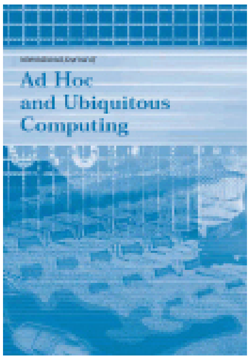

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Hybrid recommendation system based on human-computer interaction technology and smart tourism

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Hybrid recommendation system based on human-computer interaction technology and smart tourism

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Abstract: With the development of information technology, people's demand for personalised and intelligent tourism experiences is increasing, and traditional recommendation systems can no longer meet this demand. This article proposes a design based on human-computer interaction technology and the concept of smart tourism, aiming to enhance users' personalised travel experience. Firstly, the study collects user preference and demand data through human-computer interaction, analyses the data using collaborative filtering algorithms, and then recommends personalised travel routes for users based on their interest characteristics, travel routes, and transportation modes. The experimental results show that the hybrid collaborative filtering algorithm proposed in this paper outperforms a single collaborative filtering algorithm in terms of recommendation accuracy, recall, coverage, and popularity, achieving the best recommendation performance at a k value of 50. Therefore, human-computer interaction technology and smart tourism concepts can help users achieve more comprehensive, accurate, and personalised travel recommendations.

Keywords: tourism routes; personalised recommendations; smart tourism; human-computer interaction technology; collaborative filtering.

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1 Introduction

With the rapid development of information technology and the Internet, people's lifestyle and consumption habits have changed significantly. In the field of tourism (Zhang et al., 2020; Tang et al., 2021), traditional tourism methods and services are no longer able to meet the needs of modern tourists for personalised and intelligent experiences. The advancement of human-computer interaction technology (Mohammed and Karagozlu, 2021; Joseph and Murugesh, 2020), such as speech recognition, gesture control, virtual reality, and augmented reality, has brought new opportunities for collecting user preferences and providing personalised services. In the context of smart tourism, with the help of technologies such as the internet of things, big data, and artificial intelligence, the tourism industry has gradually realised information-based and intelligent management. Through in-depth mining and analysis of tourist behaviour data, smart tourism can provide personalised and precise services, optimise tourism resource allocation, improve tourist satisfaction, and promote the sustainable development of the tourism industry. Smart tourism (Mehraliyev et al., 2020; Baggio et al., 2020), as an emerging concept, utilises information technology and intelligent means to provide tourists with more intelligent and convenient services, including applications in intelligent navigation, real-time information updates, personalised recommendations, and cultural heritage protection, greatly improving the tourism experience. Therefore, this article designs a hybrid recommendation system that combines human-computer interaction technology and the concept of smart tourism, accurately collecting user needs and preferences through various interaction methods. It is particularly important to use advanced recommendation algorithms for analysis and provide personalised travel route recommendations for users. This can not only improve the accuracy and real-time performance of recommendations, but also comprehensively enhance the user's travel experience through interactive and diverse recommendation content, meeting the needs of modern tourists for intelligence and personalisation.

This article proposes a hybrid collaborative filtering recommendation system based on user interest characteristics, tourism routes, and transportation modes. A personalised tourism route recommendation system can be constructed through user data collection and pre-processing, feature extraction, collaborative filtering algorithms, and multi-algorithm weighted fusion. In the process of implementing the method, the user's interests and preferences, historical travel records, and transportation mode choices can be collected through human-computer interaction devices, and these data can be cleaned, formatted, and integrated. Then, user interest features, tourism route features, and transportation mode features can be extracted from them. Three algorithms, namely collaborative filtering based on user interest features, collaborative filtering based on tourism routes, and collaborative filtering based on transportation modes, can be applied for recommendation. Finally, personalised tourism route recommendations can be generated through weighted fusion. The research results indicate that hybrid collaborative filtering outperforms single collaborative filtering algorithms in terms of recommendation accuracy, recall, coverage, and popularity, especially achieving the best effect at a k value of 50. The average recommendation accuracy of hybrid collaborative filtering is 78.8%, the recommendation time is 3.5 seconds, and the highest user satisfaction is 89 points. This article combines user interest characteristics, travel routes, and transportation modes into a recommendation system, and achieves more comprehensive, accurate, and personalised travel recommendations through weighted fusion of multiple collaborative filtering algorithms. The innovation of this paper lies in combining human-computer interaction technology with smart tourism, and proposing a hybrid recommendation system. By integrating tourist behaviour data and preference analysis, it realises personalised and precise tourism recommendations and improves the tourist experience.

