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A Proximity-Aware Road Network–Integrated Trajectory Graph Neural Network for Road-Level Traffic Flow Prediction

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ABSTRACT: Accurate road-level traffic flow prediction remains challenging in heterogeneous urban networks, where traffic interactions extend beyond direct road connectivity. Existing graph-based models can exploit road topology or vehicle trajectories but often overlook geometric continuity and dependencies between non-adjacent yet functionally related road segments. To address this gap, this study proposes a Proximity-Aware Road Network–Integrated Trajectory Graph Neural Network (PA-RNTrGNN). The model integrates trajectory-derived movement transitions, ordered road geometry, proximity-aware structural relations, and bidirectional traffic status information. Specifically, map-matched trajectories are converted into transition matrices to preserve directional movement causality; road geometries are encoded as ordered sequences using a unidirectional gated recurrent unit (GRU); and a proximity-aware structural matrix is constructed from distance decay, directional similarity, and road-type compatibility. Experiments on the Beijing, Chengdu, and Porto datasets yield overall mean absolute error (MAE) values of 4.491, 8.537, and 0.593. Compared with Multi-Spatio-Temporal Fusion Graph Recurrent Network (MSTFGNN), the best-performing baseline in terms of overall MAE, PA-RNTrGNN reduces MAE by 4.30%, 33.92%, and 2.15% on the three datasets, while also achieving the lowest mean peak-hour MAE. The largest improvement on Chengdu highlights the effectiveness of combining trajectory-driven propagation with proximity-aware structural modeling for large and heterogeneous road networks.

KEYWORDS: Traffic flow prediction; vehicle trajectories; proximity-aware constraints; graph neural networks; road geometry; spatiotemporal modeling

1 Introduction

Accurate short-term traffic flow prediction is a fundamental task in intelligent transportation systems, supporting congestion mitigation, route guidance, adaptive signal control, and urban mobility management. In heterogeneous urban road networks, road-level traffic evolution is affected not only by historical traffic states and direct topological connectivity, but also by vehicle movement transitions, road geometry, and road functional attributes. These factors produce complex and direction-dependent spatiotemporal interactions, especially around curved roads, parallel corridors, ramps, service roads, and irregular intersections, where traffic correlations may exist between nearby or functionally related road segments that are not directly connected.

Traffic forecasting has been widely studied using deep learning and graph-based spatiotemporal models. Road-network-based models represent traffic sensors or road segments as graph nodes and use

graph structures to describe spatial dependencies. For example, the Spatio-Temporal Graph Convolutional Network (STGCN) introduced graph convolution into traffic forecasting to model spatiotemporal correlations on traffic networks [1]. The Diffusion Convolutional Recurrent Neural Network (DCRNN) further modeled traffic flow as a diffusion process on directed graphs [2], while Graph WaveNet learned adaptive spatial dependencies beyond predefined road connectivity [3]. Subsequent models, such as the Adaptive Graph Convolutional Recurrent Network (AGCRN) and Graph Multi-Attention Network (GMAN), further improved traffic prediction through adaptive graph learning and attention mechanisms [4,5]. More recent studies have further enhanced traffic prediction using dynamic spatiotemporal graphs, weather-aware multimodal fusion, and dynamic multi-graph learning [6–8]. Related recurrent graph architectures have further explored multi-scale temporal enhancement, generalized decoupling, and multi-spatiotemporal fusion [9–11], while the Long-Short Term Transformer-based Network (LSTTN) has been developed to model long-range spatiotemporal dependencies [12]. These studies demonstrate the effectiveness of graph learning, attention mechanisms, and multimodal information fusion for capturing complex spatiotemporal traffic dependencies.

Nevertheless, existing schemes still have several limitations for road-level traffic flow prediction. First, many models mainly rely on predefined topology, sensor correlations, or learned adaptive adjacency matrices, which may not explicitly preserve road geometry, driving direction, and road functional attributes. Second, although recent dynamic-graph and multimodal models improve dependency learning, they are often designed for sensor-level or region-level prediction, while fine-grained road segments are still treated as abstract graph nodes. Third, trajectory-aware methods, such as the Trajectory-based Graph Neural Network (TrGNN) [13] and road-network-constrained trajectory restoration and route-inference methods [14–16], provide useful movement information, while cross-city transfer learning has also explored adaptation across cities [17]. Recent cross-city few-shot methods, such as the Spatio-Temporal Feature Fusion and Few-Shot Learning Framework with Cross-City Knowledge Transfer (ST-FSFusion) [18], address data-scarce traffic prediction through spatiotemporal feature fusion and cross-city knowledge transfer, with a primary focus on cross-city adaptation. However, trajectory-derived transitions, ordered road geometry, direct road topology, and proximity-aware non-adjacent structural relations are rarely integrated within a unified traffic forecasting framework. Therefore, the problem is not that previous studies have not addressed traffic dependency modeling, but that the joint modeling of these complementary road-level factors remains insufficient.

To make the research gap clearer, Table 1 summarizes representative state-of-the-art techniques and their remaining limitations.

Table 1: Summary of state-of-the-art traffic prediction techniques and research gaps.

Category	Representative Studies	Main Limitation
Graph-convolution and diffusion models	STGCN [1], DCRNN [2], Graph WaveNet [3]	They mainly model predefined or adaptive graph dependencies, with limited explicit road-geometry constraints.
Adaptive, attention-based, and Transformer-based models	AGCRN [4], GMAN [5], LSTTN [12]	They improve spatiotemporal dependency learning, but road segments are often treated as abstract nodes.

(Continued)

Table 1 (continued)

Category	Representative Studies	Main Limitation
Multimodal, multi-graph, and trajectory-aware models	Weather-aware multimodal fusion [7], dynamic multi-graph learning [8], TrGNN [13]	These methods incorporate external information, multiple graphs, or trajectory-derived transitions, but do not jointly model ordered road geometry and proximity-aware dependencies between non-adjacent yet functionally related road segments.

Different from existing multi-graph learning methods that mainly combine dependency graphs derived from topology, adaptive correlations, or external factors, the Proximity-Aware Road Network–Integrated Trajectory Graph Neural Network (PA-RNTrGNN) explicitly distinguishes trajectory-derived movement causality, ordered road geometry, direct road topology, and proximity-aware non-adjacent structural relations. Compared with trajectory-enhanced graph neural network (GNN) methods that primarily use trajectories to model movement transitions, the proposed framework further integrates road geometry encoding and proximity-aware structural constraints to capture hidden interactions among nearby or functionally related road segments.

Based on these gaps, this study proposes PA-RNTrGNN for road-level traffic flow prediction. The proposed model jointly integrates trajectory-derived movement causality, ordered road geometry, direct road topology, and proximity-aware structural constraints to improve road-level traffic flow prediction in heterogeneous urban road networks. Specifically, map-matched vehicle trajectories are transformed into time-dependent transition matrices to preserve directional movement patterns. Each road segment is encoded as an ordered geometry sequence to represent local continuity, curvature, and spatial configuration. A proximity-aware structural matrix is further constructed by integrating distance decay, directional similarity, and road-type compatibility, allowing the model to capture hidden dependencies between nearby but non-directly connected road segments.

