Research on Engineering Structures & Materials
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Research Article

Optimization of spatial coupling mechanism of mountain tourism architecture based on environmental behavior theory and data-driven intelligence

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Article Info

Article History:

Received 04 Aug 2026

Accepted 16 Sep 2026

Keywords:

Environmental behavior theory;
Mountain tourism;
GGNN;
Architectural space;
Coupling mechanism optimization;
Spatial layout optimization

Abstract

Optimizing the spatial coupling mechanism of mountain tourism architecture is essential for improving spatial adaptability, functional coordination, and sustainable development under complex environmental constraints. This study proposes an artificial intelligence-driven optimization model based on environmental behavior theory for intelligent spatial analysis and decision-making. The model integrates a robustly optimized BERT pretraining approach and K-medoids clustering to extract and classify tourist behavioral characteristics, while Gated Graph Neural Networks and Temporal Convolutional Networks perform multidimensional spatial coupling analysis by considering environmental interactions and functional relationships. A Genetic Algorithm combined with Simulated Annealing is further employed to optimize the spatial coupling mechanism and improve adaptive configuration. Experimental results show that the proposed model achieves a pain-point identification accuracy of 95.32% and a coupling coordination level of 0.827, outperforming comparison models in spatial optimization effectiveness. The model contains 30.85M parameters and requires only 7.51 s for execution, demonstrating high computational efficiency. The above results indicate that the proposed framework can provide an effective data-driven method for intelligent analysis and layout optimization of mountain tourism architectural spaces, demonstrating good computational accuracy and coupling optimization effects in the case scenarios covered by the experiment, and providing methodological references and technical support for architectural spatial planning and facility configuration in similar mountain tourism areas.

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1. Introduction

1.1 Research Significance

Mountain tourism, as one of the important parts of the global tourism industry, depends on its own unique natural landscape, ecological basis, and local cultural resources, and it is one of the main driving forces for the promotion of regional economic development, rural revitalization, and the transformation of ecological value [1]. However, due to the complex mountain terrain, mountain tourism architecture generally suffers from problems such as single functions and scattered layouts, which lead to the disconnection between service facilities and scenic spot spaces, as well as redundant tourist circulation routes. These issues make it difficult to meet the current diverse and comfort-oriented demands of tourists, thereby affecting the comprehensive benefits of the mountain tourism industry [2-3]. The spatial coupling mechanism of tourism architecture can optimize architectural layout and functions by coupling the architectural space system with subsystems such as mountain terrain, effectively enhancing tourist experience, and thus holds significant theoretical value and practical significance [4]. During the process of optimization of the spatial coupling mechanism of mountain tourism architecture, by organically coupling and

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DOI: http://dx.doi.org/10.17515/resm2026-2108in0804rs

synergistically adapting architectural space systems with subsystems including mountain topography and service demands, it is possible to achieve a systematic optimization of architectural layout and functional configuration in terms of spatial structure, functional organization, and landscape integration in a state of deep unity between architecture and environment, culture and tourism, and function and experience [5].

1.2 Research Status

To optimize the spatial coupling mechanism of tourism architecture, many scholars have conducted in-depth research. To develop the economy of the tourism industry, Z. Yu et al. proposed a coupling mechanism optimization model based on coupling coordination degree. They coupled the patterns of tourism space with information like fiscal revenue per capita in local regions by using an exploratory spatial data analysis model and explored the influence of various factors on tourism space, thus optimizing architectural spatial layout [6]. Regarding the optimization of spatial coupling value in tourism architecture, M. Mieli et al. proposed a coupling mechanism optimization model based on the concept of "physical-digital integration." With tourists as the target orientation, they created "physical-digital paths" and analyzed information such as tourists' path choices and behavioral activities to optimize architectural spatial layout [7]. To improve the comprehensive benefits of scenic spots, W. Jin et al. proposed a coupling mechanism optimization model based on the Segment Anything Model. They analyzed the visual elements of scenic spot architectural spaces through the Segment Anything computer model and examined the correlation between tourists' subjective aesthetic ratings and objective scenic spot elements using computer vision analysis algorithms [8]. Addressing the optimization of architectural spatial layout, H. Tang et al. proposed a coupling mechanism optimization model based on the Latent Dirichlet Allocation model. They collected tourist satisfaction through the Latent Dirichlet Allocation model and analyzed the relationship among overall layout, spatial form, and tourists' revisit intention using the fuzzy-set qualitative comparative analysis method [9]. In order to improve the quality of tourism space and the benefits of tourism industry development, C. Tang et al. put forward a tourism architecture spatial coupling mechanism optimization model based on Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). They analyzed the key factors and operational methods of culture and tourism integration using fuzzy set qualitative comparative analysis to achieve culture and spatial architecture integration [10].

The above research indicates that existing studies mostly couple tourism space with a single dimension and have achieved certain results in tourism spatial layout optimization and functional adaptability improvement. However, these research techniques are still limited in terms of a lack of collaborative consideration of multiple systems and low computational efficiency, which makes it difficult to deal with complex mountain terrain and tourism demand issues. Therefore, this study conducts research on efficient, multi-dimensional optimization of the spatial coupling mechanism of mountain tourism architecture, aiming to break through the technical bottlenecks of existing research and construct a coupling mechanism optimization model that balances multi-system collaboration, computational efficiency, and adaptation to mountain scenarios, providing a feasible path for the scientific optimization of mountain tourism architectural spatial layout.

1.3 Motivation and Innovation

In order to overcome the problems of single dimension and poor robustness of the existing optimization methods for the spatial coupling mechanism of mountain tourism architecture, an efficient optimization method for the tourism architectural spatial coupling mechanism is needed to offer strong support for the scientific planning of mountain tourism architectural space. The Robustly Optimized BERT Pretraining Approach (RoBERTa) is a commonly used natural language processing model that can effectively extract semantic information from tourist reviews [11]. Gated Graph Neural Networks (GGNN) are an improved type of graph neural network that can capture the complex topological relationships between behavior and architectural space [12]. Therefore, this study combines RoBERTa with the K-medoids clustering algorithm for mountain tourism tourist behavior analysis, conducts behavior-space-mountain coupling relationship analysis by combining GGNN with Temporal Convolutional Network (TCN), and completes mechanism optimization through Genetic Algorithm (GA) and Simulated Annealing (SA) to construct an

optimization model for the spatial coupling mechanism of mountain tourism architecture. This model is expected to more accurately and efficiently optimize the architectural spatial coupling mechanism and promote the sustainable development of mountain tourism. The innovation of this study lies in the following two aspects: First, the application of the RoBERTa model and the K-medoids algorithm in the analysis of tourist behavior overcomes the limitations of traditional tourist behavior analysis, effectively extracts important behavioral information from online reviews of tourists, and improves the accuracy of the recognition of tourist behavioral characteristics. Second, the application and analysis of ternary information of architectural space, mountain terrain, and tourist behavior through GGNN and TCN, and the optimization of the coupling mechanism through GA and SA improved the coupling effect of the model and provided a scientific theoretical basis for optimizing mountain tourism architectural spatial layout.

2. Construction of Spatial Coupling Mechanism Optimization Model

2.1 Tourist Behavior Analysis Method Based on RoBERTa and K-Medoids

From the perspective of environmental behavior theory, mountain tourism architecture is the result of the interaction between human beings, behavior, space, and the mountain environment in the long run [13]. However, most of the traditional research on the spatial form of mountain tourism architecture has focused on planning, morphology, and structural techniques. The research has ignored the behavior patterns, psychological preferences, and spatial use of tourists, which has resulted in a poor quality of experience for tourists [14-15]. Online review texts from tourists can reflect their behavior trajectories, spatial perception, experience feedback, and travel needs in mountain tourism settings in a real and objective way. They are an important data source for extracting tourist behavior information and identifying problems in space use [16]. The theory of environmental behavior provides a theoretical basis for explaining the spatial interaction between tourists and mountain tourism architecture in this study. Its core proposition is that human behavior patterns are jointly shaped by environmental perception and environmental characteristics, while behavior in turn affects spatial usage patterns and spatial evolution directions. To transform this theory into a computable research framework, observable indicators were extracted from four dimensions: tourist behavior, spatial perception, terrain constraints, and building functionality, and established clear correspondences with subsequent algorithm modules. In the dimension of tourist behavior, the behavior semantic features extracted from online comments are used as direct representations of tourist spatial usage behavior, including semantic units such as residence location, movement path description, space congestion evaluation, and facility usage experience involved in the comments. These indicators are encoded by the RoBERTa model for semantic embedding and serve as the basic input for K-medoids clustering analysis. In the dimension of spatial perception, subjective evaluations of architectural spatial form, scale, material, and landscape perspective by tourists are used as perceptual variables, which are also derived from emotional tendencies and spatial descriptive vocabulary in comments. After being extracted by the RoBERTa model, they are combined with behavioral characteristics to participate in clustering, in order to distinguish the spatial preferences and perception patterns of different types of tourists. In the dimension of terrain constraints, the slope, aspect, and terrain undulation derived from the digital elevation model are used as objective environmental variables. These continuous variables are standardized and used as independent feature channels to input into the graph structure node attribute matrix in GGNN. Together with behavioral and spatial features, they form the initial embedding of the ternary coupling analysis. In the dimension of building functionality, variables such as functional area type, building area, spatial aspect ratio, number and location of facility configurations are used as functional representation indicators for building space. These variables are also encoded as attribute features of graph nodes, and are transmitted and aggregated with terrain variables and behavioral variables in the graph structure according to edge weights. The four types of indicators mentioned above achieve cross dimensional feature interaction through graph attention mechanism in the GGNN module, and further unfold in time steps in the TCN module to capture the dynamic coupling changes between tourist behavior and spatial use in time series. In the GA-SA optimization module, the coupling coordination degree output by GGNN and TCN is used as the target variable of the fitness function, and the functional

