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PAPER

Intelligent Tourism: Innovative Applications of Mobile Technology in Personalized Travel Planning

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ABSTRACT

With the rapid development of the global tourism industry and the widespread adoption of mobile internet technologies, personalized travel itinerary planning has emerged as a crucial method to meet the diverse needs of tourists. Traditional planning approaches, relying on fixed routes and preset attractions, often fail to provide flexible and personalized services. In this context, the application of intelligent tourism technologies has garnered increasing attention, facilitating the provision of customized itinerary planning services through mobile technologies and intelligent algorithms. Although existing study has enhanced the intelligence level of itinerary planning to some extent, it still falls short in considering the comprehensive dimensions of time and space, as well as in responding to the dynamic demands of tourists in real time. This study introduces a mobile predictive model tailored for personalized travel itinerary planning, incorporating the components of a spatio-temporal graph convolutional network (STGCN) with an attention mechanism and spatial node embedding vector components. This model effectively captures the dynamic characteristics of time and space in travel itineraries, achieving personalized recommendations and optimizations. It significantly improves the accuracy and response speed of itinerary planning, providing important support for the digital transformation and innovative development of the tourism industry.

KEYWORDS

intelligent tourism, personalized itinerary planning, mobile technology, spatio-temporal graph convolutional network (STGCN), attention mechanism, spatial node embedding vectors, travel itinerary optimization

1 INTRODUCTION

In recent years, as the global tourism industry has experienced rapid growth and mobile internet technology has become widespread, personalized travel itinerary planning has emerged as a key component in satisfying the diverse needs of travelers [1–4]. Traditional methods of itinerary planning typically rely on fixed tourist routes and preset attraction recommendations, failing to meet the demands

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for personalization, flexibility, and real-time service [5, 6]. Against this backdrop, the provision of customized itinerary planning services through advanced mobile technology and intelligent algorithms has become an important trend in the development of the tourism industry.

Personalized travel itinerary planning not only enhances the travel experience and increases satisfaction during the journey but also promotes the efficient allocation and utilization of tourism resources through precise recommendations and optimizations [7–10]. Supported by mobile internet and artificial intelligence technologies, personalized itinerary planning systems are capable of acquiring and analyzing a vast amount of tourism data in real time, offering dynamic adjustments and personalized recommendations. This significantly enhances the intelligence and convenience of tourism services [11, 12], playing a crucial role in driving the digital transformation and innovative development of the tourism industry.

However, existing study methods still exhibit several shortcomings in personalized itinerary planning. Firstly, many approaches lack a comprehensive consideration of temporal and spatial dimensions when processing tourism data, leading to insufficient accuracy and practicality of itinerary plans [13–16]. Secondly, current recommendation systems often rely on static data and fail to respond in real time to changes in tourists' dynamic needs and preferences. Moreover, traditional methods often lack the flexibility and adaptability required to handle complex tourism scenarios and diverse demands, making it challenging to provide genuinely personalized itinerary planning services [17–21].

To address these issues, this study introduces a mobile predictive model for personalized itinerary planning, incorporating spatio-temporal graph convolutional network (STGCN) components based on an attention mechanism and spatial node embedding vector components. The STGCN components, leveraging the attention mechanism, effectively capture the dynamic temporal and spatial characteristics of travel itineraries, thereby enhancing the accuracy and response speed of the planning process. The spatial node embedding vector components, through in-depth analysis of tourism scenarios and traveler preferences, facilitate personalized itinerary recommendations and optimizations. The synergistic integration of these components not only elevates the level of intelligence in personalized travel itinerary planning but also provides substantial technical support and a theoretical basis for the innovative development of the tourism industry, offering significant study value and application prospects.

2 MOBILE PREDICTIVE MODEL FOR PERSONALIZED TRAVEL ITINERARY PLANNING

A mobile predictive model aimed at personalized travel itinerary planning was developed in this study to predict the mobility of individual tourists at travel destinations based on their behavior patterns and preferences, thereby providing personalized itinerary suggestions. The principal components of this model include the extraction components of spatial node feature vectors of the heterogeneous information network and neural network components. The extraction components are tasked with extracting feature vectors from spatial nodes at travel destinations. These node feature vectors represent attributes and relational information of various types of spatial nodes, such as tourist attractions, transportation hubs, and accommodation facilities, and also encapsulate characteristic information of tourist behavior, such as duration of stay and frequency of visits. The neural network components are composed via residual connections in the temporal feature extraction module. This module includes a spatio-temporal attention mechanism module and a spatio-temporal convolution operation module capable of capturing tourists' behavior patterns across different moments and spaces. The spatio-temporal attention mechanism enables the model to focus on changes at critical time points and spatial locations, while the spatio-temporal convolution operation effectively extracts spatio-temporal features. Ultimately, these features are output through a fully connected neural network, reflecting tourists' mobility at future moments. Figure 1 shows the structure of the developed model.

