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Mobile Personalized Recommendation Model Based on Privacy Concerns and Context Analysis for the Sustainable Development of M-commerce

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Abstract: A mobile personalized recommendation service satisfies the needs of users and stimulates them to continue to adopt mobile commerce applications. Therefore, how to precisely provide mobile personalized recommendation service is very important for the sustainable development of mobile commerce. However, privacy concerns regarding mobile commerce affect users' consumption intentions, and also reduce the quality of mobile personalized recommendation services. In order to address this issue and the existing recommendation method problem in the mobile personalized recommendation service, this paper introduces six dimensions of privacy concerns and the relevant contextual information to propose a novel mobile personalized recommendation service based on privacy concerns and context analysis. First, this paper puts forward an intensity measurement method to measure the factors that influence privacy concerns, and then realizes a user-based collaborative filtering recommendation integrated with the intensity of privacy concerns. Second, a context similarity algorithm based on a context ontology-tree is proposed, after which this study realizes a user-based collaborative filtering recommendation integrated with context similarity. Finally, the research produces a hybrid collaborative filtering recommendation integrated with privacy concerns and context information. After experimental verification, the results show that this model can effectively solve the problems of data sparseness and cold starts. More importantly, it can reduce the influence of users' privacy concerns on the adoption of mobile personalized recommendation services, and promote the sustainable development of mobile commerce.

Keywords: consumer needs; personalized recommendation; privacy concern; context information; ontology tree; hybrid collaborative filtering; sustainability

1. Introduction

Recently, with the rapid development of smart devices (e.g., smartphones, tablet computers, and smartwatches), and communication networks (e.g., 4G, 5G, and social network services), users' demand for easy access to Internet resources and services anytime and anywhere is growing, and mobile commerce (M-commerce)—which is derived from the broader concept of e-commerce—is constantly developing through deeper and broader dimensions [1]. A mobile personalized recommendation service (MPRS), as a good M-commerce application, can effectively alleviate user information overload and improve the quality of services. For example, the recommendation system based on the collaborative filtering algorithm and association rules developed by Amazon contributes to about 30% of its sales [2]. However, when big data-driven Internet platforms apply recommendation technology on a large-scale,

it is found that the existing methods cannot continuously obtain users' traffic, resulting in problems, such as low recommendation accuracy and poor reliability of the predicted products [3,4]. The problems of information overload and contextual disturbance in the personalized recommendation service can be identified after analysis [5]. Traditional recommendation technology captures the behavior of the network consumer in an incomplete manner, so that the recommendation services do not meet the user's dynamic interests. Therefore, how to discern what products and information users are really interested in, in order to enrich and satisfy users' personal needs from in-depth personalization services, has become an important issue in the field of mobile personalized recommendation systems.

Currently, a lot of research uses the historical preference data of network users and their context information (such as interest tags, time, ratings, locations, social relationships, etc.) to improve the quality of recommendations [6–8]. However, since MPRS needs to continuously collect users' private information and network behavior information, mining network behavior often exposes some users' privacy information (such as IDs, locations, preferences, etc.) [9]. Security and privacy are the greatest issues of concern in MPRS [10]. That is, alleviating privacy concerns is an indispensable requirement not only for the personal demands of users, but also for assuring the sustainability of the M-commerce. Moreover, privacy protection in big data is more complicated: The contexts influencing user preferences are dynamic and different [11]. Mobile intelligent terminal equipment can not only obtain static personal information, such as names, mobile phone numbers, transaction histories, etc. [12], but also can obtain the dynamic context information anytime and anywhere, such as geographical locations, motion states (stillness, running), mood, etc. In addition, the decision-making process behind the user's disclosure of private information is closely related to the context, and the intensity of privacy concerns also change depending on the context (such as in a trading environment) [13]. Most of the existing personalized recommendation methods ignore important privacy concerns information [14], resulting in low recommendation accuracy. Therefore, how to integrate privacy concerns, contexts, and other information into the MPRS is very important to achieving the sustainable development of M-commerce.

In summary, the exploration of how to incorporate context and alleviate users' privacy concerns in mobile personalized recommendation services has attracted tremendous attention from academic and industry circles. In a previous work, the authors designed a model of users' privacy concerns that influence their willingness to adopt MPRS. According to our previous research, the adoption of MPRS is significantly constrained by six privacy concern factors—those being the user's privacy tendency, internal locus of control, openness, extroversion, easygoingness, and social group influence. These influenced the user's privacy concerns relating to areas including determining information collection, improper access, information error, and secondary use, and ultimately influenced their willingness to adopt of MPRS [15]. On this basis, the paper proposes a mobile personalized recommendation model based on privacy concerns and context analysis (PC-MPRS) to solve the problems of how to measure the intensity of privacy concerns, the definition and expression of complex multi-dimensional contexts, and improving recommendation methods incorporating privacy concerns with context information. The main purpose of this research is to satisfy the needs of users, and to stimulate them to adopt mobile commerce applications continuously, which is very important for the sustainable development of mobile commerce. Therefore, this paper studies the quantitative methods of the intensity of privacy concerns- and context-aware personalized recommendation methods. It can improve control over privacy information from the perspective of the user, to reduce privacy concerns and improve the users' willingness to disclose information, which would also enable MPRS to be more efficient and make M-commerce more sustainable.