The main contributions of this study are summarized as follows:

1. We formulate a trajectory-enhanced road-level traffic forecasting problem that distinguishes road-level traffic counts from trajectory-derived movement transitions, thereby preserving directional movement causality between road segments.
2. We propose a road geometry encoding module that represents each road segment as an ordered geometric sequence, allowing the model to capture geometric continuity, curvature, and local spatial configuration.
3. We design a proximity-aware structural constraint mechanism that combines distance decay, directional similarity, and road-type compatibility to model hidden dependencies among non-adjacent but spatially or functionally related road segments.
4. We integrate trajectory-driven demand propagation, geometry-aware road representation, proximity-aware structural constraints, and bidirectional traffic status modeling into a unified graph forecasting framework. Experiments on three real-world trajectory datasets demonstrate the effectiveness of PA-RNTrGNN, especially in heterogeneous road networks and peak-hour scenarios.

The remainder of this paper is organized as follows. [Section 2](#) describes data construction and trajectory preprocessing. [Section 3](#) presents the preliminaries and problem formulation. [Section 4](#) introduces

the proposed PA-RNTrGNN framework. Section 5 reports the experimental results, including overall performance comparison, ablation studies, interpretability analysis, convergence analysis, and efficiency evaluation. Section 6 discusses the experimental findings and analyzes why the proposed method achieves its performance improvements. Section 7 concludes this study and discusses future work.

2 Structure-Aware Data Construction and Trajectory Preprocessing

To support trajectory-enhanced and structure-aware traffic flow prediction, raw road-network data and Global Positioning System (GPS) trajectories are transformed into complementary model inputs, including the directed road-segment graph G , topological adjacency matrix A , traffic flow matrix X_t , trajectory transition matrix T_t , road geometry sequence S_i , and proximity-aware structural matrix C . Unlike conventional preprocessing pipelines that mainly aggregate trajectories into road-level traffic counts, the proposed process preserves sequential movement relationships between road segments. The overall pipeline is illustrated in Fig. 1.

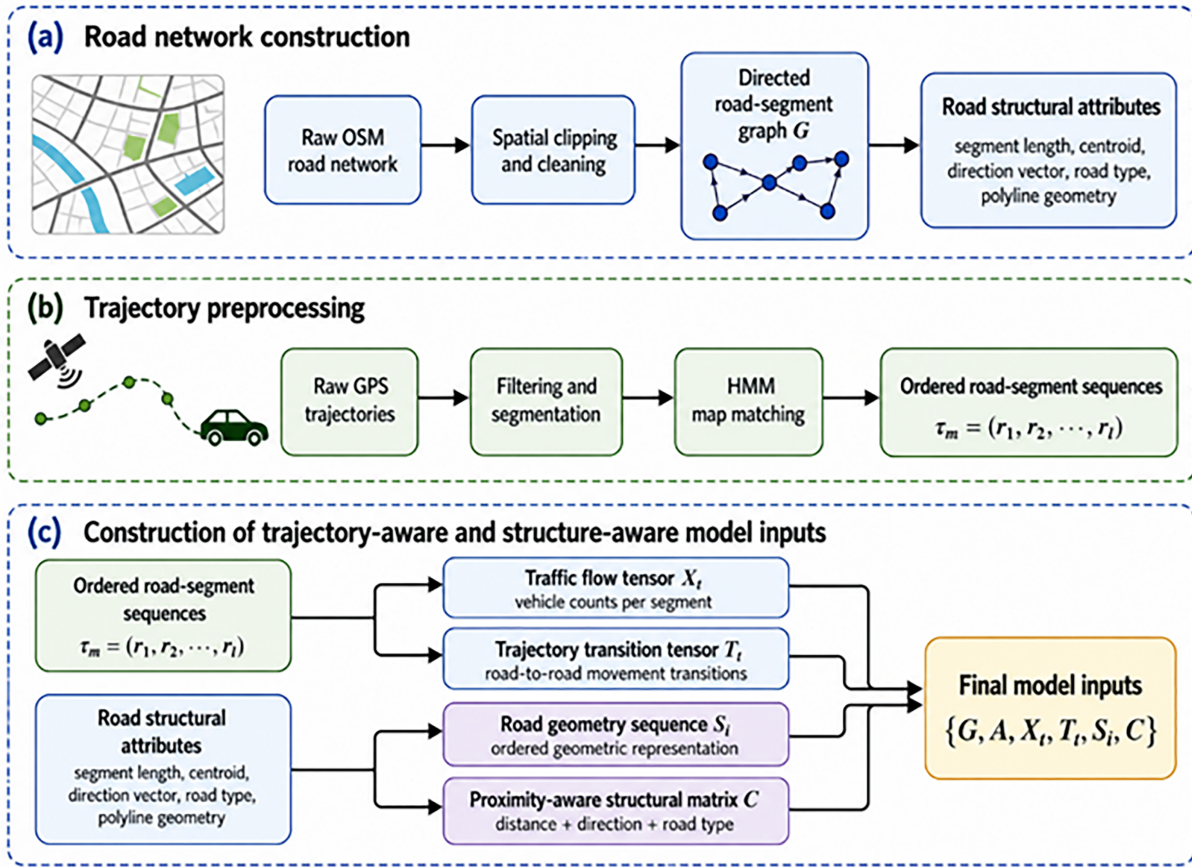


Figure 1: Structure-aware data construction and trajectory preprocessing pipeline.

2.1 Road Network Construction and Structural Attribute Extraction

The urban road network is extracted from OpenStreetMap (OSM) [19] and represented as a directed road-segment graph:

$$G = (V, E), V = \{v_1, v_2, \dots, v_N\} \quad (1)$$

here, V denotes the set of road segments and E denotes directed topological connections. For road-level traffic flow prediction, a road-segment/link-oriented representation directly aligns the graph units with the traffic states aggregated and predicted at the road-segment level, while preserving the directed topology of the road network [20].

Raw OSM data are clipped to the study area and cleaned by removing isolated or duplicate road elements. The road network is then subjected to topology correction and simplification [21]. In our implementation, consecutive road fragments connected by degree-2 intermediate nodes are merged when their geometric and directional attributes are consistent. Bidirectional roads are converted into two directed segments with opposite orientations, whereas unidirectional roads retain their original directions. For each road segment, segment length, centroid coordinate, direction vector, road type, and polyline geometry are extracted for subsequent geometry encoding and proximity-aware constraint construction.

2.2 GPS Trajectory Cleaning and Road-Segment Sequence Generation

Raw GPS trajectories often contain noisy points, missing records, abnormal speed values, and spatial deviations. Therefore, spatial clipping, speed-based filtering, and trajectory segmentation are performed following common trajectory-data preprocessing practice [22]. In this study, GPS points outside the study area are removed, and points producing unrealistic velocities greater than 35 m/s are filtered out. Long temporal gaps or prolonged stationary periods are used to split raw GPS logs into valid trajectory segments.

After cleaning, a hidden Markov model (HMM)-style network-constrained map-matching procedure is applied to align GPS records with road segments [23]. Candidate road segments are evaluated according to spatial proximity and movement consistency on the road network. For low-sampling-rate or temporarily disconnected trajectories, a path-inference step is further used to infer missing intermediate road segments according to established probe-vehicle and sparse floating-car-data path-inference methods [24,25]. The overall procedure is also consistent with established vehicle map-matching methodologies and reviews for transport applications [26,27].

