A Deep Intelligent Ant Colony-Based Approach to Personalized and Customized Route Optimization for Smart Tourism

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To enhance the travel experience of tourists and make the shortest travel personalized route, an innovative personalized route optimization method based on a deep, intelligent ant colony is proposed. The algorithm considers the tourists' travel time, cost constraints, and the experience of attractions. It establishes the objective function of tourists' personalized route optimization to maximize the utility of their travel and tourism activities and minimize the total path. Based on the attention mechanism neural network, the objective function feature matrix is extracted, which is used to replace the heuristic information matrix of the ant colony algorithm, and at the same time, the guidance information of the target point is added to understand the optimization of the ant colony algorithm. The optimized algorithm solves the objective function and obtains the optimization results of the personalized, customized route for intelligent tourism. This paper selected a tourist city with 20 4A level or above scenic spots as the test object, and conducted personalized customization optimization experiments on the tourist routes of these scenic spots using deep intelligent ant colony algorithm. The test results show that in the optimization of personalized customized routes for smart tourism, the application of feature extraction and improved ant colony algorithm has achieved a significant optimization effect of increasing the time reduction rate from 15.2% 33.7% to 44.6% 68.2%. At the same time, in various testing scenarios, including tourist non load and partial attraction load situations, the algorithm can reasonably plan the route and improve the tourist experience while ensuring the shortest total path. In the end, the optimized personalized route achieved a high level of over 93.36% in both the actual multi-objective shortest path proximity and single objective average achievement, verifying the superiority and effectiveness of this method.

Povzetek: V članku je predstavljen inovativen algoritem, ki združuje globoko učenje in optimizacijo kolonij mravelj za prilagojeno načrtovanje turističnih poti, kar izboljša personalizacijo in učinkovitost.

1 Introduction

Intelligent tourism is an emerging tourism method that provides comprehensive tourist information by sensing tourism resources, designing tourism activities, summarizing tourism information, and releasing it in time [1], [2]. Its development encompasses tourism management services and marketing at three levels, centering on the interactive experience of tourists, integration of tourism resources, customization of tourism products, and promotion of industrial innovation and upgrading. In implementing smart tourism, personalized planning of tourism routes is crucial [3], which can reduce traffic time, improve the quality of tourism, and meet the needs of tourists to choose different attractions [4]. Tourists usually plan travel routes according to time, cost, route length, attraction types, and other factors [5], [6], [7], but reducing travel time may reduce the number of attractions to play and cannot meet all the needs [8].

In reference [9], to achieve the design of heterogeneous group tourism routes, tourism safety is taken as the core goal, combined with the degree of pleasure of tourism, using artificial multi-intelligence systems for multi-objective tourism itinerary design. This method can reduce the risk of visiting scenic spots in the application process. However, the length of tourist routes is not considered. Therefore, the planned routes are often redundant. To achieve the optimal path planning in reference [10], an adaptive informed tree (AIT*) and effort informed tree (EIT*) are used to plan the path between the starting point and the target point, which is the shortest path between the two; However, in the application process of this method, it is unable to comprehensively consider the associations between multiple scenic spots for path planning, resulting in a single planning result from the algorithm. To achieve optimal path planning, reference [11] plans the path to minimize travel time. It solves this problem using the adaptive spider monkey optimization model to obtain optimal path planning results. However, in the application process, this method cannot guarantee the tourists' demand for the diversity of scenic spots. In reference [12], to ensure that the tourist routes meet the traffic conditions, route matching is carried out based on an intelligent algorithm combined with a map matching algorithm to determine and adjust the tourist routes. However, in the application process of this method, the travel time is extended. In summary, the current research can be summarized as follows:

Table 1: Related work

Reference resources	Method of use	Key findings	Limit
Reference [9]	Artificial Multi Intelligence System	Designing a multi-objective tourism itinerary with tourism safety as the core and combining it with the level of tourism enjoyment	Not considering the length of the tourism route resulted in excessive redundancy in the planned route
Reference [10]	Adaptive Informed Tree (AIT) and Effort Informed Tree (EIT)	Can effectively reduce the risk of visiting tourist attractions	Unable to comprehensively consider the relationships between multiple scenic spots, resulting in a single planning outcome
Reference [11]	Adaptive Spider Monkey Optimization Model	Plan the shortest path between the starting point and the target point	Cannot guarantee tourists' demand for diversity of scenic spots
Reference [12]	Intelligent algorithm combined with map matching algorithm	Obtain the optimal path planning result with the goal of minimizing travel time	Long travel time may reduce tourist experience

The profound wisdom ant colony algorithm is a traditional ant colony algorithm optimization algorithm, combining deep learning and ant colony algorithm formation [13]. The algorithm combines the advantages of the two algorithms to optimize the problem. In the process of the solution, the algorithm can be transformed into a different size of the business travel problem to form the corresponding heuristic matrix of information, and then based on the matrix for the solution of the business travel problem, the more careful consideration of the needs of business travel [14], to obtain the optimal solution. Therefore, a personalized customized route optimization method for smart tourism based on deep intelligent ant colony is proposed. By using attention mechanism neural networks, personalized features of tourists are captured and extracted in real time, forming a feature matrix. This matrix then replaces heuristic information in traditional ant colony algorithms, injecting dynamic and personalized guidance into the search process. At the same time, the guidance information of the target point is integrated to further optimize the search path of the ant colony, ensuring the maximization of tourism activity utility and the shortest total path while meeting the time and cost constraints of tourists. This technological innovation not only breaks the constraints of traditional tourism route planning relying on static data or simple rules, but also realizes dynamic and personalized route customization based on real-time preferences and constraints of tourists, greatly improving the personalization of tourism experience and overall satisfaction of tourists.

2 Optimization of personalized and customized itineraries for intelligent tourism

2.1 Architecture of smart tourism personalized route optimization method based on deep, intelligent ant colony

To meet the demand for tourists' personalized route planning, a smart tourism personalized customized route optimization method based on profound, intelligent ant colonies is proposed. This method is based on the restriction that a tourist can visit multiple attractions only once and replaces the distance between paths with the transportation time between attractions [15]. It considers the current popularity of attractions, crowding perception, and weights these parameters, while also taking into account tourists' perception of their tourism experience. Thus, it is determined in the paper to ensure the best tourist experience while making the shortest travel path [16]. The deep, intelligent ant colony optimization algorithm, based on the ant colony algorithm, improves the algorithm's solution efficiency by replacing the heuristic information matrix with the problem feature matrix extracted by the deep reinforcement learning method. The deep learning algorithm is applied to transform the tourist route optimization problem instance into the feature matrix of the problem, which is then used as the heuristic matrix for the ant colony algorithm to solve the personalized path planning.

The overall process of personalized route optimization for smart tourism based on deep, intelligent ant colonies is shown in Fig. 1.

The method consists of three essential parts: one is to determine the optimization objective function of smart tourism personalized routes, the second is to extract the feature matrix of the objective function by using a neural network that incorporates the attention mechanism, and the third is to obtain the optimization results of smart tourism personalized routes by using ant colony algorithm to solve the objective function based on the feature matrix.

