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Research Article

Wisdom Homestay Tourism Recommendation Platform and Marketing Strategy Based on Multi-Information Fusion Sensor Network

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At present, China's tourism market is huge, and traditional hotel accommodation is not popular with young people, and homestays are just in line with young people's yearning. And most of the current push methods are determined by consumption on large platforms such as Ctrip, which not conforms to the recommendation method of homestays, so it aims at personalized marketing research for homestays. In this paper, the multi-information fusion sensor network is used to push B&B hotels in tourist areas to achieve B&B hotel marketing and maximize profits. Using the multi-information fusion sensor network to carry out personalized platform design, platform users can easily and quickly search for the homestay they want and can realize the automatic push function to achieve the rationality of marketing. The experimental results in this paper found that the average relative speedup increased from 1.9 to 17.7 for the execution of the scoring-oriented algorithm in the algorithm compared to a single computer. Performing the sort-oriented algorithm in the algorithm, the average relative speedup increased from 1.9 to 18.8. It can illustrate the effectiveness of the design system in this paper, and the software can carry out personalized marketing for homestays.

1. Introduction

In the current background, the country house industry is developing and growing, by reconfiguring the common houses in the rural social ecology. Reconstructing traditional culture with new life and new living thinking and creating building spaces and communities with multiple functions such as accommodation, entertainment, and leisure have become an important pawn in rural revitalization. The current level of informatization of the recommendation platform of the homestay industry is backward, resulting in a low accuracy rate of platform recommendation, resulting in insufficient user satisfaction.

Based on the experience of homestay consumption, this paper analyzes the development orientation, operation mode, implementation of differentiated strategies, consumption evaluation of homestays, and discusses and analyzes the problems faced in the operation process. Through the horizontal and vertical concept comparison with many homestays at home and abroad, and large-scale experiential evaluation interviews and questionnaire analysis of consumer groups, the relevant factors affecting the homestay consumption experience are sorted out and summarized, so that homestay consumption can be rationally positioned. It provides theoretical and practical support for the improvement of the marketing strategy and operation mode of the homestay and provides a rational reference for the settlement of Ge Xianshan to other operating entities.

The main innovations of this paper are as follows: this paper proposes a multi-information fusion algorithm. The algorithm uses a single score to improve the accuracy of the recommendation. First, the unevaluated scores in a single score are estimated, and then they are converted into double scores as additional data for training and prediction. It is proved by experiments that the efficiency and accuracy are significantly improved.

2. Related Work

Information fusion technology is put forward in recent years when there is only one calculation method for various data calculations that is difficult and easy to solve, and there are many researches on it. Li et al. proposed a clustering integration algorithm based on evidence theory for the fusion process. The advantage of this algorithm was that the cluster structure information around an object was considered and its neighbors were used to describe it [1]. Miao et al. presented a new method to extract urban roads from very high resolution (VHR) optical satellite images using information-level fusion [2]. Prasath believed that digital image denoising schemes based on anisotropic partial differential equations (PDEs) were rapidly becoming an indispensable tool in computer vision problems. He proposed a fusion method for denoising images through this multiscale anisotropic diffusion [3]. This paper is based on the research of multi-information fusion sensor network, which will help the homestay tourism recommendation platform to move towards intelligence and informatization, so as to better complete the construction of related projects and lead the orderly and healthy development of the homestay tourism industry.

Homestays firstly emerged in European and American countries, mainly represented by British B&B. After that, most countries also use B&B to represent homestays, but due to cultural differences, some countries also used HomeStay, FamilyHotel, and other names to express homestays. Hong and Jung gave a multicriteria tensor model combining spatiotemporal information. The auxiliary information was classified by several features and applied to the model, so that the homestay could be recommended by combining various information [4]. Jain et al. held the opinion that there was a wealth of data related to consumer sentiment on online platforms, which may provide insight into how consumers provide feedback and how to use this feedback to predict recommendations using machine learning techniques. He designed a predictive recommendation method for predicting consumer recommendations in travel and tourism, especially in the case of airlines [5]. Wang aimed to establish an idea and framework for enhancing customer stickiness and improving the conversion efficiency of travel products from online to offline platforms through the application of personalized recommendation technology [6]. Through relevant research, it can be found that the performance of homestays is more related to the local economy and it is rarely involved in the development of the homestay industry. Therefore, for this reason, the research on the personalized recommendation system in this paper is necessary.

3. Multi-Information Fusion and Marketing Strategy

3.1. Homestay Tourism Marketing Strategy. The vigorous development of the tourism industry has brought the homestay tourism market into a new era of smart tourism, which has prompted the homestay tourism market to transform from a small industry to a large industry and from a traditional industry to a modern intelligent industry. The marketing of the homestay needs the help of social marketing. Social marketing aims to promote social change and development, and its specific content contains social concepts. And because of different forms and purposes, social marketing activities are divided into four stages, as shown in Figure 1 [7, 8].

3.1.1. Stages of Cognitive Change. Cognitive change is often seen as the initial stage of audience behavior change and it is also the most important stage. At this stage, social marketing activities are generally reflected in the popularization of new ideas, related knowledge education, the display of results of similar behaviors, and so on [9].

3.1.2. Stages of Behavior Change. The biggest difference between behavioral change and cognitive change is that the target audience needs to pay less to change their perceptions, so it is easier to achieve results. And its behavior change may need to pay a certain degree of economic cost, commuting cost, and time cost. It determines that the difficulty of behavioral change is much higher than that of simple cognitive change, and the implementation resistance of social marketing at this stage is relatively large. In order to promote short-term behavioral changes of target audiences, social marketing theory proposes that benefit compensation measures should be provided for target audiences. However, excessive use of coercive policies should also be avoided, so that the target audience makes behavioral changes voluntarily rather than coercively [10].