configuration parameters and layout parameters of the building space are used as decision variables. The coupling mechanism is optimized and adjusted through iterative optimization. The constraints in the optimization process include two types: mandatory constraints and elastic constraints. Mandatory constraints are the basic conditions that optimization plans must meet, including terrain safety constraints, building setback constraints, service radius constraints, ecological protection red line constraints, and construction accessibility constraints. Terrain safety constraints require that the slope of all building sites should not exceed 30 ° and should not be located within geological hazard prone areas or flood prone areas. The building setback constraint requires that the distance between adjacent buildings should not be less than six meters to meet the basic requirements of fire exits and sunlight. The service radius constraint requires that tourist service facilities within each functional zone cover more than 90% of the tourist area within that zone, and the coverage distance is calculated based on the standard of a five-minute walk for tourists. The ecological protection red line constraint requires that building site selection shall not occupy the core ecological protection area and water source conservation area designated by the scenic spot. The construction accessibility constraint requires that the straight-line distance between the building site and the existing main road of the scenic area should not exceed 500 meters to ensure that building materials and equipment can be transported to the construction site through the existing road network. Elastic constraints are conditions that can be appropriately relaxed during the optimization process, including building style coordination constraints and landscape view openness constraints. The former requires that the volume, material, and color of newly built or renovated buildings should maintain continuity in style with the surrounding existing building clusters, while the latter requires that the height of buildings around important scenic spots should not obstruct the main landscape corridors. Elastic constraints are incorporated into the fitness function in the form of penalty terms. When the scheme violates the elastic constraints, the fitness value is deducted according to the degree of deviation. The degree of deduction is determined by multiplying the deviation by the corresponding penalty coefficient, which is fixed after pre-experimental calibration. Through the above mapping mechanism, the qualitative propositions of environmental behavior theory can be quantitatively expressed in various algorithm modules, thus bridging the gap between the theoretical framework and the computational framework.

RoBERTa is an improved pre-trained language model. It can accurately mine behavior information from unstructured review texts and has strong semantic understanding ability. Therefore, this study uses the RoBERTa model to extract tourist behavior information, providing a behavioral data basis for spatial coupling mechanism optimization of mountain tourism architecture. The extraction mechanism based on the RoBERTa model is shown in Figure 1.

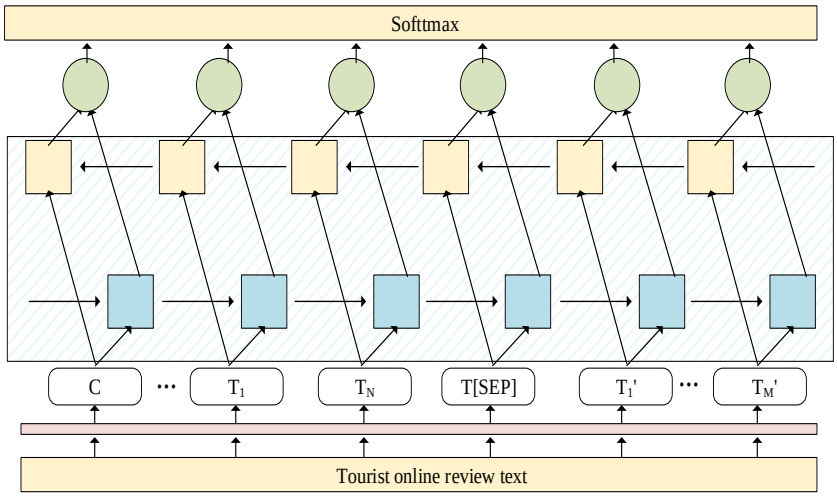


Fig. 1. Tourist behavior information extraction mechanism of RoBERTa

As shown in Figure 1, the RoBERTa model first performs tokenization on online review texts and adds special tokens before and after the character sequence as the start and separator markers.

Then, the embedding layer generates word embeddings and performs positional encoding to form sequence information. The mathematical expression of this step is shown in Equation (1).

$$I_{im}' = I_{im} + A_{im} + B_{im} \tag{1}$$

In Equation (1), I_{im}' represents the character features and sentence features of the i-th text in the tourist review corpus $S = \{s_i, s_2, ..., s_n\}$, and B_{im} represents the positional features of the text. The generated sequence information is then input into the transformer layer for semantic feature extraction. The extraction process is shown in Equation (2).

$$I_{im}^{n}' = Transformer(I_{im}'), k \in \{1, 2, ..., K\} \tag{2}$$

In Equation (2), K represents the total number of encoder layers. Finally, iterative optimization is performed to learn richer semantic representations, and the final sentiment semantic information is output through the Softmax layer. Based on the RoBERTa model, behavior information in online review texts can be extracted more accurately. However, the data related to tourist reviews is huge in volume, complex in dimensions, and contains much redundant information, which increases the computation cost [17]. K-medoids is a partition-based clustering algorithm that can effectively identify the important tourist behavior information and the core demand dimensions [18]. Therefore, to improve the efficiency and accuracy of behavior analysis, this study uses the K-medoids algorithm for clustering based on semantic features extracted by RoBERTa, and constructs a tourist behavior analysis module, named the RK module. The application mechanism of the RK module is shown in Figure 2.

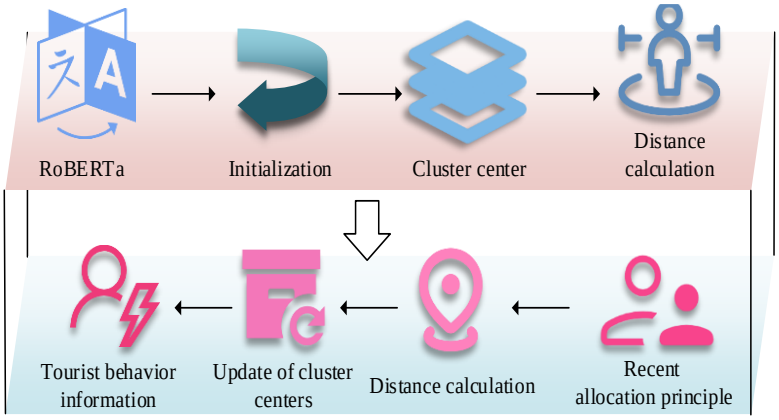


Fig. 2. Application mechanism of the RK module

In Figure 2, the behavior analysis process carried out by the RK module involves the application of the RoBERTa model to the texts of online reviews to obtain the tourist behavior features. Subsequently, the K-medoids algorithm is applied to initialize the model by randomly choosing k behavior features as the cluster centers and calculating the distance between the remaining features. Clusters are assigned based on distance. The clustering result is evaluated using a cost function, and the calculation equation is shown in Equation (3).

$$E = \sum_{i=1}^{k} \sum_{j \in C_i} |j - o_i|^2 \tag{3}$$

In Equation (3), k represents the number of clusters, and o_i represents the center point of the C_i-th tourist behavior data cluster. After that, the cluster centers are updated and reassigned. Then, the clustering evaluation function is redefined to evaluate the updated clusters. The redefined clustering evaluation function is shown in Equation (4).

$$E_{new} = \sum_{i=1}^{k} \sum_{j \in newC_i} |j - o_i|^2 \tag{4}$$

In Equation (4), ^{newC_i} represents the cluster under the new center set partition. Based on the cost function, the clustering result is judged, and iterative optimization is performed until the requirements are satisfied. The final behavior analysis result is then output.

2.2 Modeling of Architectural Spatial Coupling Relationship Based on GGNN and TCN

According to the behavior analysis module, the important behavior information in the tourist reviews can be extracted with high accuracy. However, in the actual application scenarios, the architecture of mountain tourism is limited by the terrain. It is hard to realize the coordinated optimization of the architecture space and the mountain environment with the behavior information [19-20]. Therefore, this study collects mountain spatial environmental data such as terrain slope and illumination. On this basis, a coupling analysis algorithm is used to mine the coupling relationship among environmental features, behavioral features, and architectural space, providing quantitative support for spatial coupling mechanism optimization of mountain tourism architecture. GGNN is an improved graph neural network that can accurately capture nonlinear relationships among multi-dimensional features [21]. Therefore, this study uses GGNN to perform tripartite coupling analysis of terrain, behavior, and space, to identify their interaction patterns and constraints and to improve the coupling effect of the mechanism. The application mechanism of GGNN is shown in Figure 3.