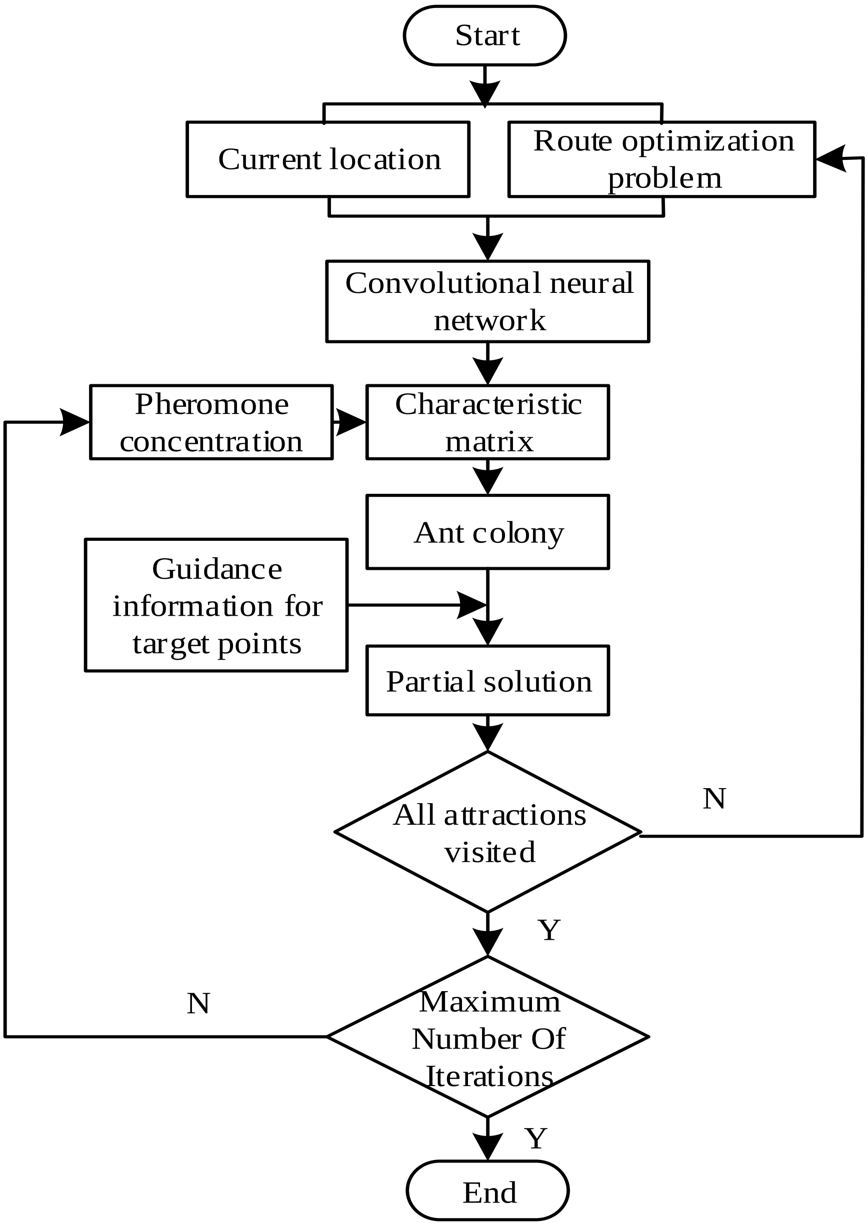


Figure 1: Overall process of personalized route development and optimization for smart tourism based on deep, intelligent ant colony

2.2 Smart tourism personalized route planning objective function determination

Setting up a tourist transportation network for $G = (V, D)$, of which $V = \{v_1, v_2, \cdots, v_n\}$ is consist of the starting point of the tourists' trip v_1, the ending point v_n and different types of attractions $v_i (i = 2,3, \cdots, n-1)$, $D = \{d_{ij}\}$ is the set of tourist transportation network paths, the d_{ij} is the direct path of attraction v_i arriving to attraction v_j. Tourist experience utility consists of two parts: the travel utility of tourists moving between nodes and the utility of tourist activities in attractions. In the travel process, tourists need to consider the mode of transportation when choosing tourist destinations [17]. Tourists who face various modes of transportation will select the mode of transportation with the most excellent utility [18], and the choice of transportation is related to its travel costs, travel time, and other service attributes. Tourist travel utility is calculated as follows:

$$U_{ij}^k = w_1 T_{ij}^k + w_2 C_{ij}^k \tag{1}$$

Where, U_{ij}^k is the travel utility of selecting k transportation mode between attractions i to j; w_1 and w_2 are weights for travel time and travel cost, respectively; the T_{ij}^k indicates choice of transportation mode k, the travel time from the attractions v_i to the attractions v_j. C_{ij}^k indicates choice of transportation mode k, travel expenses from the attractions v_i to the attractions v_j.

To maximize the utility of tourism activities, the level of tourism activity experience can be expressed in terms of tourism value indicators, i.e., the utility of tourism activities obtained by tourists at an attraction about the attributes of the attraction, the duration of the tourism activity and the cost of the attraction, the formula for the utility U_i^a obtained from tourism activities carried out at the attraction i is:

$$U_i^a = \frac{\beta_1 A_i + \beta_2 \ln(T_i^v)}{\exp(\beta_3 C_i)} \tag{2}$$

Where: A_i indicates the attractiveness of attractions i. β_1 and β_2 and β_3 denotes the parameter to be determined. T_i^v indicates the duration of tourism activities at the attractions v_i. C_i indicates the costs required to carry out tourism activities at the attractions v_i.

The optimization of tourists' travel routes should be based on the maximization of tourists' travel utility and the utility of tourism activities U_{max} and the shortest total path $\min Z$ as the goal, the goal comprehensively considers the tourists' travel time [19], cost constraints, and the sense of experience for the attractions, the establishment of tourists' personalized travel route planning optimization objective function, which is formulated as follows.

$$U\,max\left(\sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=2}^{n}\phi_1 x_{i,j}^k U_{ij}^k + \sum_{i=2}^{n-1}\phi_2 y_i U_i^a\right)_{max} \tag{3}$$

Where, ϕ_1 and ϕ_2 denote the travel utility and attraction utility weighting coefficients, respectively; the x_{ij} and y_i both denote decision variables.

To ensure that the objective function can fully meet the needs of tourists' personalized travel route planning, it is constrained as follows:

$$\begin{cases}\sum_{k=1}^{m}\sum_{j=2}^{n} x_{1,j}^k = 1\\ \sum_{k=1}^{m}\sum_{i=1}^{n-1} x_{i,n}^k = 1\end{cases} \tag{4}$$

$$\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{i,j}^k = 1 \tag{5}$$

$$\begin{cases}t_1 = t_2\\ t_1 + T_{i,j}^k = t_{sj}\end{cases} \tag{6}$$

$$\sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=2}^{n} x_{ij}^k T_{i,j}^k + \sum_{i=2}^{n-1} y_i (t_1 - t_3) \le t_0 - t_2 \tag{7}$$

$$\sum_{k=1}^{m}\sum_{i=1}^{n-1}\sum_{j=2}^{n} x_{i,j}^k C_{ij}^k + \sum_{i=2}^{n-1} y_i C_i^a \le C \tag{8}$$

$$\begin{cases}x_{i,j}^k = \begin{cases}1, & \text{Tourists choose transportation mode } k \text{ from node } i \text{ to } j \text{ for travel}\\ 0, & \text{else}\end{cases}\\ y_i = \begin{cases}1, & \text{Visiting tourist attractions } i\\ 0, & else\end{cases}\end{cases} \tag{9}$$

Among them, formula (4) is the round-trip constraint; formula (5) ensures that tourists can only choose one mode of transportation on each path; formula (6) requires that the sum of the end moment and the travel time of the tourist activity carried out in the previous attraction is equal to the start moment of the tourist activity in the next attraction [20]; formula (7) is the travel time constraint; formula (8) is the cost constraint; and formula (9) is the decision variable constraint. t_1, t_2, t_0 and t_3 denote the leaving time, departure time, return time, and arrival time attractions v_i respectively. C indicates the cost of the travel budget.

