Tourist Attraction Recommendation Model Combining User Interest Modeling and Heuristic Journey Planning Algorithm

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As the boost of science and technology, smart tourism is a new trend in the tourism industry. The use of tourist attraction recommendation models can provide tourists with a more convenient, personalized, and efficient travel experience. However, traditional recommendation models cannot accurately understand the needs of tourists and provide corresponding services. In response to this issue, this study proposes to construct a new type of tourist attraction recommendation model through user interest modeling and heuristic travel planning algorithms. This study verified the performance, and the comparative experiment demonstrates that the algorithm has an accuracy of 91%, a stable accuracy of 97%, a running time of 11.5 seconds, and a total travel planning time of 193 minutes, all of which are superior to the comparative algorithms. The analysis of the usage effect of the research model showed that the accuracy reaches 98% and the total time to effect ratio is 4.47, both of which are higher than the comparison model. In summary, the proposed tourist attraction model-based user interest modeling and heuristic itinerary planning algorithm has high accuracy, good itinerary planning effect, and feasibility. This model can provide personalized services for tourists to maximize their travel needs.

Povzetek: Prispevek predstavi model priporočil turističnih znamenitosti, ki združuje modeliranje uporabniških interesov in hevristične algoritme za načrtovanje poti za boljše osebno doživetje.

1 Introduction

Recently, as the boost of social economy, the tourism industry has also experienced rapid development, and more and more people are considering travel as a way of leisure vacation. However, with the increasing abundance of tourism resources and the growing demand for tourism products, before carrying out tourism activities, tourists often need to use the internet to obtain relevant information about tourist attractions when planning their travels [1-2]. However, due to the massive amount of travel information on the Internet, there is often an issue of "information overload", resulting in people failing to get the necessary travel information and make corresponding travel plans effectively and accurately. To solve this problem, many scholars have applied traditional recommendation systems to the tourism industry, but their effectiveness and accuracy are poor, unable to meet the personalized needs of tourists [3]. Therefore, this study will combine user interest (UI) modeling and heuristic travel planning algorithms to propose a new tourist attraction recommendation model. By modeling users' interests, it is possible to accurately grasp their needs and preferences, thereby better providing personalized recommendations for them. Meanwhile, heuristic travel planning algorithms can quickly and efficiently recommend travel arrangements for tourist attractions-based UI and time constraints [4]. By combining these two methods, the personalization and efficiency issues in tourist attraction recommendation can be better addressed, providing tourists with a better travel experience. The contribution of this study is that the research model can help tourists better choose and plan tourist attractions, improve the tourism experience and satisfaction. Meanwhile, this model also provides effective decision-making support for the tourism industry, helping scenic spots and tourism institutions better understand and meet user needs, improve service quality and competitiveness. The innovation of this study is to combine UI modeling with heuristic travel planning algorithms to establish UI models, improve recommendation accuracy and personalization, and reduce user confusion and hesitation in travel planning more accurately. The first of the research is to briefly describe the application of heuristic algorithms and research on recommendation models by scholars in recent years. The second introduces in detail the construction of a tourist attraction recommendation model by combining UI modeling with heuristic travel planning algorithms. The third is for testing the performance and analyze the effectiveness of the tourist attraction recommendation model constructed in the study. The final is to summarize and analyze the entire study [5-6].

2 Related works

As the boost of science and technology, multipath planning has become a research hotspot, and heuristic algorithms should be widely used in optimizing time problems. N. L. H. Hien et al. proposed a model using convolutional neural networks and matrix factorization for recommendation systems and information retrieval problems, and tested its accuracy by combining complex contextual features, thereby proving the accuracy of the model in context understanding and the feasibility of recommendation systems [7]. Yang et al. proposed a heuristic algorithm based the "furnace casting machine matching" pattern optimization to address the scheduling problem of the lack of refining span in steelmaking continuous casting production. After simulation experiments and analysis, the results showed that the algorithm has good process matching relationships and outstanding performance under crane constraints [8]. Paula et al. proposed an optimization method that combines customized branch and cut algorithms with heuristic algorithms to address the problem of small fleet sizes not being able to meet the requirements of multi trip vehicle path planning. After empirical analysis, the results showed that this method balances warehouse and fleet costs as well as route costs to propose the optimal number of warehouses [9]. Tawfik et al. proposed an iterative heuristic algorithm to address the difficulty of designing and pricing freight network services. After comparative experimental analysis, the outcomes showed that the algorithm possesses the characteristics of high performance, efficiency, and quality [10]. Pan et al. proposed a hybrid meta heuristic algorithm-based time function and duration function to address the issue of truck long-distance transportation being prone to timeout. After simulation experiments and analysis, the outcomes showed that the algorithm has good robustness and effectiveness under different speed curves and maximum travel time constraints [11].

With the rise of internet technology, many users obtain useful information through various platforms, and platforms make recommendations-based user needs. Therefore, recommendation models have received widespread attention. Xu et al. proposed a network learning recommendation model based personalized attractiveness enhancement to address the difficulty of predicting user behavior using sparsity in user project interactions on datasets. After comparative analysis, the outcomes showed that the model is significantly more excellent than the comparative model, and the attention mechanism can improve the interpretability of user behavior prediction [12]. Chen et al. proposed a dynamic personalized sequence recommendation model based fine-grained context to address the issue of weather factors affecting passenger travel behavior. After simulation analysis, the results showed that the model can significantly improve the accuracy of recommendations, better meet user preferences, and enhance the experience [13]. Ni et al. proposed a point factor heterogeneous similarity model based heterogeneous similarity to address the issue of difficult adjustment of browsing parameters for e-commerce website users. Through empirical analysis, the results showed that the model performs better and has effectiveness [14]. Gan and Zhang proposed a Weibo recommendation model that combines community UI and neighbor Weibo semantics to address the issue of difficulty in accurately mining the interests of Weibo users. After comparative experimental analysis, the outcomes showed that the model is significantly more excellent than existing models [15]. Edwin et al. proposed a recommendation model based practical grid computing and trust weighting methods to address the difficulty of setting preference services for consumers in cloud services. After comparative analysis, the results showed that the model has a higher accuracy [16]. Table 1 shows the summary of the research on the above related work.

