Journal of Network Intelligence ©2026 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **11**, Number **1**, February **2026**

Recommendation of Sports Tourism Destinations Based on Spatio-Temporal Graph Attention Networks

Peng-Xiao Wang[1,*]

[1]Tourism College, Xinxiang Vocational and Technical College,
Xinxiang 453003, P. R. China
wpx52000@163.com

Kuang Jing[2]

[2]Bulacan State University, Malolos 3000, Philippines
704161029@qq.com

*Corresponding author: Peng-Xiao Wang

Received November 8, 2024, revised February 19, 2025, accepted May 20, 2025.

Abstract. *The sports tourism sector has also risen rapidly in line with the fast expansion of the economy; the demand of consumers for tailored destination recommendations is also rising. Conventional recommendation algorithms make it challenging to fulfill users' individual interests since they usually overlook the spatio-temporal aspects of user activity. This work thus presents a sports tourism location selection model based on spatio-temporal graph attention network (STG-Attention). By means of the spatio-temporal graph network, the model generates a dynamic interaction model between users and destinations by combining the spatial relationship between destinations and time-series data of user behavior. Furthermore, included in the STG-Attention model is the CBAM attention mechanism, which helps the model to recognize and strengthen the influencing elements of user decision-making, so increasing the relevance and accuracy of recommendations and so improving the responsiveness to users' individualized needs. We developed a set of studies comprising model performance comparison, ablation experiments and parameter sensitivity analysis to fully assess the STG-Attention model. Regarding recommendation accuracy and generalisation capacity, all the experimental findings reveal that the STG-Attention model beats current approaches. This work offers fresh ideas and approaches for the analysis of sports tourism destination selection system as well as important references for next studies in allied disciplines.*
Keywords: sports tourism; destination recommendation; spatio-temporal maps; attention mechanisms.

---

1. **Introduction.** Personalised location recommendations are in more demand as the sports tourism sector grows quickly [1]. No longer satisfied with cookie-cutter packages, travellers seek unique experiences tailored to their personal preferences and schedules. However, most existing recommender systems fail to capture the complexity of user-destination interactions, especially ignoring the temporal and spatial dimensions of user behaviour [2]. This shortcoming motivates us to explore novel models that can provide more accurate and personalised recommendations [3].

1.1. **Related work.** In the field of sports tourism destination recommender systems, researchers have explored a variety of approaches to improve the accuracy and user satisfaction of recommender systems. These research methods can be mainly categorised as follows:

One class of research focuses on content-based recommendation methods [4], which recommend destinations that may be of interest to users by analysing the attribute characteristics of the destination [5], such as geographic location [6], climatic conditions [7], cultural background, etc., as well as the user's personal preferences [8]. The advantage of this approach is that it can bring users a novel travel experience, but it also suffers from the problem of not being able to fully consider the dynamic changes in user behaviour.

Another type of research is based on collaborative filtering methods [9], which generate recommendations by analysing the similarity between users or the similarity between destinations [10]. User similarity approaches rely on historical user behavioural data, while item similarity approaches focus on the characteristics of destinations [11]. Despite the success of collaborative filtering techniques in many recommender systems, it encounters cold-start problems when dealing with new users or new destinations. Content-based recommendation has the issue that it cannot fully take into account the dynamic changes of user behavior even if it can deliver users new trip experiences. When handling new users or new locations, the collaborative filtering approach will run across the cold-start issue instead.

In recent years, deep learning techniques have garnered significant attention in the field of recommender system research. Researchers have endeavored to employ Recurrent Neural Networks (RNN) and Long Short-Term Memory Networks (LSTM) to analyze time-series characteristics of user behavior to forecast the user's subsequent action [12]. These models excel in processing sequential data; yet, they typically necessitate substantial training datasets and encounter difficulties in elucidating recommendation outcomes [13]. Graph-based recommender systems elucidate intricate linkages by creating interaction graphs between users and destinations.

Graph Convolutional Networks (GCNs) serve as an effective instrument for discerning intricate relationships between users and destinations [14]. The methodologies have advanced in elucidating intricate links between users and destinations; yet, there remains potential for enhancement in addressing the temporal and geographical aspects of user behavior [15].

Notwithstanding the findings of current research, prevailing recommender systems continue to encounter difficulties in addressing the temporal and spatial dimensions of user behavior, managing extensive datasets, and delivering interpretable recommended outcomes [16]. This paper proposes a sports tourism destination recommendation model based on a spatio-temporal graphic attention network, which integrates spatio-temporal information and deep learning techniques to enhance the accuracy and personalization of recommendation services.

1.2. **Contribution.** In response to this context, our research presents an innovative recommendation model, STG-Attention. The key contributions of our model are as follows:

(1) **Spatio-temporal graph network**: We develop a graph network that integrates both the time dynamics of user behavior and the spatial links among users and destinations. The network employs geolocation and visit timestamps to identify seasonal trends and peak travel periods.
(2) **CBAM Attention Module**: We utilize CBAM to augment the model's capacity to discern significant feature channels and concentrate on the most pertinent spatial locations, consequently enhancing the model's performance and interpretability.

