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RESEARCH ARTICLE

A Novel Personalized Recommendation Model for Computing Advertising Based on User Acceptance Evaluation

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ABSTRACT Nowadays, computing advertising has been an intelligent Internet application which provides personalized advertising service to customers. But how to suggest suitable advertising contents to users relies on effective mining of user preference characteristics. Conventionally, machine learning-based methods were most intuitive solutions to predict unknown user features. Nevertheless, such kind of approaches highly relied on massive labelled samples, and also cost much time in algorithm training. In realistic engineering application, running efficiency acts as the top priority. To deal with this issue, this paper proposes a novel personalized recommendation model for computing advertising based on user acceptance evaluation. Firstly, the functional requirements in personalized recommendation of computing advertising is analyzed, and the perceived behavior of the algorithm ethical risks generated in computing advertising is analyzed based on collaborative filtering. Then, based on the user experience risks generated in recommendation process, a user acceptance value for personalized recommendation is calculated. We also conduct some experiments on real-world data to make empirical assessment for the proposal. It can be concluded that recommendation effect of the proposal is better than that of machine learning algorithm and ant colony algorithm.

INDEX TERMS Personalized recommendation, computing advertising, user acceptance evaluation.

I. INTRODUCTION

In the era when the Internet was not yet developed, people obtained their favorite movies, books and other information mainly through the recommendation of friends around them. But with the rapid development of technology, people's lifestyle has undergone tremendous changes. People can find valuable information through the network without leaving home, and at the same time, people can share information in the larger information space of the network [1]. However, unreasonable personalized recommendation systems can not help users improve decision-making efficiency, but will make users resent. For the user's privacy, information security, reputation, copyright, right to know, right to choose, etc. in the algorithm of computing advertising personalized recommendation system.

User perceived risk is a more abstract content, and it is difficult for users to reflect the effect of the recommendation process in real time and truly in the situational experience. According to the user perception risk in the recommendation system, we can guess what the user likes through the user's historical access records, and then find out what the user likes and push it to the user. Although computing advertising personalized recommendation system has been applied in e-commerce, some major problems of the recommendation system have not been solved well, such as data sparsity, cold start, scalability, etc [2].

This paper analyzes the functional requirements of the personalized recommendation system in computational advertising, and designs the architecture of the personalized recommendation system for the user perceived risks

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arising from the personalized recommendation system in computational advertising; Combined with the data structure of the forum, the experimental recommendation system was completed based on the existing mature development technology, and various functions required by personalized recommendation were realized [3]. Computational advertising personalized recommendation system recommends personalized products for different users according to different preferences of users' perceived risks. Personalized recommendation is an important method of information filtering, and can effectively solve the problem of information overload [4].

Perceived comfort refers to whether the design of the system can make users feel comfortable, specifically including the timing of personalized information push, the push method adopted, the layout of personalized information in the page and other contents. The concern in the user satisfaction system describes the degree of the website's emphasis on users, specifically whether it can give users a comfortable experience. In fact, it has the same meaning with perceived comfort. Computational advertising personalized recommendation can be seen as an intelligent user interest information discovery mechanism. This means that the recommendation system allows users to modify their favorite content, set new interesting content and customize the form of receiving recommendation suggestions, which seriously affect the overall user experience.

Perception is used to measure whether the system can help users complete tasks correctly and quickly. In order to better look at the user's point of view, we use perceived usefulness instead of usability for research. In the face of massive information, user perceived risks mainly include that users do not need to know their own needs. The system can intelligently understand users' needs through the collection of user context information, and then dynamically push information that meets users' preferences and interests to target users. In the actual computing advertising personalized recommendation system, there are usually a lot of goods, and the number of users will continue to increase. This makes the user perceived risk item scoring matrix of the recommendation system very sparse, which greatly affects the recommendation quality of the recommendation system.

Therefore, through collaborative filtering recommendation algorithm, how to enable the recommendation system to accurately and quickly mine users' potential interests and preferences so as to provide users with high-quality recommendations is an important problem faced by the current personalized recommendation system [5]. At the same time, users on the Internet are often happy and tired of the old. Taking the time factor into consideration in personalized recommendation will probably improve the accuracy of recommendation. Therefore, how to improve the effectiveness of user perceived risk in personalized recommendation systems is also a topic worthy of in-depth study in personalized recommendation. The following two innovations are proposed in this paper, and the specific contents are as follows:

① In this paper, the user acceptance evaluation model of personalized recommendation system is constructed. The length and quantity of advertisements are controlled within the acceptable range of ordinary users, and advertisements have certain cultural value and artistic value, which can bring positive emotional reactions to people, so users will have greater adoption of advertisements. This paper argues that the user acceptance of online video advertising is mainly reflected by the use intention, use behavior and purchase behavior, and the factors that affect them include advertising itself, personal factors, social influence and convenience conditions.