In the context of personalized travel itinerary planning, the model not only considers the overall behavior patterns of tourists but also integrates individual historical data and preference information. Specifically, assuming that the spatial network at the travel destination comprises V nodes, at any given sampling time s, a vector $A_s = \left(a_s^1, a_s^2, \ldots a_s^V\right)$ with a length of V can be obtained, representing the distribution of tourists across nodes at time s. Based on the data records $A = (A_1, A_2, \ldots, A_{So})$ from the past S_o periods, the model predicts the distribution of tourists for future S_d time periods. To facilitate personalized recommendations, the model further integrates each tourist's historical behavior data and preference information, merging the spatial node feature vectors with individual behavioral characteristics to adjust and optimize the prediction results. Ultimately, the predictive outcomes provided by the model serve as a foundation for personalized travel itinerary planning, aiding tourists in arranging their visitation routes and timings effectively, thereby enhancing the travel experience.

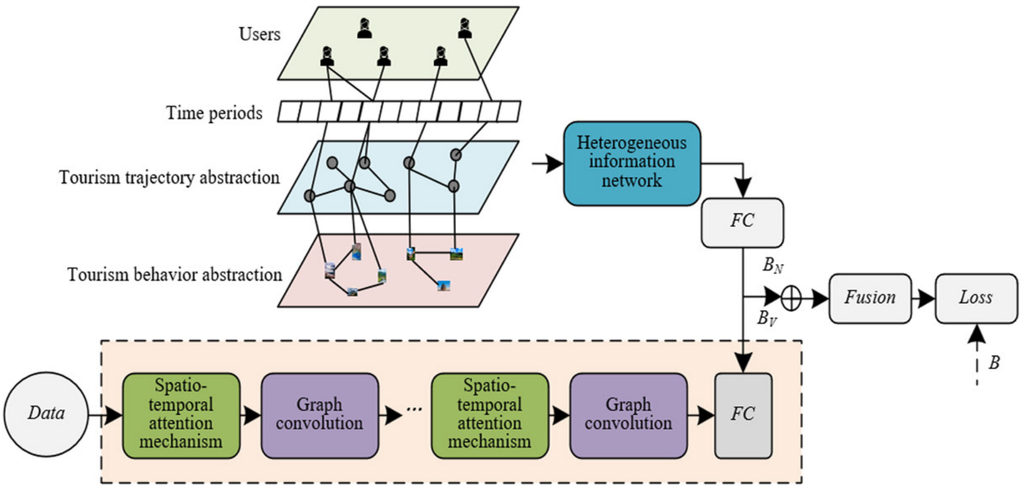


Fig. 1. Structure of the mobile predictive model for personalized travel itinerary planning

2.1 STGCN components based on an attention mechanism

The planning of travel itineraries involves a vast array of complex spatio-temporal data, encompassing the behavior patterns of tourists at various moments and locations. Moreover, tourist attractions, transportation hubs, and other significant nodes within the tourism network possess distinct attributes and connectivity relations, with varying degrees of attraction to tourists at different sites and moments in personalized travel itinerary planning. Therefore, the model constructed employs STGCN as its foundational element. It considers the dynamics of time series while processing spatial relations, adapting to the periodic and seasonal characteristics of tourism activities, thereby enhancing prediction accuracy. An attention mechanism is also integrated into the model, enabling dynamic adjustments in focus towards different nodes and time points, accentuating the impact of key nodes and critical moments.

Initially, the model constructs a spatial structure network graph $H = \{N, R, \mu\}$ of tourist attractions and transportation nodes, where N represents the set of nodes, R denotes the set of edges, and μ signifies the weight of the edges. The unit matrix is represented by U, while the adjacency matrix X and the degree matrix F represent the connectivity between nodes and the connectivity count of each node, respectively. The computation is as follows:

$$X_{u,k} = \begin{cases} \mu(u,k), \text{if } r(u,k) \in R \\ 0, \text{otherwise} \end{cases} \tag{1}$$

$$F_{uu} = \sum_{k \in N} F_{uk} \tag{2}$$

Under the framework of spectral graph theory, graph convolution operations typically rely on the graph's Laplacian matrix or normalized Laplacian matrix. These matrices are instrumental in capturing the global topological information of the graph structure, with the formulas calculated as follows:

$$M = F - X \tag{3}$$

$$\tilde{M} = F^{-\frac{1}{2}} M F^{-\frac{1}{2}} = U - F^{-\frac{1}{2}} X F^{-\frac{1}{2}} \tag{4}$$

In the specific computations, for a signal a on the graph, such as tourist traffic flow or other features on nodes, its Fourier inverse transform is represented as $a\hat{} = Ia\hat{}$, where I is the eigenvector matrix of the Laplacian matrix. According to the convolution theorem, signal convolution simplifies to point-wise multiplication in the frequency domain, with the result obtained via the inverse Fourier transform.

$$\begin{aligned} & h_\varphi *_H a \\ & = h_\varphi(M)a \\ & = h_\varphi(I\Lambda I^S)a \\ & = I h_\varphi(\Lambda) I^S a \\ & = I \begin{pmatrix} h_\varphi(\eta_1) & & \\ & \ddots & \\ & & g_\varphi(\eta_v) \end{pmatrix} I^s a \end{aligned} \tag{5}$$