Table 1: Summary of related work

Author	Research method	Model advantages
N. L. H. Hien et al. [7]	A model combining convolutional neural networks and matrix factorization was proposed to extract contextual information, and matrix factorization was used to create entity relationships to improve the accuracy of recommendation systems.	Compared to before optimization, the training information for system performance has increased and the accuracy is also higher.
Yang et al [8]	A heuristic algorithm and multi-objective optimization model based on the "furnace casting machine matching" mode optimization are proposed for the refining span problem in steelmaking continuous casting production.	The combination of heuristic algorithms and multi-objective optimization models has improved the process performance and production scheduling of furnace casting.
Paula et al [9]	Propose a decision scheme that combines heuristic algorithms and branch cutting algorithms for multi	Optimize the operational route of vehicles and ensure the cost of fleet and planned routes.

	journey vehicle routing problems.	
Tawfik et al [10]	Using iterative heuristic algorithms to solve the management of cargo transportation in the dual layer recommendation model of freight network.	The double-layer model can improve transportation efficiency and ensure quality management of goods.
Pan et al [11]	Using iterative heuristic algorithms to solve the management of cargo transportation in the dual layer recommendation model of freight network.	Research algorithms have robustness and effectiveness for vehicle paths with multiple travel times.
Xu et al [12]	Utilize convolutional neural networks and attention mechanisms to construct personalized attraction enhancing network learning recommendation systems.	The introduction of attention mechanism can accurately improve the performance of user behavior prediction.
Chen et al [13]	Use fine-grained context to extract user interest points, and use a search model to construct a dynamic personalized interest point sequence recommendation model.	Extensive experiments were conducted on the recommendation model to significantly improve its accuracy and enhance user experience.
Ni et al [14]	Analyze user browsing parameters using implicit feedback recommendation models, and adjust website user interests using factor heterogeneous similarity models.	The accuracy and feasibility of its recommended model have been determined through extensive experimental analysis.
Gan and Zhang [15]	Integrating user community interests and Weibo semantics to improve the word set and semantics of Weibo recommendation data.	Test the model's superiority through real data on Weibo.
Edwin et al [16]	Using a fidelity homogeneous origin recommendation model and utilizing trust weighting algorithms to improve trust similarity between users.	Autonomous mapping technology can optimize user clustering, while network computing and trust weighting methods can improve service capabilities.

Table 1 illustrates the diverse applications of heuristic algorithms across various fields and models. References [8] to [11] demonstrate the implementation of these algorithms in different contexts, while references [12] to [16] show the development of recommendation models and application services based on user interests and needs. In terms of the establishment of tourist attractions and preferences, the dynamic personalized interest point sequence recommendation model, when combined with a parameter analysis of vehicle transfer, has been demonstrated to enhance the experience of tourists. Nevertheless, this study also employs a comprehensive analysis of the weather, time, and budget of tourist attractions, thereby providing a more comprehensive understanding of the needs of tourists.

In conclusion, contemporary research scholars employ user interests and preference settings, in conjunction with heuristic algorithms, to address multi-objective optimization and production scheduling issues in the context of recommendation models. Nevertheless, in the context of tourist attraction planning, the user interest model employed in this study employs similarity calculation and recommendation algorithms to optimize user feedback information and personalized services. In comparison to recommendation models that integrate convolutional neural networks and attention mechanisms, this approach offers a more convenient means of processing user information and collecting features, while also providing a visual presentation that aligns with user interests and behavioral characteristics. In the context of heuristic algorithms, research combines user interests and comprehensively considers factors such as the external environment and the temporal aspects of tourist attractions in order to select the optimal travel plan. Heuristic algorithms are frequently employed in the context of vehicle scheduling problems, where multi-objective optimization algorithms are utilized to assess the viability of multiple objective factors. The heuristic travel planning algorithm in this study assigns scores to user interests and attraction attributes, while also considering user preferences for attractions and the optimal method for vehicle route planning. This provides technical references for route planning, logistics networks, transportation channels, and various route designs in the industrial field. Heuristic planning algorithms in artificial intelligence can provide efficient optimal solutions for robot path planning and mobile routes. Consequently, the study effectively integrates user interests and heuristic travel planning algorithms, and innovatively employs a mixed user interest model to consider the diverse needs of users, with the objective of developing a more comprehensive and convenient time planning scheme. This, in turn, provides new ideas for the design of recommendation models.

3 Design of a tourist attraction recommendation model-based UI and heuristic journey planning

As the boost of science and technology as well as the tourism industry, smart tourism will be the future development direction. However, traditional recommendation models have problems such as being unable to meet the needs of travelers when recommending tourist attractions. Therefore, this chapter will model based UI and combine heuristic travel planning algorithms to design and study a tourist attraction recommendation model.

3.1 Model construction-based UI

The development of internet technology has brought convenience to people's lives, and tourists can search for useful information on the internet when planning their travels. The tourism recommendation model can provide personalized tourism recommendations for users based their characteristic information. This can help users quickly find tourist destinations, attractions, itineraries, etc. that meet their needs, and improve travel satisfaction. The traditional tourist attraction recommendation model is generally composed of data collection and processing, feature extraction and selection, similarity calculation and recommendation algorithms, user feedback and personalized optimization, and visual presentation, as shown in Figure 1 [17-18].

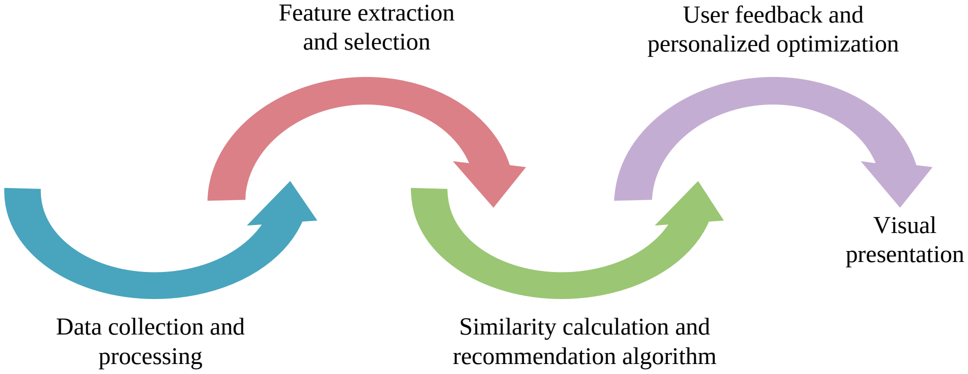

Figure 1: Composition diagram of the recommendation model of traditional tourist attractions

Figure 1 shows that traditional tourist attraction recommendation models use crawler technology to obtain travel information on various tourism websites, social media, and other platforms, and perform data cleaning and organization. Subsequently, based the collected data, natural language processing techniques are used to extract feature information of scenic spots. Meanwhile, extract user features based their personal information and preferences. Then, based the similarity between the user's features and the features of the attraction, a recommendation algorithm is used for recommendation. Finally, based user feedback, they evaluate and optimize the recommendation results. In addition, the recommendation results are presented to users in a visual manner, providing a more intuitive and convenient user experience. However, due to the uniqueness and complexity of tourism activities, traditional recommendation system user models are difficult to meet the needs of smart tourism recommendations. Therefore, this study proposes to design a tourist attraction recommendation model-based UI modeling. UI modeling is the process of abstracting user behavior and preferences into mathematical models to describe their interest characteristics and behavioral patterns. The prerequisite for a UI model is to obtain relevant information such as UI. User information mainly consists of two: static information and dynamic information, as shown in Figure 2.