3.1.3. Stages of Habit Change. In marketing theory, behavior change refers to a relatively short-term behavior, while habit refers to a long-term fixed behavior. It means that the main goal of social marketing at this stage is to make the target audience maintain the behavior change method of the previous stage through corresponding means, and finally form a good behavioral habit. Among the four stages targeted by social marketing, the habit change stage is often regarded as the most difficult implementation stage, which

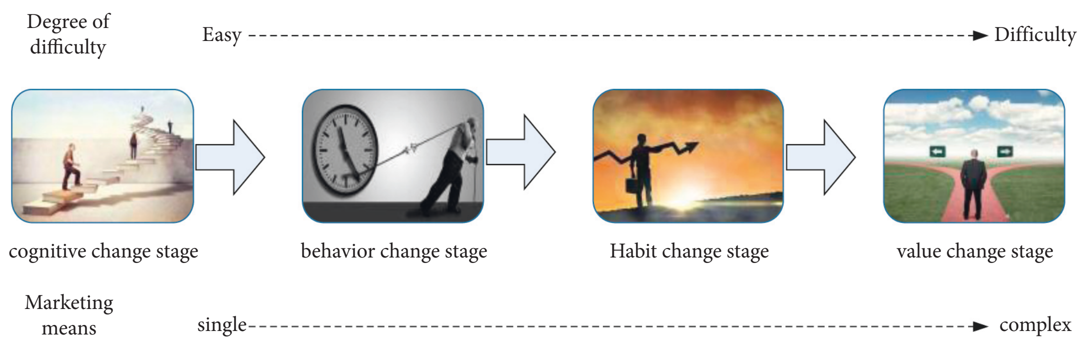


Figure 1: Social marketing activities.

not only requires the long-term investment of the marketing subject, but also puts forward higher requirements for the target audience. Behavior can be changed through some economic incentives, especially in rural societies. However, the change of habits may conflict with the folk customs that have persisted for thousands of years in the countryside. For this reason, social marketing applications in China, such as ecological environmental protection, community tobacco control, and other social movements have stagnated at this stage [11].

3.1.4. Stage of Value Change. Changes in values generally occur at the same time as the formation of habits. When social marketing promotes changes in the daily habits of target audiences, their values often change accordingly. Once the values of the target audience are changed again, their corresponding behaviors will not deviate from the established goals of social marketing even without corresponding strategic incentives. The main strategies that social marketing applies to this stage tend to be similar to those applied to the habit change stage. When the value of the target audience changes, it also means that the social interest goal pursued by social marketing is also achieved, that is, a certain social concept is truly accepted by the target audience [12].

Social marketing theory proposes a set of effective application tools to promote behavior change, as shown in Table 1.

The theoretical tools of social marketing are composed of five indicators: incentives, communication, norms, commitment, and convenience.

3.2. Multisensor Information Fusion

3.2.1. Information Fusion Method. Compared with using a single sensor to collect data, multisensor information fusion data applies data from different sensors and other external information, which greatly reduces the randomness of the data, In this study, multiple sensor modules of the same type work synchronously, thereby constructing a multi-information fusion sensor network. Among them, the data output by the sensing modules will be input to the data fusion center at the same time, and the sensing modules are independent of each other and will not affect each other, thereby greatly improving the fault tolerance rate of the system. When a certain sensor data is abnormal, the multisensor fusion technology greatly reduces the overall performance impact of the system caused by the abnormal situation by reducing the weight of this data application. It is precisely because of this feature that multisensor information fusion has become a hot research topic at home and abroad, and the research has developed rapidly and has a mature system. Sensor fusion is generally divided into different fusion levels, namely data layer fusion, feature layer fusion, and decision layer fusion [13, 14].

Table 1: Social marketing theoretical tools.

Theoretical tools	English abbreviation
Incentives	IS
Communication	CU
Norms	NS
Commitment	CT
Convenience	CE

Data Layer Fusion: direct fusion of raw sensor data. The input of the system is various types of sensor data, and different types of data are fused to extract more detailed information. The advantages of data layer fusion are strong versatility and high theoretical maturity. The disadvantages are large computational burden and poor real-time performance. The instability and uncertainty of the sensor data itself make the fault tolerance rate not very high. The block diagram of data layer fusion is shown in Figure 2(a).

Feature Layer Fusion is feature information fusion after analyzing and processing raw sensor information [15]. Compared with data layer fusion, some detailed information is discarded and relatively important information is retained to provide support for later decision-making and judgment. The advantage of feature layer fusion is that after feature extraction, the amount of data processing is reduced, thereby improving the real-time performance of system decision-making. The block diagram of feature layer fusion is shown in Figure 2(b).

Decision layer fusion: the decision layer fusion is based on preset strategies such as weights, products, and summations, so that the feature information of each modality can be kept intact. The main methods include AND-OR method, weighted majority voting method, Bayesian decision fusion method, and behavioral knowledge space method.