Personalized travel itinerary planning involves a vast array of tourist attractions, transportation nodes, and tourist behavior data, which form graphs of considerable scale. The traditional method of spectral graph convolution, which requires eigen decomposition of the Laplacian matrix, faces high computational complexity, making it inefficient for large-scale graph data. Consequently, direct application of traditional spectral graph convolution poses significant challenges in terms of performance and computational resources. To overcome this difficulty, an effective solution is the approximation of the convolution kernel $h_\varphi(\Lambda)$ using a truncated K-order Chebyshev polynomial. Assuming the scaled eigenvalue matrix is represented by $\tilde{\Lambda} = 2/\eta_{MAX}\Lambda - U_V$, where η_{MAX} represents the maximum eigenvalue of the Laplacian matrix, the formula is given as:

$$h_\varphi(\Lambda) \approx \sum_{j=0}^{J} \varphi_j S_j(\tilde{\Lambda}) \tag{6}$$

The recursive relation of the Chebyshev polynomial is as follows:

$$\begin{aligned} &S_0(a) = 1 \\ &S_1(a) = a \\ &S_j(a) = 2aS_{j-1}(a) - S_{j-2}(a) \end{aligned} \tag{7}$$

$$h_\varphi *_H a \approx \sum_{j=0}^{J} \varphi_j S_j(\tilde{M})a \tag{8}$$

In terms of the activation function of the graph convolution module, the ReLU function was chosen. Thus, for the graph structure model H and the graph signal a, the output of the graph convolution module is as follows:

$$\mathrm{ReLU}(h_\varphi *_H a) \approx \mathrm{ReLU}\left[\sum_{j=0}^{J} \varphi_j S_j(\tilde{M})a\right] \tag{9}$$

Personalized travel itinerary planning necessitates accurate predictions of tourist crowd density at various attractions and transportation nodes in the future. The accuracy of such predictions depends on the effective utilization of historical data and a profound understanding of spatial-temporal relationships. Thus, a graph signal time series of a certain length $[a_1, a_2, \ldots, a_S]$ was constructed, with each a_s representing the crowd density at various attractions or transportation nodes at time s. Furthermore, graph convolution operations were employed to process the spatial dimension features. Graph convolution is effective in capturing the movement of tourists between adjacent attractions or the connectivity between transportation nodes. Through graph convolution, the features of each node in the entire spatial network can be extracted, reflecting the complex relationships between nodes and their neighboring nodes. Subsequently, features processed by graph convolution undergo extraction along the temporal dimension. Conventional two-dimensional convolution was utilized in this study to handle time series data. Sliding over the time dimension, the convolution kernels capture patterns and trends within the time series. For example, certain attractions may experience peak visitor flows during specific time periods. These temporal patterns can be identified through two-dimensional convolution, enabling predictions of future moments. Figure 2 presents a schematic diagram of the spatio-temporal convolution operations. Assuming the convolution kernel parameters for the time dimension are represented by Θ and the output from the previous spatio-temporal convolution module is represented by $a^{(m-1)}$, the expression for the spatio-temporal convolution module is formulated as follows:

$$a^{(m)} = \mathrm{ReLU}\left[\Theta * \mathrm{ReLU}\left(h_\varphi *_H a^{(m-1)}\right)\right] \tag{10}$$

