation research.

Traffic Prediction

Moving from Single-Point Prediction to Interval Prediction

Despite significant progress in traffic prediction methodologies, there has been limited research on traffic uncertainty. Traffic uncertainty refers to the variability in traffic conditions affected by multiple factors such as special events and abrupt weather changes. Under uncertain circumstances, actual traffic demand and travel time might exceed anticipated values, leading to inefficiencies in traffic management such as navigation for emergency vehicles like ambulances. To account for this uncertainty, a viable approach is to provide prediction intervals or distributions (Chen et al. 2023a; Xu et al. 2024a), as opposed to single-point estimates. A recent study has developed a probabilistic GNN to forecast travel demand intervals in rail systems and the ridesharing market (Wang et al. 2024b). It utilized calibration errors, prediction interval width, and interval coverage probability as metrics for model evaluation. Analogously, a probabilistic GNN model was proposed to forecast sparse origin–destination flows in New York City (Liang et al. 2024). A promising direction is extending these models from travel demand forecasting to roadway traffic condition prediction.

Moreover, the determinants affecting the length of predicted confidence intervals for traffic values, which measure prediction uncertainty, remain unexplored. Given the capability of GNNs to learn general patterns in training datasets, we posit that the statistical dispersion of traffic variables within training sets may be a significant contributing factor to interval lengths.

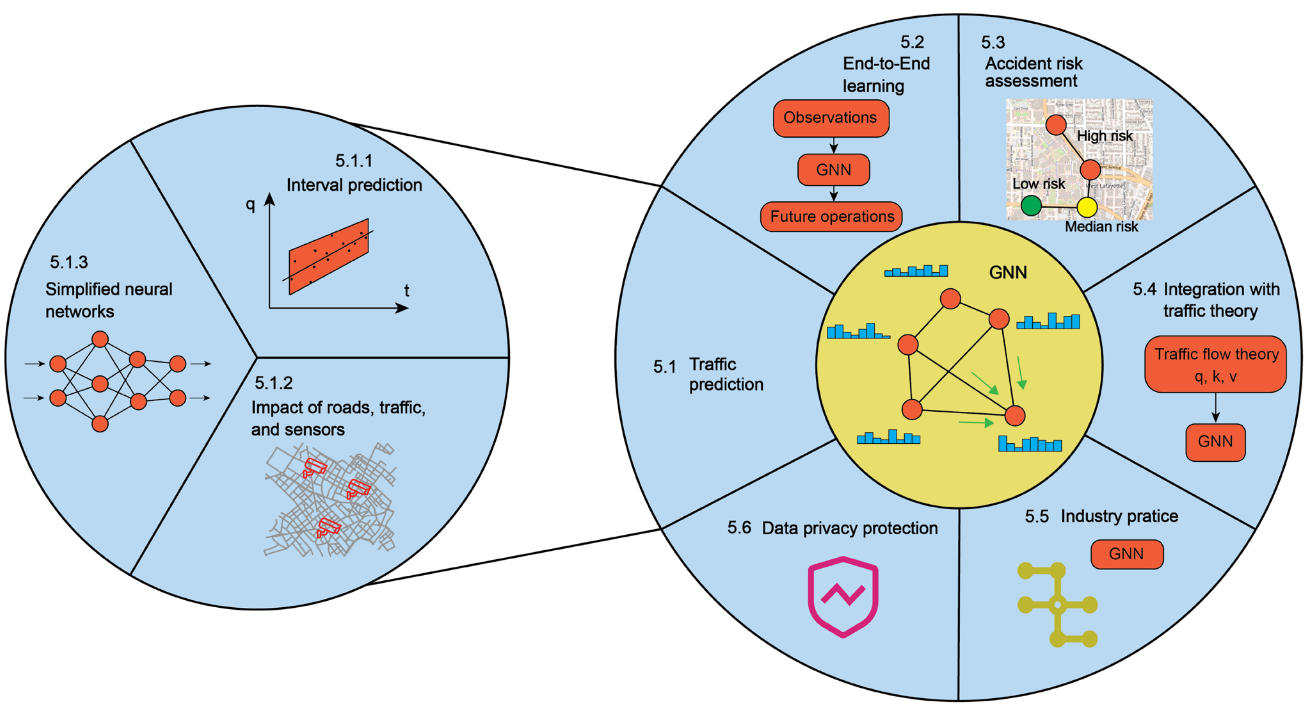

Fig. 6 Prospective directions of GNNs in transportation. These include GNNs for traffic prediction (from "Moving from Single-Point Prediction to Interval Prediction"–"Simplifying GNNs" sections), traffic operation ("Traffic Operation" section), accident mining ("Accident Prediction" section), integration with traffic theories ("Integration with Traffic Theories" section), industry practice ("Industry Practice" section), and data privacy protection solutions ("Addressing Data Privacy Issues" section). Background map © OpenStreetMap