(3) **Experimental validation**: Through comprehensive tests, including performance comparisons, ablation studies, and sensitivity analyses, we establish the superiority of STG-Attention regarding suggestion accuracy and generalization capability.

2. Theoretical analysis.

2.1. Space-time map network.

The establishment of a spatio-temporal graph network is essential in a sports tourism destination recommendation system, since it encapsulates the intricate interactions between user behavior and locations. Spatial-temporal graph networks, in contrast to typical graph networks, consider the connectivity between users and destinations as well as the information in both time and spatial dimensions [17].

The initial stage in building a spatiotemporal graph network is to specify the nodes and edges. In this study, each user and each sport tourism destination is regarded as a node inside the network. Connections between nodes indicate whether users visit or are interested in a specific site, and the weights of these edges reflect how often users visit or how strongly they are interested in a place [18].

A distance metric based on geographic location was employed to measure the physical relationship between nodes. The following formula was used to determine the distance between any two locations:

$$d_{ij} = \sqrt{(\Delta x_{ij})^2 + (\Delta y_{ij})^2} \tag{1}$$

where Δx_{ij} and Δy_{ij} denote the differences in longitude and latitude between destinations i and j, respectively.

Examining user behavior timestamps helps one to add the temporal component [19]. Consequently, within a given period the network can identify seasonal trends and spikes in visitor activity. A temporal decay factor α represents variations in user interest.

$$w_{ij}(t) = w_{ij} \cdot e^{-\alpha(t-t_{last})} \tag{2}$$

When w_{ij} denotes the initial weight of the edge connecting nodes i and j, t represents the current time, t_{last} indicates the time of the user's last interaction with destination j, and α signifies the time decay rate.

One interesting property of spatio-temporal graph networks is their capacity to adapt and recognize trends in user activity. Graph Neural Network (GNN) methods teach embedded node representations that capture intricate user behavior and destination attributes, therefore enabling the network. The following describes how the node embeddings are updated:

$$H^{(l+1)} = \sigma(W^{(l+1)}H^{(l)} + b^{(l+1)}) \tag{3}$$

where $H^{(l)}$ denotes the node embedding of the l-th layer, whereas $W^{(l+1)}$ and $b^{(l+1)}$ represent the weight matrix and bias vector of the subsequent layer, respectively, and σ signifies the activation function, such as ReLU or tanh.

Adapting to fresh data and offering real-time updated recommendations, the spatio-temporal graph network can help to better meet consumers' needs.

We apply dropout and regularization techniques to lower overfitting and improve the generalizing ability of the model. This guarantees not just generalizing to fresh data but also remarkably performance on training data. Resilient and adaptable framework for choosing sports tourism sites is given by spatio-temporal graph networks [20].

2.2. **Attention mechanisms.** The attention strategy significantly improves the capacity of the model to meet the particular needs of users in the sports tourism destination recommendation system. Different weighting for every variable helps the model to find and highlight the elements most affecting the user's choice, hence improving the relevance and accuracy of the recommendation.

We computed the attention weights by the following formula [21]:

$$\alpha_{i,j} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})} \tag{4}$$

where α_{ij} denotes the attentional weight of node i on node j, e_{ij} represents the energy function of the interaction between node i and node j, and $N(i)$ signifies the collection of neighboring nodes of node i.

The energy function e_{ij} can be delineated by evaluating many attributes between the user and the destination, including the user's preferences, the destination's popularity, and the temporal distance separating them:

$$e_{ij} = \beta \cdot f_{user}(i) + \gamma \cdot f_{dest}(j) - \delta \cdot d_{ij} \tag{5}$$

where $f_{user}(i)$ and $f_{dest}(j)$ denote the feature vectors of user i and destination j, respectively, which are automatically extracted by deep learning, including but not limited to the user's activity history, preference settings, visit frequency of the destination, and user ratings, etc. β, γ and δ are the model parameters, which control how much different features contribute to the interaction energy. d_{ij} is the temporal distance between user i and destination j, which reflects the change in the visit frequency of the user to the destination over time. j is the temporal distance between user i and destination j, which reflects the frequency of user visits to the destination over time.

This study presents the CBAM attention mechanism [22]. Using the channel attention module, the CBAM first detects the interactions across several feature channels; next, it concentrates on spatially significant areas using the spatial attention module. By means of this dual attention approach, the model finds the most spatially significant regions and detects the most informative feature channels. Incorporated in our model, the CBAM mechanism uses channel and spatial attention to find and highlight the most important aspects in users' decision-making process choosing sports tourism sites.

Our system can more precisely determine users' particular requirements and offer exact recommendations for sports tourism sites.

3. Enhancing Sports Tourism Destination Recommendations with Spatio-Temporal Graph Attention Networks: STG-Attention.

3.1. **Components for building networks with temporal and geographical correlation.** The adjacency matrix of the graph is built using the module of spatio-temporal correlation network creation to show the spatial links among nodes. Our graph's adjacency matrix can both measure node interactions and dependencies and capture their spatial relationship. The module may learn the adjacency matrix of graph adaptably to expose the probable one-way association between nodes. Every tourist destination in this module is seen as a node in the graph, and the adjacency matrix allows one to quantify and show its interactions and dependencies. The module may learn the graph adjacency matrix adaptably to expose possible unidirectional correlations between nodes.