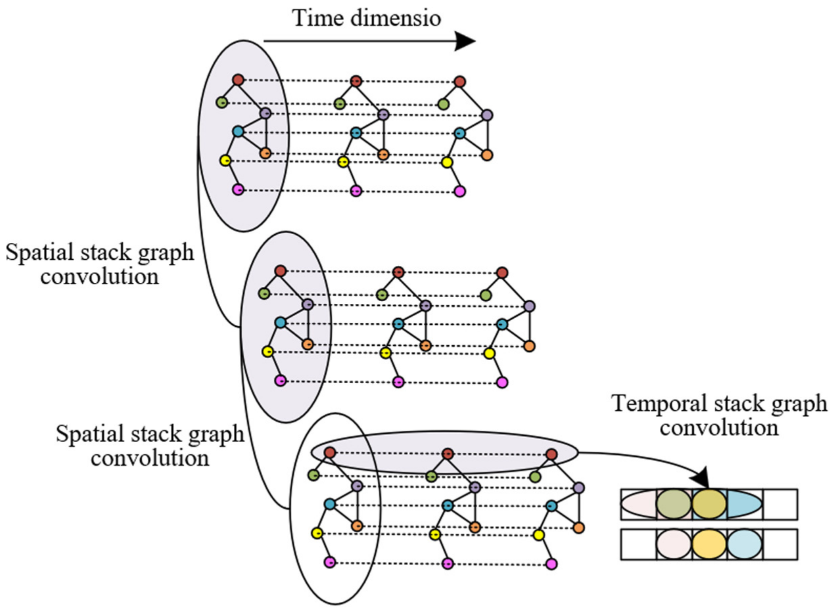


Fig. 2. Schematic diagram of spatio-temporal convolution operations

Personalized travel itinerary planning involves processing a substantial volume of spatio-temporal data, which typically exhibits complex tidal and directional characteristics. Although traditional weighted, undirected graph models can capture spatial and temporal relationships, they fail to effectively reflect the directionality of user movements. The attention mechanism, by assigning different weights to various temporal and spatial information, selectively focuses on the information most crucial for the current prediction. This approach enables the model to better capture user behavior patterns at specific moments and locations, enhancing prediction accuracy. Specifically, in the temporal dimension, by calculating the attention weight matrix for the time dimension, the model is able to identify the time points that are most critical for predicting user behavior. This process involves normalizing time series data to ensure comparability across different time points. The obtained temporal dimension attention weight matrix was used to adjust subsequent data inputs, enabling the model to more accurately capture user behavior patterns during specific time periods. This step assists the model in adapting more flexibly to changing time patterns when handling the tidal characteristics of user group movements in daily life. Assuming the input to the *e*-th layer spatio-temporal convolution module is represented by $A^{(e-1)} = (A_1, A_2, \ldots, A_{Se-1})$, the number of input channels to the *e*-th layer spatio-temporal convolution module is represented by Z_{e-1}, and the sequence length of the time dimension is represented by S_{e-1}. The model's trainable parameters are represented by N_r, y_r, Q_1, Q_2, and Q_3, and the activation function by δ. The dynamic weight matrix for the current layer is represented by R, with R_{uk} representing the dependency strength between two nodes. The formulas for calculating the attention weight matrix are as follows:

$$R = N_r \cdot \delta\left(\left(\left(A^{(e-1)}\right)^S Q_1\right) Q_2 \left(Q_3 A^{(e-1)}\right) + y_r\right) \tag{11}$$

$$R'_{uk} = \frac{\exp(R_{uk})}{\sum_{k=1}^{S^{(e-1)}} \exp(R_{uk})} \tag{12}$$

Before further feature extraction, the data was adjusted using the normalized time-dimension attention weight matrix.

$$\hat{A}^{(e-1)} = A^{(e-1)} \cdot R' = \left(\hat{A}_1, \hat{A}_2, \ldots, \hat{A}_{S_{e-1}}\right) \in \Re^{V \times Z_{e-1} \times S_{e-1}} \tag{13}$$

In the spatial dimension, a similar method was employed to generate the attention weight matrix for the spatial dimension. This matrix was used to identify and adjust spatial information, enabling the model to better capture the characteristics of user behavior at different locations.

$$T = N_t \cdot \delta\left(\left(A^{(e-1)}Q_1\right)Q_2\left(Q_3 A^{(e-1)}\right)^S + y_t\right) \tag{14}$$

$$T'_{uk} = \frac{\exp(T_{uk})}{\sum_{k=1}^{S^{(e-1)}} \exp(T_{uk})} \tag{15}$$

Assuming the element-wise Hadamard product is denoted by *, the graph convolution operation formula, incorporating the attention weight matrix, is as follows:

$$h_\varphi *_H a = h_\varphi(M)a = \sum_{j=0}^{J} \varphi_j \left(S_j(\tilde{M}) * T'\right)a \tag{16}$$

The output form of the *e*-th layer spatio-temporal convolution module, as shown below, integrates the adjusted temporal and spatial information mentioned above, allowing the model to fully utilize the key features of the time and space dimensions at each layer. This multilevel feature extraction and adjustment mechanism ensures that the model can more accurately predict user movement behaviors, thereby providing more precise and personalized suggestions for personalized travel itinerary planning.

$$A^{(e)} = \mathrm{ReLU}\left(\Theta * \left(\mathrm{ReLU}\left(h_\varphi *_H \hat{A}^{(e-1)}\right)\right)\right) \in \Re^{V \times Z_e \times S_e} \tag{17}$$

2.2 Spatial node embedding vector components

Low-dimensional embedding vectors of spatial nodes can effectively capture and represent the pedestrian traffic characteristics within a region, including critical information such as the periods of peak traffic. These details are crucial for predicting the movements and behaviors of tourists in travel itinerary planning. The varying characteristics of pedestrian traffic at different tourist sites and regions during various periods are essential for the model to accurately predict tourist behavior, thereby providing more reasonable and personalized itinerary suggestions. The heterogeneous information network of user behavior provides a wealth of temporal and spatial information. Through methods of representation learning in the heterogeneous information network, the feature vectors of nodes within these networks can be effectively extracted. By integrating these feature vectors with one-hot encoding vectors of the moments to be predicted, the association between different moments and spatial nodes can be better captured. This association is vital for understanding the behavior patterns of tourists at different moments and locations, aiding the model in making more precise predictions within the complex and variable tourism environment. The feature vectors of spatial nodes are denoted by r_{NO}, and the one-hot encoding vectors for the moments to be predicted are denoted by r_s. A fully connected neural network was employed in this study to process r_{NO}

and r_s, enhancing the model's capability to integrate and process spatio-temporal information. In this manner, the model can more comprehensively understand and utilize the crucial features in the spatio-temporal dimension, improving the overall accuracy and reliability of predictions. The expression for the output of the overall model is given below:

$$\hat{B} = Q_V \Phi B_V + Q_N \Phi B_N \tag{18}$$

The characteristics of the mobile predictive model constructed for personalized travel itinerary planning can be summarized as follows:

a) The model comprehensively considers the information in both temporal and spatial dimensions within the graph neural network components, utilizing STGCN as the foundational element. This enables accurate capture of tourists' movement patterns at different moments and locations, ensuring the model's sensitivity and adaptability to spatio-temporal dynamics, which is crucial for travel itinerary planning since tourist behaviors are often influenced by both time and space.