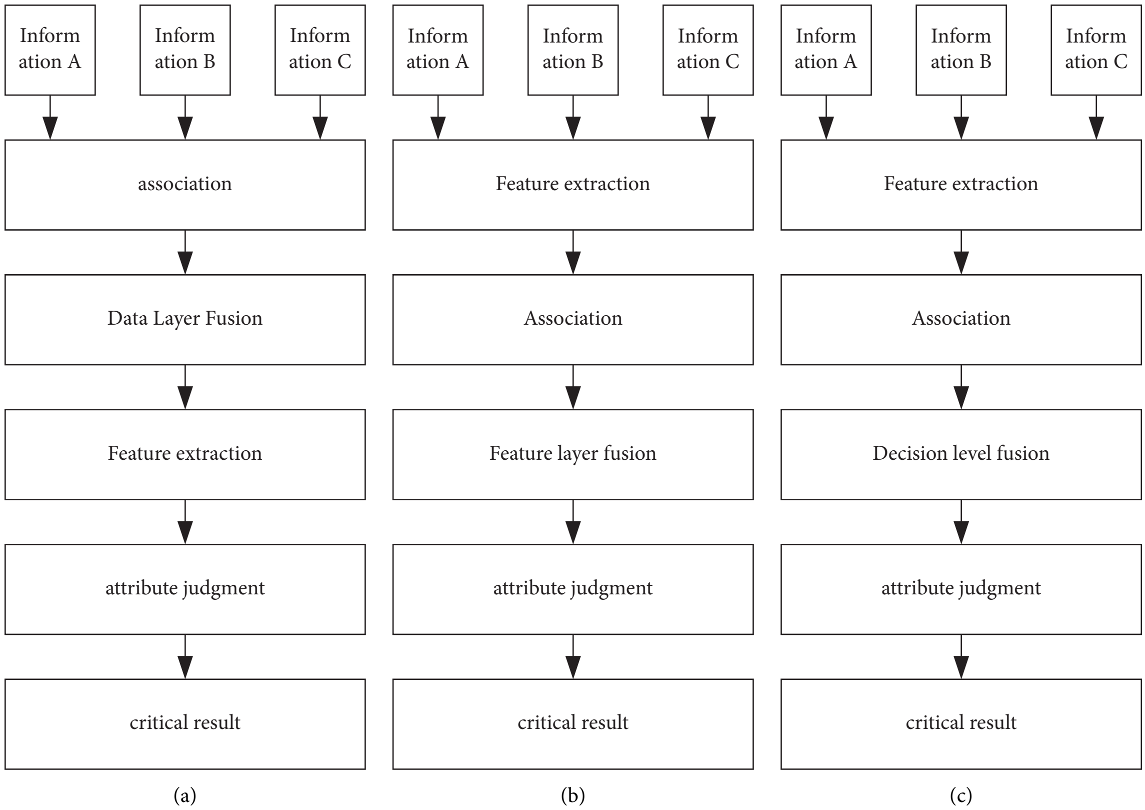


Figure 2: Multisensor information fusion. (a) Data layer fusion. (b) Feature layer fusion. (c) Decision layer fusion.

The three different levels of information fusion, data layer fusion, feature layer fusion, and decision layer fusion, have their own application backgrounds, advantages, and disadvantages. But no matter what level of information fusion, it is necessary to associate relevant information. In theory, data layer fusion provides more fine-grained information for final result determination by retaining a large amount of original data. As a result, the judgment of data layer fusion results has higher accuracy. The decision-making level fusion is less dependent on sensors, that is, sensor anomalies and other disturbances have less impact on it. Therefore, decision-level fusion has greater flexibility, stronger antijamming capability, and higher system fault tolerance [16].

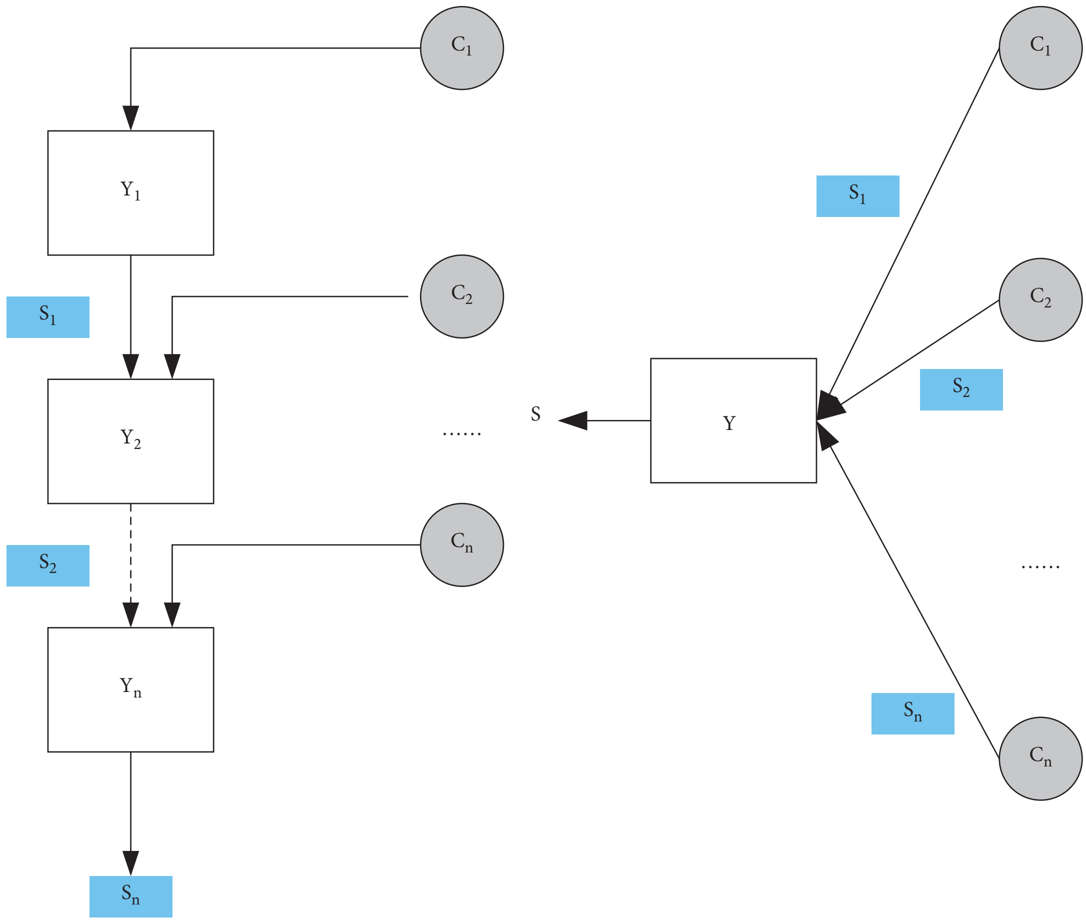
3.2.2. The Structure of Information Fusion. The series structure means that the information of two sensors is fused once, and then the fusion result is fused with the information of the next sensor, and so on, until all sensor information is fused, as shown in Figure 3(a). The parallel structure fuses information only after receiving information from all sensors, as shown in Figure 3(b) [17, 18].

