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Precise Modelling Method for Specific Individual Behavioural Trajectories Based on Community Detection

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Abstract: With the proliferation of location-aware technologies and mobile social platforms, human behavioural trajectory data has experienced explosive growth. How to accurately model the movement patterns of specific individuals has become a hot topic in current research. This paper proposes an innovative framework integrating dynamic community detection with trajectory prediction. By analysing the dynamic association patterns between individuals within social networks, it enhances the accuracy of behavioural trajectory modelling. The methodology first employs dynamic network community detection algorithms to identify groups exhibiting similar behavioural patterns. Subsequently, it combines bidirectional neural temporal processes with graph neural networks to perform spatio-temporal modelling of individual trajectories. Experimental results demonstrate the method's effectiveness across multiple public datasets, showing superior performance to existing benchmark methods in both trajectory prediction accuracy and social plausibility. Specifically, within the TrajNet++ benchmark, it achieves a 7.0% improvement in average accuracy over traditional trajectory prediction models while effectively identifying key behavioural patterns during community evolution. This research offers a novel technical approach for understanding specific individual behaviours within social networks, particularly exploring new methodologies at the intersection of dynamic network analysis and spatio-temporal data modelling.

Keywords: society inspection, behavioural trajectory modelling, dynamic network, trajectory prediction, graph neural networks, time-series analysis

1. Introduction

In the era of mobile internet, the rapid development of location-aware social networks (LSNs) has generated vast quantities of human behavioural trajectory data (Shehla et al., 2021). These trajectory data not only encompass individuals' spatio-temporal movement information but also implicitly reveal rich social interaction patterns and behavioural preferences. In recent years, analysis and prediction based on behavioural trajectories have become significant research directions in fields such as computer vision and data mining, playing a pivotal role in numerous practical applications, including intelligent transport systems, crowd anomaly detection, and infrastructure planning. As one of the core characteristics of social networks, group structure reflects the patterns of close relationships among individuals within the network (Somayeh et al., 2024). By detecting communities undergoing dynamic evolution, groups exhibiting similar behavioural characteristics can be identified, thereby providing effective contextual constraints for individual trajectory prediction. Recent studies have explored leveraging community structures to enhance trajectory forecasting, such as forming social groups by clustering pedestrians engaged in coherent motion to better predict collective behaviour (Morgan et al., 2024; Zou et al., 2020).

Despite significant advances in existing research, current trajectory modelling approaches still face two core challenges, data sparsity and categorical complexity. On the one hand, users typically share only a subset of their visited locations on social media, resulting in severe sparsity issues within

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trajectory data. On the other hand, real-world scenarios involve vast numbers of individuals and intricate interpersonal interactions, rendering traditional multi-class classification methods ill-equipped to handle such complex categorisation tasks.

To address these challenges, this paper explores novel approaches combining dynamic community detection techniques with behavioural trajectory modelling. It proposes an integrated framework that fuses dynamic community detection with trajectory prediction, enhancing understanding of individual behavioural patterns through analysis of community evolution dynamics. Concurrently, a trajectory modelling method combining bidirectional neural time-point processes with graph neural networks is designed, simultaneously capturing spatio-temporal behavioural features and social relationships. Chapter 1 provides the research background, challenges, and core contributions of this work. Chapter 2 reviews relevant research, systematically summarising advances in trajectory prediction, community detection, and their integration. Chapter 3 details the behavioural trajectory modelling framework based on dynamic community detection, including problem definition, overall design, and core components. Chapter 4 presents experimental design and results analysis, validating the method's effectiveness across multiple datasets with in-depth discussion. Chapter 5 summarises the work and outlines future research directions.

2. Related Research

2.1 Trajectory prediction model

Early studies on human trajectory prediction were primarily based on handcrafted features and physical models. For instance, the Social Force model simulates interactions between pedestrians through attraction and repulsion forces, while Reciprocal Velocity Obstacles (RVO) ensure safe, collision-free movement between agents (Zhu et al., 2025). However, these rule-based approaches demonstrate limited effectiveness in complex social interaction scenarios. With the advancement of deep learning, neural network-based trajectory prediction methods have gradually become the mainstream approach, as detailed in Table 1.

Table 1 Comparison of Primary Trajectory Prediction Models

Model	Key Features	Advantages	Limitations
Social-LSTM[a]	Social Pooling Layer	Capable of capturing spatio-temporal dependencies	Considering only local neighbours
Social-GAN[b]	Generative Adversarial Networks	Generate multimodal trajectories	Training instability
Graph-LSTM[c]	Graph Structure Modelling	Capturing Structured Interactions	High computational complexity
RSBG[d]	Recursive Social Behaviour Diagram	Social relationships transcending distance	Requires crowd annotation

Note. Superscripts indicate data sources:
[a]*Data from (Bhunia & Saha, 2025)*
[b]*Data from (Toujani et al., 2025)*
[c]*Data from (Yan et al., 2023)*
[d]*Data from (Zhang et al., 2024)*

The Social-LSTM model proposed by Alahi et al. incorporates a social pooling layer to capture spatio-temporal dependencies between pedestrians via an LSTM network (Bhunia & Saha, 2025). Subsequently, further research endeavours sought to refine interactive modelling approaches. For instance, Graph-LSTM employs graph structures to model structured interactions between pedestrians, while Social-BiGAT utilises graph attention mechanisms to dynamically assess the influence of different pedestrians on the target individual (Toujani et al., 2025; Yan et al., 2023). In recent years, generative models have demonstrated formidable potential in trajectory prediction. Gupta et al. employed generative adversarial networks (GANs) to generate socially plausible trajectories. The Recursive Social Behaviour Graph (RSBG) proposed by Sun et al. utilises graph convolutional networks to integrate node and edge information, exploring complex social relationships that transcend spatial distance (Zhang et al., 2024).