Computational principle of the module:

(1) Firstly, nodes are mapped to a high-dimensional vector space by randomly initialising their embeddings [23]. These embedding vectors are learnt during training and are

continuously updated and optimised as the model is trained, in order to facilitate a more accurate capture of the feature representation of the nodes.

(2) Subsequently, the node embeddings are multiplied with the model parameters and the tanh activation function is applied to generate the intermediate matrices M_1 and M_2, the above process is represented as:

$$M_1 = \tanh(\alpha E_1(a)\theta_1) \tag{6}$$

$$M_2 = \tanh(\alpha E_2(a)\theta_2) \tag{7}$$

$$a = \{a_0, a_1, \ldots, a_n\} \tag{8}$$

where E_1 and E_2 are node embeddings, which can be learnt during the training process; a is the input node, n is the number of nodes; θ_1 is the model parameter, and α is the hyperparameter of the control activation function.

(3) Then, the distance metric between the nodes is calculated using the intermediate matrices M_1 and M_2, and the asymmetric neighbourhood matrix is generated by subtraction, tanh activation function and ReLU activation function to reflect the unidirectional correlation strength between the nodes.

The computation of the adjacency matrix A is performed as:

$$A = \mathrm{ReLU}(\tanh(\alpha(M_1 M_2^T - M_2 M_1^T))) \tag{9}$$

(4) To ensure that the learned adjacency matrix can effectively capture the node spatial relationships and maintain the generalisation ability of the model, a sparsification strategy is adopted, i.e., for each node, the weights of the first k nearest neighbours of the node are kept unchanged, while the weights of the other nodes are set to zero. For node i, the above process can be expressed as:

$$idx = \arg\mathrm{topk}(A[i,:]) \tag{10}$$

$$A[i, -idx] = 0 \tag{11}$$

where argtopk function returns the index of the first k maxima of node i in the adjacency matrix; idx is the index of the first K maxima of node i in the adjacency matrix; $-idx$ is the complement of idx, i.e., the indexes of the nodes other than the first k neighbours. In this paper, we set the value of k to 4.

3.2. **Multidimensional spatio-temporal feature extraction module.** It comprises essentially of an attention mechanism composition, a graph convolutional layer, and a temporal convolutional layer. The temporal relevance of sports tourism activities is captured by the temporal convolution layer; the graph convolution layer generates spatially aggregated features of every node using the spatio-temporal graph of the spatio-temporal association network building module, which is in charge of capturing the spatial relevance of the sports tourism destinations; and the attention mechanism focuses on identifying significant information. Furthermore included in the module are multi-stage feature fusion techniques and residual linkage to improve the expressive capacity of the model [24].

(1) Time Convolution Layer: The information of several time spans and the nonlinear characteristics of time series can be obtained using the temporal convolution layer. Expanding convolution is employed in this layer to extract intricate temporal data; the receptive field is enlarged by a preset interval thereby allowing the network to catch a larger spectrum of contextual information without raising parameters. Using expansion factor 1, the input sequence of expansion convolution gathers the information of hidden layer; subsequently, it generates the output sequence by expansion convolution using expansion factor 2.

Using four distinct kernel sizes—$1 \times 2, 1 \times 3, 1 \times 6$, and 1×7—the layer employs an inflationary convolution to extract information over many temporal scales. This multi-scale convolution kernel helps the network to find both long-term trends in the time series and short-term perturbations, therefore offering complete data for forecasting.

One expresses the computational formula as:

$$F = \mathrm{concat}(x \times f_{1\times2}, x \times f_{1\times3}, x \times f_{1\times6}, x \times f_{1\times7}) \tag{12}$$

x is the input feature of the temporal convolution layer; f is the convolution kernel; concat helps data merging. The inflated convolution has f as its output feature.

The layer is composed of two expansion convolutions, each of which is then followed by a completely different activation function. The tanh activation function acts as a filter to convert the input time series data into a nonlinear representation. The utilization of the sigmoid activation function comes after the second expansion convolution. It serves as a gating device that controls the information. Ultimately, the outputs of these 2 expansion convolutions are multiplied together to form the final output:

$$H = \tanh(F)\mathrm{sigmoid}(F) \tag{13}$$

where H is the time convolution layer output feature.

(2) Graph Convolution Layer: The graph convolution layer utilizes the spatio-temporal graph from the spatio-temporal association network building module to assimilate information from adjacent nodes [25], provide spatial aggregation features for the nodes, and augment the model's capacity to discern spatial relationships. The layer uses a hybrid hop propagation layer to process node information. The specific hybrid hop propagation layer execution process is shown in Figure 1.