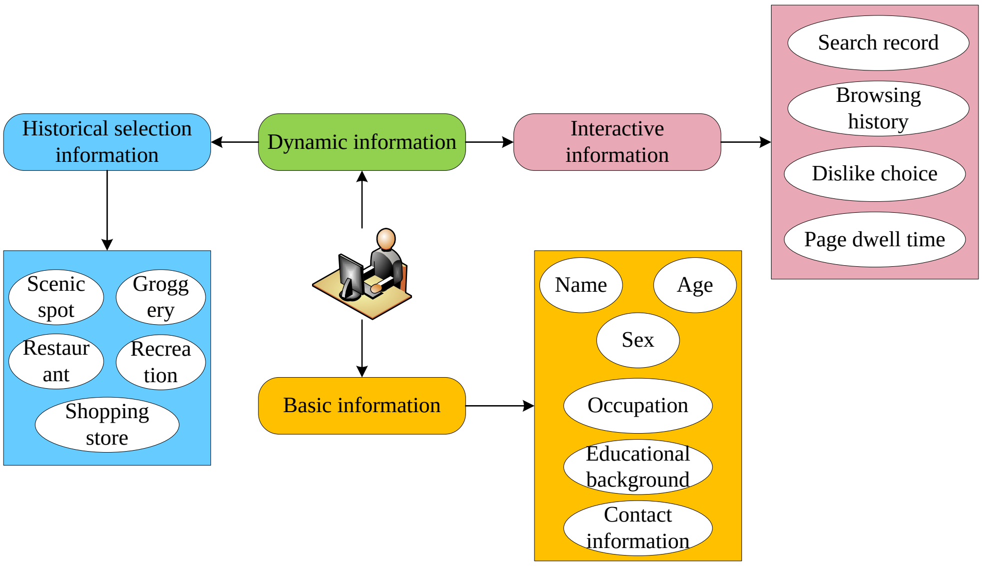

Figure 2: Collection of user information of tourists

Figure 2 shows that the static information includes the user's gender, age, etc. These data are obtained in an explicit form, which is completed by the user themselves. The acquisition of user dynamic information is mainly implicit, extracting and learning dynamic information from user historical behavior. To improve the accuracy of UI models, research has divided UI models into long-term interest and short-term interest, and established a mixed UI model. In the process of establishing a mixed UI model, this study uses a space vector-based approach to express UI, and defines the mixed UI model as a set of vectors with dimension N, as shown in equation (1).

$$U_j = \{(X_1, Y_1, Z_1), (X_2, Y_2, Z_2) \cdots (X_m, Y_m, Z_m)\} \quad (1)$$

In equation (1), U_j represents the user's interest definition value. X and Y represent the user's level of interest in the category and the user's level of interest in category X and Z refer to the time width of the interest level value. m is the vector dimension. The short-term user interest model is a computational approach that estimates the user's short-term interest based on the user's immediate interactions with the system. The short-term user interaction behavior encompasses the user's propensity to save, the frequency of visits to the attraction page, and the duration of time spent viewing the attraction page. The calculation of these three factors is shown in equations (2), (3), and (4).

$$S(i) = \begin{cases} 1, \mathit{Occurrence\ of\ preservation\ behavior} \\ 0, \mathit{Not\ saved} \end{cases} \quad (2)$$

In equation (2), attraction saving behavior $S(i)$ refers to the user's interest in attraction i when they save or bookmark attraction i.

$$F(i) = \begin{cases} 0, f_i > f_0 \\ \partial f_i, f_i \le f_0 \end{cases} \quad (3)$$

In equation (3), the quantity of visits to the tourist attraction page $F(i)$ refers to the quantity of times a user views tourist attraction i in a short period of time, indicating that the user is interested in tourist attraction i. f_i serves as the quantity of visits by the user to the attraction page i. f_0 serves as the preset access threshold. ∂f indicates that when the number of visits is less than f_0, the number of visits needs to be weighted.

$$D(i) = \begin{cases} 0, t_i > t_0 \\ \dfrac{\varepsilon t_i}{M}, t_i \le t_0 \end{cases} \quad (4)$$

In equation (4), the viewing time $D(i)$ of the attraction page refers to the longer the user views on the attraction page i, the more interested the user is in attraction i. t_i and t_i represent the user's access time to the attraction page i and the preset access time threshold. ε as well as M represent the weighting coefficient and the total word count of attraction page i. The estimated short-term interest of users in scenic spots can be obtained through $S(i)$, $F(i)$, and $D(i)$, as shown in equation (5).

$$U_{s\text{-}t}(i) = c + \alpha S(i) + \beta F(i) + \gamma D(i) \quad (5)$$

In equation (5), α, β, γ, and c all represent constants. They are used for adjusting the influence coefficients and user short-term interest models. The long-term user interest model is defined by the interest values of user registration information and the long-term accumulation of short-term interests. The expression of the long-term interest model is related to the defined interest vector and the feature updates of short-term interests. Finally, the short-term user interest model and the long-term interest model can be combined and weighted separately to obtain a mixed user interest model. Its expression is shown in equation (6).

$$U = \mu U_{l-t} + \eta U_{s\text{-}t} \quad (6)$$

In equation (6), μ and μ represent the weights of long-term and short-term interests in the mixed UI model, respectively. U_{l-t} represents a long-term UI model, which can be obtained through the long-term accumulation and transformation of user registration preference information and short-term UI models. In summary, the construction of a mixed UI model is showed in Figure 3.