Investigating the Effects of Road Types, Traffic Patterns, Sensor Placements, and Special Scenarios

Multiple critical factors of GNN-based traffic prediction models require systematic investigations. These include the effects of road types, traffic patterns, sensor placements, as well as special regions and time periods on prediction accuracy. These factors are critical for the successful transition of laboratory-developed GNN models to practical applications across diverse real-world urban, suburban, and rural areas.

First, the extensively used datasets METR-LA and PEMS-BAY (Li et al. 2017) focus on highways in California, with relatively homogeneous traffic conditions. It is insightful to extend the scope of their studies to cover urban streets, such as downtown streets in over 30 European cities from the UTD19 dataset (Loder et al. 2019). We hypothesize that GNN-based traffic prediction models applied to urban streets may exhibit higher relative error rates than highway applications, assuming consistent external conditions. This is because urban streets have more complex and heterogeneous traffic patterns including interactions between pedestrians, cyclists, and dense traffic control signals.

Second, the relationships between traffic patterns and prediction accuracy remain inadequately understood. There is little evidence to test the hypothesis that increased traffic volumes consistently result in larger prediction errors. The recently introduced LargeST dataset (Liu et al. 2024b), which includes traffic data from thousands of sensors with diverse traffic profiles, presents a versatile opportunity to solve this problem. Additionally, many prediction approaches performed the Z-score normalization (Wu et al. 2019), which standardizes data values to a mean of zero and a standard deviation of one. This data preprocessing method might mitigate the influence of traffic volumes on prediction outcomes.

Third, there is no consensus on the influence of sensor placements on GNN-based traffic prediction outcomes. Sensor locations directly influence adjacency matrices in graph convolution operations, affecting the learning process and prediction results. A study demonstrated that the traffic flow prediction errors under the coarse scale were lower than those under the finer scale in Chicago (Wang et al. 2022a). Alternatively, the relative errors for GNN-based traffic imputation were lower with the compact sensor sampling than the coarse sensor sampling in London (Xue et al. 2024a). Despite these observations, standardized criteria for characterizing sensor locations and assessing prediction accuracy are necessary before conducting systematic investigations of their effects.

Fourth, it is unclear whether current GNN-based traffic prediction approaches perform well in addressing special locations and temporal periods, which are crucial for dynamic traffic management. In particular, traffic patterns in road networks around large public venues (e.g., sports arenas and convention centers) exhibit large uncertainty due to complex traffic dynamics. Similarly, both intra-urban and inter-urban traffic conditions during special circumstances (e.g., city marathons and heavy rains) are also likely to diverge from regular traffic patterns because of factors like road closures.[2] To achieve accurate predictions in these exceptional scenarios, GNN models need to learn from sparse historical data while adapting to real-world traffic fluctuations.

Simplifying GNNs

"Graph Neural Networks" section illustrates that vanilla GNN models (like GCNs and GATs) were initially developed for general data science tasks in networks including social and biological networks. However, their graph convolution operations may be redundant for traffic prediction applications, which necessitate low latency. Hence, a promising research direction is to simplify existing GNN methods to enhance traffic prediction efficiency. To achieve this, it is essential to identify key information extracted by GNNs that contributes to their superior performance over multilayer perceptions (MLPs) in prediction tasks. Recent research has found three key factors: sensor locations, time of day, and day of the week (Shao et al. 2022). Following this, they came up with a simple but efficient MLP model that beats various GNN models in traffic prediction tasks. Besides, graph-less neural networks (GLNNs) have been proposed as mixed models, combining GNNs with high accuracy and MLPs with fast inference capabilities (Zhang et al. 2022b). GLNNs distill knowledge from GNNs and use the knowledge to train MLPs in an offline manner. The trained MLPs are subsequently exploited in online inference. Both studies provide a foundation for further simplification of existing GNN with increased traffic prediction efficiency.