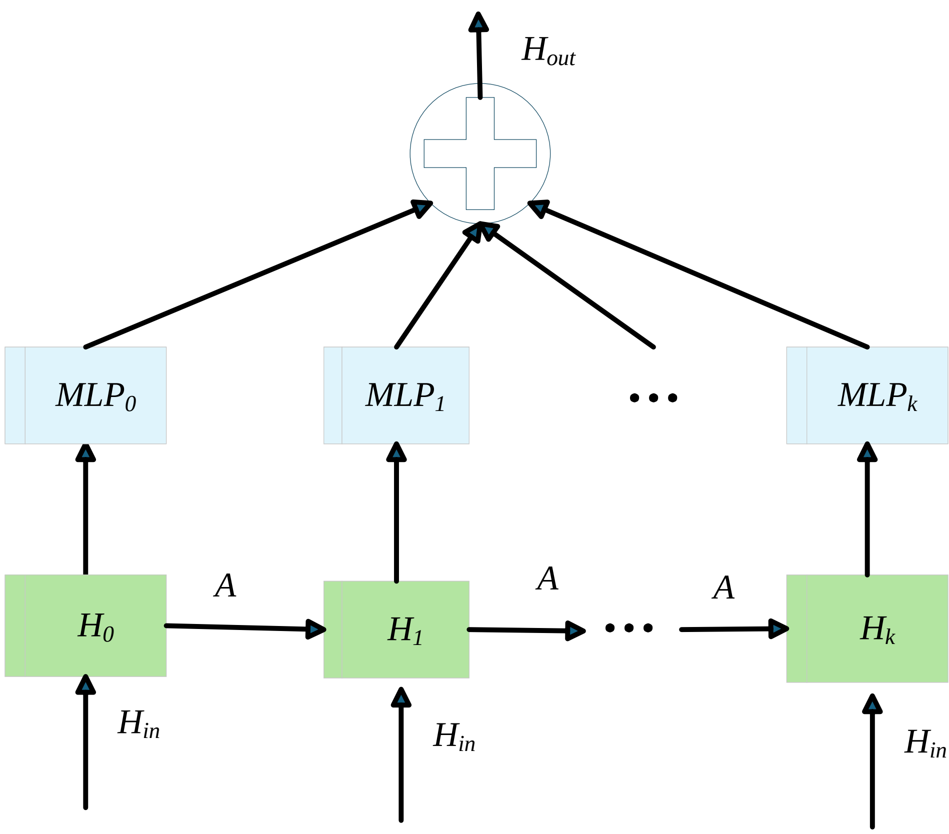

Figure 1. Mix-hop Propagation Layer

In Figure 1, H_{in} is the input feature of the graph convolutional layer, H_k is the state of the node after the k-th hop of information propagation, MLP_k is the multilayer perceptron of the k-th hop, H_{out} is the output feature, and A is the graph neighbourhood matrix. Information propagation can be represented as:

$$H_{A,k} = \beta H_{in} + (1-\beta)\tilde{A}H_{A,k-1} \tag{14}$$

where $H_{A,k}$ is the state of the node after the propagation of information from the input adjacency matrix A at the k-th hop; β is a hyperparameter controlling the proportion of the node that maintains its initial state; H_{in} is an input feature; and $\tilde{A}$ is the normalised adjacency matrix.

The information selection step is defined as:

$$H_{A,out} = \sum_{i=0}^{K} H_{A,k}W_k \tag{15}$$

where $H_{A,out}$ are the output features of the input adjacency matrix A; K is the propagation depth; W is the weight coefficient. The outputs of two hybrid hop propagation layers are combined:

$$H_{updat} = H_{A,out} + H_{A^T,out} \tag{16}$$

where H_{updat} is the graph convolution layer output feature.

(3) CBAM Attention Mechanism: In order to retain information for a long time while highlighting the feature values, this paper adopts the CBAM attention mechanism [27]. The structure of the CBAM attention mechanism is shown in Figure 2.

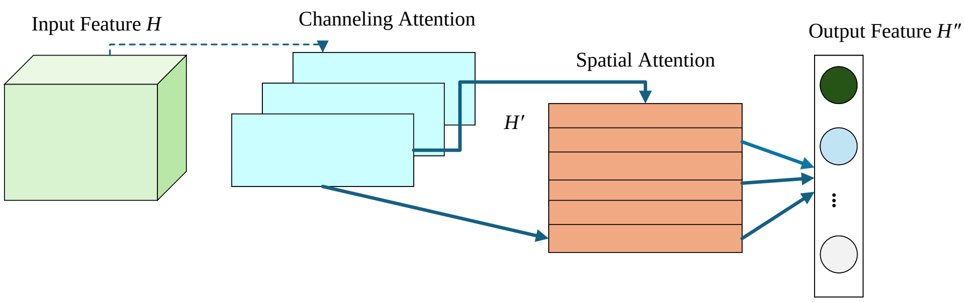

Figure 2. CBAM Attention Mechanism Structure

The channel attention weights are calculated as:

$$M_c(H) = \sigma(\text{MLP}(\text{AvgPool}(H)) + \text{MLP}(\text{MaxPool}(H))) \tag{17}$$

where the MLP is the multilayer perceptual machine; AvgPool is the average pooling operation; MaxPool is the maximum pooling operation; H is the input feature.