After map matching, each valid vehicle trajectory is represented as an ordered road-segment sequence:

$$\tau_m = (r_{m,1}, r_{m,2}, \dots, r_{m,L_m}) \quad (2)$$

here, τ_m denotes the m -th trajectory, L_m denotes its sequence length, and $r_{m,k} \in V$ denotes the road segment visited at the k -th step. This sequence preserves movement continuity and supports trajectory transition matrix construction.

2.3 Construction of Trajectory-Aware and Structure-Aware Model Inputs

Based on the map-matched road-segment sequences and road structural attributes, PA-RNTrGNN constructs four complementary model inputs: the traffic flow matrix, trajectory transition matrix, road geometry sequence, and proximity-aware structural matrix. The traffic flow matrix records how many vehicles traverse each road segment during a given interval, whereas the trajectory transition matrix describes how vehicles move between road segments.

For each time interval t , the number of vehicles traversing each road segment is counted to form the traffic flow matrix:

$$X_t = [x_{t,1}, x_{t,2}, \dots, x_{t,N}]^T \in \mathbb{R}^{N \times F} \quad (3)$$

here, N is the number of road segments and F is the traffic feature dimension. In the basic setting of this study, $F = 1$, corresponding to vehicle count.

To preserve sequential movement information, consecutive road-segment transitions are extracted from each ordered trajectory sequence to construct the trajectory transition matrix:

$$T_t = [T_{t,ij}] \in \mathbb{R}^{N \times N} \quad (4)$$

here, $T_{t,ij}$ denotes the observed transition count or transition intensity from road segment v_i to road segment v_j during interval t . Unlike X_t , which only records the number of vehicles appearing on each road segment, T_t captures directional movement relationships between road segments. Therefore, it provides trajectory-derived demand propagation information that cannot be obtained from road-level traffic counts alone.

For road structural representation, each road segment is sampled along its polyline and mapped to an ordered sequence of 50-m grid cells:

$$S_i = (g_{i,1}, g_{i,2}, \dots, g_{i,L_i}) \quad (5)$$

here, $g_{i,k}$ denotes the k -th ordered 50-m grid cell of road segment v_i , and L_i denotes the number of sampled units. This sequence preserves local geometric continuity, curvature, and direction, thereby complementing conventional graph-node representations that treat road segments as abstract nodes.

In addition, a proximity-aware structural matrix is defined as:

$$C = [C_{ij}] \in \mathbb{R}^{N \times N} \quad (6)$$

Each element C_{ij} measures the structural relevance between road segments v_i and v_j . The matrix is constructed by integrating midpoint-to-road projection distance, directional similarity, and road-type compatibility, and therefore includes both directly connected roads and non-adjacent but spatially or functionally related roads. The final data-construction outputs include G , A , X_t , T_t , S_i , and C , which are used as complementary inputs to the model modules introduced in [Section 4](#).

3 Preliminaries and Problem Formulation

This section introduces the main notations and formulates the trajectory-enhanced road-level traffic forecasting task. The formulation distinguishes traffic flow observations from trajectory-derived movement transitions and incorporates road-network priors from topology, geometry, and proximity-aware structural relations.

3.1 Notations and Road Network Representation

Following [Section 2.1](#), the urban road network is represented as the directed road-segment graph $G = (V, E)$. The topological adjacency matrix derived from G is defined as:

$$A = [A_{ij}] \in \mathbb{R}^{N \times N}, A_{ij} = 1 \text{ if } v_i \rightarrow v_j, \text{ and } 0 \text{ otherwise} \quad (7)$$

Different from A , which describes direct physical connectivity, the proximity-aware structural matrix C measures spatially and functionally relevant correlations between road segments, including non-adjacent road pairs. The set of all road geometry sequences is denoted as:

$$S = \{S_1, S_2, \dots, S_N\} \quad (8)$$

Accordingly, the road structural representation used by the model is defined as:

$$R = \{A, S, C\} \quad (9)$$

In this formulation, A describes direct topological connectivity, S describes continuous road geometry, and C describes proximity-aware structural correlations. The interval-level traffic flow matrix X_t and trajectory transition matrix T_t are dynamic inputs defined in [Section 2.3](#).

3.2 Traffic Forecasting Problem

Given a historical observation window of length L , the historical traffic-flow sequence is defined as:

$$X_{t-L+1:t} = \{X_{t-L+1}, X_{t-L+2}, \dots, X_t\} \in \mathbb{R}^{L \times N \times F} \quad (10)$$

The trajectory-derived transition sequence over the same historical window is defined as:

$$T_{t-L+1:t} = \{T_{t-L+1}, T_{t-L+2}, \dots, T_t\} \in \mathbb{R}^{L \times N \times N} \quad (11)$$

The prediction target over a forecasting horizon H is the future traffic-flow sequence:

$$Y_{t+1:t+H} = \{Y_{t+1}, Y_{t+2}, \dots, Y_{t+H}\} \in \mathbb{R}^{N \times H} \quad (12)$$

Therefore, the trajectory-enhanced road-level traffic forecasting task is formulated as:

$$\hat{Y}_{t+1:t+H} = f_{\theta}(X_{t-L+1:t}, T_{t-L+1:t}, R) \in \mathbb{R}^{N \times H} \quad (13)$$

here, f_{θ} denotes PA-RNTrGNN parameterized by θ , and $\hat{Y}_{t+1:t+H}$ denotes the predicted future traffic-flow sequence. This formulation explicitly separates road-level traffic observations from trajectory-derived movement transitions while incorporating structural priors from topology, geometry, and proximity-aware correlations.

4 Methodology

4.1 Framework Overview

This section presents the proposed PA-RNTrGNN framework. As illustrated in [Fig. 2](#), PA-RNTrGNN integrates historical traffic-flow observations, trajectory-derived transition information, road geometry, topological adjacency, and proximity-aware structural relations for road-level traffic flow prediction. The model takes the historical traffic-flow sequence $X_{t-L+1:t}$, trajectory transition sequence $T_{t-L+1:t}$, and road structural representation $R = \{A, S, C\}$ as inputs, and predicts the future traffic-flow sequence $\hat{Y}_{t+1:t+H}$.

The framework consists of five main components: trajectory-driven demand propagation, road geometry encoding, proximity-aware structural constraint modeling, bidirectional traffic status modeling, and feature fusion with temporal prediction. These components correspond to the inputs defined in [Sections 2](#) and [3](#), ensuring that trajectory movement causality, geometric continuity, direct topology, and hidden non-adjacent road relations are jointly modeled.