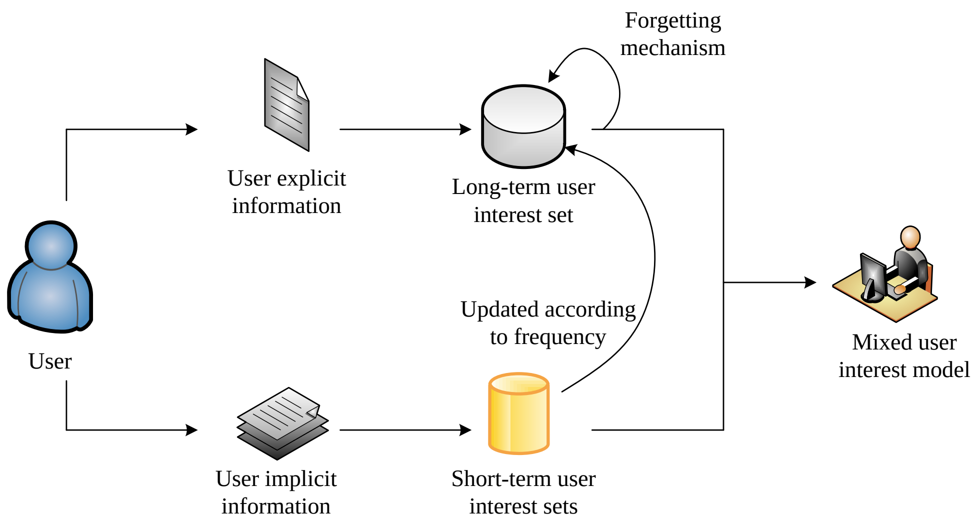

Figure 3: Mixed UI model

Figure 3 shows that both short-term and long-term interests are considered when calculating UI. The short-term UI model generally includes items that users will be interested in the near future. It is a real-time attribute, and its construction is mainly based the implicit information of users. Long term UI represents the content that users have always been interested in, which belongs to a cumulative attribute. Long term UI is mainly constructed based users' static information and short-term interests. On this basis, a mixed UI model based long and short interests is constructed by analyzing the two dimensions of user length and short.

3.2 A tourist attraction recommendation model based heuristic journey planning algorithm

After constructing a mixed UI model, personalized travel recommendations and itinerary planning can be carried out based the combination of the model and the attraction database. The attraction recommendation section utilizes a UI model to recommend the most suitable attraction based the user's characteristics and preferences. The itinerary planning section generates the best itinerary plan for users-based factors such as time, budget, preferences, and information from the attraction database. Through this approach, targeted travel recommendation results can be provided to help users better plan and enjoy their travels, as shown in Figure 4.

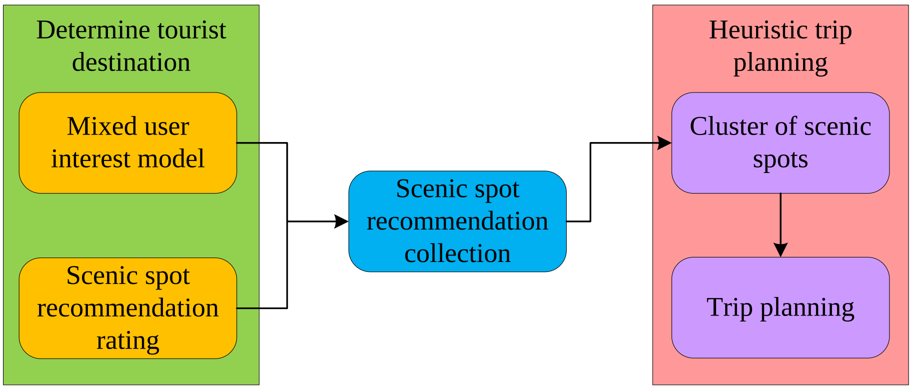

Figure 4: An overall schematic diagram of the recommended travel itinerary

Figure 4 shows that the recommendation of tourist attractions is an important basis and key factor in tourism route planning, playing a decisive role in other decisions related to tourism route planning. The core of recommended tourist attractions is to provide tourists with tourist destinations and related tourism products. However, there are two problems with recommending tourist attractions. Firstly, unlike frequent events such as shopping, tourism has limited user interaction information, making it difficult to generate effective ratings. Secondly, tourism has high real-time performance, and the selection preferences of tourism destinations are often related to the user's season, location, and time. Therefore, it is necessary to address the issues of data sparsity and timeliness when recommending tourist attractions, to provide accurate tourist attraction recommendations and personalized itinerary planning. Therefore, this study comprehensively considers the above two issues and designs a recommended rating system for tourist attractions, as shown in Figure 5.

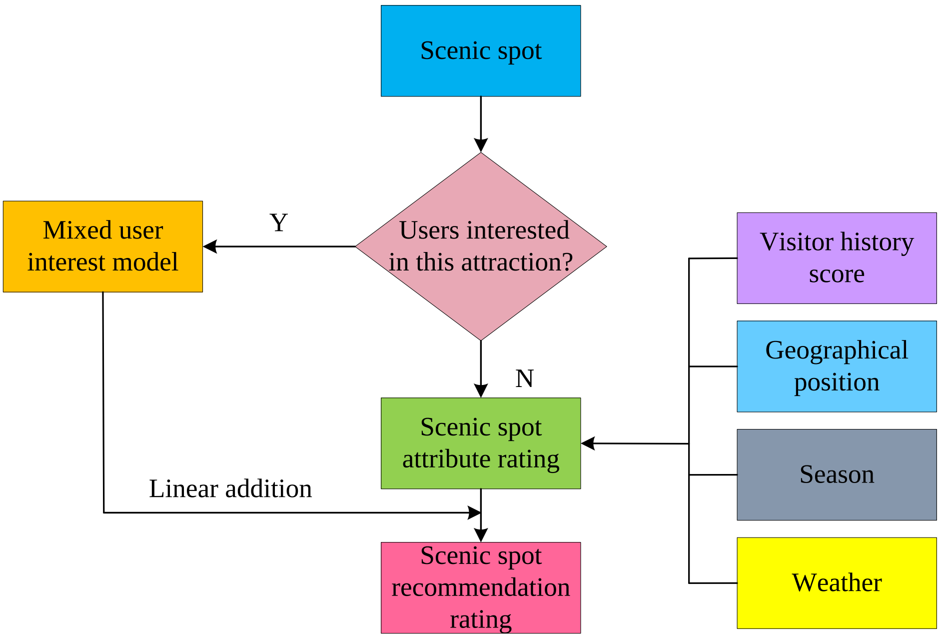

Figure 5: Diagcomposition of recommended tourist attractions

Figure 5 shows that the recommended rating for scenic spots is mainly divided into scenic spot attribute rating as well as mixed UI model rating. The scenic spot attribute rating includes the tourist history rating, geographical location, season, and weather of the scenic spot. From these four aspects, the attribute scores of scenic spots can be obtained, and the calculation process is shown in equations (7) and (8).