② This paper discusses the algorithm ethical risk perception behavior in advertising personality recommendation. Perceived usefulness is used to measure the perceived risk of users of personalized recommendation systems for computing advertisements, and whether they can perceive that the use of recommendation systems can effectively help them obtain the things or results they want. In this paper, we mainly consider perceived usefulness from two aspects: information acquisition efficiency and information acquisition quality. Because one of the main purposes of algorithmic ethical risk perception behavior in computing ad personality recommendation is to help users find relevant resources to meet their needs with minimal effort.

II. RELATED WORK

Personalized recommendation technology is of high value in both academic and commercial applications, so its research and development has been highly concerned and invested by many famous enterprises. At the same time, the rapid development of information technology has brought about the explosive growth of information, and the problems of information overload and disorder have become increasingly obvious. How to find the information set suitable for solving user problems in the complicated knowledge sea, so as to improve customer service satisfaction and enterprise competitiveness, has become a hot spot of enterprises and academic research. Therefore, this section will summarize the personalized recommendation methods and their research status.

Perumal, et al. put forward that personalized recommendation usually includes three processes: understanding user preferences, forecasting according to user preferences and user feedback [6]. At present, the main personalized recommendation methods are content-based recommendation and collaborative filtering, and some emerging researches adopt mixed recommendation strategies, which can play a role in complementing each other's strengths, such as the combination of content-based recommendation and collaborative filtering, and the combination of knowledge-based reasoning and traditional recommendation strategies.

Guo et al. put forward a game-like personalized recommendation algorithm, and made a macroscopic exposition, giving the applicable conditions of the algorithm, pointing out the premise constraints, and summarizing the structure of the data set used in the experiment [7]. Then, the offline recommendation algorithm with ''personalized features'' in the offline computing part of the algorithm is elaborated in detail. In this part, the traditional recommendation model based on collaborative filtering algorithm of articles and the space for enhancing ''personalized features'' are defined, and then the improved recommendation model is put forward, and the improved recommendation model is explained and analyzed from the perspective of modeling principle.

Li et al. proposed that LDA topic model 14 should be used to mine users' interests from three aspects: users' original blog posts, users' social relationships and users' interactive behaviors [8]. Finally, the final user interest model was obtained by combining the three user interest models based on How Net vocabulary semantic tendency calculation method. Yin et al. Through combining the recommendation results of offline recommendation algorithm, online recommendation is made during the interaction between the system and users, which effectively alleviates the problem of ''interest drift'' in offline recommendation and improves the real-time and flexibility of recommendation algorithm [9]. Finally, a feasible algorithm flow to realize the game-like idea is proposed, and the experimental results are analyzed and summarized.

Sardianos et al. thinks that in e-commerce, network users can be divided into important customers and accidental customers. Accidental customers usually browse through some external links, while there are potential users in online consumption [10]. This kind of users has also been analyzed in detail in the literature. There are great differences among different types of users' behaviors, and their purchasing power is also uneven. Pfiffelmann et al. put forward a personalized recommendation algorithm based on LDA topic model to recommend advertisements for users, which is very similar to the content-based recommendation algorithm [11]. The basic idea is to use cosine similarity formula to calculate the similarity between user's interest feature vector and Weibo advertisement feature vector, and then generate recommendation list for users according to the reverse order of similarity.

Deepa et al. put forward that in the era of rapid development of information technology, it is necessary to develop an intelligent perception system that can be applied in the comprehensive field [12]. In intelligent recommendation, users can be provided with very personalized information promotion services according to their behaviors and habits. Deng et al. shows that Weibo is the best social media product in China at present, and its related recommended products such as ''similar user discovery'' and ''people you may be interested in'' have brought a good user experience to Weibo users [13]. Besides, Tmall, Tencent Video, Netease Cloud Music, JD.COM, Dangdang and other major websites are applying personalized recommendation algorithms to recommend interesting information to users. Many of the above Internet companies have made great contributions to the development of personalized recommendation system in China.

Gao et al. think that the development of computer science and technology has also driven the level of data processing, thus providing very reliable technical support for the analysis of network users' behavior [14]. Accurate analysis of network users' behavior has important practical value and is a brand-new social form in today's society. Yu et al. shows that personalized recommendation is widely used in electronic libraries, distance education, e-commerce and other fields [15]. At present, it is mainly used in information products such as literature, documents, learning content, books, movies, music and so on, which plays a very important role in meeting users' needs and preferences and improving users' satisfaction.