Traffic Operation

As discussed in "Traffic Operation" section, researchers have utilized GNNs to predict carsharing demand and optimize profits (Chang et al. 2022). This framework is called *Predict-then-Optimize* in operation research (Elmachtoub and Grigas 2022). An alternative approach is the *End-to-End* (E2E) method, which directly derives optimization solutions from input features (Qi et al. 2023; Liu et al. 2023b). While GNNs have demonstrated efficacy in specific *Predict-then-Optimize* frameworks (Chang et al. 2022), their effects on E2E frameworks are still unexplored. Further research in this

[2] https://www.cbsnews.com/newyork/news/nyc-marathon-closures-road-bridge-street-2024/.

direction may enhance the existing operation problems with spatial components.

For classical NP-hard graph problems (like the TSP problem), there are several benchmarking datasets (like National TSP instances[3]). These datasets can strongly facilitate the development and evaluation of GNN-based operation methods on graphs. However, there is a shortage of standardized datasets and scenarios for diverse traffic control and management problems. We are positive to anticipate that new datasets in this area will emerge in the coming years. Researchers have developed GNN-based control methods for connected autonomous vehicles (Chen et al. 2021), using customized scenarios generated by the traffic simulator SUMO (Krajzewicz et al. 2012). The creation of standardized testbeds for traffic operation problems would significantly promote GNN-based methods in this field.

Accident Prediction

This subsection delineates two future directions for GNN-based traffic accident prediction. First, while existing GNN-based traffic accident predictions have primarily concentrated on overall crash occurrence (Wu et al. 2023b) and risk scores (Gao et al. 2024), significant research opportunities persist in the exploration of accident types. These include the diversity in collision categories (e.g., rear-end collisions and single-vehicle accidents) and locations (e.g., urban streets, highways, and intersections). The extent to which spatial accident relationships, revealed by GNN models, vary across these accident categories remains an open question. Second, given the intrinsic interdependence between traffic flow dynamics and accident occurrence, the integration of traffic flow features (e.g., flow rate and traffic density) as side information within GNN-based accident prediction frameworks presents a promising research direction. Note that it is symmetrical to accident-aware traffic prediction, where accident occurrence is used as supplementary information for predicting traffic (Ye et al. 2023). The direct benefit is to enhance current accident forecasting accuracy. Besides, this discovery has the potential to further unveil complicated interconnections and causal mechanisms within traffic systems and accident landscapes (Wang et al. 2013; Retallack and Ostendorf 2019).

Integration with Traffic Theories

As a drawback, the inference process of GNNs in transportation networks may not adhere to established traffic theories, resulting in limited trust from transportation engineers in GNN inference outcomes. A potential solution is the physics-informed GNN (PIGNN) (Dalton et al. 2023; Niresi et al. 2024; Mo et al. 2024), which fuses physics laws with GNNs to achieve both model interpretation and accuracy. For instance, Xue et al. (2024a) incorporated mathematical forms of macroscopic fundamental diagrams (MFDs) (Ambühl et al. 2020) with GNNs to estimate missing traffic variable values within traffic networks in Zurich and London. They constructed a fused loss function, which is the summation of the physics loss and data loss, to train the model to align with both the MFDs and real-world data.

PIGNN represents a subset of physics-informed machine learning (PINN) (Karniadakis et al. 2021), which embeds physics theories into machine learning to efficiently extract patterns from noisy data. The advantage of PINN has inspired many PINN transportation studies, including traffic flow (Yuan et al. 2021; Shi et al. 2021) and car-following modeling (Mo et al. 2021). Specifically, Mo et al. (2021) combined the Intelligent Driving Model (Treiber et al. 2000) with neural networks to model traffic dynamics along road segments in the United States.

However, despite the emergence of PIGNN studies in transportation (Zhu et al. 2022; Xue et al. 2024a), several open questions remain unsolved:

- What is the optimal balance between physics-based and GNN components in PIGNN across various transportation contexts?
- Is it feasible to develop more accurate and interpretable traffic flow theories at the regional level using PIGNN? A similar approach to human crowd modeling has been achieved by Zhang et al. (2022a).