The spatial attention module is calculated as:

$$M_s(H') = \sigma(f_{7\times 7}[\text{AvgPool}(H'); \text{MaxPool}(H')]) \tag{18}$$

where H' is the output feature that passes through the channel attention module; $f_{7\times 7}$ is a convolution operation with a kernel size of 7×7. The final CBAM output is:

$$H' = M_c(H)H \tag{19}$$

$$H'' = M_s(H')H' \tag{20}$$

where H'' is the output of CBAM.

(4) Multi-stage feature fusion: The outputs are spliced through jump connections [29]. Firstly, the temporal features are summed to obtain feature S:

$$S = \sum_{j=1}^{J} z_j \tag{21}$$

where J is the number of stages (set to 5); z is the stage features. Subsequently, global average pooling and convolution are applied:

$$S_{GAP} = f_{GAP}(S) = \frac{1}{ND} \sum_{n=1}^{N} \sum_{m=1}^{D} S(n, m) \tag{22}$$

$$Z = conv(S_{GAP}) \tag{23}$$

where f_{GAP} is the global average pooling operation; N is the number of variables; D is the number of dimensions. The weights are generated using:

$$w_j = \text{softmax}(Z_j) = \frac{e^{Z_j}}{\sum_{k=1}^{J} e^{Z_k}}, 1 \leq j \leq J \tag{24}$$

Finally, multi-stage feature fusion is achieved by:

$$F_{sum} = \sum_{j=1}^{J} w_j Z_j \tag{25}$$

4. **Performance testing and analysis.**

4.1. **Experimental setup.** We use a sports tourism dataset containing 10,000 users which covers user behaviour between 2019 and 2023. Table 1 provides a detailed description of the dataset:

Table 1. STG-Attention data sets

Feature Category	**Description**
User Features	Age, gender, occupation, travel preferences, etc.
Destination Features	Type (e.g., mountain climbing, skiing), geographical location (latitude and longitude), facility completeness, visitor count, etc.
User Behavior	Number of visits, duration of stay, rating scores, timestamps of visits, etc.

The dataset is preprocessed with missing value processing, outlier removal and normalisation. The model uses Adam optimiser with a learning rate of 10^{-5} and 200 training rounds. Other parameter settings are shown in Table 2:

4.2. **Evaluation indicators.** In this paper, mean square error, mean absolute error and coefficient of determination are used as evaluation indexes, which are calculated by the formulae respectively:

$$e_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{26}$$

$$e_{\text{MAE}} = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{27}$$

Table 2. STG-Attention model parameters

Parameter Name	**Value**
Hidden Layer Dimension	128
Number of Graph Convolution Layers	3
Number of Temporal Convolution Layers	2
Number of Attention Heads	4
Dropout Rate	0.2
Batch Size	32

$$e_{R^2} = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y} - y_i)^2} \tag{28}$$

where e_{MSE} is the mean square error; e_{MAE} is the mean absolute error; e_{R^2} is the coefficient of determination; y_i is the actual value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the average of the actual values, and n is the sample size.

4.3. **Experimental process and results.** In order to verify the validity of the STG-Attention model, we conduct the experiment according to the following steps:

(1) **Model training**: We trained our model on 80% of the dataset, fine-tuning parameters such as graph convolution layers and hidden layer dimensions to optimize its configuration. The goal was to enable the model to predict users' potential interests in various destinations based on their behavior, preferences, and destination attributes.

(2) **Model validation**: We used the remaining 10% of the data as a set of checks to help to strengthen the model. This phase seeks to prevent model overfitting and assure best performance on fresh data.

(3) **Model evaluation**: We tested the model's ultimate performance using the remaining 10% of the data as a test set. Along with the accuracy and dependability of its recommendations, this step seeks to evaluate the model's relevance in pragmatic uses.

We subsequently evaluate the model's performance by several experiments, including performance comparison, ablation investigations, and parameter sensitivity analysis.

(1) **Model performance comparison**

We analyze the performance of the STG-Attention model by means of several different recommendation models, namely Collaborative Filtering (CF), Matrix Factorization (MF), and the Deep Learning Recommendation Model (DLRM). Figure 3 shows the experimental data.

The STG-Attention model surpasses all baseline models across every evaluation metric. The STG-Attention model efficiently captures the intricate interplay between user behaviors and destination attributes to deliver personalized travel destination recommendations.

(2) **Ablation Experiments**

To assess the efficacy of each component in the model, we performed ablation experiments. We systematically eliminated the spatio-temporal graph network, the attention mechanism, and the multi-stage feature fusion module from the model, assessing the performance of each component individually. Figure 4 illustrates the outcomes of the tests.