2 Related work

Smart tourism has become a hot field in tourism research and practice in recent years, with the core of utilising advanced information technology and intelligent means to improve the quality and efficiency of tourism services. The research on smart tourism (Shafiee et al., 2021; Wang et al., 2020) covers multiple aspects, including intelligent navigation, real-time information updates, personalised recommendations, tourist behaviour analysis, cultural heritage protection, and sustainable development. Intelligent navigation technology plays a key role in intelligent tourism (Bastidas-Manzano et al., 2021). Through mobile internet, geographic information system and other technologies, it provides tourists with optimal path planning and traffic information in real-time. Real-time information updates rely on internet of things technology, combined with sensor networks, to dynamically monitor and update information such as the opening hours of scenic spots, tourist traffic, weather conditions, etc. providing timely and effective travel advice for tourists. The application of personalised recommendation systems in smart tourism is becoming increasingly widespread, providing customised travel routes and services by analysing the interests, behaviours, and preferences of tourists (Buhalis et al., 2023). Smart tourism (Gretzel, 2021; Azis et al., 2020) focuses on analysing and predicting tourist behaviour, utilising big data and machine learning technologies to analyse historical data and real-time behaviour of tourists, predict their potential needs, and optimise tourism resource allocation and services. However, despite significant progress in multiple aspects of smart tourism, current research and practice mainly focus on the application of information technology and the intelligence of services, with relatively little in-depth research on personalised recommendations. Specifically, most smart tourism systems lack precise recommendations tailored to the individual needs and preferences of tourists, often unable to provide highly personalised travel routes and services. Although smart tourism has made great progress in many aspects, current research and practice mainly focus on the application of information technology and the intelligence of services, and there is relatively little in-depth research on personalised recommendations. The existing smart tourism system lacks accurate recommendations based on tourists' personalised needs and preferences, making it difficult to provide highly personalised travel routes and services.

Tourism recommendation systems have been widely researched and applied in recent years, providing personalised recommendations for tourist attractions, routes, and activities by analysing user interest and behaviour data. Early tourism recommendation systems mainly adopted content-based recommendation methods, which achieved simple personalised recommendations by matching user interest labels with tourism resource labels (Niu et al., 2020; Meng et al., 2021). However, this method is easily limited by changes in user interests and cold start issues, resulting in low diversity and accuracy of recommendation results. With the development of technology, recommendation algorithms based on collaborative filtering (Wu et al., 2022) have gradually become mainstream, especially collaborative filtering methods based on users and projects. The user collaborative filtering algorithm (He and Hua, 2023) recommends other attractions or routes that similar users like by calculating the similarity between users. The project collaborative filtering algorithm (Huang et al., 2023) recommends tourism resources that are similar to the user's historical choices by calculating the similarity between attractions or routes. These methods have to some extent improved the accuracy and diversity of recommendations, but still face issues of data sparsity and scalability. The hybrid recommendation system (Zhou et al., 2023) combines the advantages of content-based and collaborative filtering, further enhancing the effectiveness of recommendations. A hybrid recommendation system can better meet the recommendation needs in different scenarios by integrating multiple recommendation strategies. Although tourism recommendation systems have made significant progress in algorithms and technology, there are still some shortcomings. Especially in practical applications, many systems cannot fully consider the needs and preferences of users in different contexts, and the pertinence and applicability of recommendation results need to be improved.

The application of human-computer interaction technology in smart tourism is becoming increasingly widespread, improving user experience through innovative interaction methods and increasing the intelligence and personalisation of tourism services. Speech recognition and speech assistant technology are important components of the field of human-computer interaction (Yang et al., 2024; Shi et al., 2021). Through natural language processing technology, tourists can use voice commands to query scenic spot information, book services, or obtain navigation guidance. Virtual reality (Idris and Rohmah, 2021) and augmented reality technology (Anand et al., 2023) also play important roles in smart tourism. Virtual reality technology (Martins et al., 2020) creates an immersive virtual environment that allows users to experience the scenery and attractions of their destination before departure, helping them make better travel decisions. Augmented reality technology (Litvak and Kuflik, 2020) provides users with real-time navigation and information prompts by overlaying digital information in a real environment. The popularity of mobile applications and smart devices has made multimodal interaction possible. Tourists can interact through various means such as touch, voice, and gestures through smartphones, tablets, or wearable devices. This multimodal interaction not only improves the usability and user satisfaction of the system, but also comprehensively collects user preference and behaviour data, providing a rich information foundation for personalised recommendations. The current smart tourism systems often fail to fully integrate various human-computer interaction technologies, and fail to achieve highly personalised and intelligent tourism services in practical applications.

3 Methods for personalised recommendation of tourist routes

3.1 User data collection

To provide accurate and personalised travel recommendations, it is necessary to comprehensively and meticulously collect user data from multiple dimensions. User input devices include smartphones, tablets, smartwatches, etc. Users can interact with the system through smart devices, input personal information and travel preferences. Input methods include keyboard, touch screen, voice input, gesture control, etc.

The sensors built-in in smart devices include positioning sensors, accelerometers, gyroscopes, etc. It can provide real-time location information, motion data, and environmental data, helping the system understand the user's geographical location, activity patterns, and surrounding environment. The activities of users on social media platforms, such as posted travel photos, comments, likes, and check-in records, are valuable sources of data. By collaborating with third-party tourism platforms, users can obtain booking records, historical routes, and other information to enrich their datasets.

In order to implement a personalised tourism recommendation system, a large amount of user information is collected, covering basic user information, behavioural data, etc. The total number of collected users is 500. This article selects 100,000 tourist attractions and 300,000 tourist routes. Basic information such as name, age, gender, and contact information provided by the user during registration. The user's interests and preferences filled in during registration or first use, including preferred travel types, frequently visited tourist destinations, and favourite activities. The data collection interface is shown in Figure 1.

