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Research Article

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Personalized Travel Route Recommendation Using a Hybrid PSO–ACO Algorithm

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Abstract
With the rapid growth of smart tourism, personalized travel route recommendation has emerged as a critical challenge to enhance user experience and satisfaction. Traditional recommendation systems often fail to adequately capture users' dynamic preferences, sentimental inclinations, and the multifaceted attributes of Points of Interest (POIs). To address these limitations, we propose a hybrid PSO-ACO algorithm that leverages the global search capability of PSO and the local exploitation strength of ACO, while integrating user sentiment and POI similarity into the heuristic function.. The model integrates user sentiment derived from review texts and POI similarity based on rating matrices into an enhanced ACO heuristic function. Furthermore, a PSO module is employed to optimize the initial pheromone distribution of the ACO, thereby accelerating convergence and mitigating the risk of local optima. We validated our approach on a dataset comprising reviews and ratings from 593 tourists for 37 popular scenic spots within Beijing's Forbidden City. Experimental results demonstrate that the proposed PSO-ACO algorithm significantly outperforms benchmark methods, including the elite ant system and improved genetic algorithms, across key metrics of precision, recall, and F1-score. This work provides a robust and personalized framework for intelligent travel itinerary planning.

Keywords
Travel Route Recommendation; Ant Colony Optimization (ACO); Particle Swarm Optimization (PSO); Personalized Recommendation; Point of Interest (POI) Similarity

1. Introduction

The proliferation of location-based social networks and mobile computing has spurred significant interest in intelligent travel route recommendation systems [1]. These systems aim to alleviate information overload for tourists by suggesting optimized, personalized itineraries that balance travel efficiency with user preferences [2]. The core of this problem often involves modeling user interests from sparse and heterogeneous data, such as check-in records, textual reviews, and numerical ratings [3]. This task is particularly challenging in tourism, where user preferences are highly dynamic, contextual, and influenced by both objective attraction attributes and subjective emotional responses.

Traditional methods, such as collaborative filtering and content-based approaches, often focus on accuracy but neglect the nuanced personalization needs of individual tourists. [4]. Consequently, recommendations may lack diversity and fail to align with the subjective travel experience [5]. Recent advancements have sought to incorporate contextual factors such as geographical proximity, social relationships, temporal constraints, and semantic information from user-generated content [6, 7]. For instance, keyword-aware frameworks [8] and geo-social relationship models [9] have been proposed to better align recommendations with user intent.

Despite these improvements, several challenges persist. First, modeling the complex interplay

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between objective POI features (e.g., historical significance, architecture) and subjective user perceptions (e.g., scenic beauty, fun) remains non-trivial [10]. This requires sophisticated fusion of multi-modal data—numerical ratings, textual sentiments, and spatial coordinates—into a unified optimization framework. Second, recommendation algorithms must be computationally efficient to provide real-time or near-real-time suggestions, especially for large-scale POI networks [11]. Metaheuristic algorithms, such as ACO and Genetic Algorithms (GA), have been widely applied to solve this combinatorial optimization problem, often framed as an instance of the Traveling Salesman Problem (TSP) or its variants [12, 13]. However, standard ACO is prone to slow convergence and stagnation in local optima [14]. Similarly, GA and other evolutionary algorithms can suffer from premature convergence and high computational cost in complex, high-dimensional search spaces.

To overcome these limitations, this study proposes a hybrid PSO-ACO algorithm for personalized travel route recommendation. Our research is motivated by the observation that while hybrid metaheuristics have shown promise in other domains [21], their application in tourism recommendation—particularly with rich semantic integration—remains underexplored. We hypothesize that combining PSO's global exploration capability with ACO's refined local exploitation, while explicitly modeling user sentiment and multi-attribute POI similarity, will yield more accurate, personalized, and efficient recommendations. Our main contributions are threefold:

1. **Enhanced POI Modeling:** We define a composite distance metric that integrates spatial Euclidean distance with multi-dimensional attribute similarity (both objective and subjective), calculated from user ratings and review texts. This metric captures both geographical feasibility and user preference alignment, providing a more holistic basis for route optimization.This metric captures both geographical feasibility and user preference alignment, providing a more holistic basis for route optimization.
2. **Algorithmic Innovation:** We introduce a PSO module to pre-optimize the initial pheromone matrix for the ACO, providing a better starting point for the search process. An elite ant strategy with a random factor is also incorporated to balance exploration and exploitation. This hybrid mechanism is designed to accelerate convergence and mitigate the inherent limitations of each individual algorithm.
3. **Comprehensive Evaluation:** We conduct empirical evaluations on a real-world tourism dataset. The proposed method is compared against state-of-the-art baselines, demonstrating superior performance in recommendation accuracy and convergence behavior. Furthermore, we analyze the impact of key parameters and discuss the practical implications of our findings for smart tourism applications.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 details the problem formulation and the proposed PSO-ACO methodology. Section 4 presents the experimental setup, results, and performance analysis. Finally, Section 5 concludes the paper and outlines directions for future research.

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2. Related Work

Travel route recommendation sits at the intersection of recommender systems, operations research, and spatial data mining. Early approaches often relied on collaborative filtering to identify users with similar travel histories [15]. However, the extreme sparsity of user-POI matrices in the tourism domain severely limits their effectiveness [16]. To mitigate this, matrix factorization techniques have been applied, yet they often struggle with cold-start problems and fail to incorporate rich contextual or semantic information.

To address data sparsity, researchers have integrated multiple data sources. For example, [17] combined geographical coordinates and trajectory data using density clustering to infer popular routes. Others have leveraged textual reviews and visual content to model user preferences and POI characteristics more richly. Chen et al. [18] proposed a POI recommendation model that fuses review text and image semantics using probabilistic matrix factorization, significantly improving interpretability and performance. Similarly, sentiment analysis techniques have been employed to extract user emotions from reviews, providing a deeper understanding of subjective experiences beyond numeric ratings [24, 25].Similarly, sentiment analysis techniques have been employed to extract user emotions from reviews, providing a deeper understanding of subjective experiences beyond numeric ratings [24, 25].

From an algorithmic perspective, the problem is frequently modeled as a path optimization challenge under various constraints (time, budget, interest). Metaheuristics are naturally suited for this. Wu et al. [19] developed an ACO algorithm embedded with a stochastic simulation to handle uncertain travel times. Similarly, Chen et al. [20] designed an improved GA for personalized route planning. While effective, these methods can suffer from parameter sensitivity and convergence issues. For instance, ACO's performance is highly dependent on initial pheromone settings and may converge slowly, while GA's crossover and mutation operations require careful tuning to avoid local optima.

Hybrid algorithms that combine the strengths of different metaheuristics have shown promise. The integration of PSO's global search capability with ACO's positive feedback mechanism is one such promising direction, though its application in tourism recommendation remains relatively unexplored [21]. Previous hybrid approaches, such as those applied to the probabilistic TSP [21], demonstrate the potential for improved robustness and solution quality. However, they typically operate on simpler cost functions and do not incorporate the rich, sentiment-aware user preference models required for personalized tourism.Previous hybrid approaches, such as those applied to the probabilistic TSP [21], demonstrate the potential for improved robustness and solution quality. However, they typically operate on simpler cost functions and do not incorporate the rich, sentiment-aware user preference models required for personalized tourism.

Concurrently, the rise of deep learning has introduced new paradigms. Graph Neural Networks (GNNs) have been used to model the complex relationships in POI networks [22], while Deep Reinforcement Learning (DRL) frameworks have been formulated to handle sequential decision-making in dynamic tour planning [23]. These data-driven methods offer powerful representation learning but often require large amounts of training data and lack the explicit constraint-handling mechanism of metaheuristics. Moreover, their "black-box" nature can limit interpretability, which is a valuable feature in interactive recommendation systems where users may wish to understand why a particular route is suggested.Moreover, their "black-box" nature can limit interpretability, which is a valuable feature in interactive recommendation systems where users may wish to understand why a particular route is suggested.