2.3 Attention mechanism neural network based objective function feature extraction

Since the objective function of smart tourism personalized route planning determined in the paper is a multi-objective function, to ensure the solution effect of the objective function, the features of intelligent tourism personalized route planning are extracted by constructing the neural network model of the attention mechanism, which provides the basis for the subsequent planning.

2.3.1 Structure of the neural network model of the attention mechanism

In the paper, the neural network model of attention mechanism in deep learning is used for the feature extraction of the objective function. The model consists of two parts: the encoder-decoder structure and the hybrid attention mechanism structure [21], the encoder-decoder structure is mainly responsible for the establishment of the correlation between the input of the objective function problem and the output of the features in the travelers' situation, the input of the objective function problem is the coordinate of all the attractions and the information of the currently constructed partial solution [22]. The hybrid attention mechanism structure integrates the correlation between the input and output parameters of the objective function-solving problem in the encoder-decoder. It gives different degrees of attention to the cities to be visited. Fig. 2 illustrates the structure of this model.

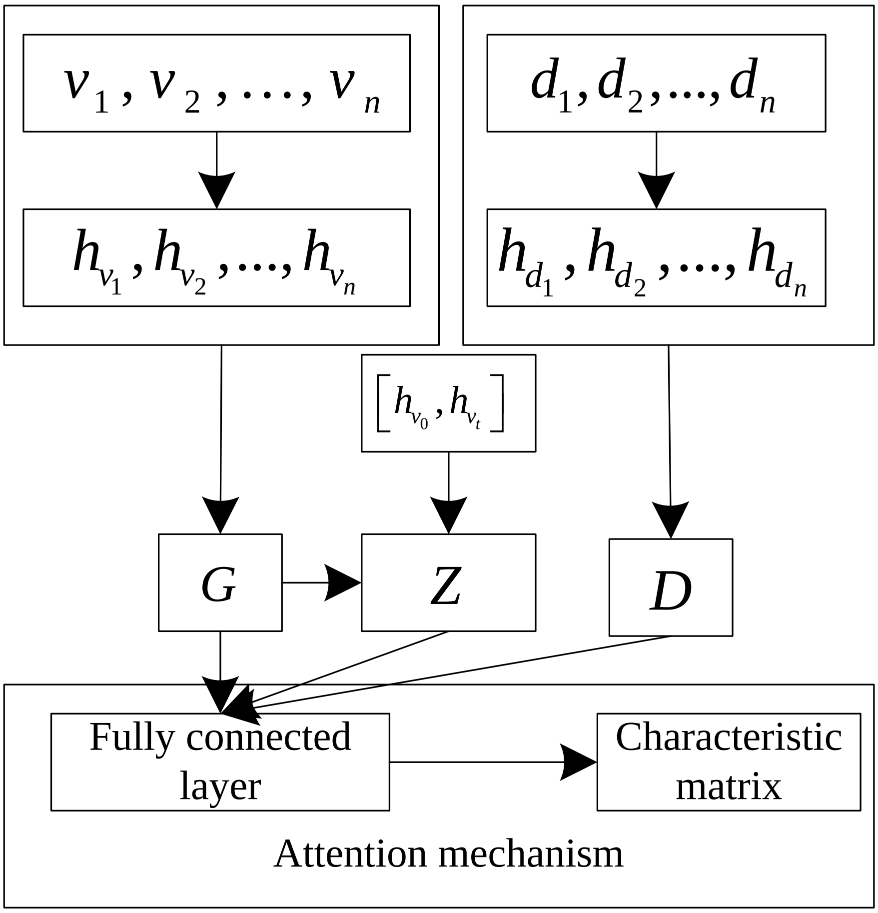


Figure 2: Attention mechanism neural network model structure

The encoder in this model uses a one-dimensional convolutional embedding layer structure to transform the problem inputs into high-dimensional vectors, fully utilizing the structural information in the attractions. The inputs to this part are the Euclidean coordinates of each attraction. In the encoder, the feature vectors corresponding to the outputs of each task are independent of each other, and thus these variables do not reflect the characterization of the set of edges for the attractions D. Consequently, it is necessary to target the set of edges of the D for characterization. This paper adopts the hybrid attention neural network structure to extract relevant features. This variable can be considered as a global variable of the scene, which contains the relevant information of the set of edges E.

The decoder is mainly used to combine the encoder input, global variable input, and current solution information [23] to output evaluations of all optional scenic spots for the next stage. Considering that the solution process of the traveling salesperson problem has specific Markov characteristics, that is, the evaluation of optional scenic spots in the next stage is only related to the initial scenic spots and the current scenic spots, so this paper will initially visit the scenic spots v_0, the current location of the attraction v_t and the distance d_t^i between the currently visited site and other sites to be visited as the input to the decoder and defines the structure of the decoder as a superficial one-dimensional embedding layer.

The hybrid attention mechanism structure is used to predict which of the following available attractions is more likely to be chosen for an optimal solution, and the attention model is used to give a higher probability of selection to the attraction that is more likely to produce an optimal solution in the next step.

2.3.2 Objective function feature extraction

In the paper, to fully grasp the characteristics of the objective function, this method adopts the hybrid attention neural network structure for the feature extraction of the objective function, and the mixed attention neural network is composed of two network structures, which are the bidirectional long and short-term memory network and the convolutional neural network, respectively.

The structure transforms the coordinate feature $[x_i, y_i]$ of the city and the distance d_t^i between the currently visited city and the other cities to be seen into the feature vectors $H = [h_{v_1}, h_{v_2}, \ldots, h_{v_n}]$ and $B = [h_{d_1}, h_{d_2}, \ldots, h_{d_n}]$ of the corresponding dimensions, after which the global variable G is obtained by hybrid attention modeling. On this basis, calculate the state variable Z using the formula:

$$Z = g\,lim\,p\,se(G; [h_{v_0}, h_{v_t}]) \tag{10}$$

Where: $[h_{v_0}, h_{v_t}]$ express performing splicing operations to v_0 and v_t.

Decode G, B and Z component models, and input the full connected layer for feature calculation. The mixed attention mechanism can project G, B and Z with each projection matrix of n, and then calculate single attention for n times respectively, and finally splicing the result [24]; obtaining the relevance of each to-be-visited attraction $\mu(y_i, x_i)$, the softmax function is used to normalize the correlation, and the specific score for the following optional scenic spots is obtained.