$$H_s = \frac{\sum_{n=1}^{n=5} n * r_n}{5 * \sum_{n=1}^{n=5} r_n} \tag{7}$$

In equation (7), H_s represents the historical evaluation of tourists to the scenic spot, with a value of 0-1. r_n represents the number of users rated as n in the historical evaluation of the scenic spot, and $n \in [1,5]$ is an integer.

$$D_s = \frac{AvgD}{AvgD + D_p} \tag{8}$$

In equation (8), D_s represents the rating of the scenic spot-based distance, with a value of 0-1. A represents the user's current location and collection of scenic spots, with p as the number and $p \in [1,5]$ as an integer. D_p represents the distance between the user's current location and all scenic spots in the A set. $AvgD$ represents the average distance in the user's current location as well as the scenic spots in the A set. Its calculation formula is showed in equation (9).

$$AvgD = \frac{\sum_{p=1}^{p=5} D_p}{\sum_{p=1}^{p=5} p} \tag{9}$$

For each scenic spot, determine the most suitable season or seasons to visit at the time of entry. In the actual calculation of scenic spot recommendation scores, dynamic scoring will be conducted based the current season. When the current season matches the most suitable season for the attraction, the season rating Se_s value for the attraction is 1, and vice versa, it is 0. Similarly, when rating the weather of a tourist attraction, when the current weather matches the most suitable weather for the attraction, the weather rating C_s value of the attraction is 1, and vice versa, it is 0. The calculation of scenic spot attribute scores is shown in equation (10).

$$S = a \times H_s + D_s + Se_s + C_s \tag{10}$$

In equation (10), a represents the historical rating weight of the tourist attraction. Therefore, the expression of user j's recommendation rating $c_{j,q}$ for attraction q is shown in equation (11).

$$c_{j,q} = MS_q + LU_{j,q} \tag{11}$$

In equation (11), S_q and $U_{j,q}$ represent the attraction attribute score of attraction q and the interest value of user j in attraction q. M and L respectively represent the adjustment coefficients between scenic spot attribute scores and interest values. After obtaining the tourism destination recommendation structure, it is necessary to develop corresponding travel itineraries based the recommendation results, the user's travel time, and the user's location. For making reasonable use of user time, this study proposes the use of heuristic travel planning algorithms for formation planning. Heuristic travel planning algorithm is an algorithm-based experience and rules, used to provide personalized and efficient travel arrangements for travelers. Compared with traditional travel planning algorithms, heuristic algorithms can quickly generate travel paths while considering time, interests, and preferences to meet user needs. When using this algorithm for itinerary planning, considering the issue of vehicle routing and the limited number of scenic spots, the sequential insertion method-based location is used to combine the order of scenic spots. Its calculation is shown in equation (12).

$$B(e,g,h) = E(e,g) + E(g,h) - \alpha E(e,h) \tag{12}$$

In equation (12), B and E respectively represent the time required to browse scenic spots. e, g, and h both represent attractions. It inserts the un routed scenic spot g into the scenic spot e and h, adjusts it to the scenic spot insertion position, compares the time consumed, and determines the shortest time consumed by the scenic spot, as shown in equation (13).

$$F(e,g,h) = \min\{B(e,g,h)\} \tag{13}$$

It determines the itinerary by inserting the shortest consumption time of a scenic spot for scenic spot insertion planning. The structure of the final tourist attraction recommendation model is shown in Figure 6.

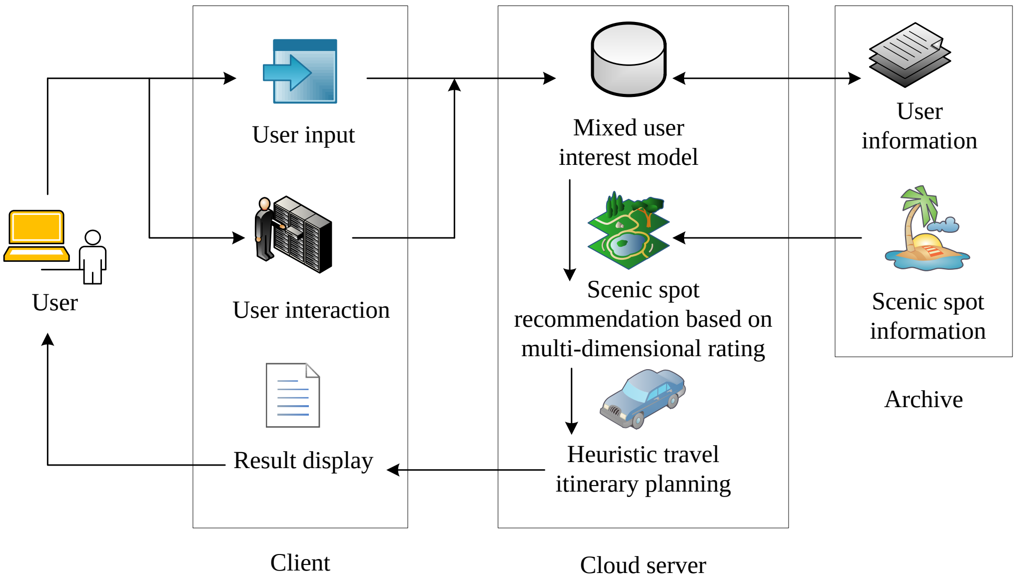

Figure 6: Schematic diagram of the recommended model structure of tourist attractions

Figure 6 shows that the research model contains three: user client, cloud server, and database. Cloud servers mainly utilize user information, scenic spot information, and interactive relationships between users to provide personalized travel recommendation services and complete interaction with databases and users. The database is mainly used to store relevant information such as tourists and attractions within the scenic spot. The function of the client is to interact with the user, receive their input, and present the recommended results of the model to the user.

4 Comparative study on the performance of heuristic journey planning algorithms and analysis of model usage effectiveness

For verifying the proposed heuristic travel planning algorithm and the effectiveness of the constructed tourist attraction recommendation model, a comparative experiment is conducted in this study. In the experiment, a certain tourism platform is used to collect real datasets of various tourist attractions in China. The experimental environment is Windows XP operating system, with 3.4GB CPU and 2GB DDR memory. Microsoft Visual Studio 2005, database server MySQL 5.0, and Microsoft Internet Information Services (IIS) 6.0 are used as development tools.

4.1 Performance comparison and analysis of heuristic journey planning algorithms

In the performance comparison test of heuristic travel planning algorithms, genetic algorithm (GA), simulated annealing algorithm (SA), and ant colony optimization (ACO) are studied as experimental control groups. Meanwhile, it took algorithm running time, accuracy, accuracy, PR curve, and travel planning time as evaluation indicators. The running time and accuracy results of the four algorithms are shown in Figure 7.