Industry Practice

A potential direction for technology companies is the refinement of existing GNN-based travel time prediction methodologies. This process necessitates the incorporation of exterior factors, including weather records, traffic propagation patterns, and special event occurrences. For example, Baidu Maps has integrated congestion propagation patterns with graph learning techniques to improve travel time estimation (Huang et al. 2022). The developed DuETA model, utilizing congestion-sensitive graphs and route-aware Transformers, has achieved superior prediction performance in major Chinese cities like Beijing, Shanghai, and Tianjin than the baseline model ConSTGAT (Table 5). Besides, transportation researchers have revealed a correlation between evening sporting events and reduced morning traffic congestion the next morning (Yao and Qian 2021). Technology companies can leverage diverse data sources, including event and foot traffic information, to enhance their intelligent transportation services.

[3] https://www.math.uwaterloo.ca/tsp/world/countries.html.

Industry participants can also play a role in enhancing traffic safety management by running roadway crash risk assessment systems. The risk evaluation outcomes generated from GNN models, when communicated to drivers, may potentially reduce crash incidents in high-risk scenarios. The viability of this idea has been supported by a recent study that developed spatio-temporal GNN models for crash risk evaluation using multi-sourced data (Liu et al. 2023a). The model addresses the inherent imbalance in traffic crash data (where non-crash data significantly outnumber crash data) by utilizing focal loss (Lin et al. 2017) during model training. While GNN-based crash risk evaluation remains a new field, it presents a promising chance for technology companies to develop robust and applicable risk-alert systems to secure roadway users.

Open data and code access is a significant future direction. While academic researchers like DCRNN (Li et al. 2017) often make their data and code in GNN studies publicly available, many technology companies (like the three studies in Table 5) have not published their data or code. This creates giant barriers for researchers to address current limitations in GNN deployment within transportation systems. Although data privacy concerns may be major constraints for these companies, they could disseminate aggregated and non-sensitive data and code. Such effort would both satisfy the data-sharing needs of GNN communities and follow data confidentiality regulations.

Addressing Data Privacy Issues

In practice, training GNN models may necessitate diverse types of datasets owned by distinct data agencies. Nevertheless, they may be not willing to share data due to concerns regarding data privacy issues. The solution is to introduce Federated Learning (FL), a method that trains machine learning models using data distributed across multiple locations (Yang et al. 2019). Specifically, the horizontal and vertical versions of Federated GNN (FedGNN) could be applied to train GNN models within transportation networks (Liu et al. 2024a). Here, horizontal FedGNN, which maintains varying graph structures across clients, is suitable for modeling diverse transportation networks in different cities. Additionally, vertical FedGNN, which is designed to operate on a collection of graphs with similar structures, could be employed to model a single city using data from multiple sources. Alternatively, Differential Privacy (DP) offers a viable solution. As a data mining technique, DP protects individual security during model training. When fused with GNNs, recent DP-GNN models could enhance individual privacy protection by clipping the gradient and adding noise to the model training process (Mueller et al. 2022).

A Structured Navigation of the GNN Design Space

In this subsection, we present a structured overview of the GNN design space in Table 7. This table highlights key papers from various domains, including traffic prediction,

Table 7 Structured navigation through the GNN design space

Study	Architecture	Spatial granularity	Temporal horizon	Advantage	Limitation	Use case	Performance
Feng et al. (2023b)	GCN	Hundreds highway sensors	Next 15, 30, 60 min	Macro–micro level	Single transportation mode	Prediction	MAE, RMSE, MAPE
Zhang et al. (2024b)	GNN	Arterial roads	Next 10, 60, 120 min	Knowledge graph	Require many data types	Prediction	MAE, RMSE, MAPE
Ding et al. (2024)	GAT	Hundreds metro stations	Next 2 years	Predict expanding demand	Single city	Prediction	MAE, RMSE, MAPE
Nie et al. (2025a)	STGNN	8 cities	Next week	Introduce LLMs	Heavy model	Prediction	MAE, RMSE
Rahman and Hasan (2023a)	Diffusion GCN	2 urban and highway networks	Not apply	Traffic assignment	Not dynamic	Assignment	MAE, RMSE
Liu and Jiang (2022)	GAT	64 km^2 urban areas	2 months	Model routing behavior	Constant traffic assumption	Control	Precision, Recall, F1 score
Chang et al. (2022)	GCN	A city	Next 30, 60, 120 min	Predict-then-Optimize	Not capture competition	Control	MAE, RMSE
Gao et al. (2024)	GAT	3 urban regions	Next 14 days	Crash uncertainty	Single city	Accident	MAE, RMSE, MAPE
Derrow-Pinion et al. (2021)	Graph Network	>10 countries	Next 10, 20, 30, 60 min	Applicable	Data not open	Industry	RMSE
Dai et al. (2020)	GCN	2 urban regions	Next hour	Applicable	Data not open	Industry	MAE, RMSE, MAPE