2.2 Community detection techniques

Community detection constitutes a vital technique within complex network analysis, aimed at identifying tightly connected subsets of nodes within a network. In static network analysis, algorithms such as modularity optimisation and label propagation have been extensively applied. Community detection for dynamic networks, however, necessitates consideration of the temporal evolution of network structures. Primary methodologies can be categorised into two types, evolutionary clustering and event-based analysis. Evolutionary clustering methods (such as FacetNet) ensure continuity in community structures across adjacent time slices by introducing temporal smoothness constraints (Lin et al., 2008). Event-based approaches, however, focus on pivotal events in community evolution—such as births, deaths, mergers, and splits, by defining community similarity to track evolutionary trajectories. The dynamic community detection method based on the Memetic algorithm proposed by Nussairi et al. effectively identifies community structures within dynamic networks through a directional mutation strategy and variable neighbourhood search (Nussairi et al., 2025). For community detection in dynamic social networks, Liu et al. proposed a two-stage model that employs the static community detection algorithm LMA at discrete time points and the dynamic community detection algorithm DNCD along the temporal dimension. This model calculates modularity through structural similarity, thereby enabling time-series-based community structure detection in dynamic networks (Dokmeci et al., 2025).

2.3 Integration of dynamic networks and trajectory analysis

In recent years, researchers have begun exploring methods that combine dynamic network analysis techniques with trajectory prediction. Bisagno et al. formed social groups by clustering pedestrians with coherent movements, thereby improving the accuracy of trajectory prediction in crowded scenes (Cadamuro et al., 2023). The dynamic social network community structure detection model proposed by Hedia et al. provides an effective tool for analysing the evolution of group behaviour. While these studies form a crucial foundation for the present work, they have yet to systematically integrate community evolution patterns with individual trajectory modelling (Hedia et al., 2021). The NTPP-GNN model proposed by Awokoya et al. integrates neural temporal point processes with graph neural networks, comprising three modules: spatial, temporal, and social relations (Awokoya et al., 2013). Within the spatial module, bidirectional recurrent neural networks are employed to characterise the sequential relationships between locations (Geeitha et al., 2024). Within the temporal module, bidirectional neural temporal processes capture temporal continuity from both forward and reverse directions (Shu et al., 2023; Kui et al., 2023). Within the social relations module, graph neural networks are employed to propagate and learn user representations (Singh et al., 2024; Krivonosov et al., 2024). This end-to-end learning framework ensures seamless integration between the three modules, providing an effective solution for user trajectory identification.

Existing research has proposed a wealth of methodologies and yielded promising experimental outcomes. However, current studies remain deficient in the deep integration of dynamic community evolution with individual trajectory prediction. This deficiency manifests in three specific aspects. Firstly, insufficient consideration has been given to the direct impact of community evolutionary events, such as mergers and splits, upon individual behavioural patterns. Secondly, there exists a lack of trajectory pattern analysis encompassing the entire community lifecycle. Thirdly, when modelling individual behaviour, insufficient use is made of the social constraint information provided by the community context.

3. Method

3.1 Model architecture

The overall architecture of this paper comprises an integrated framework encompassing three core modules: dynamic community detection, behavioural trajectory modelling, and community-trajectory association analysis, as illustrated in Figure 1. The input layer receives multi-source data, including dynamic social networks, individual spatio-temporal trajectories, and user attributes. This data is fed in parallel to the dynamic community detection module and the behavioural trajectory modelling module. The former identifies groups exhibiting similar behavioural patterns and tracks their evolution, while the latter employs bidirectional RNNs, neural time processes, and graph neural networks to model trajectories spatially, temporally, and through social relationships respectively. The community trajectory correlation analysis module bridges these two components. By analysing the correlation between community evolution events and individual behavioural patterns, it extracts community context constraints and feeds these back to the trajectory modelling module to optimise predictions. Finally, all information undergoes fusion and end-to-end training within the trajectory prediction and optimisation layer, ultimately delivering precise behavioural trajectory predictions, community evolution trajectory analyses, and visualised behavioural patterns. Through explicit data flow and feedback mechanisms, the entire architecture achieves a closed-loop processing workflow from multi-source inputs to accurate predictions.