The collected behavioural data includes historical behavioural data and real-time behavioural data. Some of the collected behavioural data are shown in Table 1.

Figure 1 Data collection interface (see online version for colours)

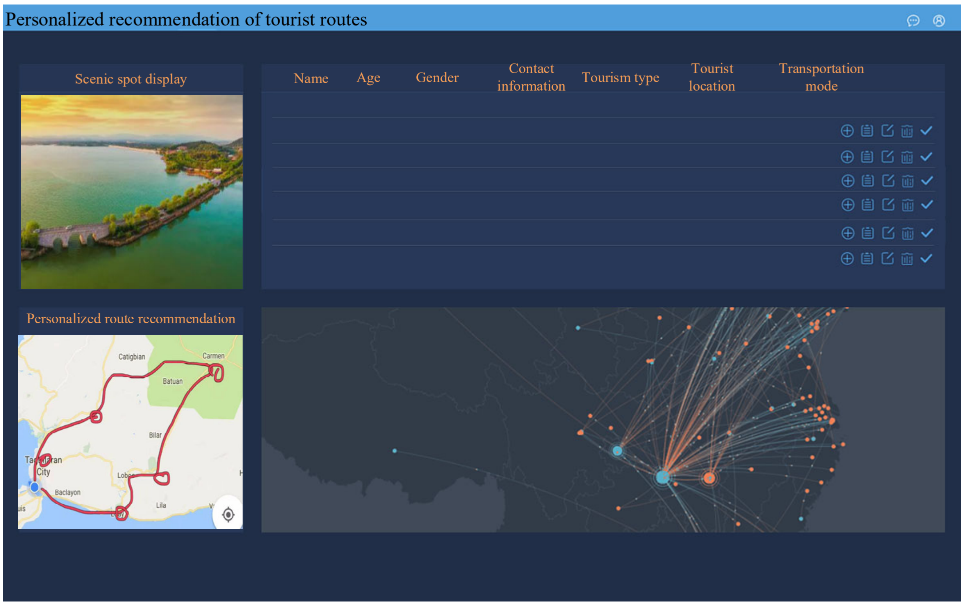


Table 1 Partial behavioural data collected

User number	*Destination*	*Attraction name*	*Access date*	*Stay time (min)*
1	Beijing	The Palace Museum	2023/04/03	180
2	Shanghai	Oriental Pearl TV Tower	2023/05/12	120
3	Xi'an	Terra Cotta Warriors	2023/06/06	150
4	Guilin	Elephant Trunk Mountain	2023/07/17	120
5	Chengdu	Chengdu Giant Panda Base	2023/08/02	120
6	Hangzhou	West Lake	2023/09/11	180
7	Suzhou	Hanshan Temple	2023/10/07	60
8	Lhasa	The Potala Palace	2023/11/02	120

This article collects past travel records of users, including visited attractions, participated activities, used transportation, and length of stay. Sensors can collect users' current geographic location, movement trajectory, and activity patterns, and monitor their travel behaviour in real-time.

Users interact with data on social media, including likes, comments, shares, and travel related content posted. By analysing user interaction data, it can understand their interests and social circles. By analysing social networks, it is possible to discover common interests and travel preferences between users and other users, thereby making social recommendations. By collecting data on the tourism transportation modes of each tourist attraction, the best tourism transportation mode for different attractions can be analysed.

3.2 *Data pre-processing and feature extraction*

The collected data can be pre-processed to ensure data quality and reliability, including data cleaning, formatting, and integration. Missing values refer to fields in a dataset that are either empty or missing. When the proportion of missing values in a field is high, the data in that field is deleted. When the proportion of missing values in a field is relatively low, the median of the data can be used to fill in, and the missing value of user age can be filled in with the average value of the age group.

The formula for the average value of the data is:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Basic user information can be merged with user interest preference tables and user behaviour data by user number to generate a comprehensive dataset containing complete user information. Repeated values can be checked again in the merged dataset, and the consistency and integrity of the data can be verified. Effective cleaning, formatting, and integration of user data can ensure high quality and consistency of data.

Feature engineering can be applied to data to extract more useful information. Feature extraction is the process of extracting user interest features, tourism route features, and transportation mode features from processed data. The extracted features can be used as input to assist the recommendation system in personalised recommendations.

User interest characteristics (Guo et al., 2020; Ding et al., 2021) include user interests, preferred travel types, and activities. These features can be extracted from the user's historical behaviour data and interest preference data. Interest and hobbies can be directly extracted from the interest and hobbies field filled in by the user. The user interest preference information includes the types of activities that the user likes (hiking, diving, museum visits, etc.), which can be directly used as user interest characteristics. The types of tourism that users prefer (natural scenery, cultural heritage, shopping and entertainment, etc.) can be extracted from user interest preference information. 1 indicates that the user likes this type, and 0 indicates that they do not like it.

The characteristics of tourist routes include information such as the geographical location, duration of stay, and types of tourist attractions. The characteristics of tourist routes can be extracted from the user's travel records and travel route data. The geographical location characteristics of each tourist route can include the longitude and latitude of the tourist destination, the geographical distribution of scenic spots, etc.