III. METHODOLOGY

A. BEHAVIOR RISK PERCEPTION IN PERSONALIZED ADVERTISING RECOMMENDATION

The recommendation system always recommends to a user's favorite author or content of a favorite category. They may think that the recommendation system is boring and cannot help them find new things. However, in later experiments, this variable will not be included in the scope of the test, because the subject may confuse the definition of accuracy and familiarity [16]. As one of the marketing means of online video, computing advertising has attracted much attention under the rapid development trend of computing advertising. Perceived usefulness is used to measure the perceived risk of users who calculate personalized recommendation systems for advertising, and whether they can perceive that the use of recommendation systems can effectively help them obtain the things or results they want [17]. The influencing factors of user perception risk of users' acceptance of computing advertising personalized recommendation system the right to privacy, information security, reputation, copyright, the right to know, the right to choose and the perceived risk of users in computing advertising personalized recommendation system algorithm are shown in Figure 1.

User perceived risk impact of personalized recommendation system is determined by perceived usefulness, perceived ease of use and perceived risk. Individual factor is individual innovation, and social impact and convenience conditions are determined by social impact and convenience conditions [18]. Among them, perceived usefulness, perceived ease of use, perceived risk, social influence and individual innovation have an impact on online video users' willingness to use, while social influence, convenience and individual innovation have a certain degree of impact on users' use behavior. Many factors act together on users' purchase behavior of online video advertisements. Computational advertising personalized recommendation can be seen as an intelligent user interest information discovery mechanism. In the face of massive information, user perceived risks mainly include that

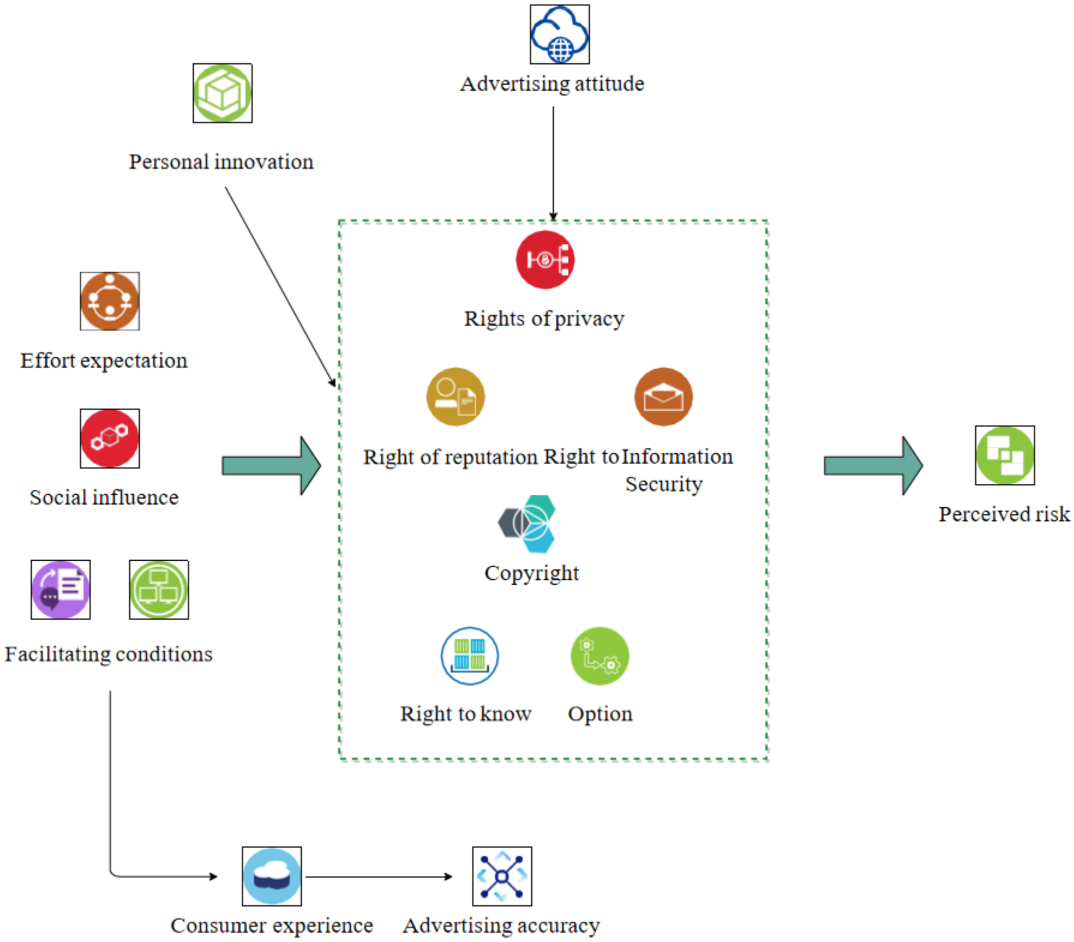

FIGURE 1. Influencing factors of user experience risk in personalized advertising recommendation.

users do not need to know their own needs. The system can intelligently understand users' needs through the collection of user context information, and then dynamically push information that meets users' preferences and interests to target users. Perception is used to measure whether the system can help users complete tasks correctly and quickly. In order to better look at the user's point of view, we use perceived usefulness instead of usability for research.

