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Effectiveness of Improved Personalized Intelligent Recommendation Model for Travel Information by Collaborative Filtering Algorithm Incorporating User Interests

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A critical issue for customized intelligent travel information recommendation is the exponential growth of travel information and the wide range of travel needs. In order to address the issues of cold start and poor recommendation results yielded by the recommendation system, in this study, a collaborative filtering method is proposed that integrates user interests. This algorithm is an item-oriented recommendation algorithm called iExpand algorithm. The algorithm views user conduct as a collection of relatively implicit interests that need to be examined, with the specific preferences of each individual user being considered. As a result, the algorithm is better able to examine the user's interests and grasp how those interests change over time. The iExpand algorithm has a 0.962 accuracy, a 0.038 loss rate, a 0.033 suggestion error, and a runtime of 1.04s. The findings for the customized intelligent recommendation model for trip information showed that the proposed algorithm has a greater recommendation accuracy and a quicker reaction time, resolving the issues of cold start.

Keywords: iExpand; user interests; collaborative filtering algorithm; personalisation; travel information

1. INTRODUCTION

One trend in the advancement of smart travel is the emergence of personalized recommendation services in the travel sector. Since travelling is a mobile, dynamic, and real-time activity, delivering relevant travel information services to users in real time is crucial for boosting user satisfaction. Travel is an experience with a strong contextual interaction element; as a result, its personalized services should be well-aligned with the user's actual context and provide immediate, accurately-targeted and effective recommendation services based on the user's contextual condition. Currently, this is a hot topic in the field of tourism services internationally [1–2]. Travelers' needs are time-sensitive and variable; therefore, their need for travel-related goods and services is frequently directly tied to their current situation. Users must be given individualized recommendations that are compatible with the characteristics of their current situation, which requires analysis and

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judgement and identification of scenario features. Some of the current recommendation algorithms have optimized scene attributes, but these algorithms do not fully account for the impact of scene attributes on user preferences or the weights of various scene attributes in the presence of multiple attributes [3–4]. Furthermore, personalized recommendation systems that are scenario-oriented are currently unable to successfully combine unique user attributes with adaptive ambient features. In order to achieve this, the study suggests conducting research on user interest-based intelligent push technology for customized travel information. In order to increase the user's satisfaction with the recommended content, the research's main objective is to first establish each user's interest model, extract the characteristics of their current scenario, and then design an efficient algorithm for recommending travel information. First, the interest preferences of users are modelled and modelled under various scene conditions. Then, the personalized travel product recommendation method based on scene characteristics is studied and, finally, the personalized travel product recommendation based on scene characteristics is achieved.

2. RELATED WORKS

Collaborative filtering is a frequently-used algorithm in the personalized recommendation field, and academics world-wide have produced a large body of research on the subject. A new weighted interpolation neighborhood regularized tri-factorized single-class collaborative filtering technique called WINTF was created by Lim et al. To anticipate unidentified transcription factor targets, the study used protein-protein interaction networks and noisy, imperfect, and biased transcription factor gene connections. Their test results demonstrated that WINTF outperformed the conventional triple split technique without weighting, interpolation, and neighborhood regularity in predicting TF genes. When assessed by independent datasets, the accuracy of the highest 495 predicted associations was 37.8%, with an enrichment factor of 4.19 compared to random guesses[5]. By presenting a novel hybrid optimization technique, Liu et al. solved the problem of customized recommendations for manufacturing service combinations (MSCs). Firstly, in order to conduct a quantitative analysis of customer preferences, the cluster collaborative filtering (CCF) approach was applied. Secondly, a brand-new genetic algorithm called PoNSGA-III was created and tested for use with multi-trait MSCs. It is based on three generations of uncontrolled ranking. Ultimately, this hybrid algorithm assigns clients to groups based on their preferences and offers them the best option [6]. With the help of collaborative user filtering and social filtering, Berkani developed product suggestions for social settings. Additionally, he employed two methods: a supervised method for recently-added users and an unsupervised one for all users initially. Finally, this study used a range of existing datasets to validate the proposed technique. Through his investigation, he was able to pinpoint how integrating various categorization techniques and social information plays a part in collaborative filtering, which enhances the accuracy of recommendations [7]. Ontology-based inquiries have been utilized by academics like Akaichi as the final stage in the selection of Web services, for analyzing past user characteristics, for studying user behavior, for computing user behavior, and for query similarity and QoS. The selection accuracy has been improved by combining syntax and semantics [8].

By merging MP neural network models for various modes of transportation, Zhou et al. proposed a novel method for matching the most scenic spots based on tourist interest and a new way for optimizing route links based on multiple modes of transportation. The suggested approach was then verified in a real-world setting. The findings demonstrated that the study's proposed techniques are feasible, useful, and can more effectively address the issue of travel suggestions. After designing and testing the algorithm, the researchers discovered that the tourist sites mined by the algorithm's objective function best matched the tourists' interest markers [9]. Zhang proposed and tested an intelligent travel path method for big data. By aligning the user's preferences with the already-existing historical trip data, an online model collecting data on the user's history trip selection pattern based on big data was created. To obtain the best customized travel routes for visitors, a travel path optimization algorithm based on association criteria was proposed. Additionally, the study examined the qualities of travel goods and provided intelligent route suggestions. The experimental results indicated that this algorithm can be executed in less than 1.5 seconds. It decreases the amount of time it takes to recommend a route and reduces the amount of error it makes, increasing the accuracy of the recommendation [10]. The direct connection of nodes for data interaction is made possible by a distributed, blockchain-based data sharing method described by Arif et al. To clarip how this system functions, several network experiments and analyses were conducted. According to the findings, this system's average processing time for data cycles was 119.1 milliseconds for server-sent machine learning results and 84.5 milliseconds for user-sent multi-criteria assessment data [11]. In conclusion, an intelligent recommendation system for trip information combines user preference information with the standard collaborative filtering method, which still has room for development in terms of recommendation performance. To the best of the researchers' knowledge, this current study is the first to integrate the iExpand algorithm with a personalized trip information recommendation system in order to improve the accuracy and speed of the system output.