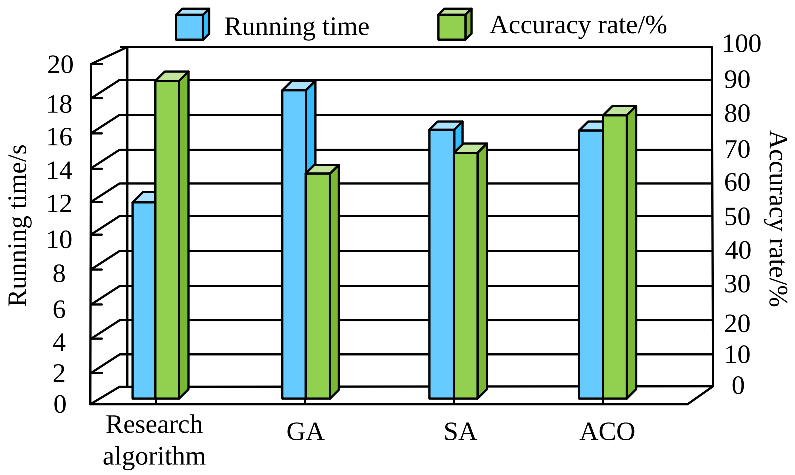

Figure 7: Running time and accuracy of the algorithm

Figure 7 shows that the running times of the research algorithm, GA algorithm, SA algorithm, and ACO algorithm are 11.5s, 18.0s, 15.5s, and 15.5s, respectively, with the shortest running time calculated by the research algorithm. The accuracy rates of the research algorithm, GA algorithm, SA algorithm, and ACO algorithm are 91%, 65%, 71%, and 82%, respectively, with the highest accuracy rate calculated by the research algorithm. These two indicators indicate that the performance of heuristic travel planning algorithms is better than that of comparative algorithms. It records the accuracy and PR curve of heuristic travel planning algorithm, GA algorithm, SA algorithm, and ACO algorithm, as shown in Figure 8.

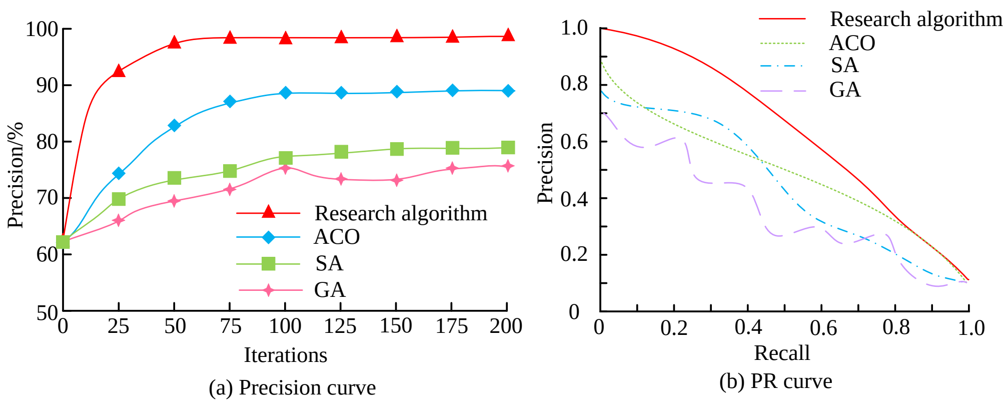

Figure 8: The accuracy of the algorithm with the PR curve

Figure 8 (a) shows that according to the accuracy curve of the research algorithm, the accuracy of the algorithm tends to stabilize after approximately 50 iterations, with a final value of 97%. According to the accuracy curve of the ACO algorithm, the accuracy tends to stabilize after approximately 100 iterations, with a final value of 86%. According to the accuracy curve of the SA algorithm, the accuracy of the algorithm tends to stabilize after approximately 125 iterations, with a final value of 77%. According to the accuracy curve of the GA algorithm, the final accuracy value of the algorithm is 76%. Figure 8 (b) shows that the PR curve areas of the research algorithm, ACO algorithm, SA algorithm, and GA algorithm are 0.89, 0.77, 0.75, and 0.61, respectively. Research algorithms are superior to comparative algorithms. Four algorithms are used to calculate the travel planning time for five scenic spots. The outcomes are showed in Table 2.

Table 2: The schedule planning time of the algorithm

Algorithm type	Attractions 1	Attractions 2	Attractions 3	Attractions 4	Attractions 5	Total
Research algorithm	30min	44min	20min	34min	65min	193min
ACO	41min	60min	33min	40min	87min	261min
SA	50min	74min	50min	49min	109min	332min
GA	55min	71min	50min	52min	114min	342min

Table 2 shows that the travel planning time of the research algorithm for five scenic spots is 30 minutes, 44 minutes, 20 minutes, 34 minutes, and 65 minutes, totaling 193 minutes. The travel planning time for five scenic spots using the ACO algorithm is 41 minutes, 60 minutes, 33 minutes, 40 minutes, and 89 minutes, totaling 261 minutes. The SA algorithm takes 50 minutes, 74 minutes, 50 minutes, 49 minutes, and 109 minutes to plan the itinerary of five scenic spots, totaling 332 minutes. The GA algorithm takes 55 minutes, 71 minutes, 50 minutes, 52 minutes, and 114 minutes to plan the itinerary of five scenic spots, totaling 342 minutes. Research algorithms have the shortest planned travel time and the best performance. Based on the evaluation indicators of all the algorithms mentioned above, it can be concluded that the heuristic travel planning algorithm has superior performance.

Finally, the above algorithms are applied to the Pokec and EVRP datasets of social networking sites for accuracy evaluation, and the superiority and robustness of the research algorithm are verified. The result is shown in Figure 9.