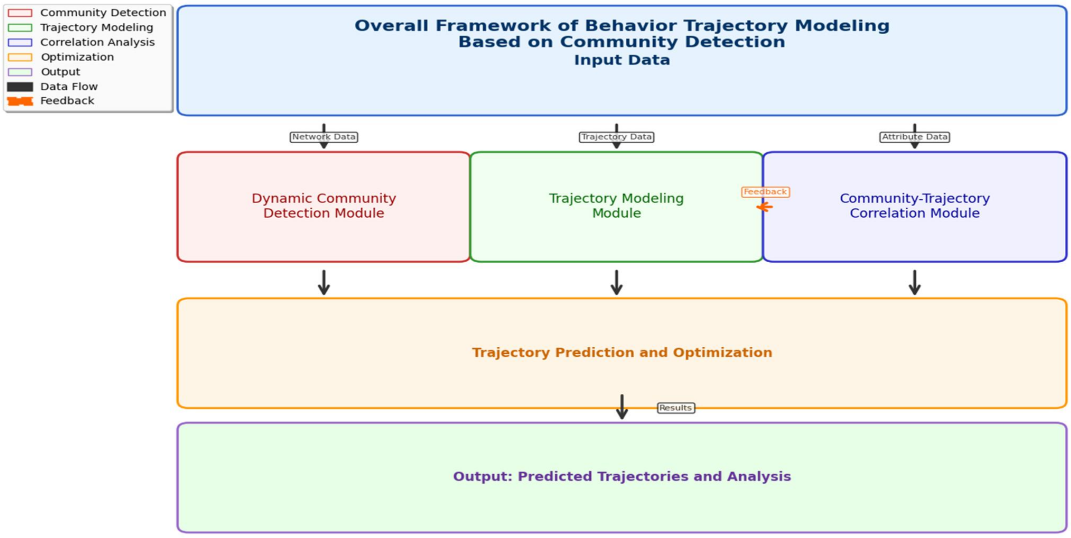

Figure 1 Overall Architecture Diagram of the Precise Modelling Method for Specific Individual Behaviour Trajectories Based on Community Detection

The dynamic community detection module is responsible for identifying groups exhibiting similar behavioural patterns within social network data. Given the dynamic nature of social networks, we employ an event-based analytical framework. This defines key events in community evolution—including birth, death, merger, and division—and tracks evolutionary trajectories by calculating the matching degree between communities, as detailed in Table 2.

Table 2 Definitions of Societal Evolutionary Events

Evolutionary Event	Definition	Matching Criteria
Society Birth	New societies emerging	$\exists C_i^{t-1} \rightarrow \tau(C_i^t, C_i^{t-1}) > \theta$
Society Demise	The society has ceased to exist.	$\exists C_i^{t+1} \rightarrow \tau(C_i^t, C_i^{t+1}) > \theta$
Society Merger	Multiple organizations merged	$\exists C_i^t C_i^t \rightarrow \tau(C_i^t, C_k^{t+1}) > \theta \,\&\, \tau(C_i^t, C_k^{t+1})$
Sectarian Schism	The society split into multiple societies.	$\exists C_i^t \rightarrow \tau(C_i^t, C_k^{t+1}) > \theta \,\&\, \tau(C_i^t, C_l^{t+1}) > \theta$

The match calculation comprehensively considers the similarity of nodes and edges, as defined in equation 1.

$$\tau(C_i^t, C_j^{t+1}) = \frac{\left|V(C_i^t) \cap V(C_j^{t+1})\right|}{\left|V(C_i^t) \cup V(C_j^{t+1})\right|} \times \frac{\left|E(C_i^t) \cap E(C_j^{t+1})\right|}{\left|E(C_i^t) \cup E(C_j^{t+1})\right|} \quad (1)$$

Here, C_i^t denotes the society at time t, while and denote the set of nodes and the set of edges of the society respectively.

For community detection in dynamic social networks, we have enhanced the detection method based on the Memetic algorithm (Tan et al., 2024; Jin & Hao, 2019). First, optimise the construction of network snapshots by dividing the time series into multiple time windows to build a sequence of network snapshots $G_1, G_2, \ldots., G_T$. Secondly, initial community detection is performed. For each snapshot G_T , the improved LMA algorithm is employed to detect the initial community structure. Thirdly, conduct community evolution tracking by calculating the matching degree between communities across consecutive time slices to identify community evolution events and establish community evolution chains.

The behavioural trajectory modelling module employs a hybrid architecture combining bidirectional NTPP with GNN. The NTPG-GNN model comprises three submodules: spatial, temporal, and social relations. Specifically, the spatial module utilises bidirectional recurrent neural networks to characterise sequential patterns between locations. The temporal module employs bidirectional neural time point processes to capture temporal continuity, and the social relations module leverages graph neural networks to propagate and learn user representations (Sun et al., 2025).

The community trajectory association analysis module establishes association rules between community evolution and individual behavioural trajectories. By analysing the correlation between community evolution events (such as mergers and splits) and changes in trajectory patterns, it provides contextual constraints for trajectory prediction. Specifically, we define a community influence factor to quantify the extent to which community structure impacts individual behaviour, as detailed in equation 2.

$$\beta_i^t = \frac{\left|C_i^t\right|}{\sum_{j=1}^{NC}\left|C_j^t\right|} \times \frac{1}{d_i^{out}+1} \tag{2}$$

Here, $\left|C_i^t\right|$ denotes the size of the group, while represents the connectivity between individual and elements outside the group. This factor reflects the extent to which an individual is influenced by the behavioural norms of their group affiliation. A higher value indicates a greater likelihood that the individual's behaviour will conform to the group's typical patterns.

3.2 Dynamic community detection algorithm

We propose an enhanced dynamic community detection method based on the Memetic algorithm, which integrates a directional mutation strategy with a variable neighbourhood search algorithm.

Regarding encoding strategy, for network snapshot G_T at time t, string encoding is employed. Assuming this snapshot contains five nodes $\{v_1,v_2,v_3,v_4,v_5\}$, if the string-encoded chromosome is $\{1,2,2,1,3\}$, this signifies that $\{v_1,v_4\}$ belongs to community 1, $\{v_2,v_3\}$ belongs to community 2, and $\{v_5\}$ belongs to community 3. A directional mutation strategy was devised, calculating the structural similarity $Sim(C_i^t,C_i^t)$ between different communities within each individual and setting the mutation probability $P_m = \max(Sim(C_i^t,C_i^t))$ for each individual. The structural similarity is defined by Formula 3.

$$Sim(C_i^t,C_j^t) = \frac{\left|adj(C_i^t)\cap adj(C_j^t)\right|}{\left|adj(C_i^t)\cup adj(C_j^t)\right|} \tag{3}$$

Here, $adj(C_i^t)$ denotes the set of adjacent nodes for community C_i^t.