The formula for $\mu(y_i, x_i)$ is:

$$\mu(y_i, x_i) = tanh(y_i \times w \times x^T + b; Z) \tag{11}$$

Where: y_i denotes the output of the bi-directional long and short-term memory network, i.e., the set of selected attractions. x denotes the feature vector of the production of the convolutional neural network layer, i.e., the set of points of interest to be chosen. w indicates the weights. b indicates a bias.

To ensure the effectiveness of feature extraction, a parameter matrix κ is introduced, and superimpose κ and $\mu(y_i, x_i)$ to obtain the feature matrix, which is calculated as follows:

$$\begin{bmatrix} J_1 \\ J_2 \\ \vdots \\ J_n \end{bmatrix} = \begin{pmatrix} \kappa_{11} & \kappa_{12} & \cdots & \kappa_{1n} \\ \kappa_{21} & \kappa_{22} & \cdots & \kappa_{2n} \\ \vdots & \vdots & & \vdots \\ \kappa_{n1} & \kappa_{n2} & \cdots & \kappa_{nn} \end{pmatrix} \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix} \tag{12}$$

Where: μ_i denotes the vector of similarity matrices.

The weight calculated by mixed distribution is normalized by softmax to obtain the corresponding weight W_i, finally, the output vector of the bidirectional network with the corresponding weights W_i computed to obtain the final objective function characterization O_i, which is calculated by the following formula:

$$W_i = \frac{exp(J_i)}{\sum_{j=1}^{n} exp(J_i)} \tag{13}$$

$$O_i = \sum_{i=1}^{n} W_i\, y_i \tag{14}$$

Where: J_i denotes the similarity feature vector.

After the calculation of O_i in accordance with the above steps, the initial starting point is set for each attraction in the scene one by one, the feature vectors of each remaining attraction are obtained, and finally, the feature vectors of all the attractions are spliced to derive the heuristic matrix M_0. To reduce the computational complexity of the model, pre-processing for M_0, which is calculated as follows:

$$P(y_t, x_t) = soft\,max\left(\frac{\mu_t^i}{\sqrt[3]{n}}\right) \tag{15}$$

Where: n denotes the size of the example. $P(y_t, x_t)$ is the conditional probability of a transfer from a selected attraction to a to-be-selected attraction.

Through formula (15), we can achieve the equal proportion of μ_i to reduce, and narrow the order of magnitude gap of the evaluation value of different scenic spots in M_0. The travel quotient problems solved in this paper are all symmetric travel quotient problems, that is, travel from city s^i to city s^j should have the same evaluation as travel from city s^j to city s^i. Therefore, this paper uses the following method to process M_0 and obtain the final feature matrix M, whose calculation formula is:

$$M = M_0 + M_0^T \tag{16}$$

Where: M_0^T represents the transposition of M_0.

2.4 Optimal path solving for tourism personalization based on improved ant colony algorithm

According to the above subsection, after completing the extraction of the feature matrix of the objective function, considering that the optimization based on the feature matrix may fall into the local optimal solution, it isn't easy to find the global optimal solution. Therefore, the ant colony algorithm is used to solve the objective function. Still, the ant colony algorithm will leave pheromone on the paths in the process of solving. Other ants will tend to choose the paths with more pheromone to search for the objective solution when they sense the residual pheromone, and the inspirational information of the ant colony algorithm is the inverse of the Euclidean distance between the current node and the next optional node, due to the lack of the objective point. Due to the lack of guidance information on the target point and the slight difference in the amount of pheromone between different paths at the early stage of the algorithm, ants have a great deal of randomness in choosing paths, which reduces the search efficiency and optimization ability of the ants. Therefore, to improve the optimal path-solving effect of tourism personalization [25], To incorporate the heuristic information matrix in the M -substitution algorithm acquired in the above subsection, based on the replacement, and then add the guidance information of the target point to reduce the invalid path search, optimize the algorithm for the personalized optimal path searchability, to ensure the optimization effect of the path.

When ants move, the probability of each path being selected is derived by the pheromone concentration and distance heuristic function [26], and a roulette algorithm selects the paths, the probability for ant m moving from the node i to node j is calculated by the formula:

$$P_{ij} = \begin{cases} \dfrac{[\xi_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{M\left\{[\xi_{ij}(t)]^{\alpha} + [\eta_{ij}(t)]^{\beta}\right\}}, j \in E_i \\ 0,\ j \notin E_i \end{cases} \quad (17)$$

Where: P_{ij} is probability of moving from node i to node j; the α is pheromone-inspired factors; the β is the expectation function factor, both of which affect the importance of the pheromone and distance heuristic functions, respectively. E_i denotes the set of destinations that the ants can reach in the next step. i is the current node; the $\xi_{ij}(t)$ represents the pheromone concentration in the moving route between different nodes i and j at time t; the $\eta_{ij}(t)$ denotes the heuristic information function, which is calculated as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (18)$$

By replacing the $\eta_{ij}(t)$ in formula (17), the guide information of the target point is added to the heuristic function to reduce the invalid path search, and the calculation formula of the improved heresy's function is as follows:

$$\widetilde{M}(t) = \frac{1}{D_{ij} + d_{jE}} \quad (19)$$

Where: D_{ij} is the equivalent distance between the current node i and the next optional node j; d_{jE} is the Euclidean distance between the node j and the target point E.

Improving the heuristic function can successfully avoid the issue of inadequate heuristic information at the early stage of the algorithm and improve its search efficiency.

The objective function is optimized once the heuristic function has been improved to a satisfactory degree. When each ant completes a step or constructs a complete path, it is necessary to update the pheromone. The pheromone updating rule is formulated as follows.

$$\xi_{ij}(t+1) = (i-\rho)\xi_{ij}(t) + \Delta\xi_{ij}(t) \quad (20)$$

$$\Delta\xi_{ij}(t) = \sum_{k=1}^{m} \Delta\xi_{ij}^{k}(t) \quad (21)$$

Where: ρ is the pheromone volatilization coefficient, and $\rho \in (0,1)$; $\Delta\xi_{ij}(t)$ is the total change in the upper pheromone on the section (i,j); $\Delta\xi_{ij}^{k}(t)$ is the amount of pheromone released by the kth ant on section (i,j).

$\Delta\xi_{ij}^{k}(t)$ usually use the ant cycle system model for calculation, and the formula is:

$$\Delta\xi_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{d_k}, \text{Ant } k \text{ passes through } (i,j) \text{ in this loop} \\ 0, \qquad\qquad \text{else} \end{cases} \quad (22)$$

Where: Q is a constant indicating the pheromone intensity. d_k is the length of the path traveled by the kth ants in this loop.