(3) **Parameter sensitivity analysis**

To assess the model's sensitivity to various parameters, we adjusted the learning rate, size of the hidden layers, and the quantity of graph convolution layers, and evaluated

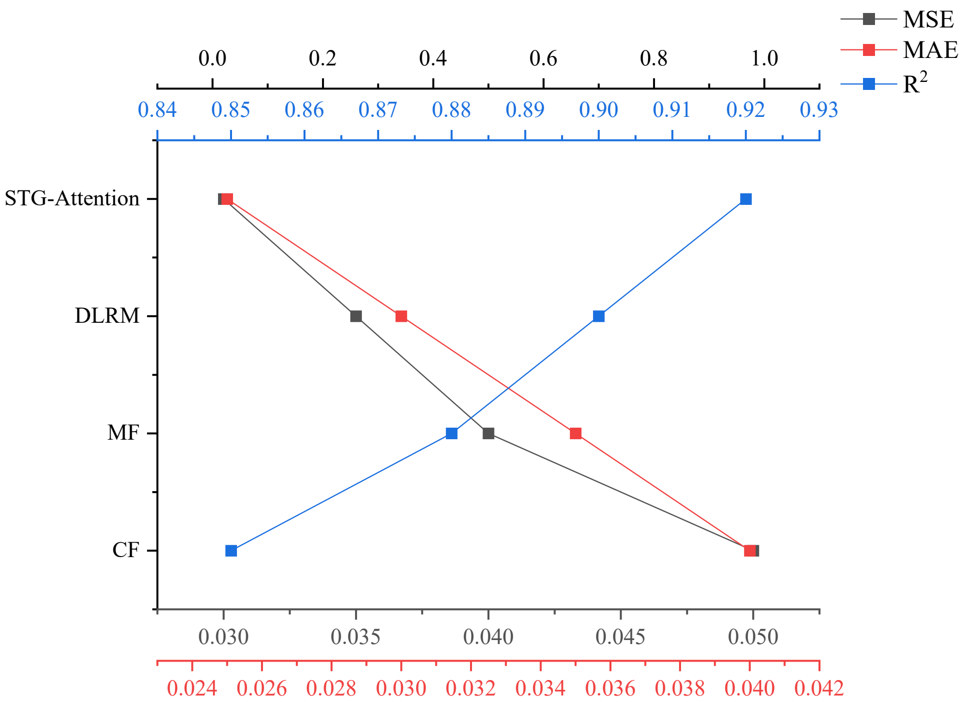

Figure 3. Comparison of Experimental Results for Model Performance

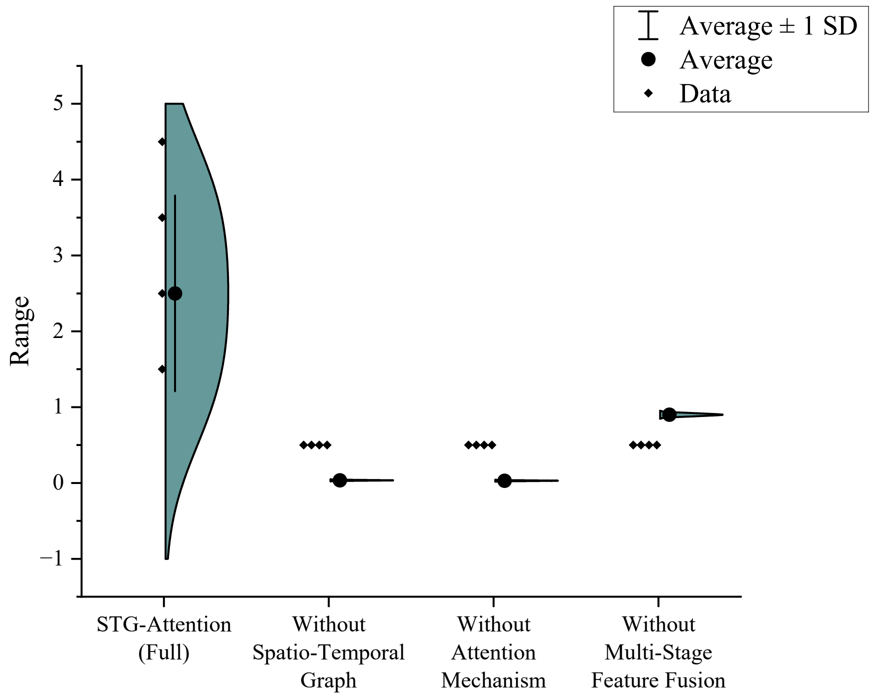

Figure 4. Results of the Ablation Experiment

the effects of these modifications on model performance. The experimental findings are illustrated in Figure 5.