b) In response to the tidal and directional dynamic characteristics of user group mobility, an attention mechanism was introduced. This mechanism enhances the model's ability to capture important features and assigns different weights to various temporal and spatial nodes, allowing the model to flexibly respond to complex dynamic changes and improve prediction performance. This is particularly significant in personalized travel itinerary planning, where tourists' movement patterns are frequently irregular and variable, and accurate capture of these dynamic features can provide more precise itinerary suggestions.

c) Experimental verification has shown that spatial node embedding vectors from the heterogeneous user behavior network contain a wealth of regional feature information, such as the timing of peak pedestrian traffic. These features reflect the user behavior patterns of specific areas, aiding in enhancing the model's predictive performance. Hence, this information was incorporated as an independent component into the constructed model in this study. This component provides a more detailed analysis of regional characteristics, enabling the model to better understand and utilize the features of different attractions and regions in personalized travel itinerary planning, thus offering tourists more personalized and optimized itinerary options.

3 EXPERIMENTAL RESULTS AND ANALYSIS

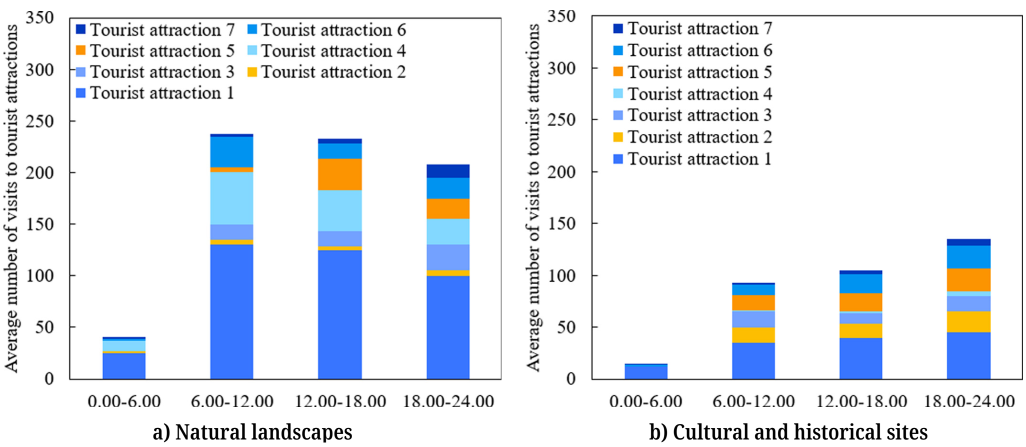
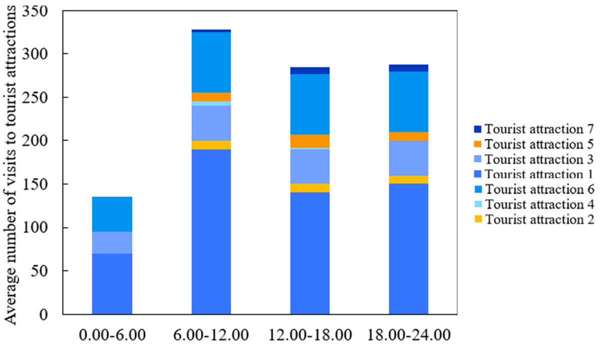


Fig. 3. *(Continued)*



c) Modern entertainment venues

Fig. 3. Distribution of mobile visits to tourist attractions in personalized itinerary planning

According to the data presented in Figure 3, significant differences can be observed in the distribution of visit frequencies to various types of tourist attractions within a 24-hour period. For natural landscape attractions, the majority of visits are concentrated in the morning and afternoon, particularly between 6:00–12:00 and 12:00–18:00, with the highest visit frequency occurring during the morning period (130 visits) and the afternoon period (125 visits) at Tourist Attraction 1. The peak visit times for cultural and historical sites are primarily in the morning and afternoon, with notably higher visit frequencies during the 6:00–12:00 and 12:00–18:00 intervals, where Tourist attraction 1 recorded 35 and 40 visits, respectively. Modern entertainment venues exhibit high visit frequencies throughout the day, especially during the early morning (0:00–6:00) and evening (18:00–24:00) periods, with Tourist Attraction 1 receiving 70 visits in the early morning and 150 visits in the evening. These distributions of visit frequencies indicate significant temporal patterns in tourists' visit times to attractions, providing crucial references for personalized travel itinerary planning. Natural landscape sites are generally more popular during the daytime, possibly due to ample daylight suitable for outdoor activities and sightseeing. Visits to cultural and historical sites peak in the morning and afternoon, probably because these attractions are often associated with educational and historical learning, and visitors prefer to visit during the time when they are mentally alert. Whereas modern entertainment venues experience high visitation distributed throughout the day, particularly during midnight and evening periods, reflecting their entertainment and leisure characteristics suitable for nightlife and all-day entertainment activities. Based on these findings, the mobile predictive model for personalized travel itinerary planning can more accurately capture tourists' time preferences, optimizing visit schedules to enhance satisfaction with the tourism experience and the rationality of the itinerary.