Since the objective function constructed in the paper considers the tourists' sense of experience for the attractions, to ensure that the formulated personalized path meets the tourists' needs for the attractions, the selection probability between the attractions is calculated, and the weight between the attractions needs to be restricted before the probability calculation, which is calculated by the following formula:

$$w_{ij} = \begin{cases} \dfrac{d_{ij} \cdot k_j}{N_j \cdot q_j}, \tilde{R} \le R_j \\ \dfrac{d_{ij} \cdot \tilde{R}}{N_j \cdot q_j}, R < \tilde{R} < N \\ \dfrac{d_{ij} \cdot \tilde{R} \cdot e^{\gamma \cdot (\tilde{R} - N)}}{N_j \cdot q_j}, \tilde{R} \ge N \end{cases} \quad (23)$$

$$P_{ij}^{k} = \frac{[\xi_{ij}(t)]^{\alpha} \cdot [\widetilde{M}(t)]^{\beta}}{\sum_{k \in E_i}\left([\xi_{ij}(t)]^{\alpha} \cdot [\widetilde{M}(t)]^{\beta}\right)} \quad (24)$$

Where: $\tilde{R}$ is current number of people in the scenic area for attraction j. γ is the relative importance of the number of people on the tourist experience when the number of people in a picturesque spot exceeds the load. N_j is the maximum number of persons loaded for attraction j. R_j i critical mass that does not affect the tourist experience for attractions j. q_j indicates the current attraction popularity rating.

Based on the above steps, pheromone updating is carried out, in updating the pheromone, first judge: whether the current round of iteration makes the path optimization degree is higher, if yes, then update the residual pheromone; on the contrary, only volatile pheromone without increasing the residual pheromone. The optimization and updating formula of pheromone is as follows:

$$\begin{cases}\tau_{ij}(t+1)=(1-\varepsilon)\tau_{ij}(t)+\sum\tau_{ij}^{k}, \sum w(t+1)\geq\sum w(t)\\ \tau_{ij}(t+1)=(1-\varepsilon)\tau_{ij}(t), \sum w(t+1)<\sum w(t)\end{cases} \quad (25)$$

Where: ε is the pheromone volatilization constant; the $\sum w(t)$ denotes the sum of all path weights.

The steps for solving the optimal path for tourism personalization based on the improved ant colony algorithm are described as follows:

Step 1: Initialization of parameters. Set the number of cycles that $N_c = 0$, the maximum number of cycles N_{max}, emptying of the taboo table S_k. Order the initialization pheromone of (i, j), the $\tau_{ij}(0) = \tau_0$, of which τ_0 is a constant, and at the initial moment, the $\tau_{ij}(0) = 0$; Calculate $\tilde{M}(t)$.

Step 2: Place m ants on n attractions, then the city where the ant k is located added to the S_k of the ant k.

Step 3: Number of cycles $N_c = N_c + 1$ and the number of ants $K = 1$.

Step 4: Computing the path selection probability $P_{ij}^{k}(t)$ for ant k, moving to the next attraction as determined by a random factor j, then j is added to the taboo table S_k of ant k, at this point $K = K + 1$.

Step 5: If satisfied $K \geq m$, perform step 4; otherwise, perform step 6.

Step 6: Calculate the travel expenses for each ant's path, the $\tilde{C}$ and travel experiences F, which is used to obtain the value of the composite objective function $min\, S$ and U_{max} and record the current optimal solution; if the optimal solution is the current optimal solution, then conduct a local search to determine whether the optimal solution needs to be updated.

Step 7: Update the path pheromone, after update, the pheromone $\tau_{ij}(t)$ of each edge (i, j) is judged, greater than τ_{max} amend to τ_{max}, less than τ_{min} amend to τ_{min}.

Step 8: If satisfied $N_c > N_{max}$, then the next step is performed; otherwise, the taboo table S_k is cleared, perform step 3.

Step 9: Output the result of the objective function, i.e., the optimal path result of tourism personalization.

3 Test analysis

To verify the application effect of the method in the intelligent tourism personalized customization route optimization, this paper selects a tourism city as the test object. The city has 20 scenic spots above the 4A level and 66 scenic spots above the 3A level. This paper only uses 20 scenic spots above the 4A level as the test scenic spots of this method and uses the technique in this paper to customize and optimize the tourism routes of these scenic spots; the application effect of the process is tested. Fig. 3 displays the plane distribution of 20 test scenic spots in the city.

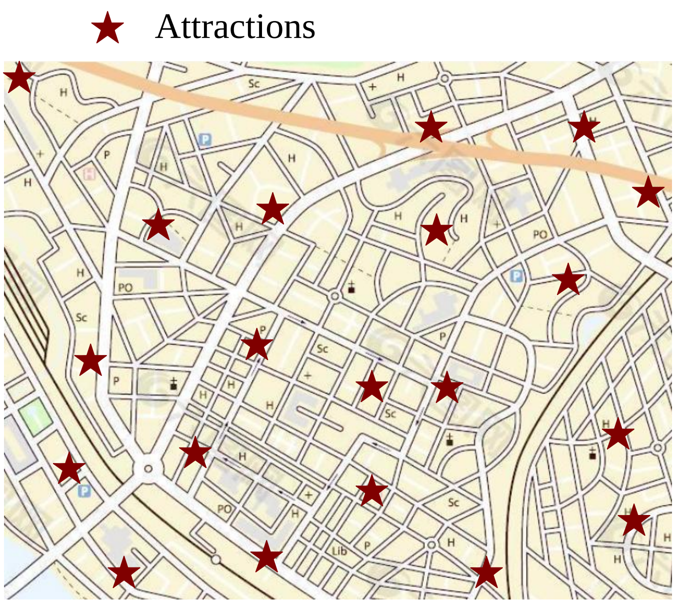


Figure 3: Schematic diagram of the planar distribution of 20 test scenic spots in the city

The relevant parameters for each attraction are displayed in Table 2.

During the experiment, the test dataset covered detailed information of 20 attractions with a 4A rating or higher, including location coordinates, opening hours, ticket prices, and tourist reviews, as well as personal preference data of tourists, such as time preferences, cost budgets, and attraction type preferences. In order to evaluate the performance of the proposed optimization path algorithm, the algorithm parameters shown in Table 3 were set. Meanwhile, multiple evaluation metrics were employed to comprehensively and meticulously assess the effectiveness and practicality of the algorithm.

Table 2: Relevant parameters of each scenic spot

Scenic Area Number	Current number of people/person	Fame rating
1	447	75.6
2	503	80.2
3	329	70.1
4	766	88.4
5	384	70.3
6	422	72.0
7	803	94.6
8	777	90.1
9	526	76.6
10	607	80.4

Table 3: Details of algorithm parameter settings proposed

Category	Describe	Specific values/parameters
Neural Network Architecture	Input layer	Node count: 10 (scenic feature dimension)
	Hidden layer 1	Number of nodes: 64, activation function: ReLU
	Hidden Layer 2	Number of nodes: 32, activation function: ReLU
	Output layer	Node count: 1, activation function: Sigmoid
Training parameters	Learning rate	0.001
	Optimizer	Adam optimizer
	Loss function	Mean Square Error (MSE)
	Batch size	32
	Training epochs	100
	Early stop strategy	Stop if the loss of the validation set does not decrease for 20 consecutive rounds
Deep intelligent ant colony algorithm	Ant number	50
	Pheromone volatility coefficient	0.7
	Pheromone intensity	Initial value: 1, dynamically updated
	Heuristic information	Utility value matrix output by neural network
	Select probability function	Roulette selection method, incorporating target point guidance information
	Improvement point 1	Dynamically adjust inspiration information
	Improvement Point 2	Target point guidance increases the probability of selection
Hardware	CPU	Intel Core i7-9700K
	GPU	NVIDIA GeForce RTX 2080 Ti
	Memory	32GB DDR4
Software environment	Operating system	Windows 10
	Programming language	Python 3.8
	Deep Learning Framework	TensorFlow 2.4
	Other libraries	NumPy, Pandas, Matplotlib

(1) Time reduction rate: used to measure the percentage reduction in total travel time before and after optimization;

(2) Path length: Ensure that the actual total path traveled is as short as possible;

(3) Multi objective shortest path proximity: reflects the degree to which the optimized path approaches the optimal solution in multiple dimensions (time, cost, experience), quantified in percentage form;

(4) Single objective average achievement: The average achievement level of the optimization path for each single objective (such as shortest time, lowest cost, best experience), expressed as a percentage.