The results of the parameter sensitivity analysis show that the model is more sensitive to the learning rate and hidden layer dimension. The model attains optimal performance

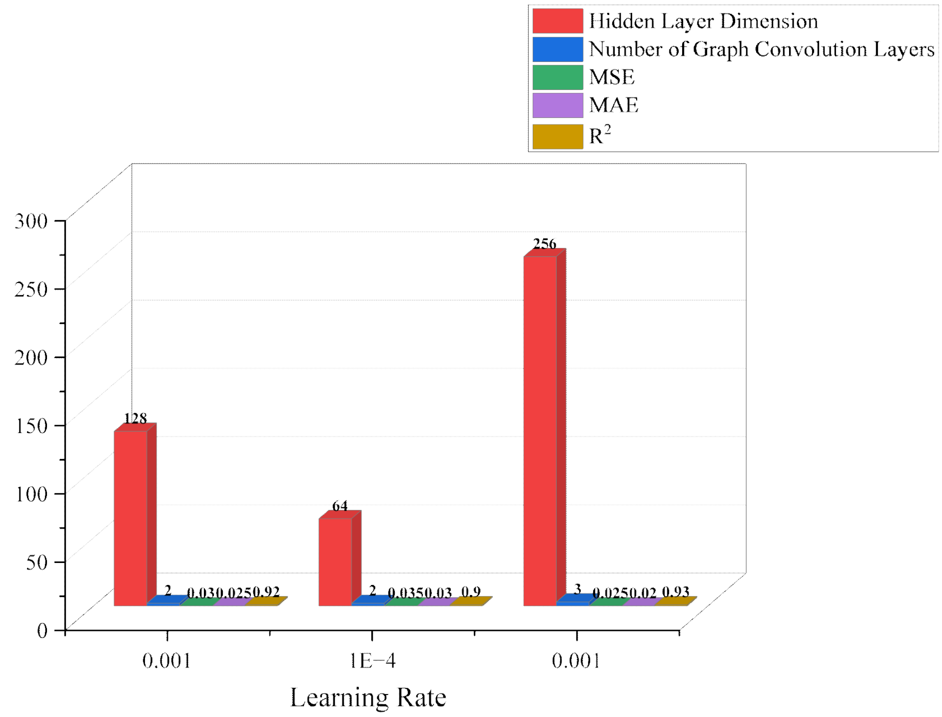

Figure 5. Experimental results of parameter sensitivity analysis

with a learning rate of 0.001, a hidden layer dimension of 128, and two graph convolution layers. Augmenting the hidden layer depth and the quantity of graph convolution layers, while diminishing the learning rate, can enhance the R^2 value of the model and decrease the MSE and MAE.

5. **Conclusion.** This work shows that choosing sports tourism destinations benefits much from our proposed STG-Attention model. This approach improves the understanding of the links between user behavior and destinations by combining an attention mechanism with a spatio-temporal graph network, therefore providing custom recommendations. Our experimental results confirm the significant improvement of STG-Attention over traditional approaches in improving suggestion precision and allowing new contexts.

Notwithstanding the preliminary success of the STG-Attention model, certain obstacles arose during the investigation. The success of the model is closely correlated with the quality and variation of the used datasets. The present dataset might not be sufficient to cover all user demographics and destinations, thereby restricting the model's performance in many different settings. Furthermore, compromising the quality of recommendations can be data bias and noise.

We intend to apply more developments and expansions to the STG-Attention concept. The aim is to enable the model to process user data from many geographies and cultural settings as well as a larger spectrum of destination information, therefore improving the generalizing and adaptability of the model. Acquiring and combining a wider range of data sources and improving data processing techniques can help to solve the increasing volume and complexity of data.

Future studies are expected to improve the performance of the STG-Attention model, therefore enabling its implementation in a wider range of real-world settings. These projects will help to improve the sports tourism recommender system development. They also seek to add fresh ideas and innovations to the more general topic of recommender systems.

REFERENCES

[1] M. Batet, A. Moreno, D. Sánchez, D. Isern, and A. Valls, "Turist@: Agent-based personalised recommendation of tourist activities," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7319–7329, 2012.

[2] A. Faghih-Imani and N. Eluru, "Incorporating the impact of spatio-temporal interactions on bicycle sharing system demand: A case study of New York CitiBike system," *Journal of Transport Geography*, vol. 54, pp. 218–227, 2016.

[3] L. Coba, P. Symeonidis, and M. Zanker, "Personalised novel and explainable matrix factorisation," *Data & Knowledge Engineering*, vol. 122, pp. 142–158, 2019.

[4] J. Shu, X. Shen, H. Liu, B. Yi, and Z. Zhang, "A content-based recommendation algorithm for learning resources," *Multimedia Systems*, vol. 24, no. 2, pp. 163–173, 2018.

[5] H. R. Seddighi and A. L. Theocharous, "A model of tourism destination choice: a theoretical and empirical analysis," *Tourism Management*, vol. 23, no. 5, pp. 475–487, 2002.

[6] H.-Y. Shih, "Network characteristics of drive tourism destinations: An application of network analysis in tourism," *Tourism Management*, vol. 27, no. 5, pp. 1029–1039, 2006.

[7] A. Bujosa, A. Riera, and C. M. Torres, "Valuing tourism demand attributes to guide climate change adaptation measures efficiently: The case of the Spanish domestic travel market," *Tourism Management*, vol. 47, pp. 233–239, 2015.

[8] X. Wang, X. R. Li, F. Zhen, and J. Zhang, "How smart is your tourist attraction?: Measuring tourist preferences of smart tourism attractions via a FCEM-AHP and IPA approach," *Tourism Management*, vol. 54, pp. 309–320, 2016.