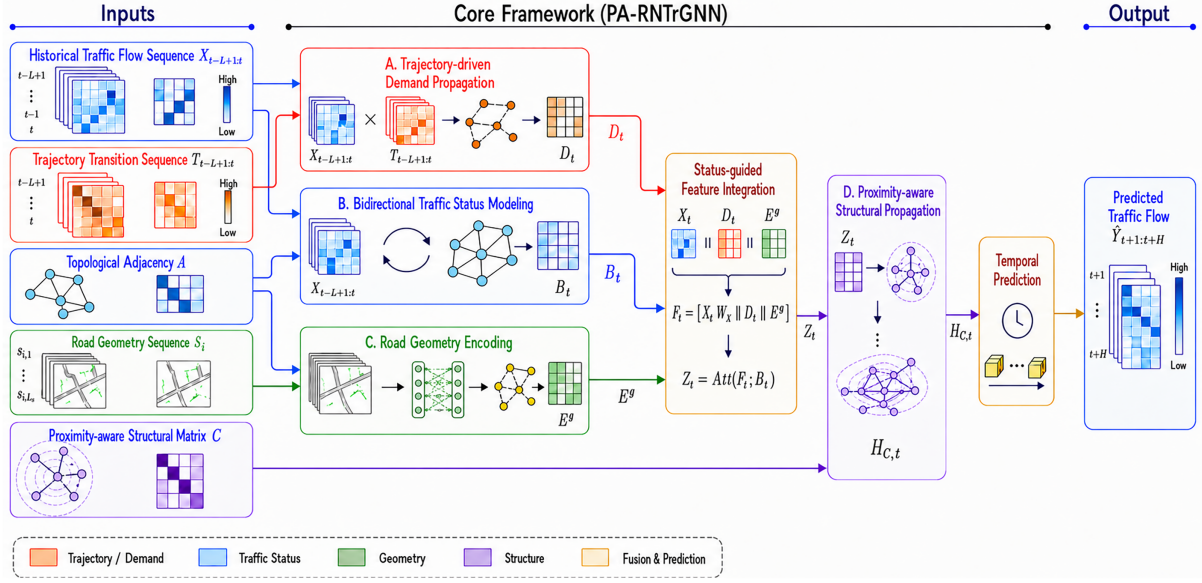


Figure 2: Overall framework of PA-RNTrGNN.

For each time interval t , the model first constructs the trajectory-driven demand representation D_t through multi-hop transition propagation. The road geometry sequence S_i is encoded by a gated recurrent unit (GRU) and refined by graph attention over the directed road graph to obtain E^g . Meanwhile, upstream and downstream traffic-status features are extracted from the directed adjacency matrix A , resulting in the bidirectional traffic-status representation B_t . The current traffic feature X_t , trajectory-driven demand representation D_t and geometry representation E^g are first integrated, with B_t guiding the generation of Z_t . The resulting status-guided representation is subsequently propagated over the proximity-aware structural matrix C to obtain $H_{C,t}$, which is finally fed into the temporal recurrent predictor to generate future traffic flows.

4.2 Trajectory-Driven Demand Propagation

The traffic flow matrix $X_t \in \mathbb{R}^{N \times F}$ records the traffic volume observed on each road segment, but it does not explicitly describe how vehicles move between road segments. To preserve directional movement causality derived from vehicle trajectories, PA-RNTrGNN uses the trajectory transition matrix $T_t \in \mathbb{R}^{N \times N}$ for demand propagation.

For each time interval t , $T_{t,ij}$ denotes the observed transition count from road segment v_i to road segment v_j . If two consecutive records cross the boundary between two 15-min intervals, the transition is assigned to the interval containing the source record, and no transition splitting is performed. To alleviate transition sparsity, we define $\bar{T}_t = T_t + A_{\text{bin}}$, where A_{bin} is the binary directed road-adjacency matrix with zero diagonal. The resulting matrix is row-normalized as:

$$P_{t,ij} = \frac{\bar{T}_{t,ij}}{\sum_{k \in \mathcal{N}_i^T} (\bar{T}_{t,ik})}, P_t \in \mathbb{R}^{N \times N} \quad (14)$$

here, $\mathcal{N}_i^T = \{j \mid \bar{T}_{t,ij} > 0\}$ denotes the effective downstream support, including observed consecutive transitions and direct downstream road neighbors. No additional top- k pruning or threshold-based selection is applied. Each row of P_t describes the transition tendency from one road segment to its possible downstream road segments.

Since $P_{t,ij}$ represents the normalized transition tendency from v_i to v_j , the transposed matrix P_t^T is used to aggregate upstream transition effects for each target road segment. The initial demand representation is defined as:

$$D_t^{(0)} = X_t \quad (15)$$

Multi-hop trajectory-driven demand propagation is then formulated as:

$$D_t^{(k)} = (P_t^T) D_t^{(k-1)}, k = 1, 2, \dots, K_T \quad (16)$$

here, K_T is the maximum trajectory propagation depth. The final trajectory-driven demand representation is obtained by concatenating different propagation depths and projecting them into a unified feature space:

$$D_t = \text{Proj}_D \left(D_t^{(0)} \parallel D_t^{(1)} \parallel \dots \parallel D_t^{(K_T)} \right), D_t \in \mathbb{R}^{N \times d_d} \quad (17)$$

This design allows PA-RNTrGNN to capture not only direct vehicle movements between adjacent road segments, but also multi-hop trajectory-derived demand propagation along road-segment sequences.

4.3 Road Geometry Encoding

Road segments are not merely abstract graph nodes. They have continuous geometric characteristics, including segment length, curvature, orientation, and local spatial configuration. To preserve these characteristics, each road segment v_i is represented as an ordered geometry sequence:

$$S_i = (g_{i,1}, g_{i,2}, \dots, g_{i,L_i}) \quad (18)$$

here, $g_{i,k}$ denotes the k -th sampled geometric unit of road segment v_i , and L_i denotes the number of sampled units.

Each grid unit $g_{i,k}$ is represented by a two-dimensional grid index and then mapped to a learnable embedding vector through a grid-embedding lookup table. For simplicity, S_i subsequently denotes the resulting ordered embedding sequence.

The ordered geometry sequence of each road segment is encoded by a gated recurrent unit (GRU) to capture its sequential geometric dependencies [28]. In our implementation, a unidirectional configuration is adopted because the geometry sequence is short, time-invariant, and ordered. It preserves the order and local continuity of the sampled grid cells, whereas simple pooling would discard this order information. These considerations provide the design rationale for using a GRU in this study.

$$h_i^g = \text{GRU}(S_i), h_i^g \in \mathbb{R}^{d_g} \quad (19)$$

The geometry-aware embeddings of all road segments are stacked as:

$$E^g = [h_1^g; h_2^g; \dots; h_N^g] \in \mathbb{R}^{N \times d_g} \quad (20)$$

Before feature fusion, the GRU-based geometry embedding E^g is processed by a graph-attention layer over the directed road graph G [29]. For each road segment v_i , the attention neighborhood is defined as $\mathcal{N}_A(i) = \{j \mid A_{ij} = 1\} \cup \{i\}$, where i is the central node and its inclusion in the neighborhood introduces a self-loop. After this refinement, the graph-enhanced representation is still denoted by E^g . The proximity-aware matrix C is not included in this attention neighborhood; it is used separately for weighted multi-hop structural propagation.

Since both the road geometry and the directed road graph are time-invariant, the refined embedding E^g is shared across all time intervals and concatenated with interval-level traffic representations during feature fusion.

4.4 Proximity-Aware Structural Constraint Modeling

The topological adjacency matrix A describes direct physical connectivity between road segments. However, urban traffic interactions are not limited to directly connected roads. Parallel roads, nearby corridors, ramps, service roads, and roads with similar directions or functional types may exhibit correlated traffic dynamics even without direct topological links. Therefore, PA-RNTrGNN constructs a proximity-aware structural matrix C to supplement the conventional topological adjacency matrix.