Table 8 Open traffic datasets from late 2022

Data	Type	Area	Temporal range	Spatial range	Release date
Glasgow traffic flow (Li et al. 2025)	Flow	Glasgow	2019–2023	470 sensors	February 2025
New Zealand national (Li et al. 2024b)	Flow	New Zealand	2013–2022	2042 sensors	December 2024
FT-AED (Coursey et al. 2024)	Flow, occupancy, speed	Tennessee	2023	49 sensors	June 2024
U.S. 20 dataset (Xu et al. 2024b)	Flow, density, speed	U.S	2019	20 cities	March 2024
LargeST (Liu et al. 2024b)	Flow	California	2017–2021	8600 sensors	December 2023
MeTS-10 (Neun et al. 2023)	Speed	10 global cities	2019–2021	~50*50 km	November 2023
Camera data (Yu et al. 2023)	Vehicle trajectories	Shenzhen, Jinan	2020–2022	1460 and 1838 sensors	October 2023
Vehicle identification (Wang et al. 2023c)	Vehicle trajectories, flow	Xuancheng	2020	80,000 vehicles	January 2023
Traffic4cast (Neun et al. 2022)	Vehicle counts	London, Madrid, Melbourne	2019–2021	3751, 3840, 2589 detectors	December 2022
Fire evacuation (Xu et al. 2022)	Vehicle trajectories	California	2019	21,160 records	October 2022

traffic operation, accident analysis, and industry involvement. Drawing from the information in Table 7, we provide the following general guidelines:

- *Model Architecture*. GCN and GAT are the two most commonly utilized GNN models in transportation applications, primarily due to their simple and effective information propagation mechanisms. For large-scale transportation networks, where matrix multiplications in GNNs can be computationally intensive, readers can refer to sparse matrix operations[4] to enhance efficiency.
- *Spatial Granularity*. In academic research, GNN-based transportation studies typically focus on sensors, road segments, and regions within a limited number of cities. In contrast, industry applications tend to cover a broader spatial scope.
- *Forecasting Horizon*. The temporal horizon for traffic prediction typically spans approximately 1 h, whereas demand prediction and accident analysis generally involve longer forecasting periods.
- *Data Format*. Academic research typically utilizes offline data for model training and testing. However, industry applications often involve offline model training followed by online deployment.

[4] https://pytorch.org/docs/stable/sparse.html.

Collection of Data and Code

This section provides a summary of publicly available datasets, codes, and alternative learning resources tailored for GNNs and transportation networks. Given the existing reviews such as Shaygan et al. (2022), we primarily focus on recent advances since late 2022.

Datasets

For traffic prediction, several high-quality transportation network datasets can be potentially utilized in future GNN studies (Table 8). Notably, the U.S. 20 dataset (Xu et al. 2024b), LargeST (Liu et al. 2024b), MeTS-10 (Neun et al. 2023), and New Zealand national (Li et al. 2024b) include significantly more extensive areas compared to the PEMS-BAY and METR-LA (Li et al. 2017), which were confined to the Bay Area and Los Angeles. Here, the U.S. 20 dataset includes traffic flow, traffic density, and average speed data, while the LargeST contains traffic flow records. Moreover, MeTS-10 includes traffic speed data from ten global cities spanning 2019 to 2021, with a resolution of 15 min (Neun et al. 2023). Another traffic flow dataset comprises data from 470 traffic sensors across urban and suburban areas in Glasgow, UK (Li et al. 2025). While these datasets focus on specific regions, the New Zealand national dataset provides comprehensive traffic flow data covering all major state highways in New Zealand (Li et al. 2024b). Collectively, the above datasets can facilitate the analysis of GNN-based traffic prediction across diverse road types and urban–rural settings within the United States. Furthermore, for traffic anomaly detection, the FT-AED dataset collected from 49 sensors in Tennessee, U.S., serves as a valuable resource for future studies (Coursey et al. 2024).