B. CONSTRUCTION OF USER ACCEPTANCE EVALUATION MODEL FOR PERSONALIZED RECOMMENDATION SYSTEM

Unreasonable personalized recommendation system can not only help users improve decision-making efficiency, but also make users feel dissatisfied. This paper analyzes the functional requirements of personalized recommendation of computational advertising, analyzes the perceived behavior of algorithm moral hazard generated in computational advertising based on collaborative filtering algorithm, and designs the user perceived value architecture of personalized recommendation system according to the user perceived risk generated in personalized recommendation system. This hybrid method reduces or even overcomes the shortcomings of content based and collaborative filtering algorithms, and combines their advantages to recommend. Computational advertising personalized recommendation can be seen as an intelligent user interest information discovery mechanism.

In the face of massive information, user perceived risks mainly include that users do not need to know their own needs. The system can intelligently understand users' needs through the collection of user context information, and then dynamically push information that meets users' preferences and interests to target users [20]. In this paper, we mainly consider perceived usefulness from two aspects: information acquisition efficiency and information acquisition quality. Because one of the main purposes of algorithmic ethical risk perception behavior in computing ad personality recommendation is to help users find relevant resources to meet their needs with minimal effort [21]. As shown in Figure 2, the intra based collaborative filtering recommendation algorithm can be divided into project-based collaborative filtering and user based collaborative filtering.

Perceived comfort refers to whether the design of the system can make users feel comfortable, specifically including the timing of personalized information push, the push

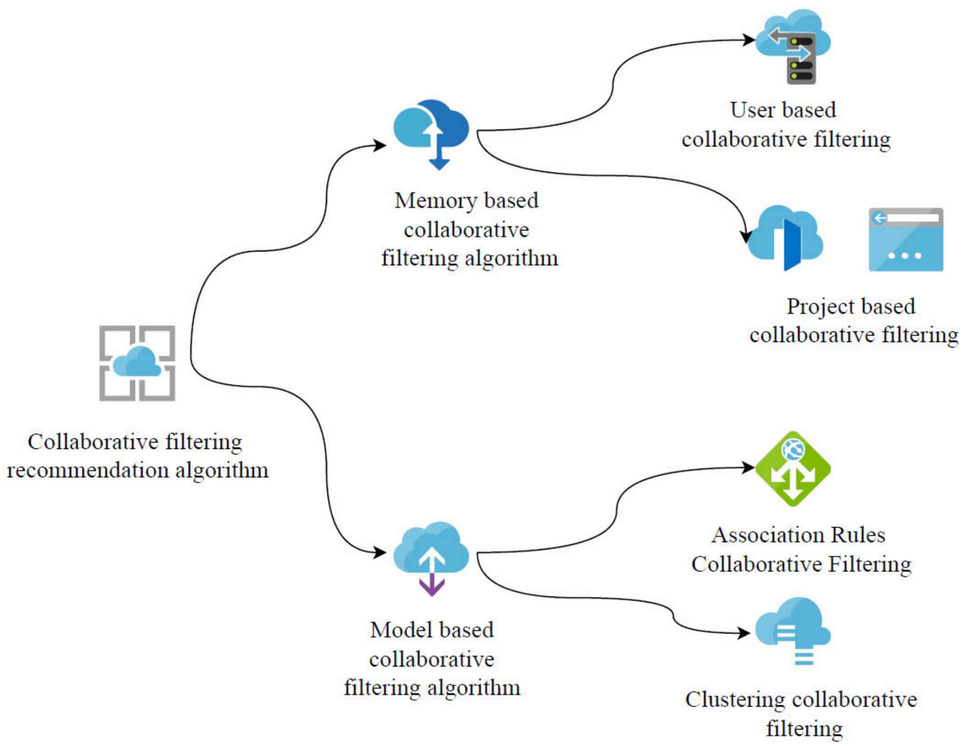

FIGURE 2. Classification process of collaborative filtering-based recommendation.

method adopted, the layout of personalized information in the page and other contents. The concern in the user satisfaction system describes the degree of the website's emphasis on users, specifically whether it can give users a comfortable experience. In fact, it has the same meaning with perceived comfort items by similar neighbors; The third step, the recommendation phase, is to rank the scores generated in the second step in descending order, and select the first items to recommend to users in turn. Collaborative filtering algorithm refers to the frequency of simultaneous occurrence of itemset A and itemset B. The calculation formula is as follows:

$$Supprt\,(A \rightarrow B) = \frac{N\,(AB)}{N} \tag{1}$$

That is, whether B will occur when A occurs, and if so, what is the probability. The calculation formula is as follows:

$$Confidence\,(AB) = \frac{N\,(AB)}{N} \tag{2}$$

A high confidence level indicates that the probability of occurrence of itemset B in transactions containing itemset A is high. The calculation formula is as follows:

$$Lift\,(AB) = \frac{\sup port\,(AB)}{Support} \tag{3}$$

For example, the most common way to predict the user's rating of an item is as follows:

$$P_{ik} = \frac{\sum_{NNU} S}{\sum_{u_j} \in NNUS} \tag{4}$$

In this formula, $S\left(u_i, u_j\right)$ represents the similarity between user i and user j, and NNU is the nearest neighbor user set of user i.