Our work distinguishes itself by developing a transparent and efficient hybrid PSO-ACO model that explicitly incorporates semantic user sentiment into the optimization process, offering a balance between sophisticated preference modeling and robust route optimization. As summarized in Table 1,

our approach uniquely combines (1) a sentiment- and attribute-aware composite distance metric, (2) a PSO-based initialization to guide ACO's search, and (3) a focus on the tourism domain with real-world validation. This positions our work at the confluence of data-enriched recommendation and hybrid metaheuristic optimization, addressing gaps left by both purely data-driven and purely algorithmic prior works.

Table 1 Positioning of our work relative to key research directions.

Research Direction	Typical Methods	Key Strengths	Common Limitations	How Our Work Addresses Them
Traditional CF & MF	User-based CF, Matrix Factorization [15,16]	Simple, effective for dense data	Sparse data, cold-start, ignores semantics	Uses multi-source data (ratings, text) for richer POI/user modeling
Context-Aware RecSys	Geo-social models, keyword-aware frameworks [8,9]	Incorporates spatial, temporal, social context	May not fully capture subjective sentiment	Integrates sentiment from reviews into heuristic function
Single Metaheuristics	Standard ACO, GA [19,20]	Good for constraint optimization, TSP variants	Slow convergence, parameter sensitivity, local optima	Hybrid PSO-ACO with PSO initialization and elite strategy
Deep Learning Methods	GNNs, DRL [22, 23]	Powerful pattern recognition, sequential modeling	Data-hungry, less interpretable, weak constraint handling	Maintains interpretability, efficient constraint handling via metaheuristics
Hybrid Metaheuristics (General)	PSO-ACO for TSP [21]	Combines global & local search strengths	Applied to simple costs, not personalized tourism	Tailored for tourism with personalized, composite distance metric

3. Methodology

3.1 Problem Description

The problem addressed in this study is abstracted as a Traveling Salesman Problem (TSP); that is, starting from the point of the weighted undirected graph, each node is traversed and accessed only once so that the total distance is the shortest. Here, the characteristic distance, Dis, is the distance between two POIs, and it is calculated using Eq. (1).

$$Dis(i,j) = \sqrt{\alpha \times dis^2(i,j) + \sum_{p=1}^{C}(1-\alpha)(\beta \times \left(c_p^i - c_p^j\right)^2 + (1-\beta) \times \left(c'^i_p - c'^j_p\right)^2)} \quad (1)$$

Suppose that the set of all POIs is P, and any two points $i,j \in P$, $dis^2(i,j)$ are expressed as the square of the Euclidean distance between any two points. The characteristic attribute set of a specific POI is set as $C=U_C \cup U_{C'}$, where U_C denotes the set of objective feature attributes of the POI, and $U_{C'}$ denotes the subjective feature attributes of the POI. For details of objective and subjective feature attributes, please refer to the following related definitions. β is used to coordinate the value of the subjective and

objective feature attributes, and *1-α* represents the weight of the information value component, calculated using Eq. (2):

$$1-\alpha=\frac{IV_{(i,j)}}{\sum_p IV}=\frac{IV_i+IV_j}{\sum_p IV},\ \ IV_i=(Rate_{good}{}_i-Rate_bad_i)\times\ln\left(\frac{Rate_good_i}{Rate_bad_i}\right) \quad (2)$$

where IV_i is the information value of point *i*, and $Rate_good_i$ and $Rate_bad_i$ are its positive and negative rates, respectively. Considering POI similarity, the user's rating of the POI was used in this study as the criterion for evaluating POI similarity to improve the judgment accuracy of similarity. The Jaccard coefficient is introduced; this coefficient is calculated using Eq. (3):

$$J(i,j)=\frac{amount(poi_i\cap poi_i)}{amount(poi_i\cup poi_i)},\quad i,j\in P \quad (3)$$

where *J(i,j)* is Jaccard coefficient of any two points *i* and *j*, $amount(poi_i\cap poi_j)$ is the number of user sets who score *i* and *j* POIs simultaneously, and $amount(poi_i\cup poi_j)$ is the number of user sets who score *i* or *j* POIs.