3. PERSONALIZED TRAVEL RECOMMENDATIONS BASED ON USER INTEREST EXTENSIONS

3.1 Framework Construction for the iEXpand Recommendation Algorithm

The process of analyzing user interest modelling, inter-interest modelling, and inter-interest transformation modelling is now the key issue and challenge in many customized

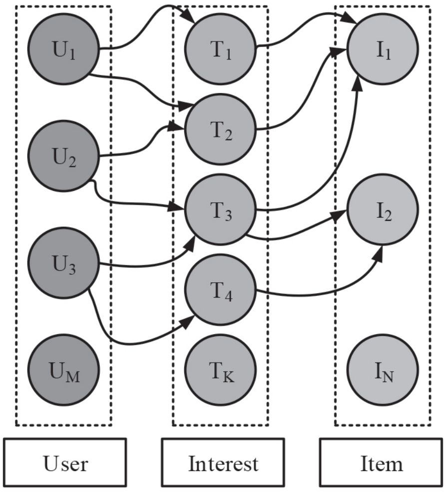


Figure 1 The Three-Layer Representation Mechanism of iExpand Algorithm.

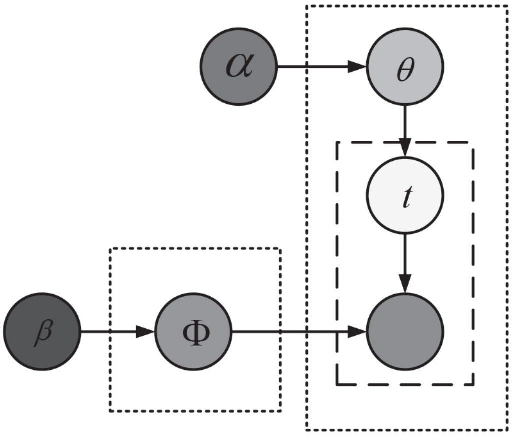


Figure 2 Schematic diagram of Latent Dirichlet Allocation model.

recommendation algorithms based on user interest modelling. Typically, in collaborative filtering-based recommendation systems, there is information only about the interaction between the user and the system, which prevents the system from fully eliciting information about the user's interests and preferences. Keywords are generally used in content-based personalized recommendation algorithms. Hence, the iExpand algorithm is proposed as a means of resolving the aforementioned issue. Each user's choice of an interest is handled as an implicit factor in the algorithm, which is analogous to a "topic" in a probabilistic topic model. This approach allows the algorithm to examine user activity as a collection of relatively implicit interests. The study builds an interest association graph between users by first extracting data on users' interests and then using the Latent Dirichlet Allocation (LDA) model to determine the probabilities of transferring various interests to one another [12–14]. After analyzing the extended user interests, the iExpand algorithm scores the items and creates a user-focused suggestion list.

The iExpand algorithm assumes that users' implicit interests play a part in influencing how they make choices. The user in the iExpand algorithm is expressed as a probability distribution in the interest space, and the user's interests are also distributed over items. A three-level relationship representation of the three elements of user-interest-item is shown in Figure 1 based on the analysis of pertinent studies on probabilistic topic models.

The positions are all transferrable because iExpand believes that the temporal order of user behavior and the order of users in the user set are both unchanged. Based on this, the LDA model can be used to gather data about users' preferred areas of interest, as depicted in Figure 2.

In Figure 2, α and β are hyperparameters of the LDA model, ϕ is a variable satisfying the Dilley distribution, t denotes user interest, and θ denotes the user multiple interest distribution. When analyzing an item, implicit interest can be used as a feature of the item. Each item, on the other hand, generally has more than one characteristic element at the same time; hence its attribution to more than one implicit interest. On the other hand, it is possible for different items to have the same characteristics, which means that they belong to the same interest. Typically, the features of items in a collaborative filtering algorithm system are not well understood in most situations. Fortunately, the LDA model, as a user interest simulation tool, can methodically and scientifically discover the properties of each of these items without requiring a priori item knowledge.