The psychological expectation generated when users predict the possible negative results that do not conform to their expectations in the process of using a mobile Internet advertisement. Which makes their willingness to adopt computational advertising more positive. The implementation of similar user discovery algorithm based on interactive links involves a lot of similarity calculation. It can be seen that computing similarity is the key operation to find similar users. Cosine similarity is mainly used to calculate the similarity of document type data. Its value range is $[-1, +1]$. The smaller the value is, the smaller the similarity is. The specific formula is as follows:

$$Co\sin e\,(A, B) = \frac{(A_i, B_i)}{\sqrt{\sum_i^n (A_i)}} \tag{5}$$

where vector $A = (A_1, A_2, \ldots A_n)$ and vector $B = (B_1, B_2, \ldots, B_n)$.

Thus, the defect of the original cosine similarity is avoided. The specific formula is as follows:

$$Co\sin e\,(A, B) = \frac{\left(A_i - \bar{X}\right)}{\sum_{i=1}^n \left(A_i - \bar{X}\right)} \tag{6}$$

The vectors $A = (A_1, A_2, \ldots A_n)$, $B = (B_1, B_2, \ldots, B_n)$ and $\bar{X}$ are the mean values of A and B.

Pearson correlation coefficient reflects the degree of linear correlation between the two variables. The value range of the similarity coefficient is [−1, +1], and the specific formula is as follows:

$$Pearson\,(A,B) = \frac{\sum_{i=1}^{n}\left(A_i - \bar{A}\right)}{\sqrt{\sum_{i=1}^{n}\left(A_i - \bar{A}\right)}^{2}} \tag{7}$$

The mean values of vectors $A = (A_1, A_2, \ldots A_n)$, $B = (B_1, B_2, \ldots, B_n)$, $\bar{A}$ and $\bar{B}$ are A and B respectively.

The Jackard similarity coefficient mainly calculates the proportion of the intersection of A and B in the merging set of A and B. The value range of the similarity coefficient is between [−1, +1], and the specific formula is as follows:

$$Jaccard\,(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{8}$$

where the intersection number of $|A \cap B|$ and $|A \cup B|$ is the union number.

Tanimoto coefficient is an extension of Jeckard's similarity coefficient, which is mostly used to calculate the similarity of document data. Its similarity system

The value range is [−1, +1], which is 1 when it completely overlaps and 0 when it does not overlap. The closer it is to 1, the more similar it is. The specific formula is as follows:

$$Tanimoto\,(A,B) = \frac{\sum_{i=1}^{n}(A_i \times B_i)}{\sqrt{\sum_{i=1}^{n}\left(A_i^2\right)}} \tag{9}$$

where the intersection number of $A = (A_1, A_2, \ldots, A_n)$ and $B = (B_1, B_2, \ldots, B_n)$ is the union number.

Euclidean distance mainly measures the distance between two points in the coordinate system. The formula for calculating the Euclidean distance between the vector A and the vector B is as follows:

$$Dis\tan ce\,(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)} \tag{10}$$

The length and quantity of advertisements are controlled within the acceptable range of ordinary users, and advertisements have certain cultural value and artistic value, which can bring positive emotional reactions to people, so users will have greater adoption of advertisements. The user acceptance evaluation model of personalized recommendation system is shown in Figure 3.

In this model, the social impact is that if users think that the people they care about around them will agree to accept certain types of online video advertisements to a large extent, then users will have a strong willingness to use online video advertising services, and the acceptance of online video advertisements will be greatly improved. Based on the collaborative filtering algorithm of users, the user-item scoring matrix M is established first. The element $R\,(i,j)$ in the user-item matrix indicates the rating value of user i on item j.

$$M = \begin{Bmatrix} R_{11} \ldots R_{1n} \\ R_{m1} \ldots R_{mn} \end{Bmatrix} \tag{11}$$

Then, it is expected to calculate the similarity between the target user and other users to get the nearest neighbor user set $U = \left(u_1, u_2, \ldots, u_p\right)$ in descending order of similarity. $sim\,(i,j)$ indicates the similarity between user i and user j. The cosine similarity calculation formula is:

$$sim\,(i,j) = \cos\,(i,j) = \frac{\vec{i}, \vec{j}}{\left|\vec{i}\right| \left|\vec{j}\right|} \tag{12}$$

In the nearest set U', the calculation formula for predicting the unrated items of the target users is:

$$R_{vi} = \bar{R}_v + \frac{\sum_{u_j} sim\,(u,v)}{\sum_{u_j} sim\,\left(u_j, v\right)} \tag{13}$$

Among them, user v predicted score of the project is represented by i, and the average score of user v evaluated project is represented by $\bar{R}_v$.