$\overrightarrow{poi_ratings(i)}$ is the user rating vector of point *i*, and * represents the vector dot product. Based on this value, the POI similarity can be obtained using Eq. (4).

$$poi_sim(i,j)=J(i,j)\frac{\overrightarrow{poi_ratings(i)}*\overrightarrow{poi_ratings(j)}}{|\overrightarrow{poi_{ratings(i)}}|\times|poi_ratings(j)|},\quad i,j\in P \quad (4)$$

The similarity and characteristic distance, *Dis*, of the POI are integrated into the heuristic function, as expressed by Eq. (5).

$$Sim(i,j)=\frac{poi_sim(i,j)}{1+Dis(i,j)},\quad i,j\in P \quad (5)$$

3.2 Related Definitions

Definition 1 (Point structure): If a point i, i∈P, is set, the elements that constitute the POI are mainly the longitude, latitude, and characteristic attributes of the POI. For details, refer to Definition 2.

Definition 2 (Characteristic attributes of points): According to the user's comments on a specific POI, variables can be used to represent the attributes of the POI. Words such as "Yongzheng," "Yongle," "Qianlong," and other emperor years can appear in the user's comment, indicating that the POI exhibits a degree of historicity, and "wood structure," "brick house," etc. show that the POI possesses architectural attributes. Different users have various preferences for different characteristic attributes of attractions. Among the POI score data collected from mainstream travel social networking sites, most were calculated by weighting the scores of six dimensions, including the history of the POI. In addition, users focused more on three objective characteristic attributes: the history, direction, and architecture of the POI [8]. According to users' ratings of POIs, the three subjective attributes of the POI's scenery, interest, and cost-effectiveness can reflect users' interests and preferences better. The attribute values were assigned according to the proportion of the word segmentation phrases included in the relevant characteristics in the overall segmentation phrases, as listed in Table 2.

Table 2. Characteristic attributes and attribute values of POI

Characteristic attribute	Attribute value
Historicity	Depends on the proportion of historical word

Directionality	Depends on the proportion of directional word
Architectural	Depends on the proportion of architectural word
Scenery	Depends on the proportion of scenery score in the total subjective score
Fun	Depends on the proportion of interest score in the total subjective score
Cost performance	Depends on the proportion of cost-effectiveness score in the total subjective score

3.3 Travel Route Recommendation Approach Based on Particle Swarm−Ant Colony

First, the ant colony algorithm is introduced in this section [16]. There are three main techniques for updating the pheromone. The ant-circulatory system update method was used in this study because, compared with the other two, this method reflects the global characteristics and minimizes the algorithm falling into the local optimum. Specific symbol definitions are listed in Table 3.

When ants travel around each POI node, the pheromone change value left on each POI is expressed by Eq. (6):

$$\Delta\tau_{ij}^{k}(t+1) = \begin{cases} \frac{Q}{L_k}, & k\ th\ ant\ pass\ route(i,j) \\ 0, & otherwise \end{cases} \quad (6)$$

Table 3 Parameters of the Ant Colony optimization algorithm

Symbol	Meaning
m	Number of ants
n	Number of visited cities
Dis(i,j)	Improved distance formula for calculating distance
η(i,j)	Heuristic value of attractions from *i* to *j*
$\tau_{ij}^{k}(t+1)$	Pheromone concentration of scenic spots from *i* to *j* at time (t + 1)
tabu	Taboo list
$allowed_k$	Meaning of node set that can be accessed next time based on current node

where Q is the number of released pheromone ants, and L_k is the length of the path visited by the kth ant.

At time t, the kth ant searches for the next city according to the following transition probability (7).

$$p_{ij}^{k}(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{j\in allowed_k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}, & j \in allowed_k \\ 0, & otherwise \end{cases} \quad (7)$$

Weight α is a pheromone factor representing the effect of the pheromone concentration on path selection. When α is zero, the ants choose completely according to the greedy rule. Weight β is a heuristic factor representing the effect of the improved distance formula of two POIs on path selection.