In contrast to the technique used to generate item suggestions, which produces hidden variables in accordance with the user selection items collected, the extraction of user interest

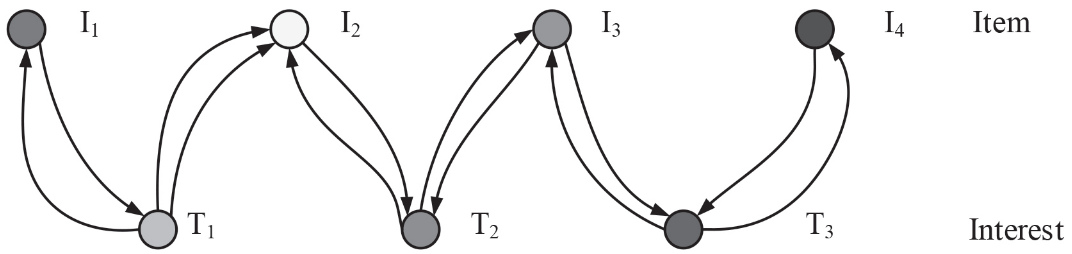


Figure 3 Bipartite graph for projects and interests.

data within the LDA model is an implicit derivation process. To calculate the potential values of the hidden variable, the study used Gibbs sampling and derivation [15–17]. Equation (1) can be used to determine the likelihood that a user will be interested in a particular item.

$$\varphi_{ij} = P(I_i|T_j) = \frac{C_{ij}^{NK} + \beta}{\sum_{n=1}^{N} c_{nj}^{NK} + N\beta} \tag{1}$$

In Equation (1), T_j denotes the set of interests, I_i denotes the set of items, and φ_j the probability of an interest being on an item. C_{ij}^{N} denotes the $N \times K$ vector matrix, where N denotes the number of items and K denotes the number of interests. With ϕ_{ij} denoting the probability of a user having a particular interest, expressed with Equation 2.

$$\phi_{ij} = P(T_j|U_i) = \frac{C_{ij}^{MK} + \alpha}{\sum_{k=1}^{k} C_{ik}^{MK} + K\alpha} \tag{2}$$

In equation (2), U_i denotes the user and C_{ik}^{MK} denotes the vector matrix of $M \times K$, where M denotes the number of users. Equation (1) and Equation (2) show that users with different preferences will obtain different interest distributions. In the iExpand algorithm, the probability of extracting each interest can be calculated with Equation (3).

$$\vec{v} = P(T_i) = \frac{C_{ij}^{MK} + \alpha}{\sum_{k=1}^{K}\sum_{m=1}^{M} C_{mk}^{MK} + K\alpha} \tag{3}$$

where $\vec{v}$ in equation (3) stands for the likelihood that an interest will be piqued. To make it easier to generate the user's interest association graph and to analyze and operate the transfer probability between interests. This allows for the calculation of items as intermediate variables, after which equation (4) can be used to express φ_{ij}.

$$\varphi_{ij} = P(T_j, T_i) = \frac{P(T_j, I_i)}{P(I_i)} = \frac{\theta_{ij}\vec{v}_j}{\sum_{k}^{K} \vec{v}_k\theta_{ik}} \tag{4}$$

In contrast to the Cell Transmission Mod (CTM), the iExpand algorithm analyses and models the correlations between users' interests from a probabilistic perspective. Once the value of the hyperparameter α is established, it suggests that the distribution of users' interests is completely independent of one another. Figure 3 depicts the bipartite graph for goods and interests.

In Figure 3, a bipartite graph represents the interrelationship between items and interests. The edge weights of interest-to-item are denoted as ω ; the edge weights of item-interest are denoted as λ. Projection analysis is performed based on the bipartite graph to obtain the interrelationships between user interests. The interest relationships between users, i.e. the probability of interest-to-interest, are expressed with equation (5).

$$\theta_{ij} = P(T_j|T_i) = \sum_{n=1}^{N} P(T_j|I_n)P(I_n|T_i) = \sum_{n=1}^{N} \vartheta_{nj}\vartheta_{ni} \tag{5}$$

Formula (5) describes the relationship between users' interests, which is expressed as the probability of interest to interest. In the iExpand algorithm, the user's interest is treated as a random process, and there may be interaction between interests. Once the value of the hyperparameter ϑ is established, it suggests that the distribution of users' interests is completely independent of one another [18–20]. The research is to construct the change of the user's interest path, so that the evolution of the user's interest at each step can be statistically analyzed through the corresponding probability distribution. The specific expression is shown in formula (6).

$$\vec{\theta}^{(s+1)} = (1-c)\vec{\theta_l}^{(s)}\vartheta + c\vec{\theta_l}^{(0)} \tag{6}$$

$\vec{\theta_l}^{(0)}$ stands for the beginning vector in equation (6), and $\vec{\theta_l}^{(s)}$ stands for the vector of the sth step of the tour. Hence, when constructing a random wander, equation (7) can be used to represent all users.

$$\begin{cases} \theta^{(s)} & = \theta, s = 0 \\ \theta^{(s+1)} & = (1-c)\vec{\theta_l}^{(s)}\vartheta + c\theta, s \geq 0 \end{cases} \tag{7}$$

In equation (7), c denotes the restart probability of the interest vector and $(1 - c)$ denotes the information loss incurred by the interest vector as it wanders.