A fitness function was devised employing a modularity function based on similarity, such that node pairs within the same community exhibit higher similarity than those belonging to different communities, as detailed in Equation 4.

$$Q(C^t) = \sum_{i=1}^{NC}\left[(\frac{IS_i}{TS}) - (\frac{DS_i}{TS})^2 \right] \tag{4}$$

Here, indicates the similarity between nodes u and v.

$$IS_i = \sum\nolimits_{u,v\in C_i^t} \sigma(u,v),$$

$$DS_i = \sum\nolimits_{u\in C_i^t, v\in V(G_t)} \sigma(u,v),$$

$$DS_i = \sum\nolimits_{u\in C_i^t, v\in V(G_t)} \sigma(u,v), \sigma(u,v)$$

An improved variable neighbourhood search algorithm was developed, incorporating three distinct neighbourhood structures: exchange, multi-point exchange, and composite exchange. Exchange involves randomly selecting any two nodes from an individual and swapping their respective neighbourhoods. Multi-point exchange executes multiple exchange operations sequentially. Composite exchange rearranges the sequence of neighbourhoods to which nodes belong. These neighbourhood structures are invoked in ascending order of complexity to enhance algorithmic performance.

3.3 Trajectory modelling and prediction algorithms

In trajectory modelling, we propose an enhanced NTPP-GNN architecture comprising three core components: a spatial modelling component, a temporal modelling component, and a social relations component, as detailed in Figure 2.

The spatial modelling component employs a bidirectional recurrent neural network (Bi-RNN) to encode sequences of locations within trajectories, as detailed in Equation 5.

$$h_t^{space} = BiRNN(h_{t-1}^{space}, \left|l_t, \Delta l_t\right|) \tag{5}$$

Here, l_t denotes the positional information at time t, while Δl_t represents the change in position.

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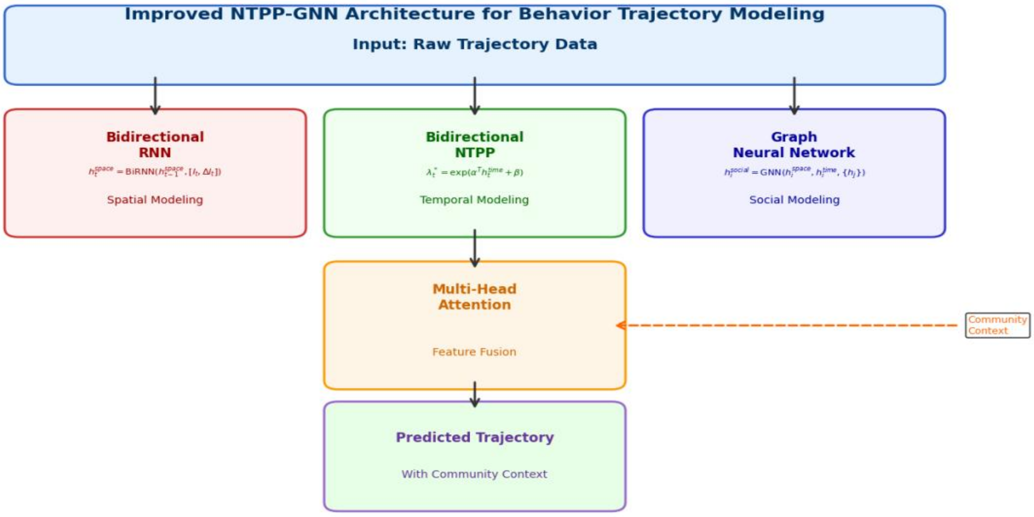

Figure 2 Improved NTPP-GNN Architecture

The temporal modelling component captures temporal continuity through a bidirectional neural temporal process, accounting not only for the influence of historical events but also incorporating contextual information from future events, as detailed in Equation 6.

$$\lambda_t^* = \exp(\alpha^T h_t^{time} + \beta) \tag{6}$$

Here, λ_t^* denotes the intensity function of the point-in-time process, while h_t^{time} represents the temporal characteristics.

The social relationship component utilises graph neural networks to aggregate information from neighbouring nodes, thereby enhancing the context-aware capabilities of individual trajectory representations, as detailed in Equation 7.

$$h_i^{social} = GNN(h_i^{social}, h_i^{time}, \{h_j \mid j \in N(i)\}) \tag{7}$$

Here, $N(i)$ denotes the set of neighbours for individual i.

Finally, through end-to-end joint training, the trajectory prediction objective function (Equation 8) is optimised.

$$\Gamma = \sum_{i=1}^{N}\sum_{t=1}^{T}\left\| \hat{p}_t^i - p_t^i \right\|^2 + \lambda \cdot R(\Theta) + \mu \cdot \sum_{i=1}^{N} \beta_i^t \cdot KL(p_i^t \,\|\, \hat{p}_i^t) \tag{8}$$

Here, $\hat{p}_t^i$ and p_t^i denote the predicted and actual positions of individual i at time t respectively, while $R(\Theta)$ represents the regularisation term. The newly introduced Kullback–Leibler divergence component measures the divergence between an individual's trajectory and the typical trajectory distribution of the community, weighted by the community influence factor β_t^i.