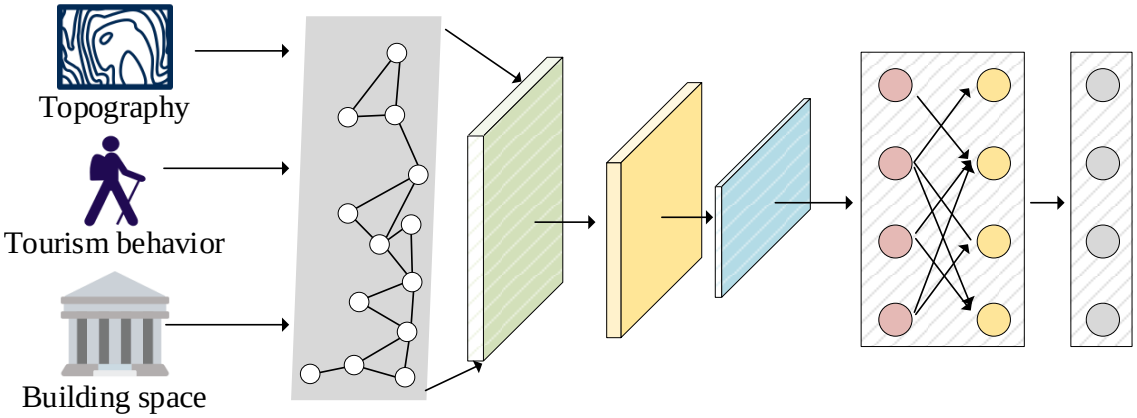


Fig. 3. Terrain-behavior-space tripartite coupling analysis mechanism based on GGNN

In Figure 3, the information related to the behavior of the tourist, the spatial information related to architecture, and the spatial information related to the mountain terrain are integrated into a directed graph model. Specifically, the graph structure constructed by GGNN consists of three core nodes: terrain elements, tourist behavior clusters, and architectural spatial variables. The terrain nodes are subdivided into slope nodes, aspect nodes, and terrain undulation nodes, and the attribute values of each node are derived from the standardized output of the digital elevation model. Tourist behavior nodes are established based on the behavior clusters obtained from K-medoids clustering, and each behavior cluster node carries attribute information such as spatial distribution density, residence duration distribution, and path selection preferences of this type of tourist. The architectural spatial nodes are established one by one based on the actual individual buildings within the scenic area, and each node carries attribute information such as functional type, building area, spatial aspect ratio, and floor height. The three types of nodes together form the set of nodes in the entire graph, including 3 terrain nodes, 8 behavior nodes, and 87 building nodes. The setting of edges in the figure is used to represent the coupling relationship between nodes, which includes the following three types of edges: edges between terrain and buildings represent the terrain constraint strength of the building's location, and edges point from terrain nodes to building nodes. The edge between behavior and architecture represents the distribution intensity of tourist behavior in different building spaces, with the edge pointing from the behavior node to the building node. The edges between buildings represent the degree of proximity of adjacent buildings in spatial topology, and the edges are undirected edges. The calculation method of edge weights is set separately based on the edge type. The weight of terrain and building edges

is taken as the ratio of the terrain comprehensive index of the building's location to the maximum terrain comprehensive index within the scenic area, to represent the relative terrain constraint strength. The weight of behavior and building edges is taken as the ratio of the number of visitors who belong to the behavior category staying in the corresponding building space to the total number of visitors received in the building space, to represent the preference intensity of behavior for a specific building space. The weight of buildings and building edges is taken as the reciprocal of the actual spatial distance between two buildings, and is compressed to the range of 0 to 1 after minimum maximum normalization to represent the spatial proximity between buildings. The dimension of the adjacency matrix is 98 × 98, and the matrix elements correspond to the weight values of the three types of edges mentioned above. Nodes without edges are set to 0 for their corresponding elements. Matrix normalization adopts a row sum normalization strategy, which divides the weight values of each row by the sum of all elements in that row, so that the sum of elements in each row is 1, in order to suppress the excessive influence of nodes with higher degrees in the information transmission process. The weight of the edges represents the coupling strength, and the nodes represent the different features related to each dimension. In order to effectively carry out the coupling analysis, the weight of each edge is set to the ratio of the repeated times to the out-degree of the starting node. The embedding vector of each node is then updated, and the update equation is shown in Equation (5).

$$v_k^t = (1 - z_k^t) \square v_k^{t-1} + z_k^t \square \tilde{v}_k^t \tag{5}$$

In Equation (5), v_k^t represents the embedding vector, $\tilde{v}_k^t$ represents newly generated coupling information, and z_k^t represents retained new coupling information. The calculation of z_k^t is shown in Equation (6).

$$a_k^t = A_{k:}[v_1^{t-1}, ..., v_{|V_x|}^{t-1}]^T H + b \tag{6}$$

In Equation (6), $A_{k:}$ represents the two corresponding columns of k in the adjacency matrix, $[v_1^{t-1}, ..., v_{|V_x|}^{t-1}]^T$ represents the embedding vectors of all nodes at time step $t-1$, and H represents the weight matrix. Then, the reset gate and update gate are used to control the coupling information. The calculation of the update gate is shown in Equation (7).

$$z_t = \sigma(W^{(z)} x_t + U^{(z)} h_{t-1}) \tag{7}$$

In Equation (7), x_t represents the input coupling information at time step t, x_0 represents the output vector information, h_{t-1} represents the hidden state, h_0 represents a zero vector, and $W^{(z)}$ and $U^{(z)}$ represent weight parameters. Then, state resetting and control are performed in the reset gate. The calculation of the reset gate is shown in Equation (8).

$$r_t = \sigma(W^{(r)} x_t + U^{(r)} h_{t-1}) \tag{8}$$

The hidden state is calculated based on the reset gate equation and is then integrated in the Softmax layer to produce the final coupling analysis result. GGNN extracts features from the three core types of data, including mountain terrain, tourist behavior, and architectural space, and performs relational processing to achieve an initial coupling analysis among them. However, because of the time property and multi-source data heterogeneity, solely relying on GGNN to model relational information cannot meet the precision requirements of optimizing the spatial coupling mechanism in mountain tourism architecture. TCN is a widely used approach to deal with time series data. This approach has strong ability in extracting time series features and can effectively capture time evolution rules of data [22-23]. Therefore, this study will use a combination of GGNN and TCN to develop a coupling analysis module named GT to analyze the dynamic coordination patterns and constraints of the tripartite coupling relationship between mountain terrain, tourist behavior, and architectural space. The application process of the GT coupling analysis module is shown in Figure 4.

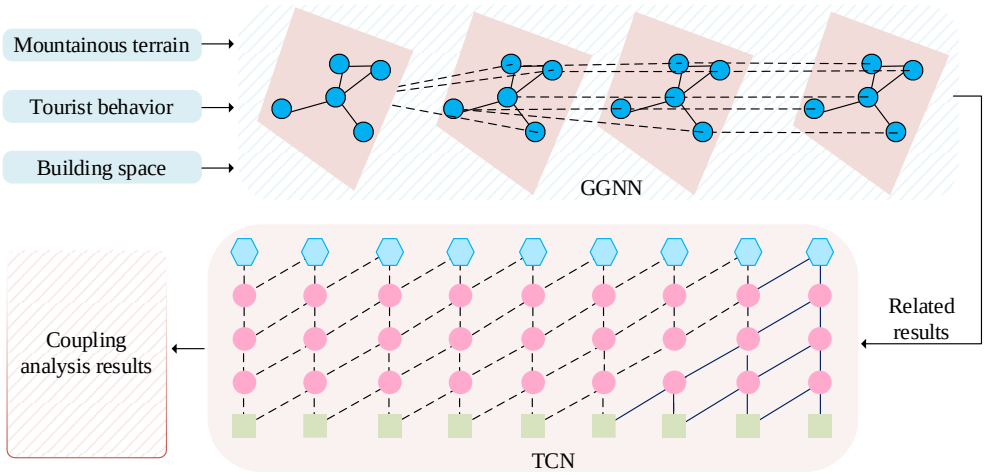


Fig. 4. Application mechanism of the GT coupling analysis module

As shown in Figure 4, in the GT coupling analysis module, GGNN is first used to process the relationships among mountain terrain, tourist behavior, and architectural space data. Then, in TCN, dilated causal convolution is used to extract temporal features of the coupling data, and a residual unit is used for training. The output of the residual unit is shown in Equation (9).

$$r_K = r_k + \sum_{i=k}^{K-1} F(r_o, W_o) \tag{9}$$

In Equation (9), K and k are the deep and shallow residual units, respectively. W_o and r_o are the parameters and coupling features of the o layer, and r_k is the coupling features of the shallow unit. $F(r_o, W_o)$ is the residual function. Based on the output of the residual unit, the temporal relationship is established, and the final coupling analysis result is obtained. The time step definition in the TCN module is based on the day as the basic unit, and time series data is constructed based on the tourist entry time recorded by the scenic spot ticketing system and the entry and exit timestamps of each functional zone. Specifically, each time step corresponds to a time series record of tourist flow in each functional zone within a natural day, including the number of people entering each functional zone per hour, the number of people leaving each hour, and the instantaneous number of people staying in each functional zone. At the same time, daily tourist comment texts are classified into corresponding dates according to their publication time, and aligned with the tourist flow data within the same day in a temporal manner, so that behavioral semantic features and spatial usage intensity are matched in the same time dimension. The total length of the time series is set to 730 consecutive natural days based on the data collection period, covering two complete annual cycles to fully reflect the impact of seasonal changes and changes in tourism peak and off seasons on tourist behavior and spatial use. Before inputting into TCN, the original time-series data is processed through a sliding window with a window length of 7 days and a step size of 1 day. This means that the coupling state features of the current date are predicted based on the tourist flow and behavior characteristics of the past 7 consecutive days, in order to construct the input-output pairs required for supervised learning. The expansion convolutional layer in TCN adopts an exponentially increasing expansion factor sequence, which is 2^0, 2^1, 2^2, and 2^3, corresponding to receptive field lengths of 1, 2, 4, and 8 time steps, respectively. After four layers are stacked, the total receptive field covers 15-time steps. Combined with the 7-day input length of the sliding window, the model can effectively capture the periodic fluctuations of tourist behavior during different time periods during the day and between weekdays and rest days, as well as the cumulative behavior change trend over multiple consecutive days. The temporal correspondence of dilated convolution follows the principle of causal convolution, which means that the output of the current time step depends only on the input information of the current and previous time steps, without introducing future information, ensuring that the prediction direction of the model in the time dimension is consistent with the actual application scenario. By defining the time dimension and configuring dilated convolutions, the TCN module can quantitatively characterize the dynamic

evolution characteristics of tourist behavior in different seasons, time periods, and tourism activity cycles, and align them with changes in terrain constraints and architectural spatial states in a temporal manner, providing a clear time reference framework for the analysis of the temporal evolution of coupling relationships.