3.2 IExpand Algorithm for Personalized Travel in Recommended Lists

The iExpand algorithm is used to rank projects based on user preferences for the projects, and the analysis is conducted through the random distribution of interested users, as shown in Equation (8).

$$P(I_j|U_i) = \sum_{k=1}^{K} P(I_j|t=k)P_s(t=k|U_i) = \sum_{k=1}^{K} \vartheta_{jk}\vartheta_{ik}^{(s)} \tag{8}$$

The technique can be used to obtain a list of trip suggestions without taking into account user evaluations of the items because the equation is used to compute and derive the best items. If user ratings are added to the system, the iExpand algorithm can also generate predictions regarding ratings. Using the Pearson correlation calculation approach, which yields the nearest neighbor set of all users and allows for the calculation of the user's overall rating of the item using equation (9), the study expands the similarity of interests between various users.

$$\hat{r_{ij}} = \hat{r_i} + \frac{\sum_{uh\epsilon Neighbor(U_i)} sim(U_i, U_h)^*(r_{h,j} - \hat{r}_h)}{\sum_{uh\epsilon Neighbor(U_i)} |sim(U_i, U_h)|} \tag{9}$$

In Equation (9), $\hat{r_i}$ denotes the average rating of the user and $\hat{r}_{h,j}$ denotes the rating of each item of the user. Typically, once a user has chosen an item, their interests are sampled and updated using the Gibbs sampling method, and then the corresponding interests are assigned to the chosen items during the iterative calculation of the algorithm, expressed with Equation (10).

$$P(t_i^u = j|t_{-i}^u, U_{u,\ldots}) \propto \frac{C_{I_i^u j}^{NK} + \vec{C}_{j-u}^u + \beta}{\sum_{n=1}^{N} C_{nj}^{NK} + \vec{C}_j^u + N\beta - 1} \times \frac{\vec{C}_{j-i}^u + \alpha}{\sum_{k=1}^{K} C_k^u + K\alpha - 1} \tag{10}$$

In equation (10), t_i^u denotes interest assignment, $\vec{c}_j^u$ denotes the number of interests assigned, and $-i$ denotes the interest assignment of the current item versus other items. After all the interests have been reassigned, the user's probability expression for each interest is found with Equation (11).

$$\theta_{uj} = P(T_j|U_u) = \frac{\vec{c}_j^u + \alpha}{\sum_{k=1}^{K} \vec{c}_k^u + K\alpha} \tag{11}$$

The iExpand algorithm involves the setting of three parameters, α, β and K. These parameters have a direct impact on the algorithm, and reasonable parameters can lead to better performance. The algorithm is iteratively calculated with equation (12).

$$\alpha^* \leftarrow \frac{\alpha \sum_{m=1}^{M}\sum_{k=1}^{K} \left[\delta\left(C_{mk}^{MK} + \alpha\right) - \delta(\alpha)\right]}{K \sum_{m=1}^{M} \left[\delta\left(\sum_{m=1}^{M} C_{mk}^{MK} + K\alpha\right) - \delta(K\alpha)\right]} \tag{12}$$

Similarly, the iteration of β in the algorithm is calculated using equation (13).

$$\beta^* \leftarrow \frac{\beta \sum_{m=1}^{M}\sum_{k=1}^{K} \left[\delta\left(C_{nk}^{NK} + \beta\right) - \delta(\beta)\right]}{K \sum_{m=1}^{M} \left[\delta\left(\sum_{n=1}^{N} C_{nk}^{NK} + N\beta\right) - \delta(N\beta)\right]} \tag{13}$$

It is simple to relate the value of the parameter K to the number of categories if the categories of the data set are known. However, it is generally quite challenging to determine the precise number of groups. The most common method for choosing the value of parameter K is to compare the magnitude of the likelihood of the dataset obtained by the operation of different parameters K, and to ultimately choose the value of parameter K in the case of the highest calculated likelihood. As a result, a default value is directly chosen. The Chib-style approach for estimating, which is founded on the fundamental principle of selecting an optional K-value candidate set and then finding the posterior probability based on Bayes [21–22], is used in this study to help determine the likelihood. In this study, a customized travel suggestion algorithm is proposed based on user preferences, as depicted in Figure 4.

This recommendation system exemplifies the intelligent and deliberate dissemination of information to other users based on core user interest preferences. If a visitor stays at a location for longer than a predetermined threshold, this suggests that the visitor is interested in the area's attractions. Information about the user's preferences is gathered in this way. When there exist n users of tourism and m areas of interest, the set of users can be represented by $U = \{u_1, u_2, \ldots, u_n\}$ and the set of areas of interest by $R = \{r_1, r_2, \ldots, r_m\}$. Each user has a corresponding interest vector, which is denoted by $V_i = \{a_{i1}, a_{i2}, \ldots, a_{im}\}$. When a user is interested in a region and spends more time there than the threshold set by the system, the interest vector is $a_{ij} = 1$; if the above conditions are not met, the interest vector is $a_{ij} = 0$. When generating recommendations for a visitor, it is important to consider not only the user's interest preferences, but also the impact that popular attractions have on the user. Considering the above, the parameter of attraction popularity is introduced, which is denoted as *Pop* (r_i) , expressed with equation (14):

$$Pop(r_i) = \frac{\sum_{1<i<n} a_{ij}}{n} \tag{14}$$

Similar user interest preferences and attraction popularity are the two key variables that have some bearing on the user's decision to visit a particular attraction. Two weights, σ and τ, are assigned to signify the user similarity and attraction similarity, and the attraction suggestion value is marked as $Rec(r_i)$, which is calculated using equation (15). This makes it easier to determine the relative importance of the two elements.