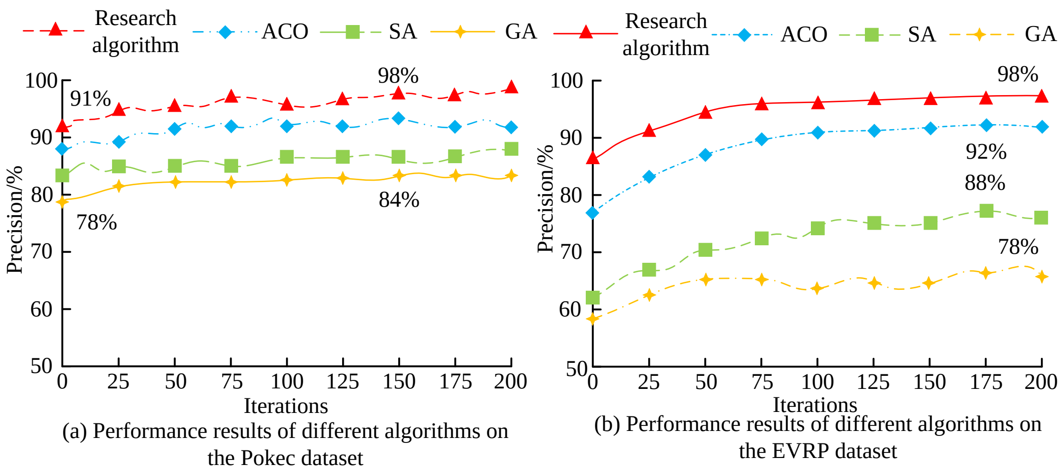

Figure 9: Comparison results of different algorithms on the Pokec dataset and EVRP dataset

Figure 9(a) indicates that the accuracy values of the algorithms on the Pokec dataset exhibit a gradual increase with the increase of iteration times. Additionally, the fluctuation of the algorithms is more pronounced. The GA algorithm exhibits a relatively low accuracy, with a maximum value of 84%, which is notably inferior to other algorithms. The heuristic travel planning algorithm and ACO algorithm exhibited superior performance, with maximum values of 98% and 92%, respectively. Figure 9 (b) illustrates that as the number of iterations increases, the accuracy of the heuristic travel planning algorithm and the ACO algorithm gradually increases, while the SA algorithm and the GA algorithm exhibit a fluctuating upward trend. The highest accuracy values observed for the heuristic travel planning algorithm and ACO algorithm are 98% and 92%, respectively. Consequently, the heuristic travel planning algorithm continues to demonstrate robust performance in performance testing with varying data sets, further substantiating its superiority.

4.2 Analysis of the actual effect of the tourist attraction recommendation model

To verify the actual effectiveness of the proposed tourist attraction recommendation model based a mixed UI model and a heuristic travel planning algorithm, this study will use a tourist attraction recommendation model based a regular UI model as the control group. Meanwhile, the accuracy of model recommendation, ROC curve, timeliness ratio, and user satisfaction are taken as evaluation indicators. The relevant outcomes are showed in Figure 10.

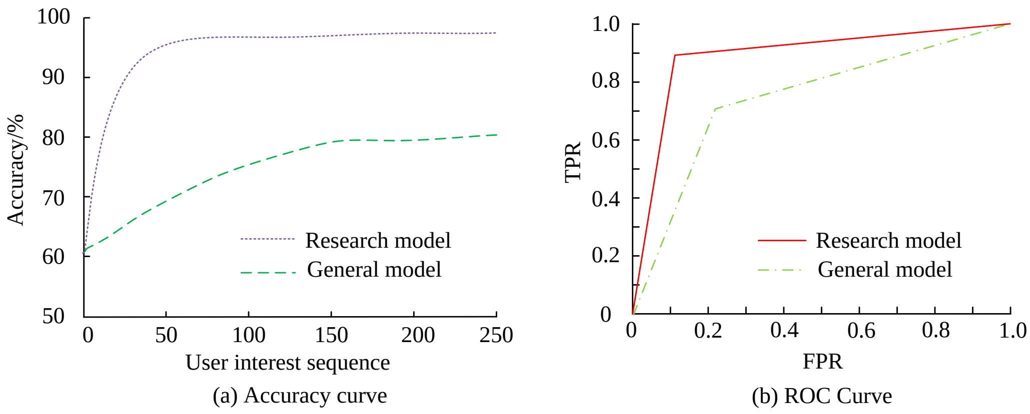

Figure 10: The accuracy of the model with the ROC curve

Figure 10 (a) shows that according to the changes in UI series, the accuracy of the recommendation model increases, with the accuracy of the research model ultimately stabilizing at 98% and the accuracy of the ordinary model ultimately stabilizing at 80%. The accuracy of the research model exceeds that of the ordinary model, and the convergence speed is significantly better than that of the ordinary model. Figure 10 (b) shows that the area under the ROC curve of the research model is 0.91, while the area under the ROC curve of the ordinary model is 0.77, indicating that the research model has superiority. It uses two models to develop a tourism strategy for a certain city and compares their time efficiency ratio, as shown in Figure 11.

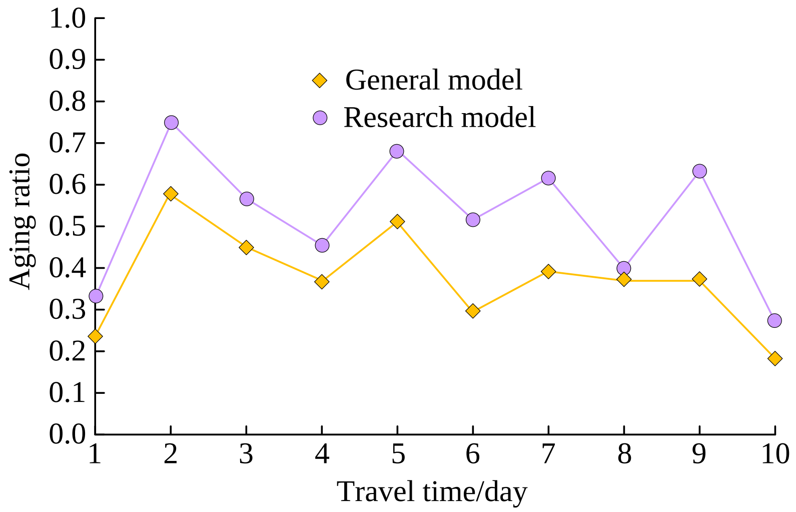

Figure 11: The time ratio of model formulation of travel strategy

Figure 11 shows that in the development of a 10-day tourism strategy, the daily time efficiency ratios of the research model are 0.32, 0.75, 0.57, 0.48, 0.68, 0.51, 0.61, 0.40, 0.62, and 0.28, respectively, with a total time efficiency ratio of 4.47. The daily aging ratios of ordinary models are 0.22, 0.58, 0.45, 0.36, 0.51, 0.30, 0.39, 0.38, 0.38, and 0.28, respectively, with a total aging ratio of 3.47. Under the condition that the overall travel time remains unchanged, the research model has a higher time efficiency than the ordinary model, and the formulated tourism strategy is more reasonable. This study invited 5 volunteers to rate their experience of using the model, with a maximum score of 10. The outcomes are showcased in Table 3.