The method in the paper in the intelligent tourism personalized customized route optimization process first extracts the characteristics of the objective function based on the results of the characteristics of the personalized customized route optimization solution. Therefore, removing the attributes of the effect is essential, randomly selecting ten attractions, using the method in the paper on extracting the characteristics of the ten attractions, to obtain the results of the visualization of its feature matrix, as shown in Fig. 4.

In Figure 4, each matrix represents a specific feature such as geographic distance, tourist ratings, and opening hours, and the color intensity in the matrix intuitively reflects the similarity or difference between attractions on that feature. Matrix A represents the geographical distance characteristics between tourist attractions. The depth of colors directly reflects the physical distance between scenic spots, which helps optimize algorithms to consider the convenience of actual travel when planning routes. After analyzing the test results in Fig. 4, it is concluded that the method in the paper can calculate the feature matrix between different attractions in the process of personalized route optimization and solving. Each attraction has its corresponding feature results, and the extracted results can present the distribution of each feature, similarity, etc., which can provide a reliable basis for optimizing and solving personalized, customized routes.

The paper uses the improved ant colony algorithm to solve the personalized route optimization. The algorithm needs to update the pheromone concentration during the solution process, and the ants are based on the pheromone concentration for the path selection, to obtain the distribution of pheromone concentration updating during the application process of the method in the paper, and the test results are shown in Fig. 5.

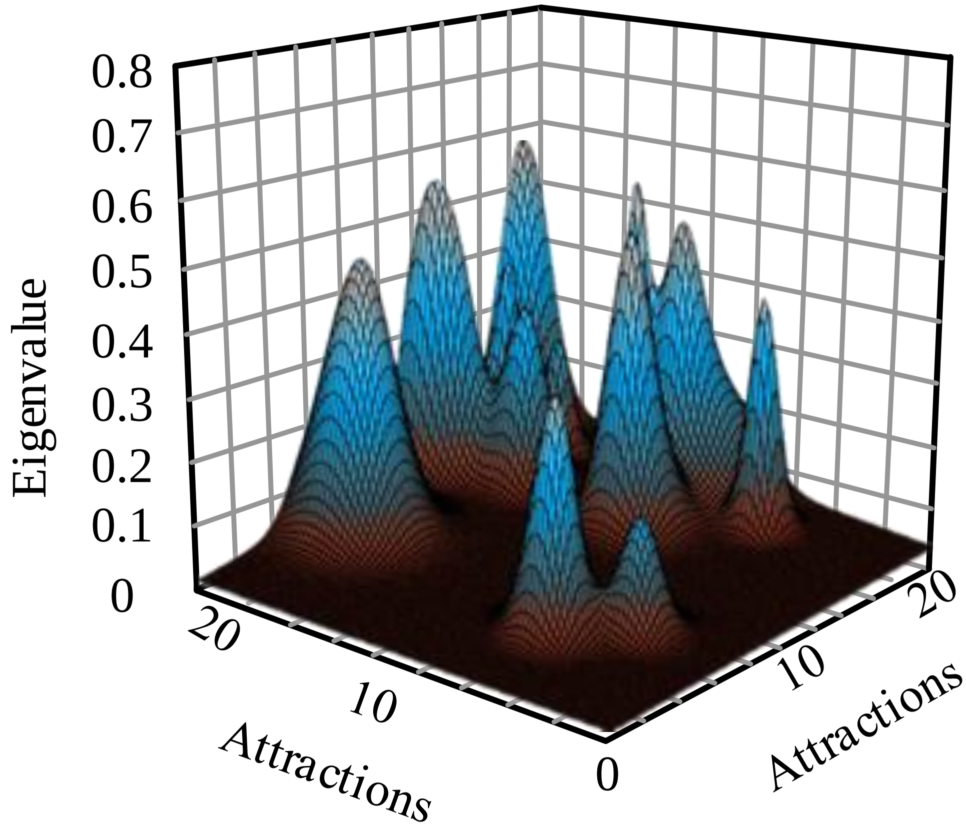


Figure 4: Visualization results of feature matrices between ten scenic spots

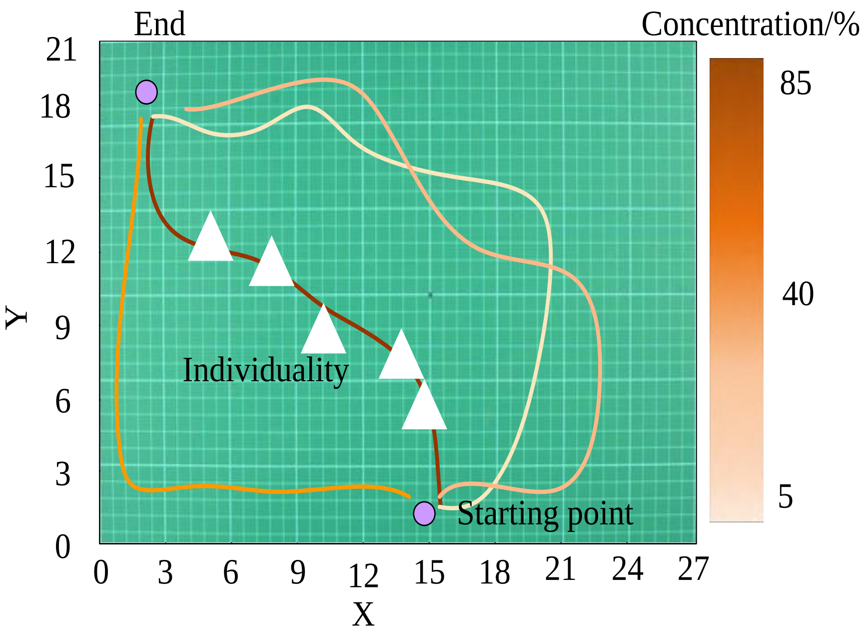


Figure 5 Update distribution results of pheromone concentration

After analyzing the test results in Fig. 5, it is concluded that the algorithm in the process of searching for excellence, with the gradual increase of pheromone concentration, ants move to the target point of the path is getting shorter and shorter, through the pheromone concentration of the update, the highest concentration of the path that is the path of searching for the optimal. Hence, the algorithm has a better application, can be based on the size of the pheromone on the path of the ant's allocation, and finally determines the path of the highest concentration of the path. The path with the highest pheromone concentration is finally resolved.