In the figure, C represents a single sensor, Y represents the fusion center, and S represents the fusion result.

3.2.3. Information Fusion Method. Sensor information fusion methods can be divided into the following categories: combination, comprehensive, fusion, and related. In this method, the choice of the user's current travel demand preference is added, that is, the user can choose the importance and degree of importance to certain features. Feature selection is the process of selecting some of the most effective features from the original features to reduce the dimension of the dataset, as shown in Figure 4.

Combination: it organizes multiple sensors into a whole. Comprehensive: it combines the parts and attributes of the analyzed object or phenomenon into a unified whole. Fusion: it combines many different types of sensors into one. Related: it refers to the degree of association between two variables.

3.3. Tourism Service Composition Method Based on Multiobjective Optimization (MO). The current tourism industry is an industry of integrated service management, including catering, shopping, accommodation, entertainment, transportation, leisure, and other services. These services constitute indicators of integrated service management. Therefore, this paper only considers the three factors of time (d), cost (p), and service quality (s) when designing the objective function [19–21]. Within the constraints of time, cost, and service quality proposed by the user, a service combination scheme integrating transportation (T), accommodation (H), and catering (R) is given. In order to make the best results, a layer of refinement is given under the transportation, accommodation and catering, and several related subattributes are given, respectively, and they will be



(a) (b)

Figure 3: Information fusion structure. (a) Series structure. (b) Parallel structure.

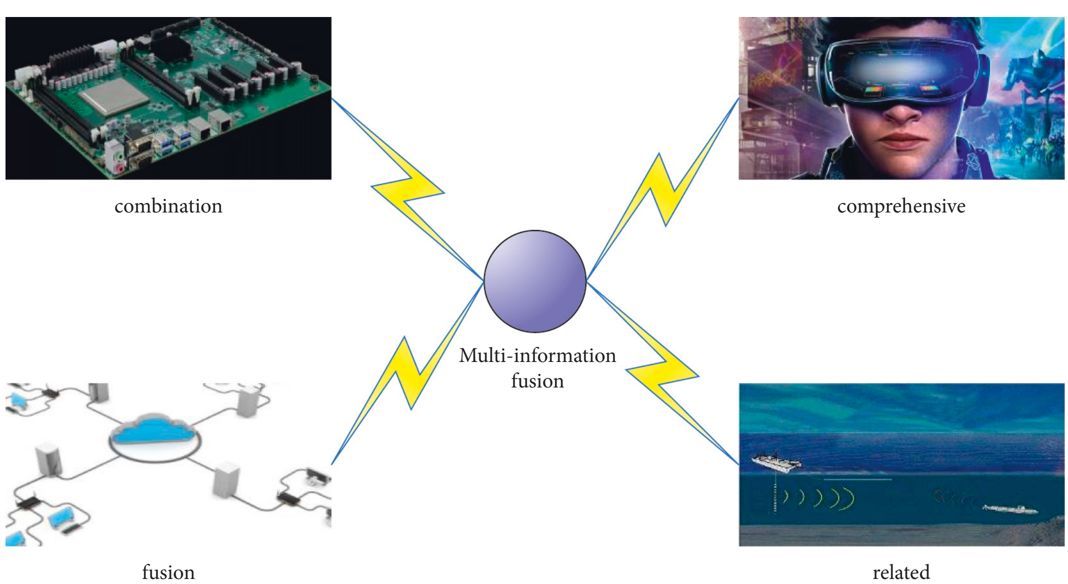


Figure 4: Sensor information fusion.

combined with the services, respectively. These properties will be more intuitively displayed through a table, as shown in Table 2.

To sum up, the optimal results that users hope to obtain are the shortest time, the lowest cost, and the best service quality. In this paper, the optimization method is used, under the constraints, some selectable variables are taken to the maximum value, so that the selected objective function can be optimal. For the sake of convenience, this paper defines a function for time d, cost p, and service quality s, respectively, as follows:

$$\begin{aligned} d &= f(x_1, x_2, \ldots, x_n), \\ p &= g(x_1, x_2, \ldots, x_n), \text{ and} \\ s &= h(x_1, x_2, \ldots, x_n). \end{aligned} \quad (1)$$

x_i ($i = 1, 2, \ldots, n$) is the parameter attribute of d, p, s. Therefore, its optimization objective is as follows:

(1) The time d is the shortest.

$$\begin{aligned} \text{Min}d &= \text{Min}(d_T + d_H + d_R), \\ d_T &= f(\text{CT}, \text{DT}), \\ d_H &= f(\text{DH}, \text{FH}, \text{LH}), \text{ and} \\ d_R &= f(\text{LR}, \text{CR}, \text{QR}). \end{aligned} \quad (2)$$

Here, d_T is the time spent by the user in transportation, d_H is the time spent by the user in accommodation, d_R is the time spent by the user in dining, and the attributes in the function f are shown in Table 2.