In the algorithm that introduces the random factor, the probability formula for transferring the next node is expressed by Eq. (7) when the random factor, q, is lower than a particular value, and vice versa, as expressed by Eq. (8) [14].

$$p_{ij}^{k}(t) = \arg\max\left(\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)\right) \quad (8)$$

The particle swarm algorithm is introduced to optimize the initial pheromone distribution of the ant colony algorithm. The particle swarm algorithm refers to a group of random particles flying at a specific speed in a particular dimensional space. During multiple iterations, one's speed is updated to change one's position according to the individual and overall extreme values, and the optimal solution to the problem is obtained. The definitions of the symbol are listed in Table 4.

Table 4 Parameters of particle swarm algorithm

Symbol	Meaning
v	Velocity vector of particle movement
x	Position vector of particle movement
w	Weight parameter
p_{best}	Individual extremum
g_{best}	Total extremum
r_1, r_2	Satisfied with (0,1) uniform distribution
c_1, c_2	Learning factor
p_{cbest}	Individual suboptimal value
g_{cbest}	Overall suboptimal value

The particle velocity and position are updated according to Eq. (9).

$$\begin{cases} v(t+1) = w \times v(t) + c_1 \times r_1 \times \left(p_{best}(t) - x(t)\right) + c_2 \times r_2 \times \left(g_{best}(t) - x(t)\right) \\ x(t+1) = x(t) + v(t+1) \end{cases} \quad (9)$$

3.4 Algorithm Design of Travel Route Recommendation Based on Particle Swarm and Ant Colony

The travel route recommendation method is based on the ant colony algorithm. First, according to the inverse document frequency algorithm, the segmentation phrases reflecting the characteristics of the i scenic spot are filtered from user u_i. The attribute value of each feature attribute of the i scenic spot is determined according to the frequency of the phrases of different feature attributes in the overall feature phrase.

Second, applying the random factor mechanism can significantly shorten the convergence time of the ant colony algorithm. When the ant colony algorithm solves specific application problems, it cannot fully consider the behavioral preferences and emotional factors of the behavioral participants (travelers), so new preferences and factors are adopted. The formula is used to compute the distance between two points instead of using a single Euclidean distance for expression. The proposed algorithm can improve convergence efficiency, and the personalized design requirements can be reflected.

By setting *Tau_max* and *Tau_min*, the value range of the pheromone is limited, and the search space of the algorithm is increased to prevent falling into the local optimum and making the algorithm premature. During the initial iteration, the higher solution speed of the particle swarm algorithm is used to obtain the suboptimal solution, adjust the pheromone distribution in the initial iteration, and prevent the random distribution of the pheromone in the initial iteration, which is caused by using only the ant

colony algorithm. Hence, the optimal solution to the combinatorial optimization problem is obtained faster.

In addition, the pheromone of the current optimal path is enhanced and increased by 1. The pheromone increment of the noncurrent optimal path is maintained between 0 and 1. Finally, the recommended path is matched with the path recommended by the official website of the Palace Museum, and the performance of the improved algorithm is reflected using two parameters: *precision* and *recall*. The flow of the above algorithm is shown in Algorithm 1.