The stay time characteristics of each attraction represent the user's stay time at each attraction. Calculate the average stay time for each attraction using the formula:

$$\overline{t} = \frac{\sum_{i=1}^{n} t_i}{n} \tag{2}$$

n represents the number of attractions, and t_i represents the user's stay time at the i^{th} attraction.

The types of attractions included in each tourist route can be represented as a vector, represented as:

$$J = [J_1, J_2, J_3] \tag{3}$$

J_1, J_2, J_3 represent the number of natural attractions, cultural attractions, and entertainment attractions, respectively.

The type of transportation can be extracted from the user's mode of transportation records. The transportation tool used by the user can be represented as a vector:

$$R = [R, R_2, \cdots, R_m] \tag{4}$$

In formula (4), m represents the total number of vehicles.

3.3 Recommendation model

3.3.1 Collaborative filtering based on user interest features

User interest features can be represented as a multidimensional vector, where each dimension represents an interest or preference. In order to perform collaborative filtering, it is necessary to calculate the similarity between users. The similarity calculation method used is cosine similarity (Park et al., 2020; Singh et al., 2020), which measures similarity by calculating the cosine value of the angle between two user interest vectors. The formula is:

$$D = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} \tag{5}$$

In formula (5), A and B are the interest vectors of two users, respectively.

The advantage of cosine similarity is that it can effectively process high-dimensional data, especially for collaborative filtering of user interest features. It measures similarity by calculating the cosine value of the angle between two vectors, ignoring the length difference of the vectors, so it still performs well in the case of sparse data. In addition, cosine similarity is easy to calculate and can avoid numerical overflow problems.

After calculating the similarity between all users, a user similarity matrix can be constructed. Each element in the matrix represents the similarity between two users.

Assuming there are three users whose interest feature vectors are A, B, and C, and the similarity matrix is:

$$H = \begin{pmatrix} 1 D(A, B)\, D(A, C) \\ D(B, A)\, 1 D(B, C) \\ D(C, A)\, D(C, B) 1 \end{pmatrix} \tag{6}$$

After constructing a user similarity matrix, recommendations are made based on the historical data of similar users. For the target user, finding the top k users with the highest similarity is called neighbour users. It can collect travel records of these neighbouring users, especially the attractions and travel routes they have visited. Based on the travel records of neighbouring users, a recommendation list for the target user can be generated, and the number of times neighbouring users have visited each attraction or route can be counted. The most visited attraction or route can be selected as the recommendation.

The process of collaborative filtering based on user interest features is shown in Figure 2.

3.3.2 Collaborative filtering based on tourism routes

Collaborative filtering based on tourism routes is a recommendation system technology that recommends similar routes to users by analysing their historical tourism routes. Each tourist route can be represented as a feature vector, including the geographical location, type of attraction, duration of stay, etc. The geographical location characteristics of each route can be represented as the longitude and latitude of the scenic spots. It can calculate the similarity between user's historical travel routes, and also measure the similarity by calculating the cosine value of the angle between two route vectors.

Can calculate the similarity between all tourism routes and construct a route similarity matrix. After constructing a route similarity matrix, recommendations are made based on historical data of similar routes. For the historical travel routes of the target user, the top k routes with the highest similarity can be found, which are called similar routes. It is possible to collect behavioural data on these similar routes, especially the attractions and stay times they contain. Based on behaviour data of similar routes, a recommendation list for target users can be generated.

3.3.3 Collaborative filtering based on transportation modes

Collaborative filtering based on transportation modes is also a technology in recommendation systems, which can recommend suitable tourist routes by combining user transportation preferences. Users can extract their transportation preferences from their historical behaviour data and explicit preference data. Transportation preferences: walking, cycling, driving, public transportation.

In order to perform collaborative filtering (Fkih, 2022; Ajaegbu, 2021), the similarity of transportation modes between users can be calculated. The Pearson correlation coefficient calculates similarity by measuring the linear correlation between the preference vectors of two user modes of transportation.

$$r = \frac{\sum_{i=1}^{n}(A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^{n}(A_i - \bar{A})^2}\sqrt{(B_i - \bar{B})^2}} \tag{7}$$

In formula (7), $\bar{A}$ and $\bar{B}$ are the mean of the two user transportation mode preference vectors, respectively.

After calculating the similarity of transportation modes among all users, a user transportation mode similarity matrix can be constructed. Each element in the matrix represents the similarity between two users. After constructing a user transportation similarity matrix, recommendations are made based on historical tourism route data of similar users.

For the target users, the top k users with the highest similarity in transportation methods can be found, and the historical travel records of these neighbouring users can be collected, especially the travel routes and transportation methods they have chosen. Based on the historical travel records and transportation preferences of neighbouring users, a recommendation list for the target user can be generated. Tourism routes can be weighted based on the similarity of transportation modes between neighbouring users and target users, and the highest rated tourism route can be selected as a recommendation.

3.3.4 Hybrid collaborative filtering

Hybrid collaborative filtering generates personalised recommendations by combining user interest features, tourism route features, and transportation mode features. This method utilises the advantages of various collaborative filtering algorithms to improve the accuracy and diversity of recommendations through weighted fusion. The advantage of hybrid collaborative filtering is that it combines the advantages of multiple collaborative filtering methods and can comprehensively utilise user behaviour, content features and contextual information to improve the accuracy and personalisation level of the recommendation system and reduce data sparsity and cold start problems.