(2) The cost p is the lowest.

$$\begin{aligned} \text{Min}P &= \text{Min}(p_T + p_H + p_R), \\ p_T &= g(\text{CT}, \text{DT}), \\ p_H &= g(\text{DH}, \text{FH}, \text{LH}), \text{ and} \\ p_R &= g(\text{LR}, \text{CR}, \text{QR}). \end{aligned} \quad (3)$$

Here, P_T is the user's spending on transportation, P_H is the user's spending on accommodation, P_R is the user's spending on food, and the attributes in the function g are shown in Table 2.

The user's ultimate customized expression may be easily stated as a linear combination of the user's previous data and the personalized outcome achieved by the current preference decision, without losing generality. The fraction of the tailored demand produced by historical data mining in the final personalized expression varies according to differences in the user's previous data. The bigger the amount of a user's specific demands obtained through previous data mining, the more historical data a user possesses. The fraction of tailored demand determined by the current user's choice increases as the user's past data decreases.

Therefore, in this model, two variables w_d and w_c are introduced. w_d indicates the size of the weight obtained according to the historical data and w_c indicates the size of the weight obtained according to the data selected by the current user.

Table 2: Properties of the service.

Time, cost, quality of service		
Traffic (T)	Accommodation (H)	Dining (R)
Intercity transportation (CT)	Distance (DH)	Star rating (LR)
Downtown transit (DT)	Facilities (FH)	Is it clean (CR)
	Star (LH)	Food quality (QR)

The most crucial component of the algorithm is the calculation of w_d and w_c, and then the size of the weight w is calculated according to the size of the values of w_d and w_c. The value of w_c is determined by the user's current personalized needs to select a degree according to the attributes listed in Table 2, and the range is [0, 1]. According to the size of the w_d and w_c values, the calculation method of the weight w is as follows:

$$w = \alpha * w_d + (1 - \alpha) * w_c. \quad (4)$$

Here, w_d is the weight of variable d,w_c is the weight of variable c, andα represents the size of the proportion of w_d, its range is [0, 1], and its calculation method is as follows:

$$\alpha = \begin{cases} 0, 0 \le n < 3, \\ \dfrac{n}{n_{\max}}, 3 \le n < n_{\max}, \\ 1, n \ge n_{\max}, \end{cases} \quad (5)$$

where $n_{\max}$ refers to the maximum value of n.

4. Wisdom Homestay Travel Recommendation Platform

4.1. Introduction to Personalized Recommendation Algorithms. The recommendation algorithm is mainly composed of three modules: user data module, recommendation algorithm module, and recommendation result module. The system collects users' personal information data and behavior data, and after algorithm analysis, generates recommendation results and pushes them to users. A typical recommendation system architecture is shown in Figure 5.

Recommended systems analyze user preferences based on user data. Therefore, user data acquisition is the core of the system, and user data can be divided into explicit data and implicit data. Explicit data usually refers to the data that users actively submit in the system, such as personal registration information and comments submitted on the system. However, due to privacy issues, some users will provide false or incorrect information when registering personal information. In this way, the accuracy of the data will be reduced and modeling and analysis based on these data will lead to the later push effect not meeting expectations. The so-called "explicit data" is the data that can intuitively reflect the user's preference and the "implicit data" refers to the data that is not very intuitive to reflect the user's preference.

Figure 5: Basic architecture of recommendation system.

The smart homestay travel recommendation system helps to improve the accuracy of platform recommendation and improve user satisfaction. The system can quickly process complex data through multi-information fusion sensing technology and build it into an effective model. The overall construction method adopts the front-end and back-end separation mode and highly encapsulates its basic components, which can be imported by using the central library, which can reduce the bloat of the project and facilitate the strengthening of the linkage between the sensing modules. In addition, the system has strong security and protects the stability of services from multiple dimensions.

4.2. Demand for Wisdom Homestay Travel Recommendation Platform. The development of China's homestay industry has gone through a long period of time. Traditional hotels are simply unable to meet the passenger flow during peak tourist periods, especially near some well-known scenic spots, and homestays have become one of the supporting facilities for local tourist services. However, as far as the business model of the entire homestay is concerned, a completed industrial model has not yet been formed. Most of the homestay operators are scattered self-employed. The business concept is also relatively backward and the business channels are limited. During the peak period of tourism, tourists often have no room to rent near popular scenic spots, and the landlord's room appears to be vacant. The Internet has a lot of room to play in this direction. Tenants can book suitable housing online in advance according to their actual needs and travel plans. For landlords, their own listings can also be fully utilized. While making full use of idle social resources to promote social development, it also brings additional benefits to landlords. The design concept of the platform is mainly to provide suitable family housing for the vast number of traveling tourists. Tourists can choose whole rental or short-term rental according to their actual needs. Reliable plans can be provided in terms of technology and security. After a series of user demand research, the detailed needs of users in this aspect and the expected effect of the platform can be fully understood.

The main function of the homestay online reservation platform is to realize the function of users booking houses on the platform and landlords publishing houses on the platform. In order to realize that different users have different permissions, the platform starts from different role settings and sets two roles for the system, namely tenant and landlord. The functional structure is shown in Figure 6.