Algorithm 1 Travel route recommendation algorithm based on particle swarm and ant colony
Input: Raw data, *random_value*, *iter_max*
Output: Optimal path
1. Handle these raw data to acquire POI info %data preprocessing, and using the inverse document frequency, according to Definition 1, calculate the attribute value of each POI
2. Use item-based collaborative filtering to calculate *poi_sim*
3. For $i \in P$:
4. For $r_j \in P$, $i \neq j$.
5. Use Eq. (5) to obtain *Sim matrix*
6. End
7. End
8. Initialize parameters % initialization parameters
9. Randomly generate fewer paths, select nodes on the better path, and leave pheromones. Determine *pbest, gbest, pcbest,* and *gcbest*
10. While $iter < iter_max$: % satisfies the iterative condition
11. If $q < random_value$: % if q is less than a random value
12. Choose the POI %. Select the POI with the highest transition probability as the next transition node
13. Otherwise: % if q is greater than or equal to a random value
14. Select next *poi* using Eq. (7)
15. Calculate the optimal path % calculate the current optimal path
16. Cross mutation operation % cross mutation operation
17. Update the crawling path, optimal value of the *i*_th ant %. Update the crawling path and optimal value of the *i*th ant according to the fitness value, and obtain the overall extreme value
18. Adjust $Tau_min < pheromone < Tau_max$
19. If the current path passes through $(i,j) \in$ current optimal path.
20. $\Delta\tau = \Delta\tau + 1$
21. Otherwise
22. $\Delta\tau = \Delta\tau + T_{i,j}/m$, $\%T_{i,j}$ represents the number of ants passing the path in the current iteration process
23. End
24. $\tau = (1-\rho) \times (\tau) + (\rho) \times (\Delta\tau)$
25. End
26. End
27. Return optimal path

4. Experiment and Performance Analysis

Smart tourism is a new model of tourism informatization development based on cloud computing, centered on mobile terminal applications, and characterized by efficient information services, such as perception and interaction. The core comprises tourist-oriented efficient tourism informatization services.

4.1 Experimental Setup

For this study, data for 37 scenic spots (POIs) within Beijing's Forbidden City was collected from the Mafengwo website, focusing on POIs with over 100 views. The corresponding review data for these 37 POIs was also compiled. T
he relevant comment data of these 37 POIs were counted. This was guided by the priority browsing of s
hort-
path and highly recommended scenic spots. The improved ant colony algorithm was used as the recom



mendation method. The 37 tourist attractions of the Forbidden City in Beijing are distributed in the Beij
ing Forbidden City tourist route (Figure 1).

Figure. 1 Distribution of 37 tourist attractions in the Forbidden City in Beijing

The influence of the number of ants in the ant colony algorithm on the algorithm's performance was investigated [17]. When other variables are kept constant, the number of ants significantly impacts the performance of the experiment, but the number of ants in the best case is not identified. In many experiments, the pheromone concentration started to stabilize when the number of ants was 16, and the time to execute the algorithm was improved. Experimental results exhibit a degree of generality, and more solutions to the TSP problem can be obtained. Therefore, 16 ants were used in this study.

Experimental indicators, that is, *precision*, *recall*, and *F*-test, were used in this study to analyze the performance of the particle swarm−ant colony algorithm, as expressed by Eq. (10):

$$precision = \frac{TP}{TP+FP}, recall = \frac{TP}{TP+FN}, \ F = \frac{2\times precision\times recall}{precision+recall} \qquad (10)$$

where *TP* is the set number of the intersection of the recommended route on the official website and the subsequence of the route provided by the recommended algorithm; *FP* is the number of subsequence sets of the route provided by the recommendation algorithm, but the official website does not recommend the route; *FN* is the set number of subsequence sets recommended by the official website, but the recommendation algorithm does not recommend the route.

For the comprehensive program running time, accuracy, and other factors, the precision, recall, and F-score values are ideal when β is 0.4. Therefore, in the following experiment, β = 0.4 was selected. The

central processing unit of the hardware platform was Corei7-8750@2.20GHz, the memory was 8 GB, the operating system was Windows 10, and the software environment was MATLAB 2019.

4.2 Experimental Results and Performance Analysis

In the original ant colony optimization algorithm, the recommended path was determined based on whether the algorithm was completely greedy (Table 5).

Table 5. Recommended path distances before and after improvement (km)

Algorithm	Original algorithm	Improved algorithm
Completely greedy	4.395	8.6361
Not completely greedy	3.4487	7.793

The ant colony optimization algorithm could shorten the recommended path when it is not entirely greedy (Table 4).