Collaborative filtering can be performed using user interest features to generate recommendation lists. Cosine similarity can be used to calculate the similarity of interests between users. A recommendation list can be generated based on the historical travel records of similar users. Collaborative filtering can be performed using tourism route features to generate a recommendation list. It can be performed using the characteristics of transportation modes to generate recommendation lists.

The final personalised recommendation can be generated by weighted fusion of the results of the three collaborative filtering algorithms mentioned above. L_1, L_2, L_3 are a recommendation lists based on user interest characteristics, tourism route characteristics, and transportation mode characteristics, with each recommendation item in each recommendation list having a rating. The process of weighted fusion is represented as:

$$\begin{aligned} L_{total} &= w_1 \cdot L_1 + w_2 \cdot L_2 + w_3 \cdot L_3 \\ w_1 + w_2 + w_3 &= 1 \end{aligned} \tag{8}$$

The process of mixed recommendation is shown in Figure 3.

Figure 2 Collaborative filtering based on user interest features (see online version for colours)

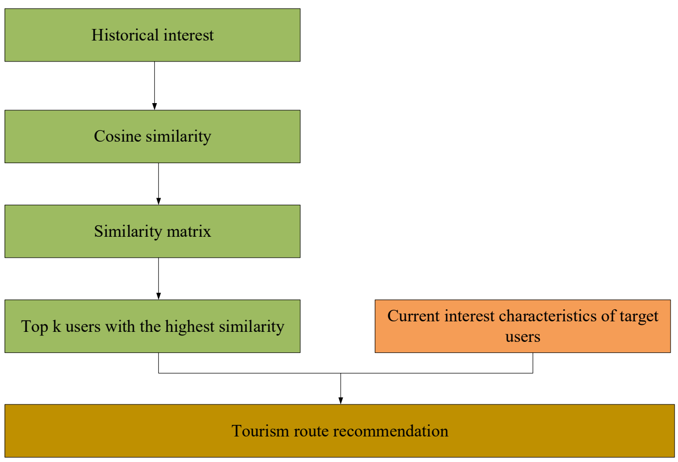


Figure 3 The process of mixed collaborative filtering (see online version for colours)

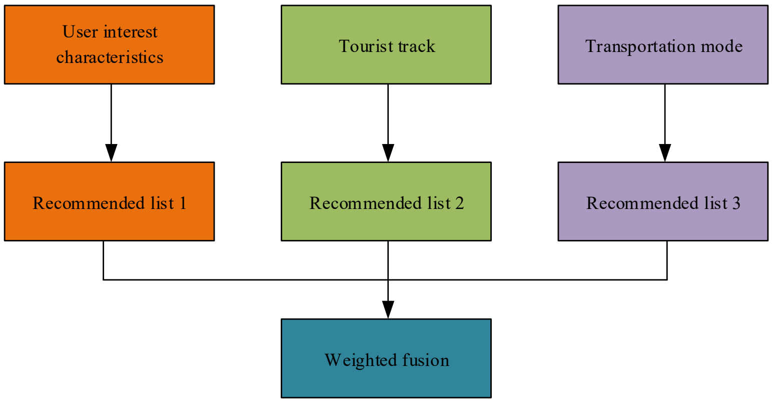


Figure 4 System interface for tourism route recommendation (see online version for colours)

Figure 5 Recommendation accuracy (see online version for colours)

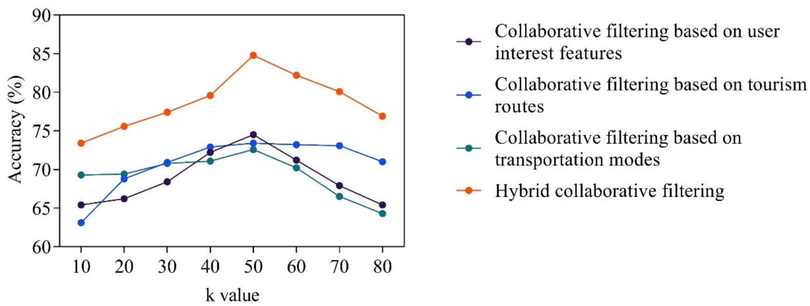


Figure 6 Recommended recall rate (see online version for colours)

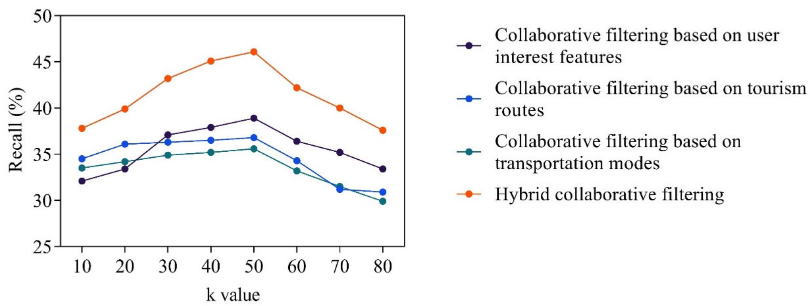


Figure 7 Coverage results (see online version for colours)