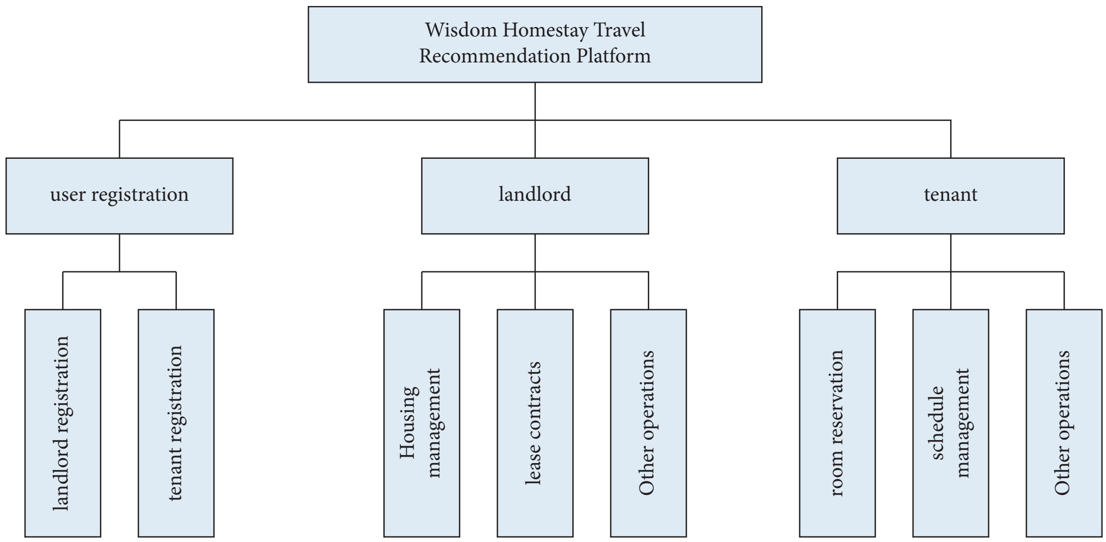


FIGURE 6: System functional architecture diagram.

4.3. Construction of Wisdom Homestay Tourism Recommendation System Platform. The construction environment of the wisdom homestay tourism recommendation system platform is shown in Table 3.

The personalized homestay online reservation platform is based on the traditional B/S structure. The client of this structure is mainly the browser, and the user can complete the access operation on the browser of his own computer. The system server of B/S structure consists of WEB server and database. The architecture of this platform is mainly designed with a three-tier B/S model, including presentation layer, business logic layer, and data layer, as shown in Figure 7(a).

The system is logically divided into front-end browser, back-end server, and database. The physical structure design of the system is shown in Figure 7(b).

The main function of the housing recommendation (personalized recommendation) module is to make personalized recommendations for the tenant's housing for reference when choosing housing, so that users can quickly find the housing that suits them. At the same time, it also increases the exposure of excellent properties as much as possible. The system divides the recommended objects into two categories: one is the new users who log in for the first time and the other is the old users of the platform. For different recommendation objects, different recommendation monitoring is adopted. The specific design is shown in Figure 8.

For users who log in for the first time, the system does not have basic user data information. At this time, the recommendation algorithm cannot recommend houses to them very well and the system can choose some popular houses to recommend. For the old users of the system, they have a certain data base. Based on their user information and historical data, the system can calculate and recommend properties suitable for them according to the collaborative filtering recommendation algorithm.

4.4. Performance of Wisdom Homestay Tourism Recommendation Platform. The performance test of the system mainly tests the security, response time, and compatibility of the system. The performance test is shown in Table 4.

In this section, this paper will evaluate the performance (that is, the execution time) of the algorithm through the distributed framework based on MapReduce on the Hadoop platform. This paper runs two implementations of D's algorithm, scoring-oriented and ranking-oriented. The dataset is ML-1M and uses different numbers of computers (1, 2, 4, 8, 16, and 32).

Figure 9 shows the execution times of the algorithms and their corresponding relative accelerations. It can be seen from the experimental results that for the algorithm in this paper, the distributed architecture based on MapReduce leads to a significant acceleration of the algorithm. The average relative speedup increases from 1.9 to 17.7 for the scoring-oriented execution of our algorithm compared to a single computer. Performing the sort-oriented algorithm in our algorithm, the average relative speedup increases from 1.9 to 18.8.

For sorting-oriented collaborative filtering, a widely used test method is the normalized discounted cumulative gain (NDCG) criterion, which is popular for evaluating sorted document results in information retrieval. In the background of collaborative filtering, product ratings specified by the user can naturally serve as a rank correlation judgment. Specifically, the NDCG metric evaluates the top n fixed products in a sorted list of products. Let U be the set of users and $r_{u,p}$ be the rating assigned by user u to the p-th product of the sorted product list in user u, the mean of the NDCG relative to the n-th position of all user U is defined as follows:

$$\mathrm{NDCG}_{\mathrm{avg}}@n = \frac{1}{|U|} \sum_{u \in U} Z_u \sum_{p=1}^{n} \frac{2^{r_{u,p}-1}}{\log(1+p)}. \tag{6}$$

Table 3: Development environment.

(1) Operating system	Windows 10 operating system.
(2) Server	Apache-tomcat, Gcoserver
(3) Database	PostgreSQL, PostGIS
(4) Development language	JAVA
(5) Compilation tools	Spring Boot
(6) Browser	Internet explorer, Google Chrome, 360 Browser, and Firefox