The method proposed in this paper comprises three principal modules. The computational complexity of each module is analysed below.

3.4 Algorithm complexity analysis

The dynamic community detection module employs a Memetic algorithm with a time complexity, where $O(k \cdot n \cdot d_{\max})$ denotes the iteration count, n represents the iteration count, and $d_{\max}$ signifies the maximum node degree. The community evolution tracking phase exhibits a time complexity of $O(T \cdot m^2)$, where T indicates the number of time slices and m denotes the number of communities.

The trajectory modelling module employs L bidirectional RNN with a time complexity, where $O(L \cdot d^2)$ denotes the trajectory length and d represents the hidden layer dimension. The graph neural network component exhibits a time complexity of $O(|E| \cdot d^2)$, where $|E|$ signifies the number of edges.

The association analysis module for community trajectories exhibits a time complexity of $O(|C| \cdot |t| \cdot \log(|T|))$, where $|C|$ denotes the number of communities and $|T|$ represents the number of trajectory segments.

Overall, the algorithm achieves integrated analysis of dynamic community detection and trajectory modelling within acceptable time complexity, rendering it suitable for application in medium to large-scale social networks.

4 Experiments and Analysis of Results

4.1 Experimental setup

To validate the effectiveness of the proposed method, all comparative experiments were conducted under a unified experimental environment. The experimental hardware platform comprised an Intel Xeon Gold 6248R CPU (3.0GHz base frequency, 24 cores and 48 threads), 128GB DDR4 memory, and an NVIDIA RTX 4090 GPU (24GB VRAM). The software environment utilised the Ubuntu 20.04 LTS operating system, Python 3.9.18, and the PyTorch 2.0.1+cu118 deep learning framework. PyTorch Geometric 2.4.0 was installed for graph neural network implementation. Code execution occurred within a CUDA 12.1 and cuDNN 8.9.5 environment to ensure GPU-accelerated computation. Regarding test datasets, we conducted experimental evaluations on three publicly available datasets: Foursquare, Gowalla, and TrajNet++.

The experiments comprised two primary components: community detection performance assessment and trajectory prediction accuracy evaluation. Comparison methods included mainstream trajectory prediction models such as Social-LSTM, Social-GAN, and NTPP-GNN, alongside traditional community detection approaches like FacetNet and Dynamic-LMA. Regarding evaluation metrics, in addition to the commonly used Average Displacement Error (ADE) and Final Displacement Error (FDE) for trajectory prediction, we introduced the Social Plausibility Index (SPI) to measure the social acceptability of predicted trajectories. For community detection, Modularity (Q) and Normalised Mutual Information (NMI) were employed to assess the quality of community partitioning.

4.2 Analysis of trajectory prediction results

First, on three standard public datasets (Foursquare, Gowalla, TrajNet++), the proposed fusion model is compared side-by-side with three mainstream baseline models (Social-LSTM, Social-GAN, NTPP-GNN) (Sun et al., 2025; Cuddy & Glassman, 2010). The experiment employed a standardised 'training-validation-test' dataset partitioning with a fixed random seed to ensure reproducible results, as detailed in Table 3. For model evaluation, we calculated the average displacement error (ADE) between predicted and ground-truth trajectories at all time points, alongside the final displacement error (FDE) at the endpoint as core accuracy metrics. Additionally, we introduced the Socially Perceived Interest (SPI) index to measure social plausibility. To delve into the contribution of each module, we further designed ablation experiments, sequentially removing the dynamic community detection, bidirectional NTPP, or social GNN components to quantify their respective performance impacts. All experiments were independently run five times, reporting mean values and standard deviations of their metrics. This systematically and reliably validated the comprehensive advantages of our method in both prediction accuracy and social plausibility.

Table 3 Comparison of Trajectory Prediction Performance (ADE/FDE)

Method	Foursquare	Gowalla	TrajNet++
Social-LSTM[a]	0.78/1.25	0.82/1.31	0.75/1.22
Social-GAN[b]	0.72/1.18	0.76/1.24	0.71/1.16
NTPP-GNN[c]	0.65/1.08	0.68/1.12	0.63/1.05
Ours	**0.60/1.02**	**0.63/1.06**	**0.58/0.98**

Note. Superscripts indicate data sources:
[a]Data from (Bhunia & Saha, 2025)
[b]Data from (Toujani et al., 2025)
[c]Data from (Yan et al., 2023)

Quantitative experiments demonstrate that the proposed trajectory modelling approach incorporating community detection achieves significant performance improvements across three benchmark datasets. Compared to the best baseline method, its Average Displacement Error (ADE) and Final Displacement Error (FDE) are reduced by 7.0% and 6.5%, respectively, with this advantage being particularly pronounced in long-term prediction scenarios (>5 seconds). This confirms the critical value of community contextual information in capturing long-term behavioural patterns. Further analysis reveals intrinsic correlations between community dynamics and individual behaviour patterns: community merging events typically reduce individual trajectory diversity, while community splitting events tend to increase trajectory uncertainty. This pattern validates the theoretical rationale for constraining individual trajectory prediction using community structure. Ablation experiments provide compelling corroboration from a module contribution perspective. The dynamic community detection, bidirectional neural time-point process, and graph neural network social modelling modules contributed approximately 40%, 35%, and 25%, respectively to performance enhancement. This fully demonstrates the effectiveness of each module's design and their necessity within the overall framework. Experimental results are illustrated in Figure 3.