Table 3: Results of user satisfaction ratings

Type of model	Evaluation criteria	Volunteer 1	Volunteer 2	Volunteer 3	Volunteer 4	Volunteer 5
General model	Intuitiveness	8.3	9.4	8.1	8.6	8.3
	Comprehensiveness	7.6	7.4	7.8	7.0	7.3
	Operability	7.6	7.5	7.1	7.6	7.3
	Precision	7.1	7.6	7.7	7.8	7.0
	Effectiveness	7.8	8.0	8.3	7.9	8.2
	Applicability	7.3	6.9	6.4	6.7	7.0
Research model	Intuitiveness	9.3	9.5	9.6	9.6	9.5
	Comprehensiveness	9.0	8.9	9.1	8.8	9.1
	Operability	9.0	8.8	8.8	9.3	9.3
	Precision	9.1	9.5	9.3	9.3	9.4
	Effectiveness	9.5	9.6	9.3	9.3	9.4
	Applicability	9.0	9.1	9.0	9.1	9.3

Table 3 shows that the average scores of the five volunteers on the intuitiveness, comprehensiveness, operability, accuracy, effectiveness, and applicability of the ordinary model are 8.54, 7.42, 7.42, 7.44, 8.04, and 6.86. The average scores of the five volunteers on the intuitiveness, comprehensiveness, operability, accuracy, effectiveness, and applicability of the research model are 9.5, 8.98, 9.04, 9.32, 9.42, and 9.1, indicating that volunteers have higher satisfaction with the use of the research model.

The research institute's recommendation model and heuristic travel planning algorithm are integrated with user interest modeling to analyze a range of statistical measures on diverse domestic tourist attraction datasets. The results are shown in Table 4.

Table 4: Significant statistical parameter results of the recommended model

Statistic	Parameter estimation value	SD	P
User interest	4.896	0.315	0.00015*
Gender of tourists - interactions	0.032	0.013	0.00001*
Tourist age -interaction	-2.143	1.105	0.00023*
Natural attractions - interactions	-3.251	1.134	0.00076*
History and Humanities - Interaction	0.794	0.316	0.00342*

Note: * represents a significant correlation between the parameter statistics of the recommendation model.

Table 4 indicates that the parameter of user interest is significantly positive, with a P-value of 0.00015. This suggests that the generation of user interest in the recommendation model has a certain impact. Concurrently, the interaction between tourist gender and age on tourist attractions is significantly disparate, with P-values of 0.0001 and 0.00023, respectively. This suggests that the gender and age variables in user interest have a significant impact on the application of recommendation models, thereby enhancing users' ability to make more effective recommendations of tourist attractions. However, for the interaction between tourist attractions, the parameter statistical P* values converge and the fitting effect is good, indicating that the heuristic itinerary planning algorithm has a superior application effect on the recommended tourist attractions. Consequently, the results demonstrate that the tourist attraction recommendation model based on the mixed user interest model and the heuristic itinerary planning algorithm outperforms the conventional model.

4.3 Discussion

A comparison of the performance of different heuristic algorithms has led to the conclusion that the heuristic travel planning algorithm has the best performance. The use of real tourism datasets for experimental performance indicators, which mainly include datasets of tourist hotels, restaurants, and other businesses, as well as user evaluation datasets, has resulted in a relatively cumbersome data set on tourist attractions and their user recommendations. The research algorithm and ACO algorithm exhibited the highest accuracy values in planning tourist attractions, at 98% and 92%, respectively. These values were considerably lower than those of the GA algorithm and SA algorithm, which averaged 193 minutes and 261 minutes, respectively. The average time consumption of the GA algorithm and SA algorithm was 332 minutes and 342 minutes, respectively. The GA algorithm, as a search heuristic algorithm, generated a multitude of group operations through its selection, crossover, and other operations, thereby increasing the operation of the algorithm. The SA algorithm was primarily employed for global search, although its convergence speed was relatively slow and susceptible to fluctuations in parameters. Furthermore, although the ACO algorithm's simulation evolution and search engine exhibit distinctive path rules and robust performance in complex scheduling problems, the algorithm's parameter settings were relatively straightforward. This may result in additional evolutionary processes being introduced to the application of tourist attraction datasets. In the evaluation of various recommendation models, the research model was rated highly by users for its intuitive recommendations and convenient operations of tourist attractions, with a basic score of 9.0 or above. Consequently, in the analysis of various evaluation indicators, the heuristic travel planning algorithm and its recommendation model can not only meet the requirements of solving complex and intersecting datasets, but also maintain good computational efficiency and accuracy. Moreover, the user interface and strategy recommendations are highly satisfactory.

5 Conclusion

Smart tourism is a major boost to the development of the tourism industry, and the importance of tourist attraction recommendation models is self-evident. However, traditional recommendation models have problems such as low accuracy and inability to meet user needs. In response to this issue, this study proposes a new tourist attraction recommendation model that combines UI modeling and heuristic travel planning algorithms. For verifying the heuristic travel planning algorithm, comparative experiments were conducted. The outcomes showed that the accuracy of the research algorithm was 91%, the accuracy was stable at 97%, and the area under the PR curve was 0.89, all of which were higher than the comparison algorithm. The research algorithm has a running time of 11.5 seconds and a total travel planning time of 193 minutes, both of which are superior to the comparison algorithm. Subsequently, experiments were conducted on the tourist attraction recommendation model constructed based UI modeling and heuristic travel planning algorithms. The outcomes showed that the model was 98%, the area under the ROC curve reached 0.91, as well as the total time efficiency ratio reached 4.47, all of which were higher than the comparison model. Meanwhile, the average scores of volunteers on the intuitiveness, comprehensiveness, operability, accuracy, effectiveness, and applicability of the research model were 9.5, 8.98, 9.04, 9.32, 9.42, and 9.1, which were higher than those of the comparative model. In summary, the tourist attraction model based UI modeling and heuristic itinerary planning algorithm has strong practicality and can offer high-quality services to tourists in a targeted manner. However, there are still some shortcomings in the research. Firstly, in the application of tourist attraction recommendation, there is a lack of data mining in terms of attraction information collection, service optimization, and tourist demand. At the same time, the recommended content of tourist attractions is difficult to align with the direction of user needs, and the rating mechanism of tourist attractions is not optimal, which leads to a lack of a platform to promote and evaluate tourist attractions and user recommendations. In the future, relevant attention mechanisms can be incorporated into tourism recommendation models to improve the quality of tourism services and align with user needs. In addition, the recommendation model proposed by the research institute is closely related to the service provision of tourist attractions and the satisfaction of user needs. Future work will require technical improvements to the system platform and the implementation of more accurate guidance.

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