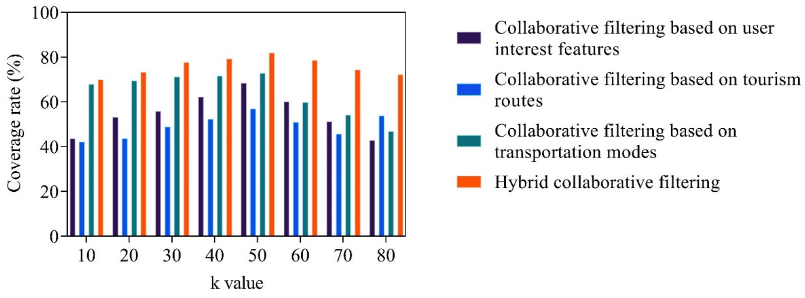


Figure 8 Popularity results (see online version for colours)

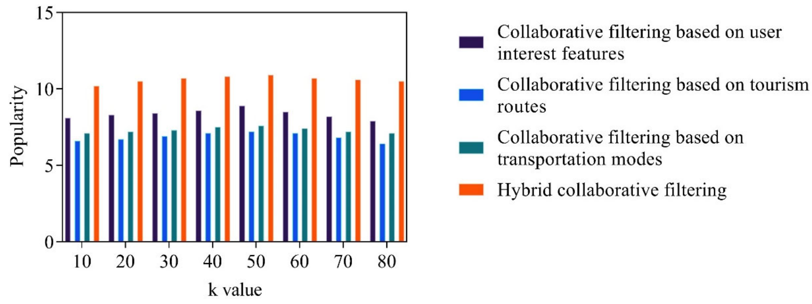
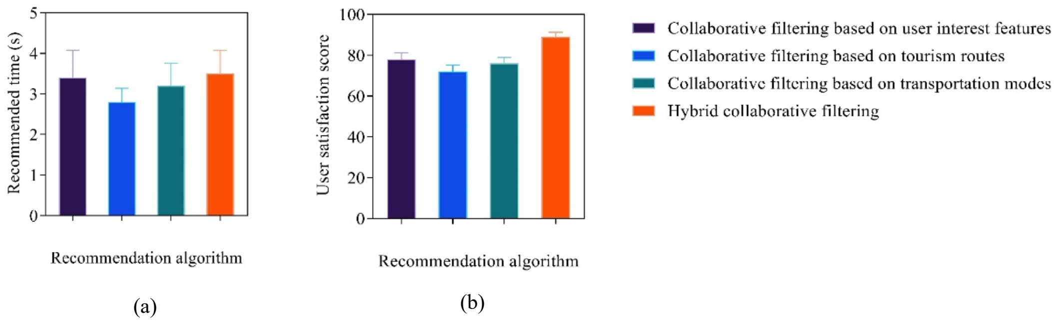


Figure 9 Recommendation time and user satisfaction, (a) recommended time, (b) user satisfaction (see online version for colours)



Hybrid collaborative filtering generates the final personalised recommendation by combining user interest features, tourism route features, and transportation mode features, using a weighted fusion method. This method combines the advantages of multiple collaborative filtering algorithms to provide more accurate and diverse recommendations, thereby achieving the goal of improving user travel experience.

3.4 Personalised travel route recommendation system

The personalised travel route recommendation system provides users with targeted travel routes through hybrid recommendation algorithms, and uses human-computer interaction technology to display the recommended travel routes to users. The graphical interface is the main way for users to interact with the system. Interface design focuses on user experience, providing intuitive operations and rich visual effects.

The interface for recommending tourist routes is shown in Figure 4.

Recommended tourist routes and attractions can be marked on the interactive map, and users can click to view detailed information. It can dynamically generate tourist routes and display them on the map based on the scenic spots and transportation modes selected by the user. When the user approaches the recommended scenic spot, the voice introduction of the scenic spot can be automatically played, including historical background, characteristics, etc. Smartphone users can see virtual route guidance and scenic spot information overlaid in real scenes. Before travelling, users can experience recommended travel routes and attractions through virtual reality devices, understand the layout and characteristics of attractions in advance, and help make better travel decisions.

The personalised travel route recommendation system combines hybrid recommendation algorithms and various human-computer interaction technologies to provide users with accurate and personalised travel route recommendations. By using graphical interfaces, voice prompts, virtual reality, and augmented reality displays, it can ensure the accuracy of recommendations, enhance the user's travel experience, further meet the diverse travel needs of users, and provide more intelligent and thoughtful travel services.

This article sets E as the set of tourist routes, U as the set of users, and $G(u)$ represents the set of N tourist routes recommended by user u. $I(u)$ represents the historical travel route selected by user u in E. $U(e)$ represents the set of users selected for route e.

This article recommends personalised travel routes for users by combining their interest characteristics, travel routes, and transportation modes. In collaborative filtering, the top k users or k routes with the highest similarity are crucial. When evaluating the performance of tourist routes, different gradient k values are set to analyse the superiority of different recommendation algorithms.

This article compares hybrid collaborative filtering with collaborative filtering based on user interest features, collaborative filtering based on tourism routes, and collaborative filtering based on transportation modes. The evaluation indicators set include accuracy, recall, coverage, and popularity. The performance of recommendation algorithms can be comprehensively reflected by recommendation speed and user satisfaction.