For each pair of road segments v_i and v_j , the structural relevance C_{ij} is calculated by jointly considering spatial distance, directional similarity, and road-type compatibility:

$$C_{ij} = W(v_i, v_j) [\alpha D(v_i, v_j) + (1 - \alpha) S(v_i, v_j)] \quad (21)$$

here, $D(v_i, v_j)$ and $S(v_i, v_j)$ denote the distance-decay and directional-similarity terms. Both terms are bounded in $[0, 1]$. $W(v_i, v_j)$ denotes the road-type compatibility weight and is applied multiplicatively to the combined distance-direction score.

$$D(v_i, v_j) = \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right) \quad (22)$$

$$S(v_i, v_j) = \frac{1 + \cos(u_i, u_j)}{2} \quad (23)$$

$$W(v_i, v_j) = w_{\text{type}}(v_i) \cdot w_{\text{type}}(v_j) \quad (24)$$

In these formulas, d_{ij} denotes the distance from the representative midpoint of road segment v_i to its projection onto candidate road segment v_j , and σ controls the decay scale. Nearby roads are assigned larger weights, while distant roads are assigned smaller weights. The vectors u_i and u_j are unit direction vectors derived from the polyline geometry of the two road segments. Roads with similar directions, such as parallel corridors, are more likely to share traffic patterns. In all experiments, the coefficient α was fixed at 0.65, and the distance-decay scale σ was fixed at 10 m across all datasets.

The term $W(v_i, v_j)$ represents road-type compatibility. Major roads, trunk roads, and expressways are assigned higher structural influence because their traffic states usually have stronger impacts on surrounding roads. The coefficient α balances the contributions of distance-based proximity and directional similarity, while $W(v_i, v_j)$ adjusts the resulting score according to road-type compatibility. In this way, each entry C_{ij} measures the structural relevance between road segments v_i and v_j , while the matrix C captures not only nearby spatial relations but also hidden structural dependencies among non-adjacent but functionally related roads. For each road segment v_i , the candidate support of the corresponding row of C is generated by retaining all road segments within the 200-m search radius.

4.5 Bidirectional Traffic Status Modeling

Traffic congestion may propagate along both downstream and upstream directions. Downstream propagation reflects vehicle movement along the road direction, while upstream influence may appear when congestion, queuing, or bottlenecks affect preceding road segments. To capture these two types of traffic status dependencies, PA-RNTrGNN constructs bidirectional traffic status features based on the directed road topology.

Let $\tilde{A}_{out}$ and $\tilde{A}_{in}$ denote the row-normalized downstream and upstream adjacency matrices. The bidirectional traffic status representation is calculated as:

$$B_t = [\tilde{A}_{out} X_t W_{out} \parallel \tilde{A}_{in} X_t W_{in}], B_t \in \mathbb{R}^{N \times d_b} \quad (25)$$

here, B_t integrates downstream and upstream traffic information. The symbol $\parallel$ inside the brackets denotes feature concatenation. This module complements the trajectory-driven demand representation. The trajectory transition matrix describes how vehicles move between road segments, whereas the bidirectional status representation describes how current traffic states diffuse through the road topology. Rather than being independently concatenated at the final prediction stage, B_t is used to guide the integration of the trajectory-driven demand and geometry-aware road representations.

4.6 Feature Fusion, Proximity-Aware Structural Propagation, and Temporal Prediction

The current traffic feature, trajectory-driven demand representation, and graph-enhanced geometry embedding are first combined to form the intermediate representation F_t . The bidirectional traffic-status representation B_t is then used to guide feature aggregation:

$$\begin{aligned} F_t &= [X_t W_X \parallel D_t \parallel E^g], \\ Z_t &= \text{Att}(F_t; B_t), \quad Z_t \in \mathbb{R}^{N \times d_z} \end{aligned} \quad (26)$$

here, $\text{Att}(\cdot)$ denotes the status-guided attention operation. Specifically, B_t is linearly projected and normalized using a softmax function to generate channel-wise attention weights. These weights are applied to the corresponding feature and propagation channels of F_t , and the weighted channels are summed to obtain Z_t . This operation allows upstream and downstream traffic conditions to regulate the contributions of trajectory-derived and geometry-aware features before structural propagation.

After construction, the proximity-aware structural matrix C is directly used in the propagation module, with $\tilde{C} = C$. The status-guided representation Z_t is subsequently processed through adaptive multi-hop structural propagation:

$$H_{C,t} = \sum_{k=0}^{K_C} \beta_k \tilde{C}^k Z_t W_C^{(k)}, H_{C,t} \in \mathbb{R}^{N \times d_c} \quad (27)$$

here, K_C is the maximum structural propagation depth, $W_C^{(k)}$ is a trainable transformation matrix for the k -th structural hop, and β_k denotes the adaptive weight of the k -th hop. The adaptive hop weights are computed as:

$$\beta_k = \frac{\exp(q_k)}{\sum_{m=0}^{K_C} \exp(q_m)}, k = 0, 1, \dots, K_C \quad (28)$$

here, q_k is a trainable scalar. Through this adaptive weighting mechanism, the model flexibly balances local proximity relations and wider non-adjacent structural dependencies. In the implementation, the maximum constraint-propagation depth is fixed at $K_C = 3$. The propagation weights are softmax-normalized and learned jointly with the model. Therefore, the model aggregates structural information over a bounded number of propagation orders while adaptively controlling their contributions, which helps limit repeated feature mixing and the associated risk of over-smoothing.

After proximity-aware structural propagation, the temporal-context vector a_s , containing the time-of-day encoding and weekday indicator, is concatenated with $H_{C,s}$. The resulting historical sequence is processed by a recurrent predictor:

$$O_t = \text{GRU}([H_{C,t-L+1} \parallel a_{t-L+1}], \dots, [H_{C,t} \parallel a_t]) \quad (29)$$

here, a_s denotes the temporal-context feature associated with interval s . Finally, a fully connected prediction head generates the future traffic-flow sequence:

$$\hat{Y}_{t+1:t+H} = \text{FC}(O_t) \in \mathbb{R}^{N \times H} \quad (30)$$

Overall, PA-RNTrGNN follows a sequential processing structure: trajectory-driven demand and road-geometry features are first regulated by bidirectional traffic status, subsequently refined through proximity-aware structural propagation, and finally processed by the temporal prediction module.

5 Experimental Evaluation

This section evaluates PA-RNTrGNN on three real-world urban trajectory datasets. The experimental design follows a complete evidence chain: overall prediction performance is first compared with representative and recent baselines, peak-hour performance is then analyzed to evaluate behavior under complex traffic propagation, component contribution analysis is used to verify the necessity of the proposed structural modules, and interpretability, convergence, and efficiency analyses are finally provided to explain the practical value of the model.

5.1 Datasets and Experimental Settings

The experiments were conducted on the Beijing, Chengdu, and Porto trajectory datasets. As summarized in Table 2, these datasets differ in taxi fleet size, road-network scale, and geographic coverage, thereby providing a suitable testbed for evaluating trajectory-aware and proximity-aware road-level traffic forecasting.

Table 2: Dataset and road-network statistics.

Dataset	#Taxis	Date	Train/Valid/Test	Roads	Edges	Region
Beijing	12,278	01 October 2012–31 October 2012	17 d/7 d/7 d	2613	7813	39.88, 116.33, 39.95, 116.45
Chengdu	14,789	18 August 2014–30 August 2014	9 d/2 d/2 d	4388	10,833	30.61, 103.96, 30.74, 104.15
Porto	437	01 May 2014–30 May 2014	17 d/7 d/6 d	1879	5251	41.12, −8.67, 41.16, −8.59

Raw GPS trajectories were processed following the data-construction pipeline described in Section 2. Abnormal GPS records were filtered, trajectories were map-matched to road segments, and road-level traffic flows were aggregated at 15-min intervals. For consistency with the original experimental protocol, peak-hour evaluation was conducted during 7:00–9:00 a.m. local time for Beijing, Chengdu, and Porto. The same interval was applied to all compared models and datasets.