2.3 Optimization Model of Coupling Mechanism for Mountain Tourism Architecture

The GT coupling analysis module can accurately describe the features and relationships in the spatial coupling mechanism of mountain tourism architecture. However, the current coupling mechanism has issues such as low computational efficiency and limited flexibility, and it cannot fully adapt to complex terrain and diverse tourist demands. GA is a commonly used optimization algorithm with strong global search ability. It can improve both computational efficiency and optimization accuracy of the coupling mechanism, and it helps address the current limitations of the method [24-25]. However, GA is sensitive to parameters and can easily fall into local optima, which affects the stability of the results. SA can reduce the risk of premature convergence through probabilistic jumps, reduce the impact of local optima, and improve global optimization ability [26]. Therefore, this study combines GA and SA to construct the GA-SA algorithm for optimizing the spatial coupling mechanism of mountain tourism architecture. The optimization process based on GA-SA is shown in Figure 5.

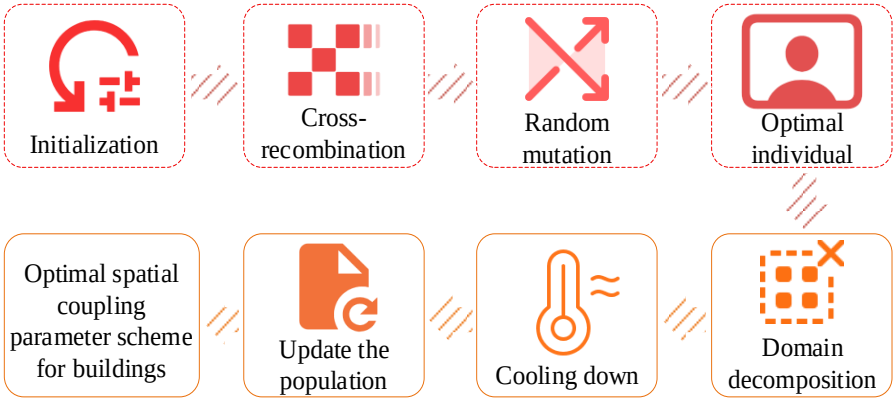


Fig. 5. Coupling mechanism optimization process based on GA-SA

As presented in Figure 5, the optimization process begins with initialization, in which certain parameters, such as the annealing factor and the maximum number of iterations, are initialized. Then, according to the properties and constraints of the coupling mechanism, a random solution is constructed to initialize the population. Finally, a fitness function is constructed according to the optimization goal. New populations are generated through crossover and mutation operations to search for the optimal solution, and the optimal coupling sequence is selected. The adaptive crossover function is shown in Equation (10).

$$P_c(i) = P_{c_\max} \cdot e^{-\frac{i}{M_g^{Kc}}} \tag{10}$$

In Equation (10), $P_{c_\max}$ represents the maximum crossover probability, i represents the current iteration, M_g represents the maximum iteration, and K_c represents the adjustment coefficient. Then, an adaptive mutation function is used to generate new candidate sequences. The adaptive mutation function is shown in Equation (11).

$$P_m(i) = P_{m_\max} \cdot e^{-\left|\frac{i-M_g/2}{M_g/(4\cdot K_m)}\right|} \tag{11}$$

In Equation (11), $P_{m_\max}$ represents the maximum mutation probability, and K_m represents the adjustment coefficient. Then, in SA, the temperature is updated to gradually shift the search from

global search to local search. The acceptance probability is used to decide whether to accept a worse solution. The acceptance probability is shown in Equation (12).

$$p = \exp\left(-\frac{E_2 - E_1}{KT}\right) \tag{12}$$

In Equation (12), E_1 and E_2 represent the energy before and after the change. If $E_1 < E_2$ is satisfied, the current state meets the expectation and is retained. If $E_1 \geq E_2$ is satisfied, a random probability is used to determine whether the current result is accepted. K represents a target constant. T represents the cooling function, which usually uses exponential cooling. The calculation is shown in Equation (13).

$$T(iter+1) = \delta \times T(iter), 0 < \delta < 1 \tag{13}$$

In Equation (13), δ is the annealing factor. In summary, this study combines RoBERTa and K-medoids for tourist behavior analysis, combines GGNN and TCN to analyze the coupling relationship among behavior, space, and terrain, and uses the GA-SA algorithm for optimization. A spatial coupling mechanism optimization model for mountain tourism architecture is constructed, named RKGTGS. The application mechanism of the RKGTGS model is shown in Figure 6.

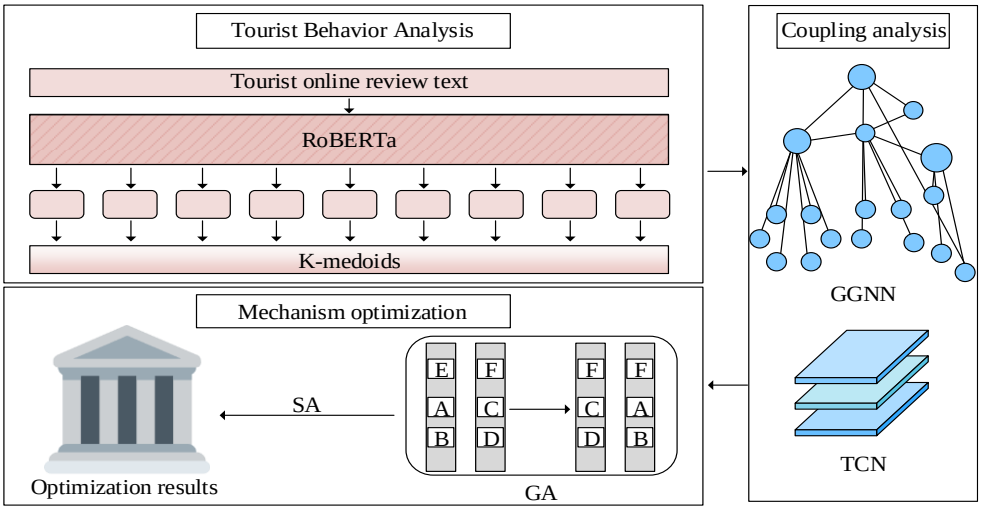


Fig. 6. RKGTGS spatial coupling mechanism optimization model

In Figure 6, in the RKGTGS model, the behavioral features of tourists are extracted by applying the RoBERTa model to the texts of tourist reviews, and K-medoids is applied for behavior analysis. Then, GGNN is applied for the analysis of the coupling relationship between behavior, space, and terrain, and TCN is applied for further analysis of the changes of these three factors. In the GA, crossover and mutation operations are used for the update of the optimal solution. SA is used for cooling to avoid local optima. Finally, iterative optimization is performed, and the final optimized result is output to complete the spatial coupling mechanism optimization.

3. Performance Validation of RKGTGS Model

3.1 Experimental Environment and Data Processing

To ensure the feasibility of model replication, the online review data used in the study was sourced from mainstream domestic tourism review platforms, collected from January 2024 to December 2025, covering mountainous tourist attractions where the research subjects are located. The planned area of the core scenic spot in the research area is about 42.6 square kilometers, and the developed tourist area is about 18.3 square kilometers. The altitude within the scenic area ranges from 980 meters to 2360 meters, with a relative height difference of 1380 meters, showing significant vertical zoning characteristics. According to the terrain parameters extracted from the digital elevation model, the area with gentle slopes less than 15 degrees in the scenic area accounts for 24% of the total area, the area with medium steep slopes between 15- and 30-degrees accounts