Beyond vehicle traffic, significant chances exist for traffic prediction in other transportation modes. Platforms like Flightradar24[5] and MarineTraffic[6] offer real-time global movement data for commercial flights and marine vessels. These raw datasets enable us to develop customized GNN models to predict the dynamics of global traffic systems at various resolutions across routine operations and special events.

For traffic operation, the growing penetration rate of sensing infrastructures has yielded substantial vehicle trajectory data from cities in the U.S. (Xu et al. 2022), China (Yu et al. 2023; Wang et al. 2023c), and Europe (Neun et al. 2022). Such datasets present opportunities for developing GNN-based vehicle routing algorithms.

Codes

In contrast to the early period of GNN research, there is currently an abundance of code resources. For example, the PyTorch Geometric (PyG)[7] serves as a user-friendly Python library on PyTorch for GNNs. In this context, PyG provides essential functionalities for GNN research, including graph construction, the design of convolutional mechanisms, and distributed training. Similarly, the Deep Graph Library (DGL)[8] enables users to run GNN models on various machine learning frameworks like PyTorch and TensorFlow. DGL incorporates a customized data structure, DGLGraph, to store and process graph information, which can be particularly beneficial for large-scale transportation network modeling. Additionally, certain open courses, such as CS224W,[9] offer fundamental GNN code resources for learners. Furthermore, several GNN researchers have made their model codes publicly available, as outlined in Table 3.

Others

The GNN research community has been actively compiling recent publications in the field. Their collections can inspire further applications of GNNs in transportation network analysis. For instance, the repository *Spatio-Temporal Prediction Papers*[10] includes collections of GNN papers in diverse domains, such as traffic forecasting (Kong et al. 2024b), human mobility analysis (Jiang et al. 2023a), pandemic prediction (Xue et al. 2022), and road safety analysis (Nippani et al. 2024). Besides, a separate repository[11] summarizes GNN studies on traffic forecasting spanning 2018 to 2024. Except for the above application studies, theoretical GNN papers have been categorized in another repository.[12] It includes GNN applications to NP-hard problems (Toenshoff et al. 2021), the expressive power of GNNs (Balcilar et al. 2021), and the combination of GNNs and differential equations (Poli et al. 2019), which has been successfully applied to traffic prediction (Choi et al. 2022). Transportation researchers may find valuable insights from tutorials including current advancements and challenges in large-scale GNNs presented at KDD 2023,[13] and the properties and practice of GNNs delivered at AAAI 2025.[14] These resources can provide valuable insights into learning methods applicable to transportation networks.

Conclusion

Deriving meaningful patterns and insights from diverse transportation network data supports a wide range of intelligent transportation tasks. The spatial correlations within transportation network data can be effectively captured by GNNs, enabling numerous GNN-based DSTN studies. In this paper, we provide a broad and timely overview of these applications, integrating perspectives from academic research and industry practice. Specifically, we begin by discussing fundamental GNN models (e.g., GCNs and GraphSAGE) and their subsequent variants (e.g., LightGCN). In the context of transportation networks, we review traffic prediction studies on traffic speed, flow, demand, and traffic operation topics such as vehicle routing. Expanding upon these studies, we identify emerging directions in traffic prediction, including probabilistic traffic prediction, factor impact analysis, and streamlined model architecture. Besides, the potential applications of GNNs in end-to-end learning for operation problems, accident risk evaluation, and the integration of machine learning and physics-based models are extensively examined. Furthermore, we delve into the involvement of technology companies in GNN-based travel time estimation, with particular attention to differences in network construction compared to academic research. To foster further academic engagement, we enumerate up-to-date learning resources, including datasets, code repositories, and various learning materials. Our review could promote the application of GNNs in addressing

[5] www.flightradar24.com/.

[6] www.marinetraffic.com/.

[7] https://pytorch-geometric.readthedocs.io/en/latest/.

[8] https://docs.dgl.ai/index.html.

[9] https://web.stanford.edu/class/cs224w/.

[10] https://github.com/uctb/ST-Paper.

[11] https://github.com/jwwthu/GNN4Traffic.

[12] https://github.com/jiaqingxie/Theories-of-Graph-Neural-Networks.

[13] https://sites.google.com/ncsu.edu/gnnkdd2023tutorial?pli=1.

[14] https://gnn.seas.upenn.edu/aaai-2025/.

transportation network challenges in the context of emerging technologies.

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Declarations

Conflict of interest The authors declare no competing interests.

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