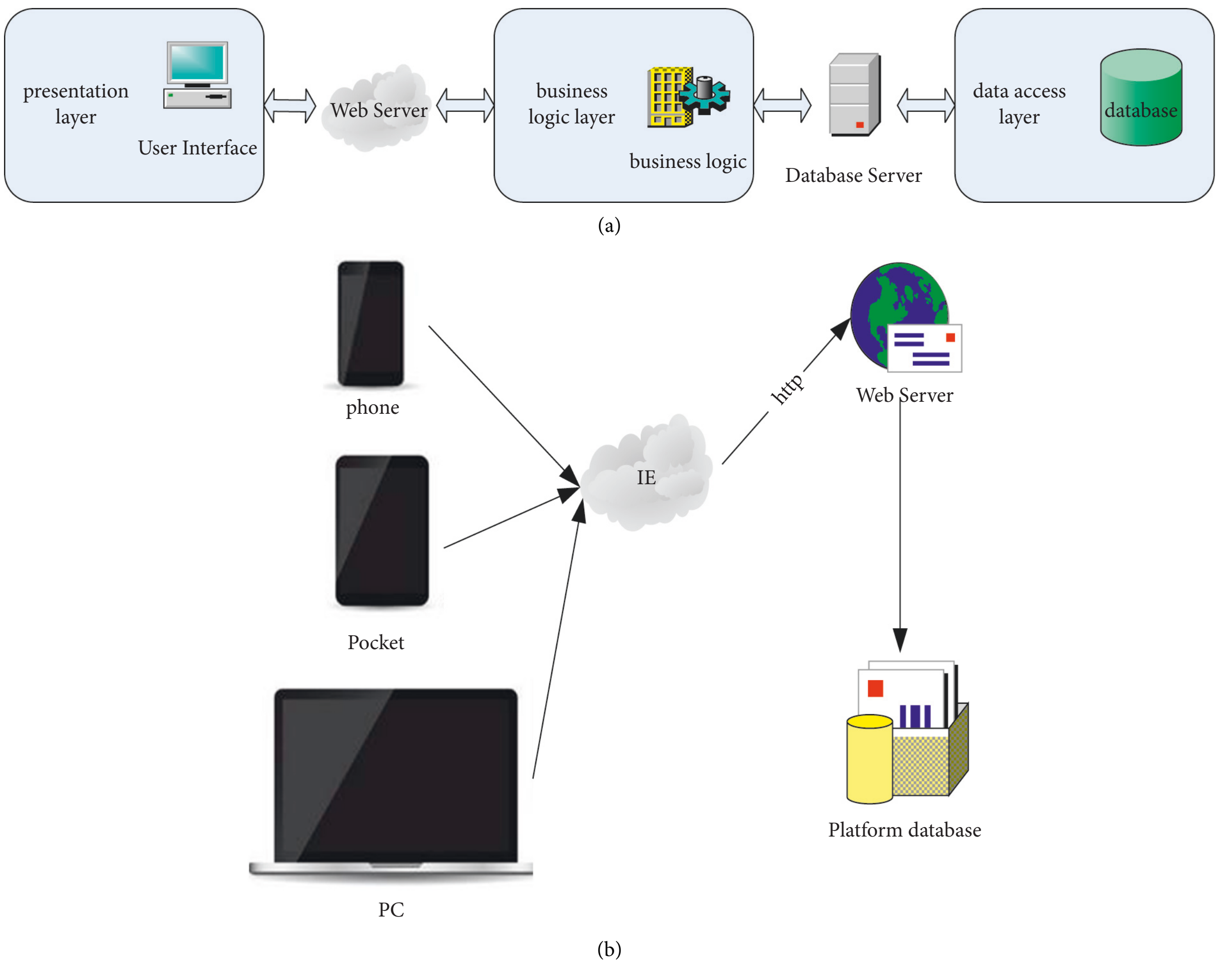


Figure 7: Overall design of wisdom homestay travel recommendation platform. (a) Three-tier architecture diagram of wisdom homestay travel recommendation platform. (b) Physical structure diagram of wisdom homestay travel recommendation platform.

The value of NDCG is in the range [0, 1] and its higher value means better sorting effect, NDCG is sensitive to the score of the highest ranked product. This is modeled by the discount factor $\log(1 + p)$ of the position in the boosted ranking, which is a very desirable property for evaluating rankings in recommended systems. Because, like web searches, most users only look at the first few products on the recommended list, and the top products are more important than others.

Figure 10 shows the performance comparison under the NDCG metrics. It can be clearly seen from the figure that our algorithm outperforms all the compared algorithms. When the dataset is ML-100K, the performance of the algorithm in this paper is the best at NDCG@3–5. At NDCG@1–2, the performance fluctuates, but is much higher than the SVM

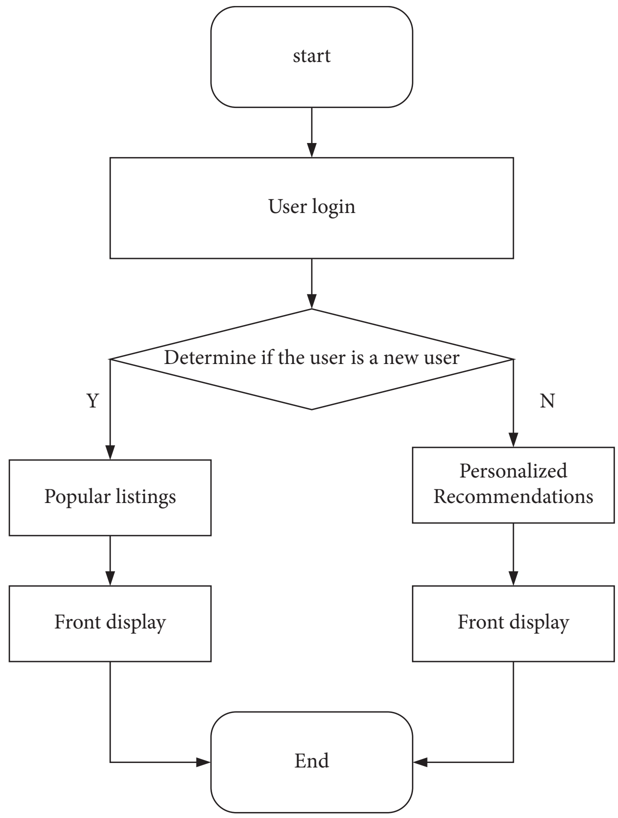


Figure 8: Listing recommendation (personalized recommendation) flowchart.

Table 4: System performance test.