for about 47%, and the area with steep slopes greater than 30 degrees accounts for about 29%. The average terrain undulation is 186 meters per square kilometer, and the overall terrain conditions are complex, which poses strong rigid constraints on building site selection and spatial layout. There are a total of 87 tourist buildings in the scenic area, divided by functional types, including 24 retail buildings, 18 catering buildings, 21 accommodation buildings, 10 entertainment buildings, 8 tourist service buildings, and 6 cultural exhibition buildings. The buildings mainly consist of 1 to 3 floors, with a total construction area of approximately 67000 square meters. The basis for selecting this case is as follows: firstly, the scenic area covers a complete vertical altitude gradient from the valley bottom to the mountain top, which can fully reflect the multi-level constraint effect of mountainous terrain on architectural spatial layout, providing an ideal natural experimental field for studying the coupling relationship between terrain and architecture. Secondly, the scenic area has a rich variety of building types and clear functional zoning, which can support a systematic analysis of the coupling relationship between different functional spaces and tourist behavior. Thirdly, the scenic area has a sufficient number of tourists and abundant online comment data, providing a sufficient sample size for research based on semantic analysis of tourist behavior. Fourthly, the problems in functional configuration, spatial organization, and terrain adaptation of this scenic area have a high degree of universality in the southwestern mountainous tourism areas of China. Its spatial coupling optimization needs are highly similar to those of similar domestic scenic areas. Therefore, the research conclusions of this case have reference value for promotion to other similar mountainous tourism areas. The comment data has been anonymized after collection, and all identifiable information such as user nicknames, avatars, and personal profiles have been removed. Only the comment text content and timestamp information have been retained. The data usage process strictly complies with the data usage terms and privacy policies of each platform, and is only used for academic research purposes. The terrain data is sourced from a 30-meter resolution digital elevation model provided by a geographic spatial data cloud platform. After resampling to a 10-meter resolution, it is used to extract key terrain indicators such as slope, aspect, and terrain undulation. By utilizing Excel spreadsheet tools, reviews containing information such as tourists' travel time, days of the tour, tourism destinations, travel routes, and stay locations in the retail zone (A), catering zone (B), accommodation zone (C), entertainment zone (D), service zone (E), and scenic zone (F) were compiled and counted. Information such as "narrow and crowded trails," "insufficient mountaineering facilities," and "complex terrain causing tourists to get lost" regarding the pain points of the destination were also manually annotated. The experiment used ArcMap software for outlier screening, elimination, and standardization processing, normalizing values such as slope and lighting to [0,1]. The manual annotation process is jointly completed by three researchers with backgrounds in architecture or tourism management. The annotation content includes hidden pain points and spatial experience issues of tourists in the comments. The annotation consistency is tested by Kappa coefficient, with a value of not less than 0.85. The majority of the annotation results is taken to reach the conclusion. The model parameter configuration is as follows: the RoBERTa model uses pre trained Chinese Roberta wwm ext weights, with a hidden layer dimension of 768, 12 attention heads, and 12 encoder layers. The number of clusters k in the K-medoids clustering algorithm is determined to be 8 by the elbow rule. The number of graph convolutional layers in GGNN is 3, with 128 hidden units per layer and a time step of 5. The dilation convolution layer of TCN is 4, the convolution kernel size is 3, and the dilation factor increases exponentially by 2. In the GA-SA optimization algorithm, the population size is 50, the maximum number of iterations is 200, the initial crossover probability is 0.85 and linearly decays to 0.55 with iterations, the initial mutation probability is 0.15 and linearly decays to 0.05 with iterations, the simulated annealing initial temperature is 100, and the cooling coefficient is 0.95. In addition, the training of the RoBERTa model uses the Chinese ruberta wwm ext jointly published by Harbin Institute of Technology and iFlytek as the pre training weight, which is obtained through pre training on large-scale Chinese corpus based on the full word masking strategy and is suitable for Chinese semantic understanding tasks. The maximum sequence length for input text is set to 512 characters. Any excess will be truncated, and any shortfall will be filled with padding. The comment text is segmented and constructed into word pairs before input to adapt to the input format of the pre trained model. The learning rate during the fine-tuning phase is set to 2e-5, using a linear warm-up and decay strategy. The warm-up steps account for 10% of

the total number of iterations, the batch size is set to 32, the total training epochs are 15, and the patience value of the early stopping strategy is set to 3 epochs. When the validation set loss does not decrease for 3 consecutive epochs, the training is terminated in advance to prevent overfitting. The training set and validation set are randomly divided into layers from the annotated samples in an 8:2 ratio. The training set contains 4320 annotated comments, and the validation set contains 1080 annotated comments. When dividing, it is ensured that the distribution ratio of each pain point category in the training set and validation set is consistent with the overall distribution. The pain point category labels are set to five categories, corresponding to path congestion, insufficient facilities, unclear directional signs, crowded space, and lack of recreational facilities. Each comment text is judged by the annotator to determine whether it involves the above categories. Multiple labels are allowed for annotation, that is, one comment can be labeled as multiple pain point categories at the same time. The loss function adopts binary cross entropy loss to adapt to the requirements of multi label classification tasks. The probabilities of each category output by the model are mapped to the 0 to 1 interval through the Sigmoid activation function to calculate the loss value. The accuracy of pain point recognition in the final report is the evaluation result of the model on the test set, which is independent of the training and validation sets and consists of 500 manually annotated comments that did not participate in the training and validation processes. The annotation process is completely consistent with the training and validation sets, and the test set is only evaluated once after the model training and hyperparameter adjustment are completed to reflect the final generalization performance of the model. SPSS software was adopted as the analysis software; the Spearman tool was used to analyze coupling relationships, and SPSSAU was used to calculate coupling degree and coupling coordination degree. The specific experimental environment is shown in Table 1.

Table 1. Experimental environment

Configuration	Content
Operating system	Windows10
Processor	Intel core i5-6200U
Memory	12GB
Programming language	Python
Analysis software	SPSS 22.0
Data processing	ArcMap 10.7
Optimizer	Adam
Open-source deep learning framework	TensorFlow, Keras

3.2 Evaluation of Tourist Behavior Analysis Performance

Tourist behavior analysis is an important prerequisite for multi-dimensional coupling of architectural space. Therefore, this study established a behavior analysis experiment to evaluate the tourist behavior analysis effect of the RKGTGS model. To verify the model's superiority, the experiment compared the model with the tourist behavior analysis model based on maximum likelihood inverse reinforcement learning (MLIRL) and the tourist behavior analysis model based on continuous bag of words-latent Dirichlet allocation (CBOW-LDA). To ensure the fairness of comparative experiments and the effectiveness of conclusions, the study standardized the five baseline models used in terms of input data, training configuration, hyperparameter tuning range, and evaluation indicators. All models accept the same input data sources, including desensitized tourist comment texts, terrain digital elevation model data, and architectural spatial variable encoding data. For baseline models that can only handle a single data type or cannot directly complete behavior analysis tasks, the study adapts their functionality based on the original design intention in the literature, so that they can participate in comparison within a unified framework. Specifically, the MLIRL model and CBOW-LDA model were originally used for tourist behavior pattern mining and preference analysis. In the experiment, their output results were used as feature inputs for subsequent coupling analysis, rather than directly participating in ternary coupling calculations. The ACO-SA model, SFO-BPNN model, and VFWOA model were originally optimization search algorithms. In the experiment, they were embedded into the same coupling

analysis process, with coupling suitability as the optimization objective, to optimize them in the same problem space. The training epochs for all models are uniformly set to 200 epochs, and the patience value for the early stop strategy is set to 20 epochs. The hyperparameter optimization adopts a grid search strategy, and the search range of each model is set based on its original literature recommendation values, and the optimal configuration is selected on the same validation set. In terms of evaluation indicators, the behavior analysis task uniformly adopts the accuracy of pain point recognition and the prediction deviation of dwell time, while the coupling optimization task uniformly adopts the loss value, parameter size, execution time, coupling coordination degree, and behavior trajectory overlap rate to ensure that each model is compared at the same scale. For the missing functional modules in the baseline model, research is conducted to supplement necessary data preprocessing interfaces and result post-processing logic while maintaining the core algorithm unchanged, so that it can adapt to the task of ternary coupling analysis. At the same time, the adaptation changes of each model are clearly recorded to avoid introducing additional performance deviations due to implementation differences. The above settings aim to minimize the interference caused by inconsistent experimental conditions on the conclusions.

To ensure the objectivity and reproducibility of the model performance evaluation, the following evaluation indicators are used for evaluation. Pain point recognition accuracy is used to measure the accuracy of the model in identifying spatial usage issues from tourist comment texts. Its calculation method is the ratio of the number of correctly identified pain points by the model to the total number of manually annotated pain points, with a numerical range between 0 and 1. The larger the value, the better the recognition effect. The pain points manually annotated include five common problems: path congestion, insufficient facilities, unclear directional signs, crowded space, and lack of recreational facilities. Three annotators independently annotated them based on a unified coding manual, and the final result was based on the majority consensus. The prediction deviation of stay time is used to evaluate the estimation accuracy of the model for the duration of tourist stay in each functional area. Its calculation method is the standard deviation of the difference between the predicted stay time of the model and the actual stay time manually calculated, in minutes. The smaller the value, the more accurate the prediction. The actual duration of stay is obtained based on the arrival and departure time information explicitly mentioned in tourists' online comments, as well as the entry and exit timestamps of various functional areas recorded by the scenic area's intelligent ticketing system. After cross validation, the average value is taken as the manual benchmark value. The coupling coordination degree is used to quantify the degree of collaborative matching between terrain conditions, tourist behavior, and architectural space. Its calculation is based on the coupling degree model and the coordinated development index, with a numerical range limited to 0 to 1. The closer it is to 1, the stronger the coordination between the three systems. In the calculation process of this indicator, the terrain dimension is represented by a comprehensive index of slope, aspect, and undulation, the behavior dimension is represented by a comprehensive index of tourist density, duration of stay, and activity type, and the spatial dimension is represented by a comprehensive index of functional ratio, facility coverage, and spatial connectivity. The weights of the three are determined by the entropy method. The behavior trajectory overlap rate is used to evaluate the degree of agreement between the optimized spatial guidance path of the model and the actual walking trajectory of tourists. Its calculation method is the ratio of the length of the overlapping path between the two to the total length of the actual trajectory, with a numerical range between 0 and 1. The larger the value, the better the guidance effect of the optimized spatial layout on the actual behavior of tourists. The actual trajectory data comes from the tourist flow counts between the main nodes in the scenic area, which are normalized to form a benchmark flow matrix. The accessibility rate of functional nodes is used to measure the degree of conformity between the actual shortest time required for tourists to reach each functional node from any starting point in the building space and the theoretical shortest time. Its calculation method is the ratio of the number of accessible nodes to the total number of functional nodes, with a value between 0 and 1. The larger the value, the more significant the optimization effect of spatial accessibility. All the indicators based on manual annotation mentioned above are annotated using a double-blind independent annotation and third-party decision-making process. The annotators do not participate in model design and result prediction. The consistency of annotation is tested using the Kappa coefficient, and the Kappa value of each