Table 1. Comparison of experimental results of different prediction methods

Model	Sample 1		Sample 2	
	RMSE	MAPE	RMSE	MAPE
ASTGCN	50.24	29.56%	49.36	29.58%
ST-GAT	48.26	28.45%	47.56	28.54%
ST-VAE	32.54	17.23%	34.25	19.35%
LSTM	37.58	20.31%	36.21	20.14%
GRU-GCN	29.65	14.56%	19.58	15.36%
STGCN	30.12	15.36%	29.65	15.48%
Bi-LSTM-GCN	27.89	14.59%	28.12	14.23%
The model proposed in this study	26.35	12.36%	25.26	12.23%

It is evident from Table 1 that the model proposed in this study exhibits superior performance across all evaluation metrics. Specifically, the model achieved a root mean square error (RMSE) of 26.35 and a mean absolute percentage error (MAPE) of 12.36% in Sample 1, while the RMSE was 25.26 and the MAPE was 12.23% in Sample 2, both significantly lower than those of the comparative models. By contrast, the traditional attention-based spatial-temporal graph convolutional network (ASTGCN) model recorded an RMSE of 50.24 and 49.36 and a MAPE of 29.56% and 29.58% in Samples 1 and 2, respectively. Although the Spatio-Temporal Variational Autoencoder (ST-VAE) and Bi-directional Long Short-Term Memory (Bi-LSTM)-Graph Convolutional Network (GCN) models performed relatively well on some metrics, they were unable to surpass the performance of the proposed model. For instance, the Bi-LSTM-GCN recorded an RMSE of 27.89 and a MAPE of 14.59% in Sample 1, and an RMSE of 28.12 and a MAPE of 14.23% in Sample 2, both of which are higher than those of the proposed model. These results demonstrate that the STGCN components based on the attention mechanism and spatial node embedding vector components proposed in this study have a significant advantage in capturing temporal and spatial dynamics. This advantage is reflected not only in prediction accuracy but also in the model's stability and generalizability. In contrast, although the traditional STGCN and recurrent neural networks are capable of capturing certain spatio-temporal features, they struggle with the dynamic complexities of travel itinerary changes. Furthermore, the proposed model, through in-depth analysis of tourism scenarios and tourist preferences, achieves more precise personalized itinerary recommendations and optimizations, providing a more efficient and reliable solution for travel itinerary planning. This further attests to the exceptional performance of the attention-based STGCN and spatial node embedding vectors in enhancing the accuracy and response speed of itinerary planning.

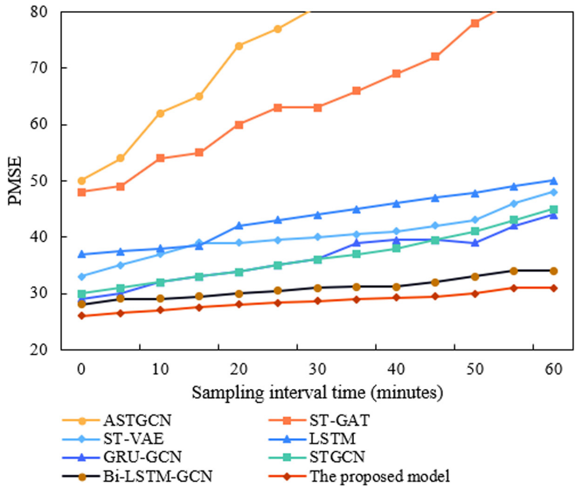


Fig. 4. Variation of RMSE with sampling interval for different prediction methods

Data from Figure 4 indicate that as the sampling interval time increases, the RMSE values for all models generally exhibit an upward trend, but there are notable differences in the magnitude and absolute values of these increases. The model proposed in this study consistently shows the lowest RMSE values across all sampling intervals. For example, at a sampling interval of 0 minutes, the RMSE of the proposed model is 26, while at an interval of 60 minutes, the RMSE increases to 31, still the lowest among all models. In contrast, the RMSE of the ASTGCN model rises from 50 to 81, and the RMSE of the spatial-temporal graph attention network (ST-GAT) model increases from 48 to 82, reflecting significant error growth. It is noteworthy that models such as ST-VAE, long short-term memory (LSTM), and gated recurrent unit (GRU)-GCN also show a notable rise in RMSE as the sampling interval increases. However, their rates of increase and absolute values remain higher than those of the proposed model. These experimental results demonstrate that the STGCN components based on the attention mechanism and spatial node embedding vector components proposed in this study effectively capture and process the temporal and spatial dynamics in travel itineraries at various sampling intervals, maintaining a lower prediction error. This stability and low error rate highlight the model's robustness and generalizability when dealing with changes in sampling intervals. By contrast, traditional models such as ASTGCN and ST-GAT exhibit significant error accumulation with increasing sampling intervals, indicating their shortcomings in capturing long-term dynamic changes.