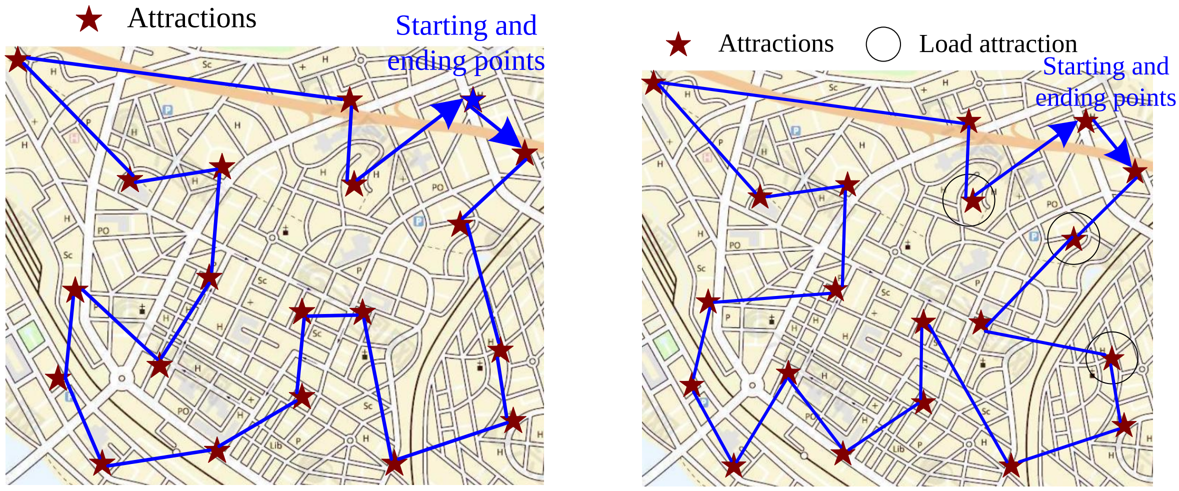
In this paper, the feature matrix of the objective function is mainly applied to substitute the heuristic information function of the ant colony algorithm in solving the objective function. At the same time, the guiding information of the target point is added to reduce the ineffective path search and optimize the algorithm's ability to search for the sexually optimal paths. The time reduction rate is used in the paper as an average index to evaluate the optimization effect of the algorithm. Table 3 displays the test outcomes before and after optimizing the algorithm under different numbers of attractions.

After analyzing the test results in Table 3, it is concluded that the time reduction rate is 15.2%~33.7% when the algorithm makes routes between different numbers of scenic spots before optimization. After optimizing the algorithm in this paper, the time reduction rate is between 44.6% and 68.2% when making routes between different numbers of scenic spots. The result of the time reduction rate is significantly better than before optimization. Therefore, the optimization effect of this method is good, which can better realize the optimization of intelligent tourism personalized customization routes and obtain the best route formulation scheme.

To verify the application effect of the method in the paper, in the attractions of non-loaded tourists and part of the attractions tourists load (of which three attractions occur tourists load) two cases, using the method in the paper to carry out the personalized route optimization in the two cases, to obtain the optimal path of the planning results, as shown in Fig. 6.

After analyzing the test results in Fig. 6, it is concluded that in the case of non-load of tourists in scenic spots and some scenic spots, the optimization of the personalized, customized route, can ensure the shortest total path to achieve the goal of personalized travel route planning optimization of tourists, in addition, when the tourist load occurs in some scenic spots, this method can reasonably carry out the time planning of the loaded scenic spots, and load the scenic spots, so as not to increase the route planning length without ensuring the experience of tourists, and meet the goal of personalized travel route planning and optimization.

To further verify the application effect of the methods in the paper, the reference [9] method, the reference [10] method, the reference [11] method, the reference [12] method are selected as the comparison methods of the optimization methods in the paper, and the results of the total length of the customized routes of the five algorithms are tested in the route customization of tourists with ten different starting points, and the entire length of the customized routes are tested in the premise of completing tours to 20 sightseeing spots, as shown in Table 4.



(a) Results of tourist non load (b) Results of tourist load in some scenic spots

Figure 6: Planning results of the optimal route

Table 4: Test results of time reduction rate under different numbers of tourist attractions

Number of attractions/piece	Before optimization	After optimization
2	16.6	50.2
4	17.3	55.7
6	21.1	60.3
8	24.9	62.7
10	26.7	48.9
12	30.5	60.1
14	15.2	68.2
16	32.4	66.6
18	33.7	50.5
20	30.6	44.6

Table 5: Total length results of customized routes using five methods

Starting point	Reference [9] Method	Reference [10] Method	Reference [11] Method	Reference [12] Method	The method in the text
1	119.6	122.2	118.6	123.7	109.6
2	120.5	122.4	120.7	119.7	111.3
3	119.5	124.8	122.8	120.6	112.4
4	121.2	123.4	120.7	121.1	108.3
5	120.6	121.1	120.8	125.3	114.4
6	122.2	121.6	120.3	122.1	113.8
7	116.8	118.4	120.2	119.7	111.1
8	118.8	119.7	120.7	118.5	104.3
9	121.1	122.5	123.6	120.9	112.2
10	120.9	122.3	122.1	124.5	112.3

Based on the analysis of the test results in Table 4, it is concluded that when ten tourist routes located at different starting points are formulated by reference [9] method, reference [10] method, reference [11] method, and reference [12] method, respectively, the four methods can obtain the total path planning results, and the full path planning results of the four methods are slightly different; After the route customization among all scenic spots is carried out with the method in this paper, the route planning result is significantly less than that of the other four methods at the same starting point, of which the longest planned route is 114.4 km. Therefore, the method in this paper has a good application effect and can obtain the shortest route planning result while ensuring the maximum utility of tourists.

To further verify the optimization effect of the method in the paper for the personalized route of intelligent tourism, after the route planning by the process, the actual multi-objective shortest path proximity and single-objective average degree of realization are used as evaluation indexes to judge the optimized routes by the method in the paper. The values of the actual multi-objective shortest path proximity and single-objective average degree of realization are all in the range of 0 to 100%. The larger the value, the better the optimization effect of the personalized route is. After analyzing the customized optimization of routes with different distances by the method in the paper, the actual multi-objective shortest path proximity and single-objective average realization of the optimized routes are shown in Table 5.

After analyzing the test results in Table 5, it is concluded that after using the method in the paper to optimize and customize the personalized routes, the actual multi-objective shortest path proximity and single-objective average realization of each route optimization are above 93.36% and the maximum values of the two reach 98.68% and 99.03%, respectively. Therefore, the method in this paper has a good application effect, which can ensure the optimization of personalized route customization effect and enhance the tourists' experience.

In order to evaluate the computational efficiency and scalability of the proposed personalized customized route optimization method for smart tourism based on deep intelligent ant colony, this paper compares it with a baseline method (greedy algorithm). The experiment was conducted on three different sized datasets: a small dataset (containing 10 attractions, each with 5 features), a medium-sized dataset (containing 50 attractions, each with 10 features), and a large dataset (containing 200 attractions, each with 15 features), to observe the changes in algorithm performance with increasing data volume. The experimental results are shown in Table 6.

According to Table 6, as the size of the dataset increases, the running time of both algorithms significantly increases. This indicates that the computational complexity of the algorithm is positively correlated with the size of the dataset. The proposed algorithm has a slightly longer running time on small datasets than the baseline algorithm, but the increase in running time is relatively large on medium and large datasets. This may be due to the proposed algorithm adopting more complex optimization strategies when dealing with complex scenes, resulting in an increase in computational complexity. Despite running for a long time on large datasets, it is still able to complete calculations in a reasonable amount of time (about 12 seconds), indicating that the algorithm has a certain degree of scalability. In contrast, although the baseline algorithm has a shorter running time on large datasets, its optimization effect is not as comprehensive and accurate as the proposed algorithm. In summary, the proposed algorithm has shown good performance in personalized tourism route optimization. Despite its high computational complexity, it still has good scalability at a reasonable dataset size.