For model selection and hyperparameter tuning, each candidate configuration was trained on the training subset and evaluated on the validation subset. The checkpoint with the lowest validation mean absolute error (MAE) was selected, whereas the test subset was used exclusively for the final evaluation.

5.2 Baseline Models

To provide a comprehensive evaluation, PA-RNTrGNN was compared with representative baselines spanning diverse spatiotemporal dependency modeling paradigms. DCRNN [2] and the Dynamic Graph Convolutional Recurrent Network (DGCRN) [30] were selected to represent diffusion-based and dynamic recurrent graph forecasting methods, while the Decoupled Dynamic Spatial-Temporal Graph Neural Network (D2STGNN) [31] and Spatio-Temporal Differential Equation Network (STDEN) [32] were included as strong spatiotemporal graph neural network baselines. Since the proposed model explicitly uses trajectory-derived transitions, TrGNN [13] was used as a trajectory-aware baseline. It used the same road-segment graph and forecasting horizon, while retaining its original trajectory-transition propagation mechanism without adding the proposed geometry and proximity-aware constraint modules. In addition, four recent open-source graph forecasting models, namely the Space-Specific Graph Convolutional Recurrent Transformer Network (SSGCRTN) [33], Principal Spatio-Temporal Causal Graph Convolutional Network (PSTCGCN) [34], Multi-Spatio-Temporal Fusion Graph Recurrent Network (MSTFGRN) [35], and Spatio-Temporal Graph Mixformer (STGM) [36], were included to reflect recent advances in spatially specific graph learning, causal spatiotemporal modeling, multi-spatiotemporal fusion, and long-range and short-range spatiotemporal interaction modeling. All models were evaluated using identical data splits and metrics to ensure a fair comparison.

5.3 Overall and Peak-Hour Prediction Performance

Table 3 reports the overall prediction performance on the three datasets. PA-RNTrGNN and MSTFGRN, the strongest baseline in terms of overall MAE, were evaluated over three independent runs using the same random seeds and data splits. The results are reported as the mean $\pm$ standard deviation, and statistical significance was assessed using a two-sided paired t -test. In Tables 3 and 4, an asterisk indicates a statistically significant improvement over MSTFGRN at $p < 0.05$. Compared with MSTFGRN, PA-RNTrGNN reduces the mean MAE from 4.693 to 4.491 on Beijing, from 12.919 to 8.537 on Chengdu, and from 0.606 to 0.593 on Porto, corresponding to improvements of 4.30%, 33.92%, and 2.15%. The paired tests show significant MAE improvements on all three datasets and significant root mean square error (RMSE) improvements on Beijing and Chengdu.

Table 3: Overall prediction performance against representative and recent baselines.

Model	Beijing		Chengdu		Porto	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
D2STGNN	8.811	16.261	23.589	68.164	0.695	1.556
STDEN	8.807	16.210	27.958	76.741	0.751	1.422
DCRNN	5.045	9.383	27.654	75.539	0.642	1.245
DGCRN	4.846	8.916	15.164	53.177	0.626	1.309
TrGNN	4.718	8.847	14.541	53.077	0.630	1.205
SSGCRTN	4.790	8.930	13.982	52.640	0.619	1.214
PSTCGCN	4.745	8.870	13.426	51.340	0.612	1.207
STGM	4.758	8.905	13.208	50.980	0.614	1.209
MSTFGRN	4.693 $\pm$ 0.010	8.795 $\pm$ 0.041	12.919 $\pm$ 0.060	50.623 $\pm$ 0.120	0.606 $\pm$ 0.003	1.197 $\pm$ 0.009
PA-RNTrGNN	4.491 $\pm$ 0.006*	8.420 $\pm$ 0.112*	8.537 $\pm$ 0.003*	45.928 $\pm$ 0.016*	0.593 $\pm$ 0.002*	1.190 $\pm$ 0.006

Table 4 reports the peak-hour prediction performance from 7:00 to 9:00 a.m. The same three-run evaluation and statistical-testing protocol was applied. PA-RNTrGNN achieves the lowest mean MAE and RMSE on all three datasets. The paired tests show significant MAE improvements on all three datasets and significant RMSE improvements on Beijing and Chengdu. In particular, PA-RNTrGNN reduces the mean peak-hour MAE on Chengdu from 15.863 for MSTFGRN to 8.816. These results demonstrate the effectiveness of integrating trajectory-driven demand propagation, road-geometry encoding, bidirectional traffic status modeling, and proximity-aware structural constraints under peak-hour traffic conditions.

Table 4: Peak-hour (7:00–9:00 a.m.) prediction performance.

Model	Beijing		Chengdu		Porto	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
D2STGNN	6.094	11.880	28.227	83.470	0.604	1.295
STDEN	7.172	14.278	28.503	79.137	0.693	1.239
DCRNN	5.091	10.010	28.375	78.445	0.593	1.157
DGCRN	4.993	9.496	23.592	70.608	0.593	1.248
TrGNN	4.848	9.299	17.896	55.434	0.582	1.116
SSGCRTN	4.880	9.160	17.120	54.980	0.579	1.130
PSTCGCN	4.810	9.050	16.385	52.780	0.575	1.124
STGM	4.795	9.010	16.120	52.160	0.574	1.122
MSTFGRN	4.765 ± 0.012	8.939 ± 0.036	15.863 ± 0.081	51.454 ± 0.148	0.572 ± 0.003	1.124 ± 0.009
PA-RNTrGNN	4.651 ± 0.028*	8.620 ± 0.051*	8.816 ± 0.038*	36.412 ± 0.105*	0.568 ± 0.004*	1.112 ± 0.018

Overall, the results in **Tables 3** and **4** demonstrate that PA-RNTrGNN improves overall and peak-hour traffic prediction across different urban road networks, especially in terms of MAE. The consistent MAE advantage suggests that the proposed design, which integrates trajectory information, road geometry, and proximity-aware structural relations, can effectively capture heterogeneous road interactions under both regular and congested traffic conditions.

5.4 Component Contribution Analysis

Ablation experiments were conducted to evaluate the contributions of the proximity-aware structural design, road geometry encoding, bidirectional traffic-status propagation, and trajectory-driven propagation. **Table 5** reports the MAE of the full model and its variants. For consistency, the full model and all ablation variants were evaluated using the same representative random seed and data split. The full model consistently achieves the best performance across all three datasets, demonstrating the complementary contributions of these components.