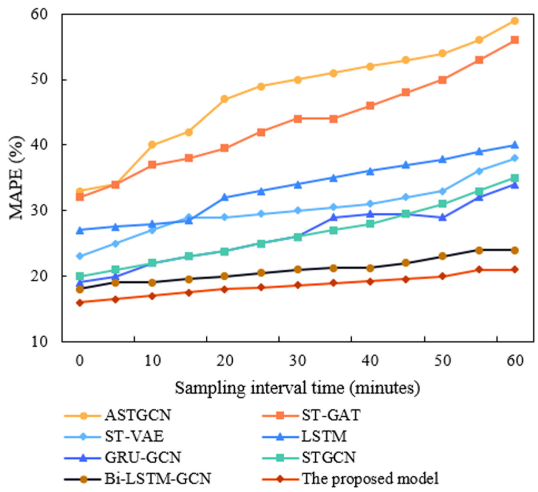


Fig. 5. Variation of MAPE with sampling interval for different prediction methods

Data from Figure 5 indicate that as the sampling interval time increases, the MAPE values for all models generally exhibit an upward trend. However, there are notable differences in the growth rates and absolute values between models. The model proposed in this study consistently shows the lowest MAPE values across all sampling intervals. For instance, at a sampling interval of 0 minutes, the MAPE of the proposed model is 16, while at an interval of 60 minutes, the MAPE rises only to 21, still the lowest recorded. In contrast, the MAPE of the ASTGCN model increases from 33 to 59, indicating a significant rise. The MAPE of the ST-GAT model increases from 32 to 56, and that of the ST-VAE and the LSTM increases from 23 to 38 and from 27 to 40, respectively. Other models, such as Bi-LSTM-GCN, GRU-GCN, and STGCN, also show a noticeable increase in MAPE with increasing sampling intervals, but their final absolute values remain higher than those of the proposed model. These experimental results demonstrate that the STGCN components based on the attention mechanism and spatial node embedding vector components proposed in this study effectively capture and process the temporal and spatial dynamics in travel itineraries at various sampling intervals, maintaining a lower prediction error. This stability and low error rate underscore the model's robustness and generalizability when dealing with changes in sampling intervals. In contrast, traditional models such as ASTGCN and ST-GAT exhibit significant error accumulation with increasing sampling intervals, indicating their deficiencies in capturing long-term dynamic changes.

4 CONCLUSION

A mobile predictive model for personalized travel itinerary planning was proposed in this study, primarily composed of STGCN components based on the attention mechanism and spatial node embedding vector components. The STGCN components are capable of comprehensively capturing the dynamic temporal and spatial features within travel itineraries, thereby enhancing the accuracy and response speed of itinerary planning. The spatial node embedding vector components, through in-depth analysis of tourism scenarios and tourist preferences, can achieve personalized itinerary recommendations and optimizations. Experimental results demonstrate that the proposed model exhibits significant advantages in the distribution of mobile visits to tourist attractions across natural landscapes, cultural and historical sites, and modern entertainment venues, accurately reflecting tourists' actual behavior patterns. In comparative experiments with different prediction methods, whether in terms of RMSE or MAPE, the proposed model consistently shows the lowest error across various sampling intervals, confirming its superior predictive performance and stability. This study holds significant value in the field of personalized travel itinerary planning. By incorporating the STGCN components based on the mechanism attention, the model effectively captures the complex dynamic features within travel itineraries, improving prediction accuracy and response speed. Moreover, the spatial node embedding vector components, through deep analysis of tourism scenarios and tourist preferences, provide more personalized itinerary recommendations, meeting the diverse needs of tourists. This not only enhances the user experience but also offers an intelligent solution for the tourism industry, aiding in the digital transformation of the sector.

5 REFERENCES

[1] G. M. Majid, I. Tussyadiah, and A. Pal, "Intelligent automation for sustainable tourism: A systematic review," *Journal of Sustainable Tourism*, vol. 31, no. 11, pp. 2421–2440, 2023. https://doi.org/10.1080/09669582.2023.2246681

[2] A. Rydzik and C. S. Kissoon, "Decent work and tourism workers in the age of intelligent automation and digital surveillance," *Journal of Sustainable Tourism*, vol. 30, no. 12, pp. 2860–2877, 2022. https://doi.org/10.1080/09669582.2021.1928680

[3] H. Liu, "Intelligent tourism information service model considering tourist experience in the environment of internet of things," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, 2022. https://doi.org/10.1155/2022/5252218

[4] G. Maquera, B. B. da Costa, Ó. Mendoza, R. A. Salinas, and A. N. Haddad, "Intelligent digital platform for community-based rural tourism—A novel concept development in Peru," *Sustainability*, vol. 14, no. 13, p. 7907, 2022. https://doi.org/10.3390/su14137907