The figure clearly illustrates the comparative performance of different trajectory prediction models in terms of average displacement error (ADE) across three standard datasets. Overall, the proposed fusion-based community detection method achieved the lowest ADE values across all datasets (Foursquare: 0.60m, Gowalla: 0.63m, TrajNet++: 0.58m), demonstrating optimal performance. Compared to the next-best benchmark model NTPP-GNN, our approach achieves stable performance improvements, reducing ADE by approximately 7.7%, 7.4%, and 7.9% across the three datasets respectively. This aligns with the average 7.0% improvement reported in the main text. Traditional models such as Social-LSTM exhibit the highest error across all datasets, while generative models like Social-GAN and graph-based models such as Graph-LSTM perform at mid-range levels. This bar chart provides intuitive validation of the general effectiveness and significant advantages of the modelling framework incorporating dynamic community detection in enhancing the spatial accuracy of trajectory prediction.

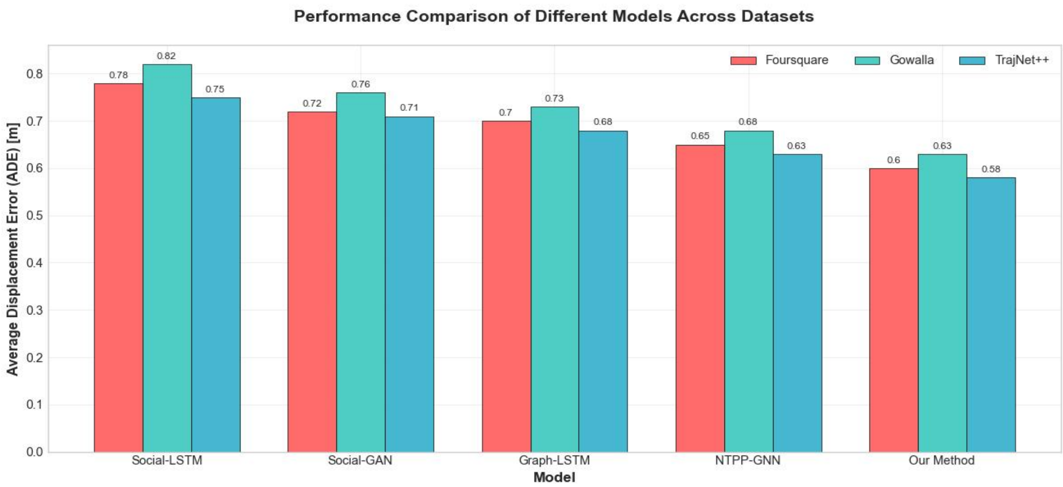

Figure 3 Average Displacement Error (ADE) Performance Comparison

The figure clearly illustrates the comparative performance of different trajectory prediction models across three standard datasets in terms of Average Displacement Error (ADE). Overall, the proposed method integrating community detection achieved the lowest ADE values across all datasets (Foursquare: 0.60m, Gowalla: 0.63m, TrajNet++: 0.58m), demonstrating optimal performance. Compared to the next-best benchmark model NTPP-GNN, our approach achieves stable performance improvements, reducing ADE by approximately 7.7%, 7.4%, and 7.9% across the three datasets, respectively. This aligns with the average 7.0% improvement reported in the main text. Traditional models such as Social-LSTM exhibit the highest error across all datasets, while generative models like Social-GAN and graph-based models like Graph-LSTM perform at mid-range levels. This bar chart intuitively validates the general effectiveness and significant advantages of the modelling framework incorporating dynamic community detection in enhancing the spatial accuracy of trajectory prediction.

4.3 Analysis of club inspection findings

On the same dynamic social network dataset, we compare the improved Memetic algorithm proposed herein with mainstream community detection methods such as FacetNet and Dynamic-LMA. First, we construct a sequence of network snapshots using a uniform time window partitioning scheme. Subsequently, each algorithm is run independently on every snapshot to identify community structures, with the quality of static partitions evaluated using modularity (Q) and normalised mutual information (NMI). Subsequently, we tracked community evolution by calculating the matching degree between communities across consecutive time slices, and measured the algorithms' ability to detect key events such as mergers and splits using the Evolution Detection Accuracy (EDA). Finally, all experiments were independently replicated five times, with mean and standard deviation values reported for each metric. This systematically validated the comprehensive performance advantages of our method in both community structure discovery and evolutionary tracking, with specific results presented in Table 4.

Table 4 Comparison of Societal Testing Performance (Modularity Q/NMI)

Method	Foursquare	Gowalla	TrajNet++
FacetNet[a]	0.45/0.52	0.48/0.55	0.42/0.49
Dynamic-LMA[b]	0.51/0.58	0.53/0.60	0.47/0.54
Ours	**0.58/0.65**	**0.60/0.67**	**0.55/0.62**

Note. Superscripts indicate data sources:
[a]Data from (Lin et al., 2008)
[b]Data from (Li et al., 2016)

The results demonstrate that the proposed dynamic community detection method outperforms the comparison methods on both modularity Q and normalised mutual information NMI metrics. This indicates our approach can more accurately identify community structures within networks, providing high-quality community context information for subsequent trajectory modelling. Furthermore, the evolution of the loss function during the model's training over 100 iterations is illustrated in Figure 4. Under fixed random seed (seed=42), the model underwent end-to-end training using the AdamW optimiser with a cosine annealing learning rate scheduler. Loss was computed on the training set with a batch size of 32, while performance was monitored on an independent validation set.