indicator is not less than 0.80 to ensure the statistical reliability and consistency of the annotation results. This serves as the only manual reference standard for model evaluation. The accuracy of tourism pain point analysis is the overlap ratio of pain points of tourist behavior identified by the model in text and pain points manually annotated, which can reflect the effect of model analysis on tourist behavior preferences. Therefore, a comparison and analysis were conducted on the accuracy of behavior pain point analysis, and the comparison results are shown in Figure 7.

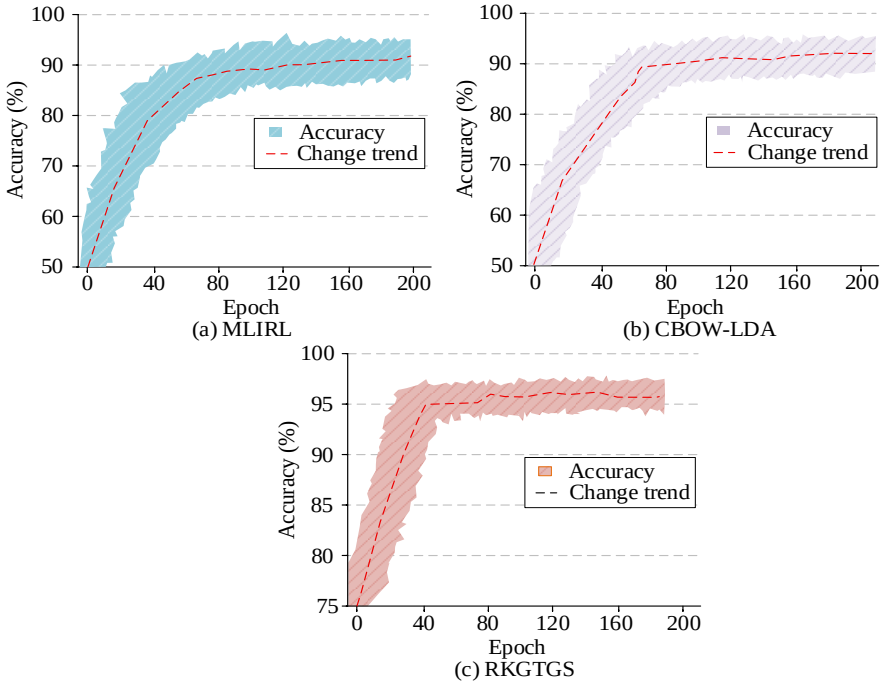


Fig. 7. Accuracy of behavior pain point analysis

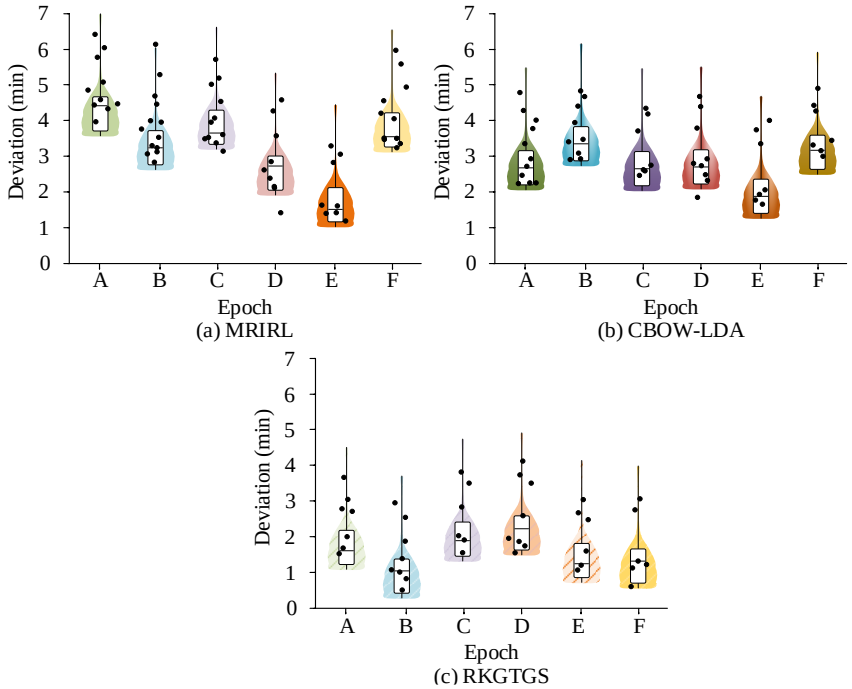


Fig. 8. Stay time prediction deviation under different functional zones

Note: A: Retail area, B: Catering area, C: Accommodation area, D: Entertainment area, E: Service area, F: Scenic area.

As shown in Figure 7(a), the MLIRL model had a stable state after 100 iterations, indicating that the model has low convergence efficiency. In addition, the accuracy of behavior pain point recognition of the model in a stable state was 90.34%, indicating that the model has high accuracy. As shown

in Figure 7(b), the accuracy of behavior pain point recognition of the CBOW-LDA model in a stable state was 91.25%, indicating that the model has higher accuracy than that of the MLIRL model. As shown in Figure 7(c), the behavior pain point recognition accuracy of the RKGTGS model in the stable state was 95.32%, higher than that of the comparison models, showing higher analysis precision. Furthermore, after 40 iterations, this model reached a stable state earlier than the comparison models, indicating that the convergence efficiency of this model is superior to the comparison models. Overall, the proposed model has better analysis precision and convergence speed. The stay time prediction deviation represents the standard deviation of the model's prediction results for tourist stay time, which can directly reflect the model's behavior analysis effect. To more accurately evaluate the model's behavior analysis effect, this study compared and analyzed the stay time prediction deviation of each model under different functional zones, and the comparison results are shown in Figure 8.

In Figure 8(a), under different functional zones of mountain tourism architectural space, the maximum tourist stay time prediction deviation of the MLIRL model was 4.52 min, showing relatively poor performance. In Figure 8(b), the maximum tourist stay time prediction deviation of the CBOW-LDA model was 3.39 min, lower than the MLIRL model, demonstrating higher accuracy. In Figure 8(c), the standard deviation of the RKGTGS model for zone A was 1.52 min, for zone B was 1.01 min, and the maximum standard deviation was 2.25, all lower than the comparison models, showing higher analysis precision. On the whole, the deviation of the stay time prediction of the proposed model in the six zones outperformed the compared models in terms of analysis precision. To sum up, the proposed model can more precisely analyze different patterns of tourist behaviors and stay time, which means that the analysis precision of this model is better and can better optimize the architectural spatial coupling mechanism.

3.3 Validation of Coupling Mechanism Optimization Performance

In the experiment of analysis of tourist behavior, the RKGTGS model showed better analysis precision. Based on this, the present study designed a performance analysis experiment for the analysis of the performance of the architectural spatial coupling mechanism optimization model. This study compared the model with ant colony optimization-SA algorithm (ACO-SA), sailfish optimization algorithm-back propagation neural network (SFO-BPNN), and virtual force-based whale optimization algorithm (VFWOA) to more intuitively analyze model performance. To verify the model's stability, this study compared the loss value curves during the coupling mechanism optimization process, and the comparison results are shown in Figure 9.