Removing all proximity-aware constraints causes the most substantial performance degradation, increasing the MAE by 29.48% in Beijing, 167.41% in Chengdu, and 21.75% in Porto. Among the three individual structural factors, removing road-type compatibility produces the largest degradation in Beijing and Porto, increasing the MAE by 0.56% and 7.08%, whereas removing adaptive weights has the largest effect in Chengdu, increasing the MAE by 6.98%. Removing directional similarity also increases the MAE by 0.25%, 4.05%, and 2.36% on the three datasets, confirming that directional information provides complementary structural guidance. Among the three representation and propagation modules, removing bidirectional traffic-status modeling causes the largest degradation in Beijing and Chengdu, increasing the MAE by 7.69% and 11.48%. In Porto, removing trajectory propagation produces the largest increase in MAE, reaching 6.07%, compared with 3.71% for bidirectional traffic-status modeling and 1.01% for road geometry encoding. These

results indicate that different road networks rely on different structural information: bidirectional traffic-state diffusion is particularly important for Beijing and Chengdu, whereas road-type compatibility and trajectory-derived movement information play more prominent roles in Porto. Overall, the results demonstrate that proximity-aware constraints, road geometry, bidirectional traffic dependencies, and trajectory transitions provide complementary structural and dynamic information for traffic prediction.

Table 5: Component contribution analysis of PA-RNTrGNN.

Model Variant	Beijing MAE	Chengdu MAE	Porto MAE
Full Model	4.485	8.536	0.593
w/o Direction	4.496	8.882	0.607
w/o Road Type	4.510	8.870	0.635
w/o Adaptive Weights	4.498	9.132	0.608
w/o Constraints	5.807	22.826	0.722
w/o Road Geometry Encoding	4.562	8.556	0.599
w/o Bidirectional Traffic Status Modeling	4.830	9.516	0.615
w/o Trajectory Propagation	4.558	8.940	0.629

5.5 Interpretability, Convergence, and Efficiency Analysis

5.5.1 Interpretability of Proximity-Aware Structural Relations

To further explain the role of the proximity-aware structural matrix, [Fig. 3](#) visualizes the matrix C used by the model. Panels (a) and (b) are generated from the exported model matrix. The global heatmap shows clear structured patterns rather than random noise, while the zoomed off-diagonal region highlights non-adjacent but structurally related road segments. Panel (c) provides a schematic explanation of how distance decay, directional similarity, and road-type compatibility jointly determine hidden structural relations.

5.5.2 Convergence Analysis

To examine the optimization stability of PA-RNTrGNN, the validation-loss curve on the Beijing dataset is presented in [Fig. 4](#). The validation loss decreases from approximately 0.71 to below 0.60 during the first 10 epochs and gradually converges to around 0.57 after 20 epochs. Only minor fluctuations are observed thereafter, without a sustained increase or unstable oscillations. This pattern indicates that the model rapidly learns the main spatiotemporal dependencies and subsequently reaches a stable optimization region, supporting the validation-based checkpoint-selection strategy.

5.5.3 Computational Complexity and Efficiency

The main computational cost of PA-RNTrGNN arises from graph propagation, graph-attention aggregation, and recurrent temporal modeling. Its computational and memory requirements increase mainly with road-network size, relation density, and propagation depth.

All inference-time measurements were conducted on the same workstation equipped with an NVIDIA GeForce RTX 3090 graphics processing unit (GPU), two Intel Xeon Gold 6248R processors, and 128 GB of random-access memory (RAM). All models were evaluated using the same test subsets and a batch size of 64. The reported times cover inference over the complete test set and exclude data loading and preprocessing time. The comparative inference-time results are summarized in [Table 6](#).

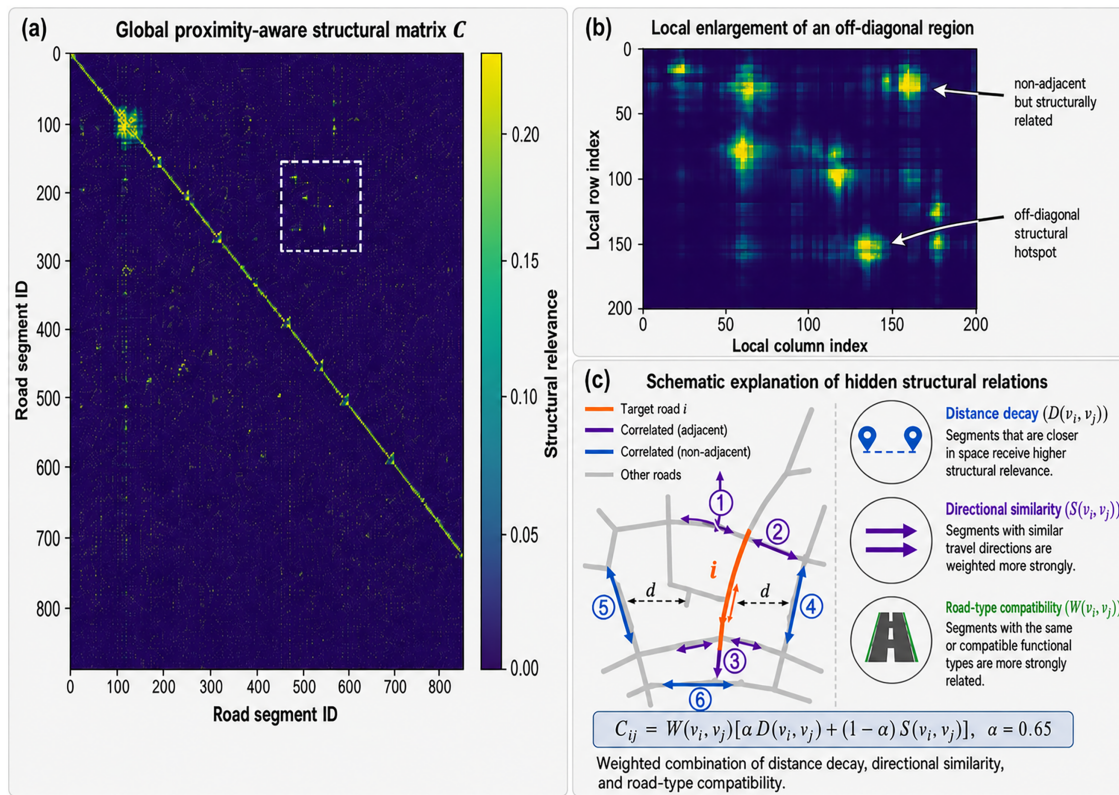


Figure 3: Interpretability of the proximity-aware structural matrix C . (a) Visualization of C based on the real model constraint matrix. (b) Zoomed-in off-diagonal region showing non-adjacent but structurally related road segments. (c) Schematic example illustrating how distance decay, directional similarity, and road-type compatibility jointly determine hidden structural relations.

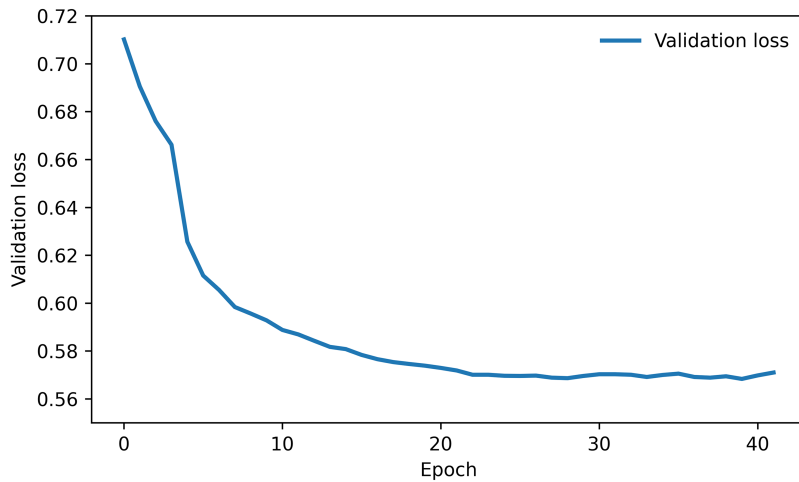


Figure 4: Validation loss convergence on the Beijing dataset. The validation loss decreases rapidly during the early training stage and then gradually stabilizes, indicating stable optimization behavior.