The formula for calculating the accuracy of tourism recommendations is:

$$Acc = \frac{\sum_u |G(u) \cap I(u)|}{\sum_u |G(u)|} \tag{9}$$

The recall rate is:

$$Rec = \frac{\sum_u |G(u) \cap I(u)|}{\sum_u |I(u)|} \tag{10}$$

Coverage is an important indicator in the evaluation of recommendation systems, which is used to measure the diversity of different items that recommendation systems can recommend. The formula is expressed as:

$$Cov = \frac{|U_{u \in U} G(u)|}{E} \tag{11}$$

The role of coverage is to evaluate the diversity and breadth of the recommendation system, to ensure that the system not only recommends popular items, but also recommends more long-tail items, to increase users' opportunities to be exposed to different content, to improve user experience, and to avoid the uniformity and repetitiveness of recommendation results.

The popularity represents the popularity of recommended tourist routes among tourists, and the formula is:

$$Pop = \frac{\sum_{e \in G(u)} Size(U(e))}{Size(G(u))} \tag{12}$$

Subjective analysis is reflected in the satisfaction of users with recommended routes. The satisfaction score of users is calculated, and a score range of 0–100 is set. The higher the score, the more satisfied the user is with the recommended route. Analysing user satisfaction with recommended routes aims to evaluate the effectiveness of the recommendation system and user experience. By understanding user satisfaction, we can optimise the recommendation algorithm, improve the accuracy and personalisation of the system, and better meet user needs.

4 Results

4.1 Recommendation accuracy

The accuracy of recommendations reflects the degree to which the recommendation results are closely related to the user's actual preferred route. The set k values are 10, 20, 30, 40, 50, 60, 70, and 80. The accuracy results of different recommendation algorithms are shown in Figure 5.

From the results of recommendation accuracy, it can be seen that the accuracy of mixed collaborative filtering is always the highest, with an average recommendation accuracy of 78.8%. There are differences in recommendation accuracy under different k values. The accuracy of the four recommendation algorithms shows a data trend of first increasing and then decreasing, reaching the peak accuracy when k is 50. When k is 50, the accuracy of collaborative filtering based on user interest features, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering are 74.5%, 73.4%, 72.6%, and 84.8%, respectively. When the k value is low, the number of neighbours is insufficient, resulting in insufficient diversity and accuracy of recommendation results. When the value of k is too high, there are too many neighbours, which introduce more noisy data and leads to a decrease in recommendation accuracy. A k value of 50 is a balance point that provides accurate recommendations with enough similar users or routes, while avoiding interference from too much irrelevant data. A single recommendation algorithm cannot fully cover all user needs. By combining multiple information sources, hybrid collaborative filtering improves the accuracy of recommendations and can more comprehensively capture user preferences. It can provide more accurate and personalised recommendations, significantly improving overall recommendation performance.

4.2 Recommended recall rate

The recall rate measures the proportion of items that a recommendation system can find that users actually like, reflecting the comprehensiveness of the recommendation system. The recall rate results of different recommendation algorithms are shown in Figure 6.

The recommendation recall of the four recommendation algorithms first increases and then decreases, reaching its highest point when k is 50. The recommended recall rates for collaborative filtering based on user interest characteristics, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering at $k = 50$ are 38.9%, 36.8%, 35.6%, and 46.1%, respectively. A k value of 50 is the optimal balance point, which can maximise the recall rate while ensuring the diversity of recommendation results. Specifically, hybrid collaborative filtering has the highest recall rate. By integrating three information sources: user interest characteristics, travel routes, and transportation modes, it can more comprehensively capture users' multidimensional preferences, provide a wider range of recommendation coverage, and significantly improve the recall rate. In contrast, a single collaborative filtering method has limitations in terms of information sources, with a slightly lower recall rate compared to mixed collaborative filtering, but it also reaches its respective optimal states at a k value of 50.

4.3 *Recommended coverage rate*

Coverage measures the proportion of different items that a recommendation system can recommend, reflecting the diversity of the recommendation system. The recommendation coverage results of different recommendation algorithms are shown in Figure 7.

The coverage of hybrid collaborative filtering is higher than collaborative filtering based on user interest features, tourism routes, and transportation modes. And when k is 50, all four recommendation algorithms reach the highest coverage point. When k is 50, the coverage rates of collaborative filtering based on user interest features, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering are 68.4%, 56.9%, 72.8%, and 81.9%, respectively. The coverage of hybrid collaborative filtering is significantly higher than the other three single collaborative filtering algorithms, and reaches its highest point at a k value of 50. This is because hybrid collaborative filtering integrates information from three dimensions: user interest characteristics, travel routes, and transportation modes, enabling more comprehensive recommendations to users from multiple perspectives. This fusion of multi-source information enables recommendation systems to discover more long tail items, namely those that are not very popular but meet specific user interests, thereby increasing the diversity and coverage of recommended content. When the k value is 50, the system finds a balance point where there are enough similar users or routes to provide diverse recommendations, while avoiding the introduction of too much irrelevant or noisy data. A low k value cannot fully utilise the diversity of data, while a high k value can introduce a large amount of irrelevant information, which in turn reduces the effectiveness of recommendations. 50 neighbours provide the best balance of diversity and relevance. Hybrid collaborative filtering significantly improves the coverage of recommendation systems through multi-source information fusion, long tail effect mining, capturing user interest diversity, and improving data utilisation.