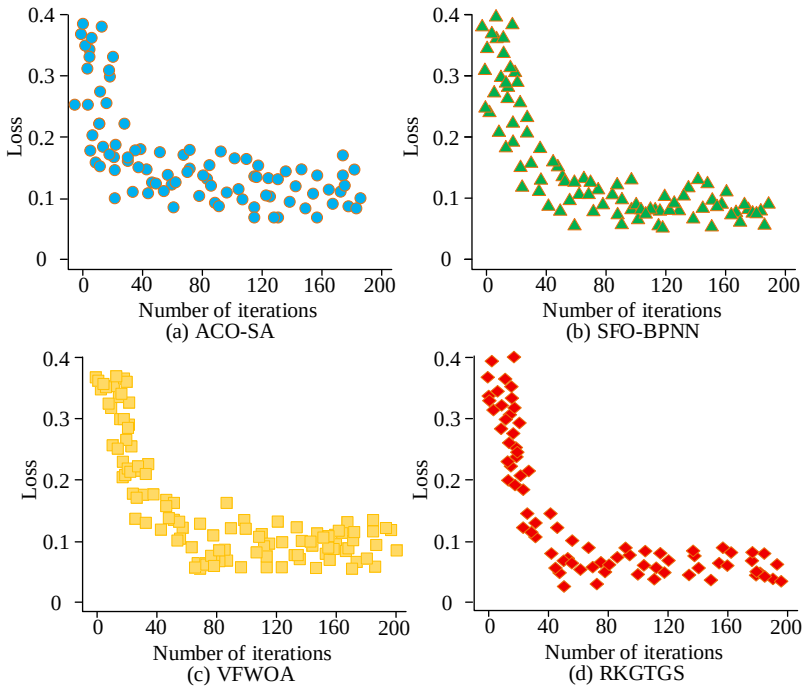


Fig. 9. Loss value curve comparison results

In Figure 9(a), the loss value of the ACO-SA model in the stable state was 0.125, showing relatively weak performance. In Figures 9(b) and 9(c), the loss values of the SFO-BPNN model and VFWOA model in the stable state were 0.096 and 0.853 respectively, showing better optimization effects compared to the ACO-SA model. In Figure 9(d), compared with the comparison models, the RKGTGS model showed better performance. As can be seen, the loss value of the RKGTGS model in the stable state is 0.062, which is lower than the loss value of the comparison models. Moreover, the RKGTGS model reached the stable state after 40 iterations earlier than the comparison models. In addition, the loss value curve of this model was smoother, further verifying that this model has better stability. To further verify model performance, this study compared and analyzed the parameter quantity and execution time during the coupling mechanism optimization process, and the comparison results are shown in Figure 10.

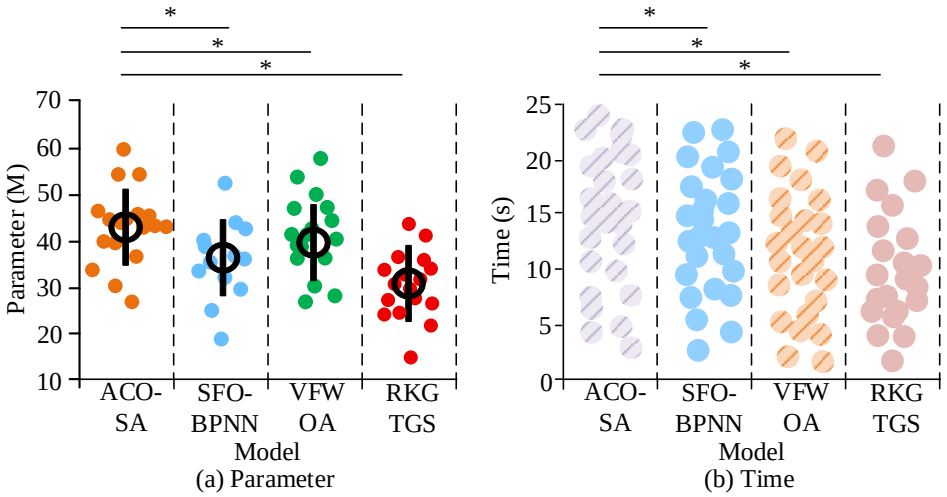


Fig. 10. Comparison of parameter quantity and execution time

*Note: * indicates p<0.5*

In Figure 10(a), the median parameter quantity of the RKGTGS model during the coupling mechanism optimization process was 30.85 M, lower than the comparison models' 42.72 M, 37.56 M, and 39.42 M, demonstrating a smaller model size. As shown in Figure 10(b), compared to the comparison models, the RKGTGS model had lower execution time during the coupling mechanism optimization process. The median execution time of this model was 7.51 s, significantly better than the comparison models ($p<0.5$), showing superior performance. Overall, the proposed model's performance in both parameter quantity and execution time was superior to the comparison models, indicating that this model has better computational efficiency. In summary, compared to the comparison models, the proposed model has higher stability and computational efficiency, and can better complete coupling mechanism optimization.

3.4 Analysis of Spatial Coupling Mechanism Optimization Performance

In the performance analysis experiment, compared to the performance of ACO-SA model, SFO-BPNN model, and VFWOA model, the performance of RKGTGS model was higher, implying that this model can more stably perform model performance analysis. To further verify the model's coupling mechanism optimization effect, this study adopted the same comparison method as the performance analysis experiment to analyze the model's coupling mechanism optimization effect. To verify the effectiveness of each component in the model, this study established an ablation experiment. Using GGNN as the baseline model, the coupling mechanism optimization effects of GGNN+TCN (Scheme I), GGNN+TCN+RK (Scheme II), GGNN+TCN+RK+GA (Scheme III), and the complete RKGTGS model (Scheme IV) were compared. The mean absolute error (MAE) and root mean squared error (RMSE) of coupling adaptability both represent the deviation between the "terrain-behavior-space" coupling adaptability predicted by the model and the expert manual annotation values. The smaller the value, the higher the coupling precision, indicating better optimization effect of the model. Therefore, this study compared and analyzed the MAE and RMSE

of coupling adaptability of each scheme under architectural spaces of different functional zones, and the analysis results are shown in Figure 11.

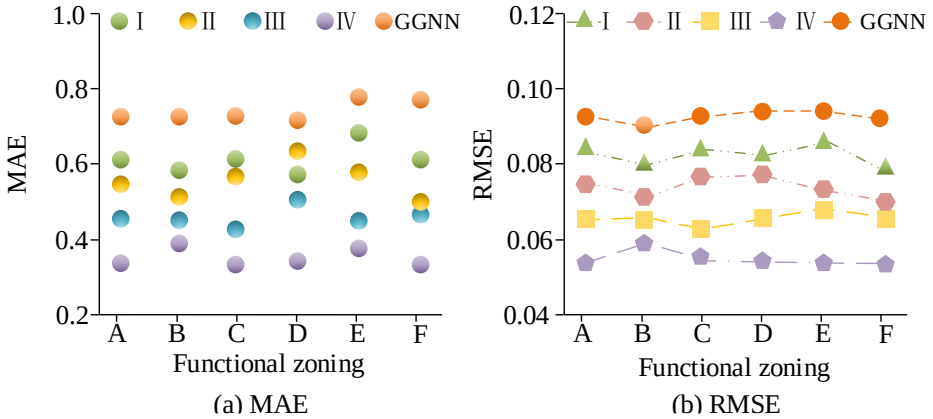


Fig. 11. Ablation experiment results

Note: A: Retail area, B: Catering area, C: Accommodation area, D: Entertainment area, E: Service area, F: Scenic area.

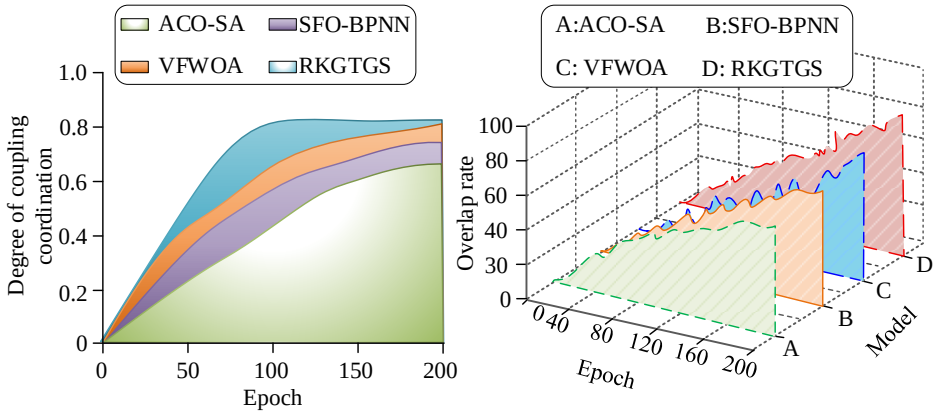
In Figure 11(a), the average MAE of Scheme I for architectural spaces of different functional zones was 0.613, which was 0.138 lower than the GGNN model, indicating the effectiveness of TCN. The average MAE of Scheme II was 0.564, lower than Scheme I, fully verifying the effectiveness of the RK module. The average MAE of Scheme III was 0.445, lower than Scheme II, indicating that after optimization using the GA algorithm, the model's coupling mechanism optimization effect improved. In addition, the average MAE of Scheme IV was 0.378, superior to other schemes, demonstrating the effectiveness of the SA algorithm as well. In Figure 11(b), the average RMSE of Scheme IV was 0.058, significantly lower than other schemes, further illustrating the effectiveness of each component. Overall, with the gradual integration of each component, the model's performance continuously improved, effectively verifying the scientific nature and feasibility of the proposed hybrid model. In this study, the correlation analysis of the behavior of tourist consumption and the variables related to the architectural space, including the terrain complexity, the number of plazas, the number of corridor spaces, the number of rest rooms, the style, the number of public toilets, the location of public toilets, and the location of guide maps, is carried out through each model and compared with the results of the manual correlation analysis to calculate the analysis deviation. The comparison results are shown in Table 2.