[9] L. Fu and X. Ma, "An improved recommendation method based on content filtering and collaborative filtering," *Complexity*, vol. 2021, no. 1, pp. 5589285, 2021.

[10] A. G. Martín, A. Fernández-Isabel, I. Martín de Diego, and M. Beltrán, "A survey for user behavior analysis based on machine learning techniques: current models and applications," *Applied Intelligence*, vol. 51, no. 8, pp. 6029–6055, 2021.

[11] H.-N. Kim, A.-T. Ji, I. Ha, and G.-S. Jo, "Collaborative filtering based on collaborative tagging for enhancing the quality of recommendation," *Electronic Commerce Research and Applications*, vol. 9, no. 1, pp. 73–83, 2010.

[12] L. Larasati, S. Saadah, and P. E. Yunanto, "Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) Methods to Forecast Daily Turnover at BM Motor Ngawi," *Indonesian Journal of Artificial Intelligence and Data Mining*, vol. 7, no. 1, pp. 141–147, 2024.

[13] T. Ching et al., "Opportunities and obstacles for deep learning in biology and medicine," *Journal of the Royal Society Interface*, vol. 15, no. 141, pp. 20170387, 2018.

[14] H. Mansoor, M. S. Gull, H. Rauf, M. Khalid, and N. Arshad, "Graph Convolutional Networks based short-term load forecasting: Leveraging spatial information for improved accuracy," *Electric Power Systems Research*, vol. 230, pp. 110263, 2024.

[15] D. J. Peuquet, "It's about time: A conceptual framework for the representation of temporal dynamics in geographic information systems," *Annals of the Association of American Geographers*, vol. 84, no. 3, pp. 441–461, 1994.

[16] J. Hastings, M. Glauer, R. West, J. Thomas, A. J. Wright, and S. Michie, "Predicting outcomes of smoking cessation interventions in novel scenarios using ontology-informed, interpretable machine learning," *Wellcome Open Research*, vol. 8, no. 503, pp. 503, 2023.

[17] K.-H. N. Bui, J. Cho, and H. Yi, "Spatial-temporal graph neural network for traffic forecasting: An overview and open research issues," *Applied Intelligence*, vol. 52, no. 3, pp. 2763–2774, 2022.

[18] S. Min, Z. Gao, J. Peng, L. Wang, K. Qin, and B. Fang, "Stgsn—a spatial–temporal graph neural network framework for time-evolving social networks," *Knowledge-Based Systems*, vol. 214, pp. 106746, 2021.

[19] R. Rawassizadeh, E. Momeni, C. Dobbins, J. Gharibshah, and M. Pazzani, "Scalable daily human behavioral pattern mining from multivariate temporal data," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 11, pp. 3098–3112, 2016.

[20] A. Ali, Y. Zhu, and M. Zakarya, "Exploiting dynamic spatio-temporal graph convolutional neural networks for citywide traffic flows prediction," *Neural Networks*, vol. 145, pp. 233–247, 2022.

[21] L. Bramlage and A. Cortese, "Generalized attention-weighted reinforcement learning," *Neural Networks*, vol. 145, pp. 10–21, 2022.

[22] L. Du, Z. Lu, and D. Li, "Broodstock breeding behaviour recognition based on Resnet50-LSTM with CBAM attention mechanism," *Computers and Electronics in Agriculture*, vol. 202, p. 107404, 2022.

[23] A. Joshi, R. De Smet, K. Marchal, Y. Van de Peer, and T. Michoel, "Module networks revisited: computational assessment and prioritization of model predictions," *Bioinformatics*, vol. 25, no. 4, pp. 490–496, 2009.

[24] Y. Wang and C. Jing, "Spatiotemporal graph convolutional network for multi-scale traffic forecasting," *ISPRS International Journal of Geo-Information*, vol. 11, no. 2, pp. 102, 2022.

[25] L. Ge, K. Wu, Y. Zeng, F. Chang, Y. Wang, and S. Li, "Multi-scale spatiotemporal graph convolution network for air quality prediction," *Applied Intelligence*, vol. 51, pp. 3491–3505, 2021.

[26] Q. Xia and J. M. Jornet, "Multi-hop relaying distribution strategies for terahertz-band communication networks: A cross-layer analysis," *IEEE Transactions on Wireless Communications*, vol. 21, no. 7, pp. 5075–5089, 2021.

[27] W. Wang, X. Tan, P. Zhang, and X. Wang, "A CBAM based multiscale transformer fusion approach for remote sensing image change detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 6817–6825, 2022.

[28] B. Zhang, Y. Zhang, and S. Wang, "A lightweight and discriminative model for remote sensing scene classification with multidilation pooling module," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 8, pp. 2636–2653, 2019.

[29] Q. Cui, H. Sun, Y. Kong, X. Zhang, and Y. Li, "Efficient human motion prediction using temporal convolutional generative adversarial network," *Information Sciences*, vol. 545, pp. 427–447, 2021.

[30] K. Hu et al., "Overview of temporal action detection based on deep learning," *Artificial Intelligence Review*, vol. 57, no. 2, pp. 26, 2024.