4.4 *Popularity of tourist routes*

Popularity measures the popularity of items recommended by a recommendation system, reflecting the degree to which the recommendation system tends to recommend popular items. The popularity of tourist routes is shown in Figure 8.

The popularity of hybrid collaborative filtering is also higher than the other three recommendation algorithms. The popularity of collaborative filtering based on user interest features, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering at $k = 50$ are 8.9, 7.2, 7.6, and 10.9, respectively. User preferences are often multidimensional, and a single collaborative filtering algorithm can only capture preferences in a certain dimension. For example, collaborative filtering based on user interest characteristics mainly focuses on user interests and hobbies, while collaborative filtering based on tourism routes and transportation modes respectively focuses on user historical tourism routes and transportation preferences. By comprehensively considering these dimensions, hybrid collaborative filtering can more comprehensively reflect the true interests of users and recommend more popular routes. In contrast, a single collaborative filtering algorithm tends to favour specific dimensions when recommending, resulting in lower popularity. Hybrid collaborative filtering can comprehensively reflect users' complex preferences by integrating multi-dimensional information such as user interests, travel routes and transportation methods, thereby providing more comprehensive and personalised recommendations. This method overcomes the shortcomings of single collaborative filtering in terms of dimensionality restrictions, improves the accuracy of recommendations and user satisfaction, and is therefore significantly more popular than other recommendation algorithms.

4.5 *Recommended time and user satisfaction*

By analysing the results of accuracy, recall, coverage, and popularity, a k value of 50 was selected. The recommended time and user satisfaction are shown in Figure 9.

In Figure 9(a), the recommendation time of four algorithms is shown, and the collaborative filtering based on tourism routes has the shortest average recommendation time. The average recommendation time for collaborative filtering based on user interest characteristics, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering are 3.4 seconds, 2.8 seconds, 3.2 seconds, and 3.5 seconds, respectively. Figure 9(b) shows the user satisfaction of four algorithm recommendations, with a maximum satisfaction score of 100. The average satisfaction scores for collaborative filtering based on user interest characteristics, collaborative filtering based on tourism routes, collaborative filtering based on transportation modes, and hybrid collaborative filtering are 78, 72, 76, and 89, respectively.

The collaborative filtering algorithm based on tourism routes mainly relies on matching the user's historical tourism routes when calculating recommendations. Compared to the multi-dimensional data processing of user interest characteristics and transportation modes, tourism route data is usually more concentrated and clear, with lower matching computational complexity, resulting in shorter recommendation times. The hybrid collaborative filtering algorithm combines data from three dimensions: user interest characteristics, tourism routes, and transportation modes, and requires comprehensive processing and calculation of various information. It has the highest computational complexity, resulting in a relatively long recommendation time. However, it comprehensively considers the various needs and preferences of users, providing more personalised and accurate recommendation results, which can better meet their needs and improve user satisfaction. Although hybrid collaborative filtering has the longest recommendation time, it has the highest user satisfaction, indicating that users are more inclined to accept systems with slightly longer computation time but more accurate recommendation results. On the contrary, although collaborative filtering based on tourism routes has the shortest recommendation time, due to insufficient personalisation, user satisfaction is the lowest.

5 Conclusions

This article studies a hybrid collaborative filtering algorithm that combines user interest characteristics, travel routes, and transportation modes to provide personalised travel route recommendations for users. The results show that hybrid collaborative filtering outperforms single collaborative filtering algorithms in terms of recommendation accuracy, recall, coverage, and popularity, especially achieving the best effect at a k value of 50. This article develops a multi-dimensional information fusion recommendation system, which significantly improves the personalisation of recommendation results and user satisfaction. The application of human-computer interaction and hybrid collaborative filtering in tourism route recommendation can meet the diverse tourism needs of users, improve user experience, and have broad application prospects. Although hybrid collaborative filtering performs well in improving recommendation accuracy and user satisfaction, this study still has some limitations. First, the computational complexity of the hybrid collaborative filtering algorithm is high, which may lead to longer system response time and affect user experience. Second, the algorithm relies heavily on the quality and quantity of data and sparse or incomplete data may lead to poor recommendation results. In addition, this study does not fully consider the dynamically changing interests and preferences of users, and may not be able to reflect the latest needs and behaviour patterns of users in real-time, thus affecting the accuracy and effectiveness of recommendations. Future research can further optimise the hybrid collaborative filtering algorithm, reduce its computational complexity, and improve real-time recommendation performance. In addition, more contextual information, such as the user's instant location and social network data, can be introduced to enhance the adaptability and accuracy of the recommendation system. With the development of artificial intelligence technology, combined with advanced methods such as deep learning and reinforcement learning, it is possible to bring about a smarter and more personalised recommendation system, further improving the user experience. At the same time, regular updating and maintenance of the algorithm to adapt to the dynamic changes in user preferences is also an important direction for future research.

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