If the user has not rated the project excessively, then the user's rating for this project is 0. The cosine similarity formula between project i and project j is:

$$sim\,(i,j) = \cos\,(i,j) = \frac{\vec{i}, \vec{j}}{\left|\vec{i}\right| \left|\vec{j}\right|} \tag{14}$$

Assuming that the user sets of jointly scored items i and j are represented by U_{ij}, then the similarity $sim\,(i,j)$ formula between item i and item j is as follows:

$$sim\,(i,j) = \frac{\sum_{u \in U}\left(R_{u,i} - \bar{R}_i\right)}{\sqrt{\sum_{u \in U_i}\left(R_{u,i}\right)}} \tag{15}$$

where $\bar{R}_i$ represents the average score of project i by all users who have scored project i, and the prediction score method of user u for target project T is as follows:

$$R_{u,T} = \bar{R}_T + \frac{\sum_{n \in M} sim}{\sum_{n \in M} sim\,(T,n)} \tag{16}$$

However, the calculation of user acceptance of personalized recommendation system based on in-memory collaborative filtering is time-consuming and has poor scalability. Model-based collaborative filtering firstly establishes a model for all data offline, and then makes online recommendation based on this model. It improves scalability at the expense of accuracy. The accuracy and scalability of recommendation system are the challenges faced by collaborative filtering applications. Combining and utilizing their advantages, we can get a good recommendation effect.

IV. RESULT ANALYSIS AND DISCUSSION

For the user's privacy, information security, reputation, copyright, right to know, right to choose, etc. in the algorithm of computing advertising personalized recommendation system. User perceived risk is a more abstract content, and however unreasonable personalized recommendation systems can not only help users improve their decision-making efficiency,

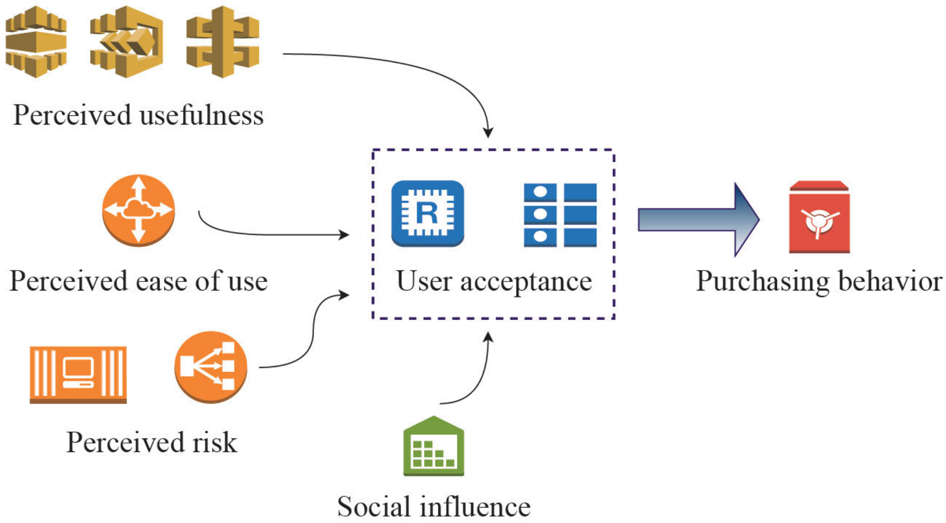

FIGURE 3. User acceptance evaluation model of personalized recommendation system.

but will make users resentful. This paper analyzes the functional requirements in personalized recommendation of computing advertisements, analyzes the perceived behavior of the algorithm ethical risks generated in computing advertisements based on collaborative filtering algorithm. And this paper designs the user perceived value architecture of personalized recommendation system according to the user perceived risks generated in personalized recommendation system.

We can guess what the user likes through the user's historical access records, and then find out what the user likes and push it to the user. The impact of personalized recommendation ads on users' willingness to accept, and users' perception of the ethical risk of algorithms generated in personalized recommendation ads have been studied. Therefore, experiments have been carried out to solve the above problems. Due to the different degree of data sparsity, the actual situation of the recommendation system can be better simulated. Therefore, the performance of collaborative filtering algorithm, machine learning. The experimental results are shown in Figure 4. It can be seen that the algorithm proposed in this paper has better recommendation effect than machine learning algorithm and ant colony algorithm.