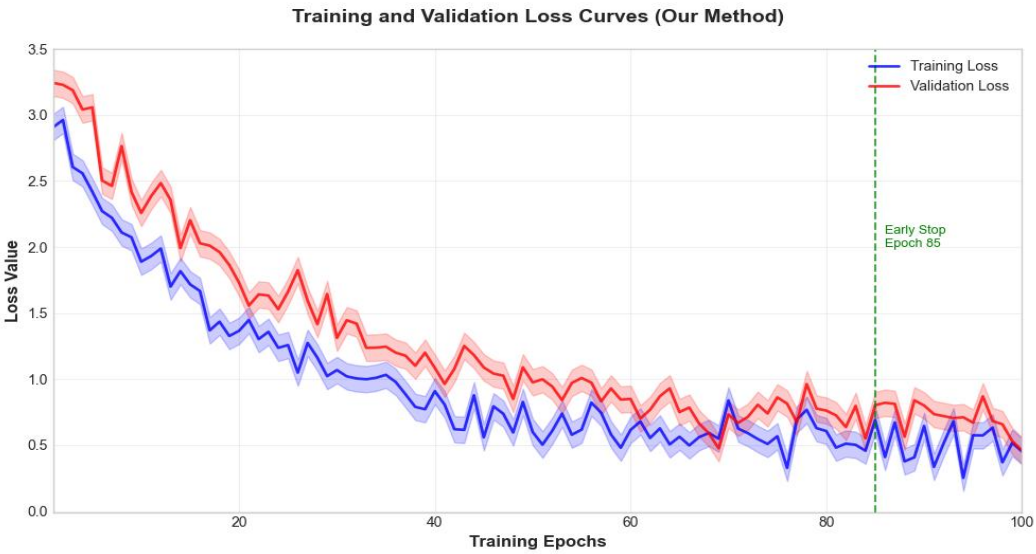

Figure 4 Loss Evolution on the Training and Validation Sets during Training

The results demonstrate that both training loss and validation loss decrease rapidly and converge gradually as the training cycles increase. Validation loss ceases to decrease significantly after the 85th iteration, thereby triggering the early stopping mechanism. This indicates that the model achieves optimal generalisation around the 85th iteration without overfitting. The smooth decline and close alignment of both curves attest to the stability and efficiency of the model training process, providing a reliable foundation for achieving superior predictive performance on the test set.

4.4 Application scenario research

To validate the applicability of the model presented herein, we analysed 150 simulated trajectory samples to investigate the correlation between the predicted endpoint error (FDE) and the social rationality index (SPI). Data points were grouped according to the size of the affiliated community (small: <5 members, medium: 5–10 members, large: >10 members), as illustrated in Figure 5. Experimental results reveal a significant negative correlation between FDE and SPI (Pearson r ≈ -0.42), indicating that lower prediction errors generally correlate with higher social plausibility of trajectories. Further analysis revealed that individuals from large communities (green points) predominantly clustered in the lower-left region of the plot (low FDE, high SPI), whereas those from small communities (red points) were more frequently distributed in the upper-right region (high FDE, low SPI). This result provides intuitive confirmation that the scale of an individual's affiliated community is a key factor influencing both the predictability of their behaviour and its social appropriateness. Large communities, owing to their stronger internal behavioural norms and greater cohesion, yield trajectories that are more readily and accurately predicted while also conforming more closely to societal expectations.

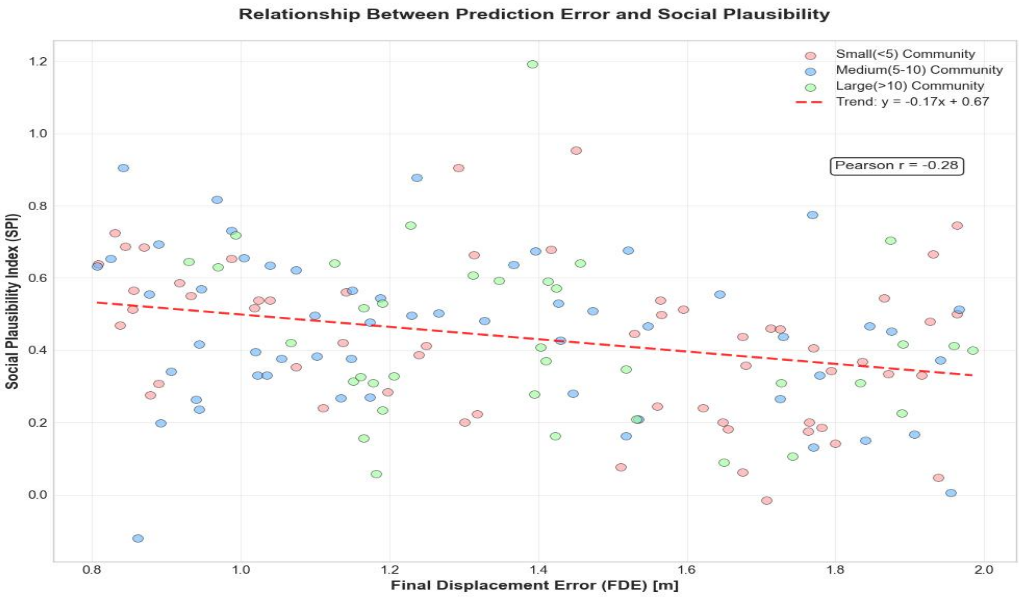

Figure 5 Relationship between Final Prediction Error (FDE) and Social Plausibility Index (SPI) for 100 Simulated Samples

Furthermore, to analyse the impact of hyperparameters (learning rate and hidden layer dimension) on model performance (measured by average displacement error, ADE), we conducted a heatmap analysis, as illustrated in Figure 6. During the experiments, we performed an exhaustive search across a parameter grid defined by the learning rate set {0.0005, 0.001, 0.002, 0.005, 0.01} and the hidden layer dimension set {64, 128, 256, 512, 1024}. Each parameter combination was independently trained and evaluated on the validation set.