Table 2. Comparison of coupling correlation analysis deviation

Variable	ACO-SA	SFO-BPNN	VFWOA	RKGTGS
Terrain complexity	0.067	0.053	0.037	0.026
Number of plazas and corridor spaces	0.078	0.062	0.068	0.031
Number of restrooms	0.059	0.061	0.051	0.024
Architectural style	0.091	0.073	0.058	0.019
Number of public toilets	0.132	0.058	0.043	0.028
Location of public toilets	0.057	0.049	0.049	0.033
Location of guide maps	0.074	0.066	0.048	0.031

In Table 2, in the correlation analysis on terrain complexity, the correlation analysis deviation of the RKGTGS model was 0.026, less than the 0.067, 0.053, 0.037 of the comparison models, indicating that the analysis effect is better. In the correlation analysis on architectural space, the analysis deviation of the RKGTGS model on the number of rest rooms was 0.024, on architectural style was 0.019, on the location of public toilets was 0.033, indicating that the analysis effect is superior. Overall, the correlation analysis deviation of the proposed model was lower than the comparison models, indicating that the proposed model can more effectively analyze the coupling relationship among architectural space, mountain terrain, and tourist behavior, demonstrating that the proposed model has excellent coupling mechanism optimization effect. The coupling

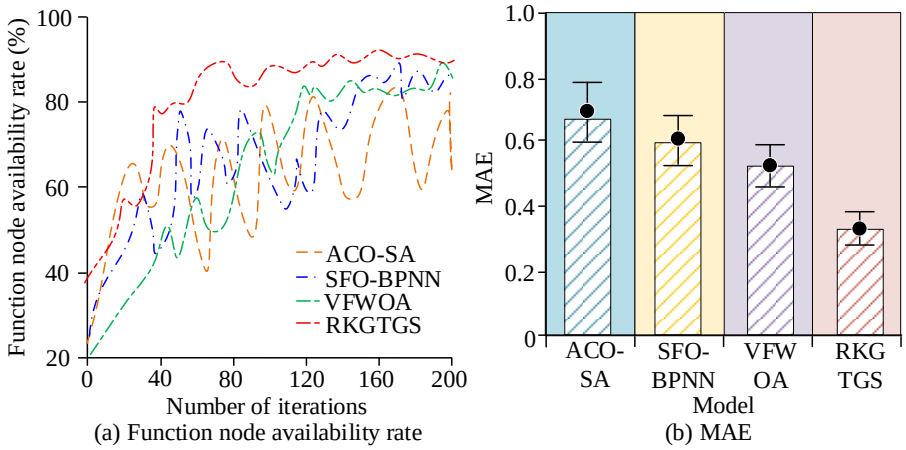
coordination degree is a commonly used indicator in the field of geography, which can quantify the synergistic coordination degree of "terrain-behavior-space," with a value range of [0,1]. The closer to 1, the better the coupling coordination effect, indicating higher optimization value of the model. The behavior trajectory overlap rate represents the ratio of the overlapping length between tourists' actual trajectories and optimized spatial guidance paths to the total length of actual trajectories. The higher the ratio, the better the optimization effect of the model. To further analyze the model's coupling mechanism, this study analyzed the coupling coordination degree and behavior trajectory overlap rate, and the analysis results are shown in Figure 12.



(a) Degree of coupling coordination (b) Overlap rate

Fig. 12. Comparison of coupling coordination degree and behavior trajectory overlap rate

In Figure 12(a), the coupling coordination degree of the RKGTGS model in the stable state is 0.827, which is higher than that of the comparison models. It can be concluded that the RKGTGS model has a better optimization effect on the coupling mechanism. As shown in Figure 12(b), the RKGTGS model optimized the coupling mechanism in the tourist behavior trajectory, whose overlapping rate in this area is 81.33%, which is higher than those of the comparison models at 61.35%, 66.54%, and 72.11%. The functional node accessibility rate represents the ratio of the shortest time for tourists to reach each functional node in the architectural space to the number of functional nodes. The higher the ratio, the better the optimization effect of the model. Therefore, this study compared the functional node accessibility rate and coupling adaptability MAE value of each model, and the comparison results are shown in Figure 13.



(a) Function node availability rate (b) MAE

Fig. 13. Functional node accessibility rate and coupling adaptability MAE value

In Figure 13(a), the functional node accessibility rate of the proposed RKGTGS model in the stable state was 87.45%, higher than the comparison models, showing better optimization effect. As shown in Figure 13(b), the MAE value of the RKGTGS model was 0.354, which is superior to the other models. Thus, the optimization effect of the model is superior, implying that this model can better optimize the mountain tourism architectural spatial coupling mechanism to improve the economic benefits of the mountain tourism industry.

4. Further Discussion

To optimize the spatial layout of mountain tourism architectural space, this study proposed a mountain tourism architectural spatial coupling mechanism optimization model based on environmental behavior theory. In the tourist behavior analysis experiment, it was found that the behavior pain point recognition accuracy of the RKGTGS model was 95.32%, higher than the comparison models, demonstrating higher analysis precision. In addition, after 40 iterations, this model reached a stable state earlier than the comparison models, indicating that the convergence efficiency of this model is superior to the comparison models. Furthermore, under different functional zones of mountain tourism architectural space, the maximum standard deviation of the RKGTGS model was 2.25, lower than the comparison models, showing higher analysis precision. This benefits from the proposed model's use of the highly stable RoBERTa model to extract semantic information related to tourist behavior from online review texts, enhancing the model's tourist behavior analysis effect. This result is similar to the conclusion obtained by K. Liang et al. in 2024, both adopting pre-trained language models for semantic information extraction, but the proposed model demonstrated better performance in accuracy and convergence efficiency [27]. In the performance analysis experiment, the result showed that the smoothness of the loss value curve for the RKGTGS model was higher, and the loss value in the stable state was 0.062, which was lower than the comparison models, indicating the high stability of the model. Meanwhile, the parameter quantity of the RKGTGS model was 30.85 M, and the execution time was 7.51 s, both higher than the comparison models, indicating the high performance of the RKGTGS model. This is because the performance of the proposed model is improved through the application of the GA-SA algorithm with global search ability to optimize the coupling mechanism. The above results coincide with the research results of B. Zhang et al. in 2023, where the objective optimization is performed through the application of the GA algorithm, and the improvement of the GA algorithm is performed to further enhance the performance of the model [28].

In order to further verify the optimization effect of the coupling mechanism optimization of the model, this study set the coupling mechanism optimization effect analysis experiment to verify the optimization effect of the model. In the optimization effect analysis experiment, the analysis deviation of the RKGTGS model on the number of rest rooms in architectural space was 0.024, on architectural style was 0.019, on the location of public toilets was 0.033, which is superior to that of the comparison models. In addition, the coupling coordination degree of the proposed model was 0.827, higher than the comparison models, demonstrating better coupling mechanism optimization effect. This benefits from the proposed model's adoption of the GGNN network for graph structure modeling, conducting coupling analysis on mountain tourism architectural space, tourist behavior, and mountain terrain, effectively improving the model's optimization effect. This conclusion is consistent with the conclusion proposed by G. Hassanshahi et al. in 2023. The authors adopted terrain data and tourist behavior data as data sources and processed the data by deep learning algorithms to achieve a better improvement in accuracy and application effect. However, the application effect of the proposed model is better [29]. After the RKGTGS model optimized the coupling mechanism, the tourist behavior trajectory overlap rate in this area was 81.33% and the functional node accessibility rate was 87.45%, higher than those of the comparison models, showing better optimization effect. This is due to the positive effects of the proposed model using the GA algorithm in optimizing the coupling mechanism and the improvement of the GA algorithm by using the SA algorithm, thus strengthening the optimization effect of the proposed model. The above results are similar to the research results of R. Gao et al., in which the optimization algorithms were used to improve the performance of the model, and the proposed model showed a better application effect [30].

5. Conclusions

Based on the theory of environmental behavior and data-driven intelligent algorithms, a RKGTGS model for optimizing the spatial coupling mechanism of mountain tourism architecture was constructed, and empirical verification was conducted in a typical mountain tourism area in southwestern China. The research results show that the behavior analysis module combined with the RoBERTa model and K-medoids algorithm can effectively extract behavioral semantic features

and spatial pain points from online tourist comments. It is significantly better than the baseline methods in terms of pain point recognition accuracy and prediction deviation of stay time, indicating that the module has good behavior information mining ability in mountainous tourism scenarios. The combination of GGNN and TCN can comprehensively characterize the coupling relationship and temporal evolution characteristics between terrain constraints, tourist behavior, and architectural space. It has achieved better analysis results in the coupling coordination index than the single graph neural network method. At the same time, it shows a good balance between model size and computational time, proving the coordination ability of this combination strategy between coupling analysis accuracy and computational efficiency. The GA-SA optimization algorithm further optimizes the coupling mechanism and performs better than various comparative algorithms in terms of coupling coordination, behavior trajectory overlap rate, and functional node reachability, verifying the effectiveness of this optimization strategy in improving spatial adaptability and behavior guidance effect. However, the above conclusions are based on data obtained from a single mountain tourism area case, and the validity of the research results is limited by the terrain conditions, building scale, and tourist behavior characteristics of the case. The research has not yet been extended and validated for mountainous tourism areas under different geological conditions, altitude gradients, and customer source structures, so the generalization ability of the model needs further testing. In addition, the optimization indicators of the research institute focus on quantitative dimensions such as spatial coupling coordination and behavioral adaptability at the spatial planning level, and specific economic output indicators or industry income data have not yet been included in the optimization objectives and evaluation system. Future research plans to conduct cross case validation in more diverse mountain tourism areas and explore incorporating multiple constraints such as environmental impact assessment and economic input-output analysis into the optimization framework to further enhance the practicality and promotional value of the model.

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