As one of the marketing methods of online video, computer advertising has received extensive attention under the rapid development trend of computer advertising. Perceived usefulness is used to measure the perceived risk of users who calculate personalized recommendation systems for advertising, and whether they can perceive that using a recommendation system can effectively help them get what they want or results. Using the dataset the experimental results are shown in Figure 5. From the figure, we can see that the recommendation effect of this paper is better than that of machine learning algorithm and ant colony algorithm.

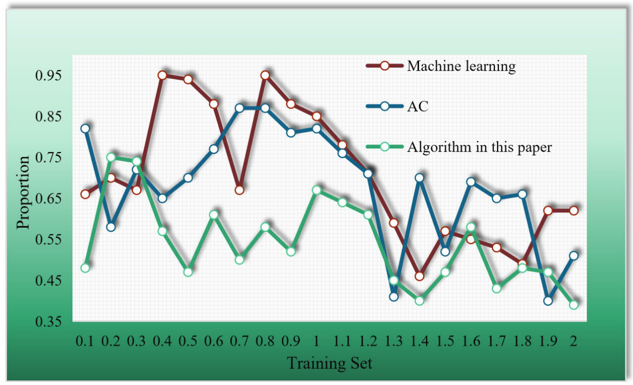

FIGURE 4. The influence of different training set proportions on recommendation results.

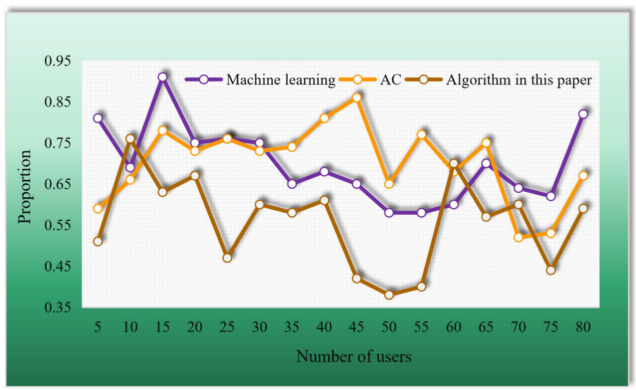

FIGURE 5. Influence of the number of neighbor users on recommendation results.

There are 334,580 pairs of user goods in this paper. We divide the user preference into ten grades, and the degree is 0.1~0.5. Therefore, we need to map the functions in order to make the average value of the categories of user preference equal. After mapping, it is shown in Table 1.

TABLE 1. Preference value of love degree after mapping.

Function Range	Preference value
0-0.06	0.1
0.06-0.12	0.2
0.12-0.15	0.3
0.15-0.17	0.4
0.17-0.19	0.5

TABLE 2. Ranking results of personalized recommendation system indicators.

Ranking	Option	Average comprehensive score
1	Perceived usefulness	6.59
2	Perceived security	5.39
3	Perceived comfort	5.37
4	Perceived ease of use	5.17

After calculating the personalized recommendation of advertisements and receiving the interview, the interviewed users rank the importance of the four indicators: perceived security, perceived usefulness, interactive contact, and perceived ease of use. They give the first indicator 8 points, the second indicator 7 points, and the third indicator 6 points, and so on. Finally, the scores of each indicator are summed up and divided by the sample size 50 to get their comprehensive scores. After sorting by 30 people, the results are shown in Table 2. It can be found that the most important indicators are ''perception'', and users pay more attention to the direct perception experience when using personalized recommendation of computational advertising. The number one indicator is perceived usefulness, which indicates whether personalized recommendation can accurately recommend the ads users like.

TABLE 3. Average correlation evaluation results of recommended projects.

	1	2	3	4	5
Developer	3.7	3.5	3.7	3.7	3.5
Market personnel	2.9	2.9	3.1	2.9	2.7
User representative	2.3	2.7	3.3	2.5	2.9
Average correlation	2.868	2.934	3.268	2.934	2.934

It is supposed to calculate the relevance evaluation of the recommendation results of personalized recommendation of advertisements, sort some data from the list evaluation, and extract the relevant data of 10 tasks for processing. The results are shown in Table 3. From the experimental results, the average score of advertising personalized recommendation items is about 3 points, so the system basically meets the design expectation in the relevance of recommended items. However, the relevance evaluation of the system recommended items by ordinary user representatives is still low. In addition, the ratings of evaluators usually decrease with the increase of ranking order of personalized recommended items in advertisements, which shows that the recommendation ranking algorithm is effective for dealing with common items from another angle.

The standard of recommendation quality selected in this experiment is the average absolute error, which is a widely used method to measure the recommendation quality of recommendation algorithms. Therefore, the machine learning algorithm, ant colony algorithm and the algorithm in this paper are used in this experiment, and the experimental results are shown in Figure 6. The experiment shows that the another important issue in recommendation systems is the perceived value of users. When people's perceived risks change constantly, the recommendation results generated by traditional recommendation systems will not meet the needs of users.