From the pheromone update, there was a related update strategy known as the elite management ant strategy (EMAS) [18]. In addition, there was the maximized management ant strategy (MMAS) [19], in which the optimal path pheromone is strengthened, and the suboptimal path pheromone is weakened. A method combining user clustering, improved genetics, and rectangular area path-planning algorithms has been proposed to design personalized travel routes for users [20]. By combining the three update schemes, their optimization algorithms were obtained and compared with the particle swarm−ant colony algorithm in terms of each index (Tables 6−8).

Table 6. Comparison of algorithms in terms of precision

Algorithm	Iteration					
	1	400	800	1200	1600	2000
EMAS [18]	0.100	0.096	0.113	0.113	0.096	0.096
MMAS [19]	0.091	0.097	0.097	0.097	0.097	0.097
IGA [20]	0.090	0.098	0.098	0.099	0.099	0.100
PS-AC	0.100	0.108	0.108	0.114	0.114	0.114

Table 7. Comparison of algorithms in terms of recall

Algorithm	Iteration					
	1	400	800	1200	1600	2000
EMAS [18]	0.038	0.035	0.044	0.044	0.033	0.033
MMAS [19]	0.041	0.048	0.048	0.048	0.048	0.048
IGA [20]	0.040	0.047	0.047	0.047	0.047	0.046
PS-AC	0.044	0.053	0.055	0.053	0.051	0.051

Table 8. Comparison of algorithms in terms of F-value

Algorithm	Iteration					
	1	400	800	1200	1600	2000
EMAS [18]	0.062	0.056	0.069	0.069	0.055	0.055
MMAS [19]	0.053	0.061	0.061	0.061	0.061	0.062
IGA [20]	0.055	0.062	0.062	0.062	0.062	0.062
PS-AC	0.057	0.070	0.070	0.065	0.065	0.065

The particle swarm−ant colony method exhibited better performance than EMAS [18], MMAS [19], and the improved genetic algorithm [20] in terms of precision, recall, and F-value (Tables 6−8).

5. Conclusions and Outlook

Smart tourism is a rapidly evolving field. It includes applications of technologies, such as cloud computing, the Internet of things, high-performance information processing, next-generation

communication network, and intelligent data mining, in industrial development, tourism experience, and administrative management. It enables information and physical tourism resources to be highly and systematically integrated and deeply developed and activated. It serves the public, enterprises, governments, and other stakeholders in a new future-oriented tourism form. Smart tourism is based on comprehensive communication and information technology, with the interactive experience of tourists as the core and with comprehensive industry information management as the guarantee. It is characterized by stimulating industrial innovation and upgrading industrial structures. Smart tourism involves applying new technologies, such as mobile cloud computing and the Internet, with the aid of portable terminal Internet devices to actively receive tourism-related information and arrange and adjust travel plans promptly. Simply, smart tourism involves the real-time interaction between tourists and the network such that the itinerary enters the tactile era.

The proposed travel path recommendation approach can provide good suggestions for users interested in travel and diversified items according to users' wide range of interests. The recommended tourist attractions are personalized, diverse, and novel. User satisfaction is significantly improved. Furthermore, the user's text comments are adopted in the heuristic function design, promoting convergence and recommendation personalization.

The proposed approach is based on a hybrid of Particle Swarm Optimization and Ant Colony Optimization. The related attributes and similarity of the POI are calculated using a user rating matrix and integrated into the ant colony heuristic function. The advantages of particle swarm optimization and ant colony optimization are combined, elite ants' mechanisms are introduced in the ant colony algorithm, convergence efficiency is improved, and the convergence time is shortened. The proposed recommendation approach has certain limitations, particularly regarding the evaluation methodology, dataset sparsity, and the chosen evaluation metrics. The dataset is sparse, and inconsistency exists between objective and subjective evaluations. Additionally, the test dataset is limited and cannot be generalized. In a future study, we plan to overcome the above shortcomings.

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Declarations

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Data Availability

The datasets generated and/or analyzed during the current study are not publicly available due to their origin from a commercial travel website (Mafengwo) under specific terms of use, but are available from the corresponding author on reasonable request for academic purposes.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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