[5] M. Redmond, A. M. Campbell, and J. F. Ehmke, "Data-driven planning of reliable itineraries in multi-modal transit networks," *Public Transport,* vol. 12, pp. 171–205, 2020. https://doi.org/10.1007/s12469-019-00221-0

[6] Y. L. Hsueh and H. M. Huang, "Personalized itinerary recommendation with time constraints using GPS datasets," *Knowledge and Information Systems*, vol. 60, pp. 523–544, 2019. https://doi.org/10.1007/s10115-018-1217-7

[7] P. Yochum, L. Chang, T. Gu, and M. Zhu, "An adaptive genetic algorithm for personalized itinerary planning," *IEEE Access*, vol. 8, pp. 88147–88157, 2020. https://doi.org/10.1109/ACCESS.2020.2990916

[8] Y. Ding, L. Zhang, C. Huang, and R. Ge, "Two-stage travel itinerary recommendation optimization model considering stochastic traffic time," *Expert Systems with Applications*, vol. 237, p. 121536, 2024. https://doi.org/10.1016/j.eswa.2023.121536

[9] A. A. da Silva, R. Morabito, and V. Pureza, "Optimization approaches to support the planning and analysis of travel itineraries," *Expert Systems with Applications*, vol. 112, pp. 321–330, 2018. https://doi.org/10.1016/j.eswa.2018.06.045

[10] K. H. Lim, J. Chan, S. Karunasekera, and C. Leckie, "Tour recommendation and trip planning using location-based social media: A survey," *Knowledge and Information Systems*, vol. 60, pp. 1247–1275, 2019. https://doi.org/10.1007/s10115-018-1297-4

[11] Y. Zhang and J. Tang, "Itinerary planning with time budget for risk-averse travelers," *European Journal of Operational Research*, vol. 267, no. 1, pp. 288–303, 2018. https://doi.org/10.1016/j.ejor.2017.11.023

[12] F. Rahmafitria, P. L. Pearce, H. Oktadiana, and H. P. Putro, "Tourism planning and planning theory: Historical roots and contemporary alignment," *Tourism Management Perspectives*, vol. 35, p. 100703, 2020. https://doi.org/10.1016/j.tmp.2020.100703

[13] J. A. D. Benito, K. Zerva, S. i Rubio, and D. Blasco, "Do not cross the line: Planning the limits of tourism in Barcelona," *Boletín de la Asociación de Geógrafos Españoles*, no. 83, 2019. https://doi.org/10.21138/bage.2835

[14] M. H. Esfehani and J. N. Albrecht, "Planning for intangible cultural heritage in tourism: Challenges and implications," *Journal of Hospitality & Tourism Research*, vol. 43, no. 7, pp. 980–1001, 2019. https://doi.org/10.1177/1096348019840789

[15] E. McLoughlin and J. Hanrahan, "Evidence-informed planning for tourism," *Journal of Policy Research in Tourism, Leisure and Events*, vol. 15, no. 1, pp. 1–17, 2023. https://doi.org/10.1080/19407963.2021.1931257

[16] E. McLoughlin and J. Hanrahan, "Local authority sustainable planning for tourism: Lessons from Ireland," *Tourism Review*, vol. 74, no. 3, pp. 327–348, 2019. https://doi.org/10.1108/TR-12-2017-0198

[17] M. López Sánchez, M. Linares Gómez del Pulgar, and A. Tejedor Cabrera, "Perspectives on proximity tourism planning in peri-urban areas," *European Planning Studies*, vol. 30, no. 12, pp. 2456–2473, 2022. https://doi.org/10.1080/09654313.2021.1961690

[18] H. V. Nguyen, L. Diane, and D. Newsome, "Kinh and ethnic tourism stakeholder participation and collaboration in tourism planning in Sapa, Vietnam," *International Journal of Culture, Tourism and Hospitality Research*, vol. 14, no. 4, pp. 579–597, 2020. https://doi.org/10.1108/IJCTHR-12-2018-0179

[19] J. C. Ponte, G. Couto, P. Pimentel, Á. Sousa, and A. Oliveira, "Municipal tourism planning in an island territory: The case of Ribeira Grande in the Azores," *Tourism Planning & Development*, vol. 18, no. 3, pp. 340–364, 2021. https://doi.org/10.1080/21568316.2020.1816567

[20] J. A. Ivars-Baidal and J. F. V. Rebollo, "Tourism planning in Spain. From traditional paradigms to new approaches: Smart tourism planning," *Boletín de la Asociación de Geógrafos Españoles*, no. 82, pp. 1–31, 2019. https://doi.org/10.21138/bage.2765

[21] J. Yang and L. Xia, "Study on tourism planning of edible fungus park from the perspective of agricultural tourism integration: Taking Muer Town in Zhashui County as a case," in *IOP Conference Series: Earth and Environmental Science*, vol. 632, 2021, no. 5, p. 052059. https://doi.org/10.1088/1755-1315/632/5/052059

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