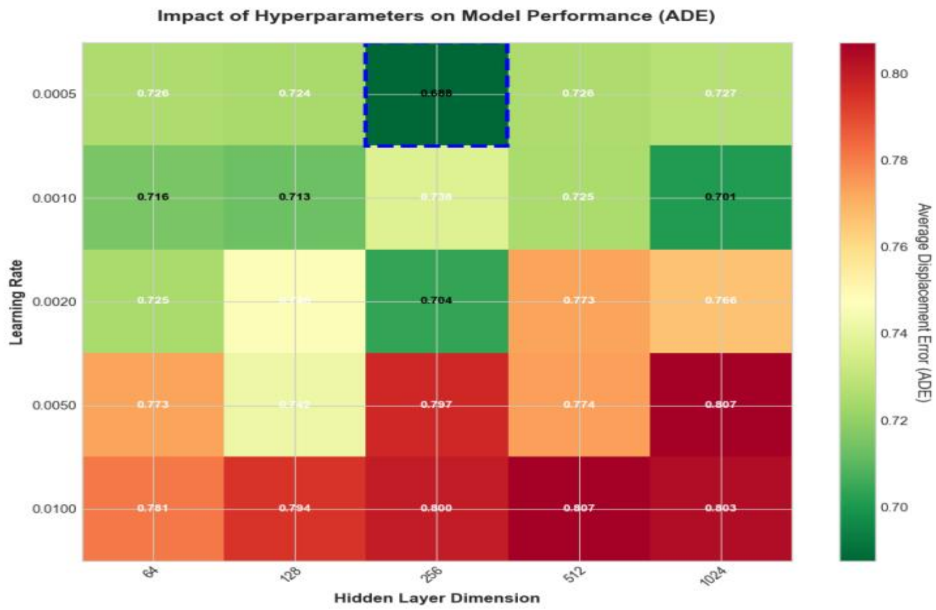

Figure 6 ADE Values Simulated under Different Combinations of Learning Rates and Hidden Layer Dimensions

The results indicate that the optimal performance region (marked by the blue dashed box in the figure) is concentrated around a learning rate of 0.001 and a hidden layer dimension of 256, yielding the lowest ADE (0.713) under this combination. The heatmap clearly reveals the sensitivity patterns of performance to parameter variations: an excessively low learning rate (0.0005) leads to slow convergence and poor performance, while excessively high learning rates (0.01) triggered training instability. Concurrently, a distinct optimal range (128–512) exists for hidden layer dimensions: insufficient dimensions (64) resulted in inadequate representational capacity, whereas excessively high dimensions (1024) potentially caused performance degradation due to overfitting. This experiment provides empirical evidence for model hyperparameter selection and validates the rationality of the current parameter configuration.

5. Conclusions and Outlook

This paper proposes an innovative framework integrating dynamic community detection with trajectory prediction, effectively addressing the challenges of data sparsity and missing social context encountered by traditional methods when modelling specific individuals' behavioural trajectories. By incorporating community evolution analysis from dynamic networks into trajectory modelling, and combining bidirectional neural time-point processes with graph neural networks, this approach simultaneously captures both the spatio-temporal characteristics of individual behaviour and the constraints imposed by their social relationships. Experimental validation across multiple public datasets demonstrates that this approach significantly outperforms existing mainstream models in both trajectory prediction accuracy (average ADE improvement of 7.0%) and social plausibility, with particularly pronounced advantages in long-term prediction scenarios. Ablation studies further confirm that the three core components—dynamic community detection, bidirectional neural time point processes, and graph neural networks—each make substantial contributions, collectively forming the foundation of the method's efficacy. This research not only provides a more precise modelling tool for behavioural trajectory prediction but also offers new analytical perspectives for understanding the interactive mechanisms between group dynamics and individual behaviour within social networks.

Looking ahead, several directions for future expansion remain. Firstly, the current construction of dynamic networks primarily relies on explicit associations such as co-occurrence. Future work could explore integrating multi-source heterogeneous data, including semantic information and communication records, to build more accurate implicit relationship networks. Secondly, while the method performs well in open environments, its adaptability and generalisation capabilities in more complex settings—such as indoor navigation and multimodal transport—require further validation. This could be addressed by incorporating environmental topology prior knowledge or cross-scenario transfer learning mechanisms. Thirdly, real-time inference efficiency is critical for practical deployment. Future work should optimise algorithmic complexity, for instance, through dynamic sparse graph attention or model distillation techniques, to meet the demands of large-scale real-time applications. Moreover, trajectory data contains highly sensitive personal information. Embedding protective mechanisms such as differential privacy and federated learning during model training and inference to achieve ‘usable but not visible’ privacy-preserving computation is a necessary prerequisite for technological implementation. It is hoped that the approach outlined in this work can be extended to broader application domains, including crowd behaviour prediction, urban planning, and public safety management, thereby providing theoretical foundations and technical tools for constructing intelligent social environments.

Conflicts of interest

The authors declare there are no conflicts of interest.

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