Serial	Testing scenarios	Test steps	Test results
1	Safety	Log in to the system if the user is not registered	Pass
2	Response time	Record the time taken by the system to jump to the main interface of the system	Pass
3	Compatibility	Login and system functionality testing on different browsers	Pass

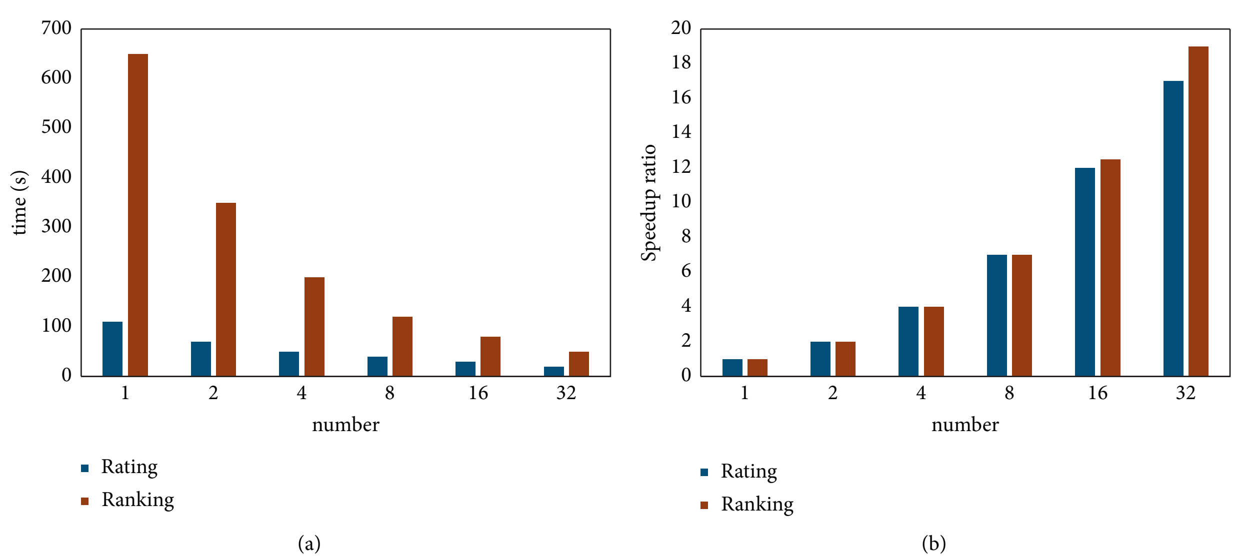


Figure 9: Comparison of system scoring and ranking performance. (a) Execution time relative to different numbers of computers. (b) Speedup relative to different numbers of computers.

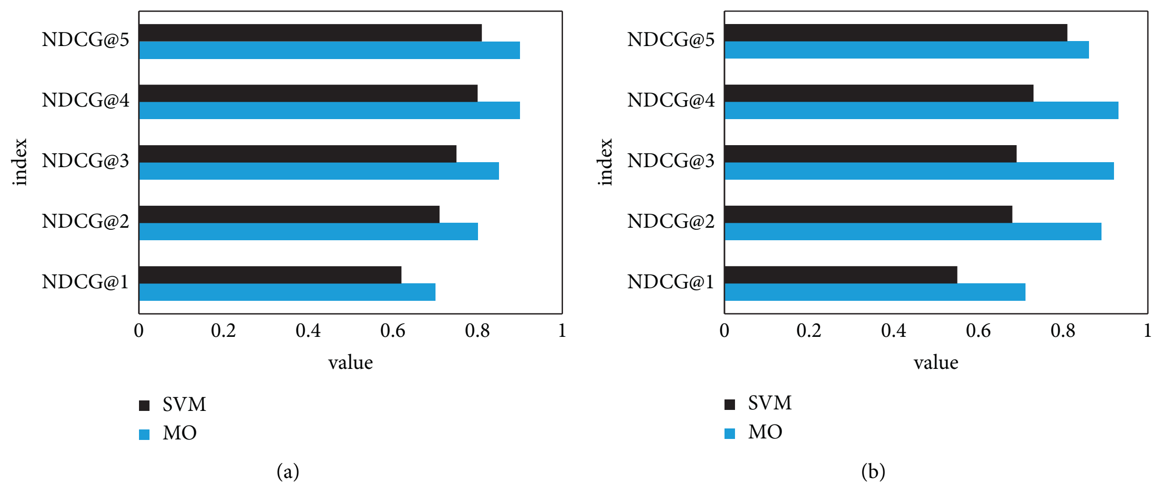


Figure 10: Algorithm ranking accurate performance analysis. (a) Performance comparison when the dataset is ML-100K. (b) Performance comparison when the dataset is ML-1M.

algorithm. When the dataset is ML-1M, the performance of our algorithm is the highest at NDCG@2–5. At NDCG@1, it is also much higher than the SVM algorithm.

5. Conclusions

This paper first analyzed the requirements of the personalized system, mainly introduced the shortcomings of the traditional recommendation methods provided by the current website and the necessity of using the algorithm in this paper for recommendation. Secondly, the architecture of the system was introduced. Then, the system database was introduced in detail, including user information data and hotel information data. In addition, the function design and function realization process of the system were described, and the function result diagram was given. Finally, the function and performance of the system were tested. Due to the limitation of time and energy, there are still some deficiencies in this paper and further efforts are needed in future study and life. (1) In terms of data sources, the data in this paper are the historical data of Ctrip. This data lacks real-time performance and up-to-date hotel appraisal data. In the future, Ctrip website data should be captured in real time based on expanding the total amount of data to improve the accuracy of recommendations. (2) Due to limited time, the hotel recommendation algorithm has not been tested and used by many tourists. Therefore, special problems may be encountered during the actual recommendation process. In the future work, it is necessary to combine the practical application of the algorithm to continuously optimize the algorithm.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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