Table 6: Total inference time on the complete test set under the same hardware environment (s).

Model	Beijing	Chengdu	Porto
D2STGNN	62	98	27
STDEN	28	45	12
DCRNN	38	61	20
DGCRN	79	129	35
TrGNN	54	87	26
SSGCRTN	66	106	29
PSTCGCN	58	92	25
STGM	55	89	24
MSTFGRN	72	116	32
PA-RNTrGNN	36	58	19

PA-RNTrGNN contains approximately 11.87 million trainable parameters and requires 36, 58, and 19 s for inference on the Beijing, Chengdu, and Porto test sets. The experiments cover road networks containing up to 4388 road segments, supporting the feasibility of the model for the city-scale networks considered in this study. Table 7 summarizes the candidate hyperparameter ranges and final implementation settings.

Table 7: Implementation settings and candidate hyperparameter ranges of PA-RNTrGNN.

Item	Candidate Range/Setting	Final Setting
Trainable parameters	Fixed by model architecture	11.87M
Optimizer	Adam	Adam
Learning rate	$\{1e-3, 5e-4, 1e-4\}$	$1e-4$
Batch size	$\{32, 64, 128\}$	64
Maximum training epochs	$\{100, 150, 200\}$	200
Early-stopping patience	$\{5, 10\}$ epochs	5 epochs
Checkpoint selection	Validation MAE	Lowest validation MAE

5.5.4 Hyperparameter Sensitivity Analysis

Parameter sensitivity was evaluated on the Beijing validation set. The candidate ranges were designed to cover shallow-to-deep structural propagation, narrow-to-broad proximity neighborhoods, and different distance-direction trade-offs. Specifically, K_C was varied from 1 to 4, R from 100 to 300 m, and α from 0.35 to 0.80. During the evaluation of each parameter, only the parameter under investigation was varied, while the remaining parameters were kept at the settings used in the full model. The distance-decay scale σ was fixed at 10 m, and all training settings were kept consistent with Table 7.

As shown in Table 8, increasing K_C from 1 to 3 reduces the validation MAE from 4.885 to 4.720, demonstrating the benefit of multi-hop structural propagation. However, it rises to 4.754 at $K_C = 4$, suggesting that deeper propagation may introduce weakly relevant information and redundant feature mixing. For the proximity search radius R , the lowest MAE is obtained at 200 m; a smaller radius may exclude relevant non-adjacent roads, whereas a larger radius may introduce irrelevant candidates. Similarly, $\alpha = 0.65$ achieves the best performance by providing an effective balance between distance and other structural information. Accordingly, $K_C = 3$, $R = 200$ m, and $\alpha = 0.65$ are used in the final model.

Table 8: Hyperparameter sensitivity results on the Beijing validation set.

Parameter	Candidate Values	Validation MAE	Selected Value
K_C	1, 2, 3, 4	4.885, 4.776, 4.720, 4.754	3
$R(m)$	100, 150, 200, 250, 300	4.801, 4.752, 4.720, 4.738, 4.766	200
α	0.35, 0.50, 0.65, 0.80	4.789, 4.752, 4.720, 4.748	0.65

6 Discussion

The superior performance of PA-RNTrGNN mainly results from the joint modeling of trajectory-derived movement patterns, direct road-topology propagation, and proximity-aware structural relations. By combining distance decay, directional similarity, and road-type compatibility, the model captures hidden interactions among nearby or functionally related roads while reducing propagation between spatially close but structurally inconsistent segments. The larger improvement on Chengdu, which has the largest and most heterogeneous road network, together with the substantial degradation after removing the proximity-aware constraint matrix, confirms the importance of modeling dependencies beyond direct adjacency, such as those among parallel roads, ramps, service roads, and related corridors.

PA-RNTrGNN also maintains strong performance during peak hours, when upstream and downstream propagation, route choices, and interactions among nearby roads become more pronounced. Its lower peak-hour MAE across all three datasets indicates that trajectory information and proximity-aware relations improve traffic propagation modeling under high-demand conditions. The smaller improvement observed on Porto may be related to its smaller and less heterogeneous road network, which provides fewer non-adjacent dependencies beyond direct topology. Limited trajectory coverage may further weaken transition-based propagation, making sparsely observed segments and low-demand periods more difficult to predict.

Although the experiments cover three cities with different network scales and mobility patterns, cross-city transfer learning is not directly evaluated because road-segment nodes, topology, and trajectory-transition patterns are not naturally aligned. In addition, low-sampling-rate GPS data, map-matching errors, and sparse traffic observations may affect the construction of trajectory-transition matrices and ordered road-segment sequences. Specifically, map-matching errors may introduce spurious or missing transition edges, whereas sparse trajectories provide fewer reliable transitions and increase the model's reliance on the road-topology prior. These effects may weaken trajectory-driven prediction on sparsely observed roads and during low-demand periods. Future work will investigate transferable road-segment representations, uncertainty-aware map matching, controlled trajectory down-sampling and transition-perturbation experiments, and more robust trajectory-transition construction for reliable road-level traffic forecasting.

7 Conclusion

This study proposed PA-RNTrGNN, a proximity-aware road network-integrated trajectory graph neural network for road-level traffic flow prediction. By jointly modeling trajectory-derived movement transitions, road geometry, direct topology, and proximity-aware structural relations, the proposed framework captures both connected and non-adjacent road dependencies in heterogeneous urban networks. The separation between traffic flow observations and trajectory transition information enables a more explicit representation of directional traffic propagation.

Experiments on three real-world trajectory datasets demonstrate that PA-RNTrGNN achieves competitive and consistent prediction performance compared with representative and recent spatiotemporal

graph forecasting models. The model shows clear advantages in overall MAE and peak-hour prediction, especially on larger and more heterogeneous road networks. Ablation results confirm the contribution of the proximity-aware structural design, while visualization, convergence, and efficiency analyses further support the interpretability, optimization stability, and computational feasibility of the proposed framework.

Future work will explore the integration of multi-source traffic information and evaluate the transferability of PA-RNTrGNN across cities with different road-network structures and mobility patterns.

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Availability of Data and Materials: The datasets used in this study include the Beijing, Chengdu, and Porto taxi trajectory datasets. The Porto taxi trajectory dataset is publicly available from the ECML/PKDD 2015 Taxi Service Trajectory Prediction Challenge repository hosted by Kaggle and the UCI Machine Learning Repository. The Chengdu taxi trajectory dataset is available from the DataCastle platform. The Beijing taxi trajectory dataset is not publicly available due to data-use restrictions but may be made available by the corresponding author upon reasonable request and subject to permission from the data provider. The processed road-level traffic flow matrices, trajectory transition matrices, and road-network-derived features generated during this study are available from the corresponding author upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Code Availability: The source code of PA-RNTrGNN is publicly available at: <https://github.com/Mr-zhang4/PA-RNTrGNN>.

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