$$Rec(r_i) = \sigma \cdot Q'(r_j) + \tau \cdot Pop(r_j) \tag{15}$$

where $Q'k(r_J)$ is the recommended value of an attraction that a user who is similar to the user in question did not visit. When selecting sites, tourists are also influenced by other factors such as the surroundings, current location, and weather. For the purpose of creating attraction recommendations tailored to visitors' interests, the study combines

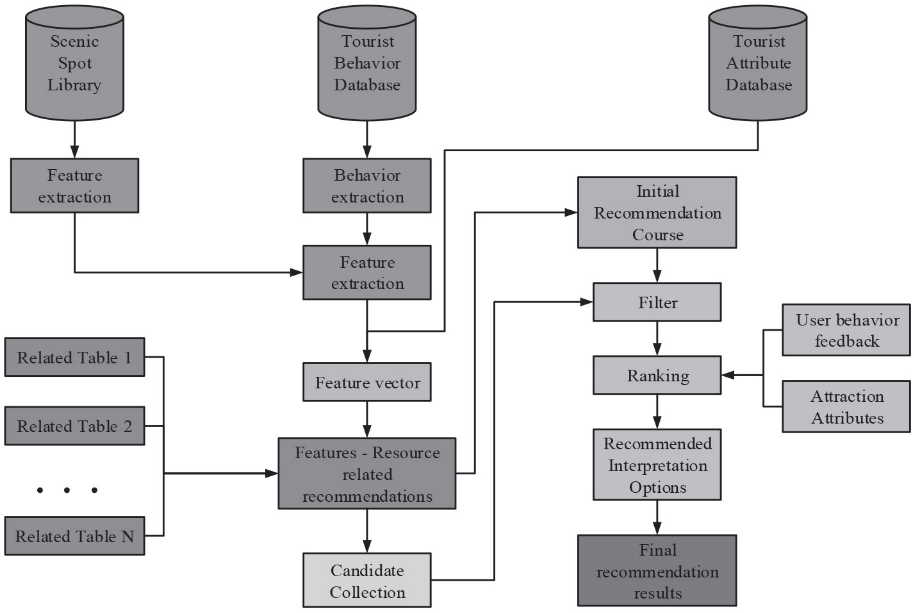


Figure 4 Flowchart of a personalized travel recommendation model based on user interests.

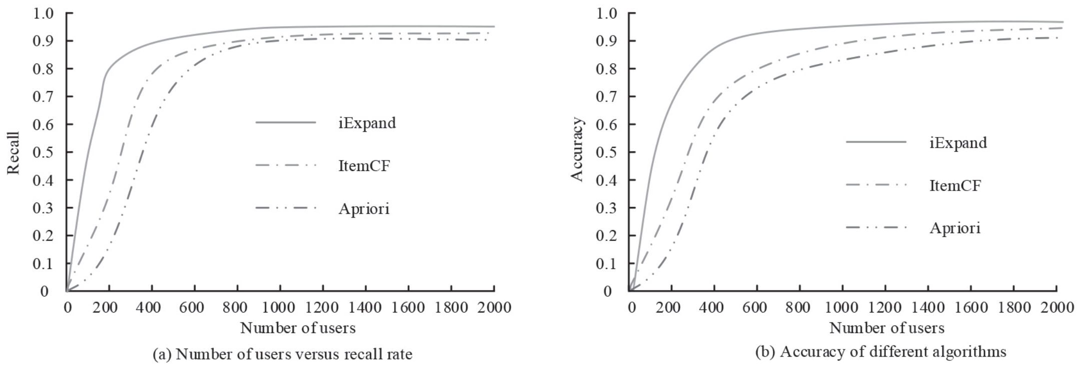


Figure 5 Effects of various user numbers on algorithm performance.

four influencing factors: target city, user interest preferences, popular attractions, and contextual perception information.

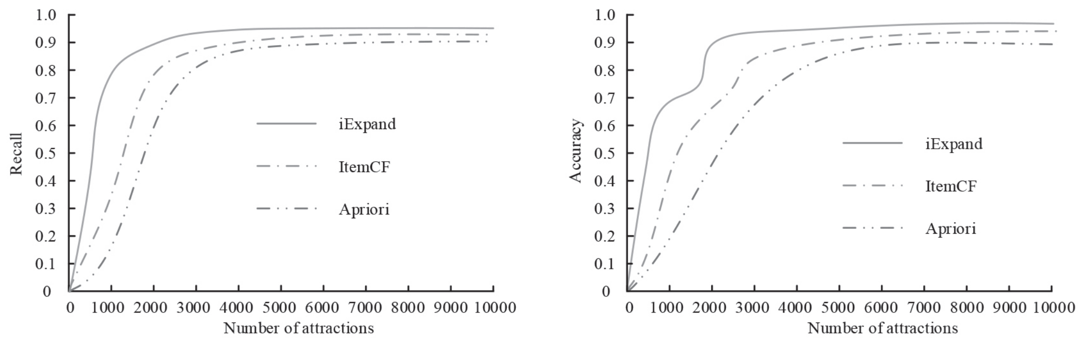
4. PERFORMANCE ANALYSIS OF IMPROVED PERSONALIZED INTELLIGENT RECOMMENDATION MODELS FOR TRAVEL INFORMATION

4.1 Analysis of the Influence of Different Parameters on the Algorithm

Experiments were conducted to compare the performance of Item Collaborative Filtering (ItemCF) and the Apriori algorithm with the that of the proposed iExpand method in order to evaluate the efficacy and viability of the proposed algorithm. The dataset used for the tests was derived from the Catwalk website, which collected tourism statistics from 2021 to 2022, including 20,000 travelers, 12,000 common tags, 10,000 data items about scenic resources, and data on the interpersonal relationships of 20,000 travelers. Measures of recall, accuracy, and F-measure value were used to compare the strengths and limitations of algorithm performance.