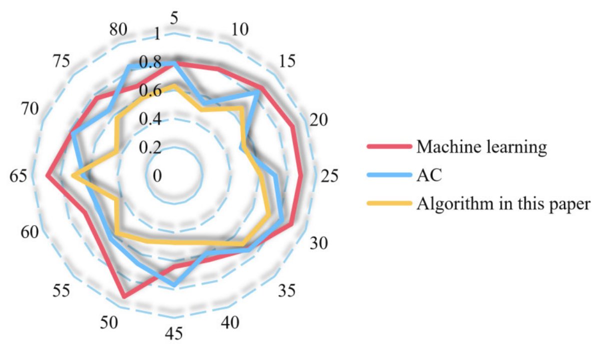

FIGURE 6. Comparison chart of average error.

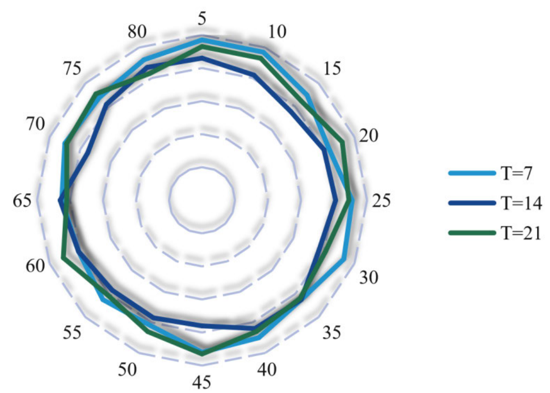

FIGURE 7. Time Interval comparison experiment.

In order to verify the recommendation accuracy of this method, this paper designed several groups of experiments to compare. Because there is no user age eigenvalue in the dataset, and there is no user comment forwarding information in the dataset,. Using the public comment data set, calculate the impact of the time interval T of updating the user item scoring matrix on the recommendation quality. In the experiment, T=7, T=14, T=21 respectively. The experimental results are shown in Figure 7. From the experimental results, we can see that the collaborative filtering algorithm with time forgetting curve is generally superior to the traditional collaborative filtering algorithm. The value of time interval T has different effects on the final recommendation results. Too large or too small a value of T will reduce the quality of recommendation. From the experimental results, we can see that when T=14, the recommendation effect is better. At the same time, we can see that when the number of nearest neighbors is about 70, the recommendation result is the best.

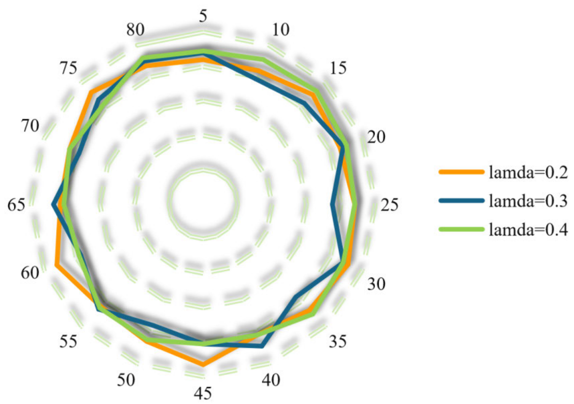

FIGURE 8. Comparison of different values.

Using data set, the influence of social similarity and rating similarity of users on recommendation quality is tested. Choose different values for the experiment. In this paper, the values are 0.2, 0.3 and 0.4, and the experimental results are shown in Figure 8. Through the experimental results, we can see that the system's recommendation quality can be improved by integrating the calculation of user social relations and mobile trajectory similarity into the calculation of user rating similarity. From the experimental results, we can see that too large or too small will have a negative impact on the quality of the results. When lamda=0.3 or so, the recommended effect is the best.

V. CONCLUSION

Personalized recommendation system has important application value in social economy, and has been applied in many fields, such as music and film recommendation, book and commodity recommendation, advertisement and information recommendation, social recommendation such as friends or groups, media recommendation such as news and microblog, education recommendation such as learning videos and educational resources. This paper starts from computational advertising, researches the user acceptance of personalized recommendation systems, and studies the impact of personalized advertising on user acceptance intentions.

Users' perceptions of the ethical risks of algorithms generated in personalized recommendation ads are studied, and a model is built in this paper, perceived comfort refers to whether the design of the system can make users feel comfortable, specifically including the timing of personalized information push, the push method adopted, the layout of personalized information in the page and other contents. The concern in the user satisfaction system describes the degree of the website's emphasis on users, specifically whether it can give users a comfortable experience.

In fact, it has the same meaning with perceived comfort. Another important issue in recommendation systems is the perceived value of users. When people's perceived risks change constantly, the recommendation results generated by traditional recommendation systems will not meet the needs of users. How the perceived value of users of personalized recommendation system meets the needs of people in the time dimension has become one of the core issues of recommendation systems.

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