Table 6: Optimization Effect Test Results for Different Routes

Route length /km	Multi-objective shortest path proximity	Average achievement of a single objective
3	95.07	95.58
6	97.22	96.14
9	96.14	99.03
12	94.27	97.22
15	97.35	95.28
18	93.36	94.14
21	94.82	97.08
24	98.11	95.66
27	98.68	94.47
30	97.69	98.11

Table 7: Scalability experiment of the proposed method

Dataset size	Number of attractions	Number of features	The running time of the proposed algorithm (s)	The running time of the baseline algorithm (s)
Small datasets	10	5	0.012	0.008
Medium sized dataset	50	10	0.456	0.234
Large datasets	200	15	12.345	6.789

4 Discussion

4.1 Discussion on algorithm advantages

In the field of personalized customized route optimization for smart tourism, the method proposed in this study has demonstrated significant advantages compared to state-of-the-art methods (SOTA) in multiple aspects. The following is a detailed discussion of these differences, including routing optimization efficiency, computational complexity, and practical applicability.

This study significantly improves the efficiency of routing optimization by introducing feature matrices to replace the heuristic information function of traditional ant colony algorithms and combining it with the guidance information of the target point. From the results in Table 2, it can be seen that the optimized algorithm has increased the time reduction rate from 15.2% 33.7% to 44.6% 68.2% in route planning between different numbers of scenic spots, which far exceeds many SOTA methods. This indicates that the method proposed in this study is more efficient in finding the optimal path and can converge to the optimal solution faster, thereby reducing user waiting time and improving user experience.

Although the method used in this study performed well in optimizing efficiency, its computational complexity did not significantly increase. Ant colony algorithm itself is a heuristic search algorithm, and its computational complexity mainly depends on the number of iterations and the number of ants. This study improved the pheromone update mechanism and introduced a feature matrix. Although some preprocessing steps were added, it did not significantly affect the overall computational complexity. In contrast, some SOTA methods may use more complex mathematical models or optimization algorithms, which can achieve better optimization results, but have higher computational costs and are not conducive to real-time applications.

In practical applications, the method proposed in this study demonstrates stronger adaptability and flexibility. As shown in Figure 6, the method proposed in this study can achieve the optimization goal of personalized travel route planning for tourists while ensuring the shortest total path in both non load and partially loaded tourist scenarios. Especially when there is a tourist load at some scenic spots, this method can reasonably plan the time of the loaded scenic spots, avoid overcrowding of tourists, and improve the tourist experience. Furthermore, from the results in Table 3, it can be seen that the route planning results of our method are significantly lower than other SOTA methods at the same starting point, which further proves its superiority in practical applications.

Compared with existing research methods, this study's approach addresses the limitations of previous work in the following aspects:

(1) Considering multi-objective optimization comprehensively: Traditional methods often only focus on a single objective (such as shortest path, least time, etc.), while the method proposed in this study achieves multi-objective optimization (such as safety, pleasure level, diversity of scenic spots, etc.) by introducing feature matrices and target point guidance information, better meeting the personalized needs of tourists.

(2) Adapting to complex scenarios: Traditional methods often struggle to effectively cope with complex scenarios such as tourist loads. The method of this study effectively solves this problem through reasonable time planning and load attraction planning, improving the robustness and practicality of the algorithm.

(3) Improving optimization effect: By improving the pheromone update mechanism of ant colony algorithm and introducing feature matrix, this research method has achieved significant improvement in optimization effect, not only increasing the time reduction rate, but also ensuring the quality of the optimized route.

In summary, the method proposed in this study has demonstrated significant advantages over SOTA methods in terms of routing optimization efficiency, computational complexity, and practical applicability. These advantages are mainly due to the in-depth improvement of algorithm mechanisms and comprehensive consideration of practical problems, making this method have a wider application prospect in the field of personalized route optimization for smart tourism.

4.2 Ethical discussion

With the development of personalized tourism services, data privacy has become an issue that cannot be ignored. This study attaches great importance to the privacy protection of user data when designing and implementing algorithms. We use encryption technology to process sensitive information such as user location, preferences, etc., ensuring that unauthorized third parties do not access the data during transmission and storage. In addition, strict data access control has been implemented to ensure that only authorized personnel can access and process user data. In algorithm design, we also try to avoid collecting unnecessary personal information and only analyze it through anonymization or aggregation of data when necessary to reduce the invasion of individual privacy. These measures not only comply with the requirements of data protection regulations, but also demonstrate respect and protection for users' privacy rights.

Personalized travel route recommendations have had a positive impact on tourist behavior. By providing routes that align with personal interests and preferences, tourists can enjoy the travel process more and reduce the fatigue and dissatisfaction caused by blind sightseeing. Meanwhile, personalized route recommendations can also guide tourists to discover more unique attractions and activities, enriching their travel experience. However, it should also be noted that excessive reliance on personalized recommendations may lead to a homogenization of tourists' travel behavior, reducing exploration and discovery of unknown areas. Therefore, while providing personalized services, tourists should also be encouraged to maintain an open and curious attitude, actively explore and experience different cultures and landscapes.

Personalized travel route recommendations have also had a profound impact on local communities. On the one hand, reasonable route planning can balance the tourist flow of various attractions, reduce congestion at popular attractions, and thus protect the local ecological environment and cultural heritage. Meanwhile, by guiding tourists to relatively less popular attractions, it can promote the balanced development of the local economy and increase residents' income. On the other hand, personalized route recommendations may also exacerbate the commercialization trend of certain scenic spots, damaging the original cultural atmosphere and ecological environment. Therefore, when developing personalized routes, it is necessary to fully consider the interests and demands of the local community, ensuring that tourism activities are coordinated with local culture and environment.

In summary, the method of this study has demonstrated its superiority in multiple aspects, while also recognizing that in the process of optimizing personalized customized routes for smart tourism, it is necessary to attach great importance to data privacy protection, ethical considerations, and the impact on tourist behavior and local communities. Only in this way can we better promote the development of smart tourism and provide tourists with better, safer, and more sustainable tourism experiences.

5 Conclusion

Intelligent tourism personalized, customized routes are the basis for ensuring tourists' sense of experience, and reasonable tourism routes can reduce excessive traffic time and enhance the utility time of tourism. Hence, the paper proposes an intelligent tourism personalized customized route optimization method based on the deep, intelligent ant colony algorithm. The method considers the tourists' experience, travel time, and the best path between attractions to realize route optimization and improve the quality of tourism services and tourists' satisfaction. After testing the application effect of the method, it is concluded that it has a good application effect, can obtain the characteristic results of the objective function, and can get the best-customized tourism routes to meet the travel needs of tourists based on the excellent performance of optimization search.

Competing of interests

The authors declare no competing of interests.

Authorship contribution statement

Zhao Ziyue: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Data availability

On Request

Declarations

Not applicable

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

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All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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