Figure 5 shows how the recall and accuracy of various algorithms are affected by the number of users. The impact of the number of users on the recall rate is depicted in Figure 5(a). When the number of users is between 0 and 800, there is a definite increase in the recall rate. When there are more than 800 users, the recall curve slowly and steadily shifts. The iEXpand algorithm's recall rate is 0.957, the ItemCF algorithm's recall rate is 0.943, and the Apriori algorithm's recall rate is 0.902. The results of the impact of user count on accuracy rate are displayed in Figure 5(b). When the user count is between 0 and 600, there is a definite increase in the accuracy rate. When there are more than 600 users, the accuracy curve starts to gradually converge. The iExpand algorithm's accuracy is 0.968, the ItemCF algorithm's accuracy is 0.954, and the Apriori algorithm's accuracy is 0.913. The findings indicate that the algorithm is somewhat influenced by the user base, and that a narrower user base will reduce the system's ability to make recommendations.

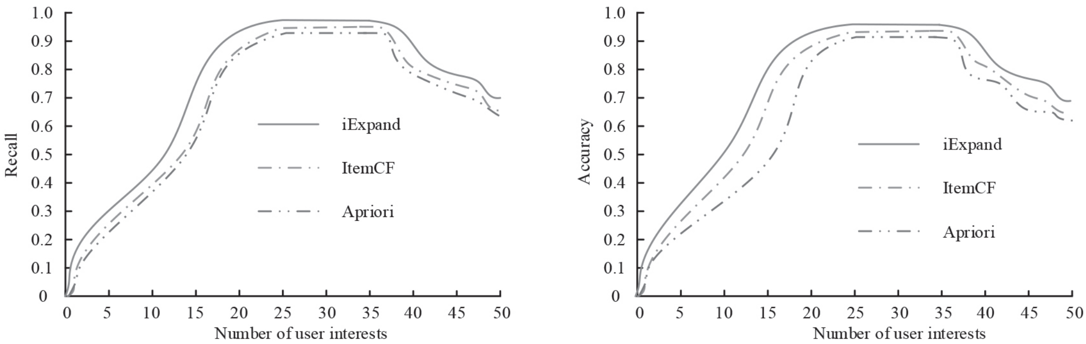
The impact of varying the number of attractions on the algorithm's recall and accuracy is shown in Figure 6. The impact



(a) Number of users versus recall rate

(b) Accuracy of different algorithms

Figure 6 Results for the impact of the number of scenic spots on the performance of the algorithm.



(a) Number of users versus recall rate

(b) Accuracy of different algorithms

Figure 7 Effect of user interest number on algorithm performance.

of the number of attraction items on the recall rate is depicted in Figure 6(a). When there are between 0 and 4000 attraction items, there is a definite rising trend in the recall rate. When there are more than 4000 users, the recall curve slowly and steadily shifts. The iEXpand algorithm's recall rate is 0.955, the ItemCF algorithm's recall rate is 0.924, and the Apriori algorithm's recall rate is 0.911. The effects of the number of attractions on the accuracy rate are shown in Figure 6(b). There is a definite increase in the accuracy rate when the user count is between 0 and 4000. When there are more than 4,000 attraction items, the accuracy curve starts to gradually converge. The iExpand algorithm's accuracy is 0.961, the ItemCF algorithm's accuracy is 0.942, and the Apriori algorithm's accuracy is 0.897. The findings indicate that the algorithm's performance is somewhat influenced by the number of attractions, and that the system produces poorer recommendation results when the number of attractions is in sufficient.

The impact of the amount of user interests on the algorithm's recall and accuracy is shown in Figure 7 as results. The impact of the amount of user interests on the recall rate is seen in Figure 7(a). When the number of user interests is between 0 and 20, there is a definite increase in the recall rate. When there are between 20 and 35 user interests, the recall curve is at its steepest. When there are more than 35 user interests, the recall rate tends to decline. The iEXpand method, the ItemCF algorithm, and the Apriori algorithm had the highest recall rates, respectively, of 0.972, 0.935, and 0.929. The effects of the amount of user interests on the accuracy rate are shown in Figure 7(b). When there are between 0 and 20 users, there is a definite increase in the accuracy rate. When there are between 20 and 35 user interests, the accuracy curve is at its steepest. When there are more than 35 users with interests, the accuracy tends to decline. The iExpand algorithm's accuracy was 0.977, the ItemCF algorithm's accuracy was 0.956, and the Apriori algorithm's accuracy was 0.922. The findings indicate that user interests have an impact on algorithm performance as well, and that the algorithm's recommendation effect will be diminished if there are too few or too many user interests.

The findings of the F-measure values for the various algorithms are shown in Figure 8. The F-measure values for the three techniques for various user counts are shown in Figure 8(a). For user counts greater than 800, the F-measure for the iExpand algorithm is 0.961, the F-measure for the ItemCF algorithm is 0.948, and the F-measure for the Apriori algorithm is 0.907. The F-measure for the three algorithms for various numbers of attractions is shown in Figure 8(b). Figure 8(c) displays the F-measure values of the three algorithms for various user interest counts. For example, the iExpand algorithm's F-measure value is 0.978, the ItemCF algorithm's F-measure value is 0.945, and the Apriori algorithm's F-measure value is 0.904 for a user interest count ranging from 25 to 30. The Apriori algorithm's F-measure was 0.926.

4.2 Performance Analysis of Personalized Recommendation Models for Travel Information

Once the influence of the model parameters has been established, the performance of the model can be determined. The recommended average accuracy, loss rate, error values,

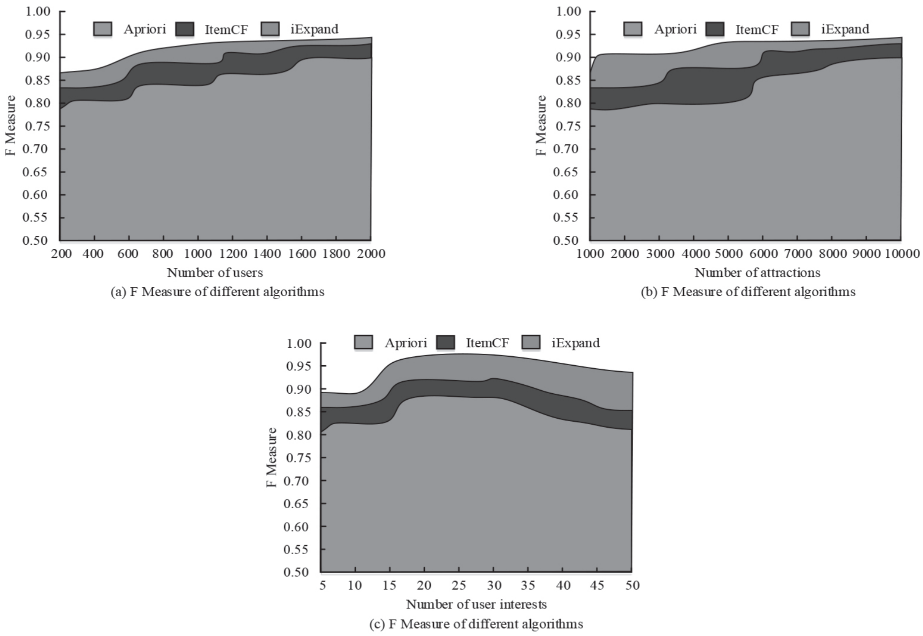


Figure 8 Comparison of F metric results of different algorithms.

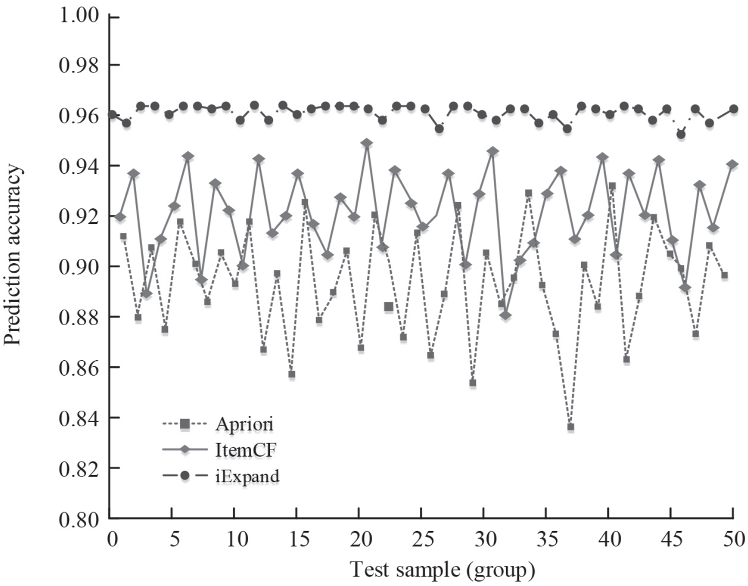


Figure 9 Results for recommendation accuracy of the model.

and model run duration measures are used to assess model performance. For each statistic, fifty different trials were run in order to eliminate the impact of unique values. Figure 9 shows the accuracy of the proposed model.

Figure 9 represents the accuracy results of the model in the personalised recommendation of tourist information. The average accuracy of the Apriori algorithm in the model is 0.903, the average accuracy of the ItemCF algorithm is 0.936, and the average accuracy of the iExpand algorithm is 0.962. The accuracy of recommendation is 0.059 and 0.026 higher than that of the Apriori and ItemCF algorithms respectively. The recommendation accuracy of the proposed model was improved by 0.059 and 0.026 compared with the Apriori algorithm and ItemCF algorithm respectively.

The loss rate outcomes of the model in the customized suggestion of tourist information are shown in Figure 10. The loss rate of the ItemCF algorithm, the loss rate of the iExpand algorithm, and the loss rate of the Apriori algorithm are 0.079, 0.052, and 0.038 respectively in terms of travel information recommendation. The loss rate of the model proposed in the study was reduced by 0.041 and 0.014

Figure 11 shows the outcomes of the model's error values for customised travel information recommendations. The Apriori algorithm's error value in the model is 0.074 in Figure 11(a). The error value of the ItemCF algorithm in the model is 0.048 in Figure 11(b). The iExpand algorithm's error value in the model is 0.033 in Figure 11(c). The proposed model has the least number of errors, indicating that the model performs well as a recommendation tool.

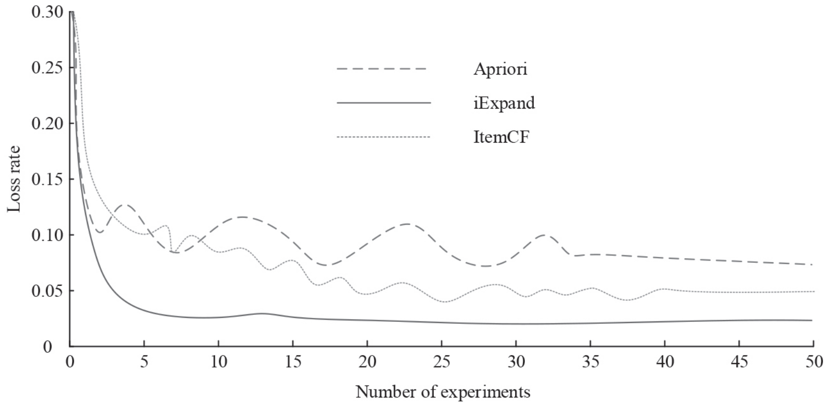
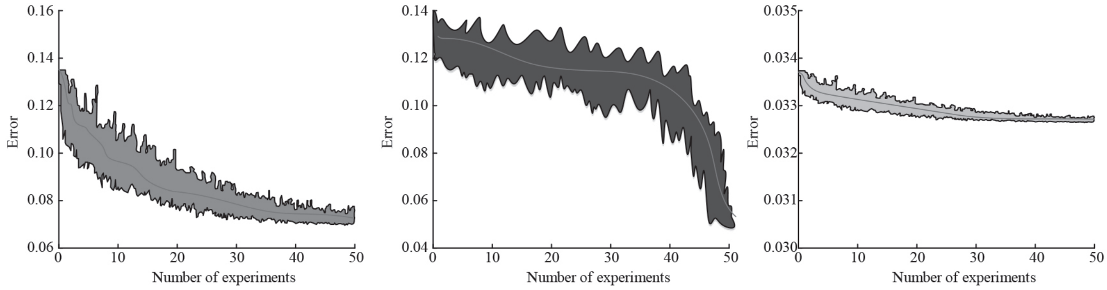


Figure 10 Loss rate results for the model.



(a) Error of Apriori algorithm
(b) Error of ItemCF algorithm
(c) Error of iExpand algorithm

Figure 11 Error value results for the model.

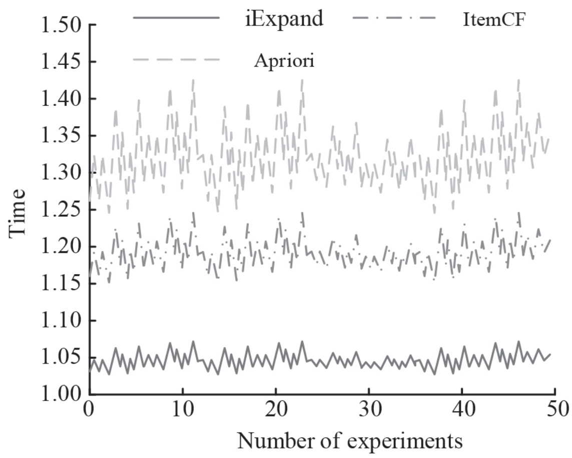


Figure 12 Running time of the model.

The model's runtime results for customized travel information recommendations are shown in Figure 12. These include the Apriori method, which takes around 1.33 seconds to run, the ItemCF algorithm, which takes about 1.18 seconds to run, and the iExpand algorithm, which takes about 1.04 seconds to run. The results show that the algorithm proposed in this study has the best operating efficiency as a personalized recommendation model for travel-related information, and is therefore able to deliver the required information more quickly.

5. CONCLUSION

In individualized recommendation systems for travel-related information, over-fitting and cold-starting of user interests are two issues that affect the accuracy of recommendation algorithms. The iExpand customized recommendation system, which can collect accurate information about user interest preferences as well as real-time changes occurring over time, is proposed as a solution to the problem. Through experiments, the study confirms the performance of the suggested method. The experimental findings demonstrate that factors such as the number of users, attractions, and interests have an impact on the accuracy of the iExpand algorithm's recommendations. When there are more than 800 people, over 4,000 attractions, and between 25 and 30 interests, the iExpand algorithm performs at its best. Additionally, the personalized recommendation model for travel information has a loss rate of 0.038, an accuracy of 0.962 for its recommendations, an error of 0.033 for its recommendations, and a running time of 1.04 seconds. The findings showed that the algorithm suggested in the study can match real-time requirements and has a high suggestion accuracy. However, this study has one significant shortcoming which is its focus on the recommendation system research, which may fulfil the requirements of user interests, but there are still many users who are unaware of their own interests. Therefore, in order to improve the development and use of the recommendation model, in future research, more data should be collected in regard to user behavior and preferences.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Data availability statements

The data will be made available on request.

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