The main contributions of this study can be summarized as follows:

(1) The model studies the intensity measurement method to measure above-mentioned privacy concerns factors and its application in personalized recommendation service. It considers reducing privacy concerns in personalized recommendation process from the perspective of user privacy, thus promoting users to accept MPRS.
(2) This paper studies the method of context analysis, extracts the user's context preference, and further studies the influence of context information on the recommendation process.
(3) The hybrid collaborative filtering recommendation method based on privacy concerns and context analysis is proposed, and the potential association relationships among context, user, and privacy concerns are mined, and the user's privacy concerns intensity and context preference are combined to generate appropriate content to be recommended to target users.

The rest of this paper is organized as follows. After the introduction part, related work is discussed in the literature review part. In the third part, it proposes a novel Mobile Personalized Recommendation Model based on Privacy Concerns and Context Analysis. In the fourth part, it evaluates the performance of the proposed model, and finally, discussion, major conclusions, and future work are summarized in Sections 5 and 6.

2. Literature Review

2.1. Research on Mobile Personalized Recommendation Service Considering Context

A mobile personalized recommendation service is the new model that traditional Internet recommendation service adapts to the rapid development of mobile e-commerce [16,17]. It has the characteristics of mobility and context correlation [18,19]. Scholars at home and abroad have carried out extensive research on the contextual issues in mobile personalized recommendation services, such as He and Liu improved the recommendation effectiveness by analyzing a psychological trait of human beings, exploratory behaviors, and the proposed model demonstrated superior recommendation performances and good interpretability [16]. Lu and Guo proposed the measurement of user interest model combining with contextual preference, and found that fusion measurement of context and item information achieves better results [18]. The existing research mainly focus on four aspects:

(1) The definition of context and its data collection, including the concept of context, its classification and identification, collection, and preprocess of context data; Schilit [20] proposed that context included internal context and external context, which was a group of entities status information related to users and tasks.
(2) Context expression and modeling, including semantically expression of context connotation, and context tree model based on hierarchical relationships on domain ontology. Different application scenarios lead to scholars' inconsistent understandings of the contexts. Palmisano [21] summarized more than one hundred definitions and expression patterns of contexts.
(3) Expression and model of customers' contextual interest, including the construction of the customer interest model after context analysis, the influence of the context on customers' interest drift model, etc. Xu [22] verified that analyzing relevant context information was beneficial to predict customer interests in mobile commerce services more accurately. In addition, the mobile personalized recommendation system can recommend different promotion items under different contexts of shopping venue [23], and can also improve the interest of mobile commerce users and sales performance according to context recommendation [24]. Ren [25] found that context in users' interest mining had a great influence on network users' behaviors, and users were highly dependent on the context when making rational behavior decisions, which produced contextual effects when users adopted mobile personalized recommendation services.

(4) Contextual recommendation algorithm and system application, including the improvement of personalized recommendation algorithm and the application in the related fields combining with context pre-filtering, post-context filtering, and context modeling. Adomavicius et al. [26] demonstrated that contextual information could indeed improve the quality of recommendations to a certain extent in mobile personalized recommendation systems. Some well-known e-commerce enterprises in the online music, news, and travel industries have also begun to use context recommendation systems on a large scale [27]. Colomo [6] studied the personalized travel recommendation service, used location-based service technology to realize the geographical positioning of tourist services. Then, it integrated the location information into the personalized recommendation algorithm, and combined the historical consumption preferences and location context to recommend suitable restaurants and scenic spots to users.

2.2. Research on Mobile Personalized Recommendation Service Considering Privacy Concerns

On one hand, MPRS provides accurate recommendation services by analyzing users' basic attributes, network behaviors, context status, and other information. MPRS continuously records and updates the above information by using personalized recommendation systems. On the other hand, users' privacy concerns in mobile commerce and the lack of effective privacy policy hinder the development of personalized recommendation services [28]. Since personalized recommendation systems can use location-based service to monitor and track the user's behavior trajectory, it makes users worry about the leakage of personal location privacy information. Moreover, mining behavior tracking can obtain private information related to personal safety, such as the user's workplace and the residential address [29]. Wang [30] studied the actual user privacy protection mechanism, and proposed a user privacy quantification mode based on ubiquitous vector. The model comprehensively computed the influence intensity of privacy from the perspective of individual users and platform. Dinev [31] found that users paid attention to private personal information when they were concerned about the perceived risk of their private information, and the intensity of privacy concerns varied with the context. For example, user's password information is relatively important in e-commerce and financial platforms, but not that important in bulletin board system forums and social platforms. When Sutanto studied the adoption of mobile personalized recommendation services, he [32] focused on the different influences of institutional and policy factors on user behaviors. Okazaki [33] studied the context adjustment mechanism through which users' privacy behavior had impacted mobile service adoption behavior. Taddei [34] studied the impact of users' relationship strength in social networks to privacy concerns, and found that friends had the similar privacy concerns over online social networks as those friends in realistic society, and the closer the relationship was, the higher the similarity of privacy concerns was.

Most of the existing research has not studied the factors that affect the user's privacy concerns, and lack the innovation of mobile personalized recommendation method under privacy concerns. It is too limited to the privacy protection technology methods, focusing on data encryption, anonymity, disturbance, elimination of redundant data, and other computer technologies to protect the privacy in recommendation process. On the one hand, it lacks the analysis of users' psychological cognitive behaviors in the study of the mechanism of privacy concerns, and fails to quantify the impact of specific factors of privacy concerns on users' consumption behaviors. On the other hand, it lacks the mining methods and recommendation strategies of mobile users' preference pattern considering privacy concerns. These make the current MPRS unable to effectively alleviate users' privacy concerns and perceived risks, which hinders the sustainable development of M-commerce.

2.3. User-Based Collaborative Filtering Recommendation Method

"Collaborative Filtering" (CF), based on the existing "user-item" interaction history, uses the collective wisdom of people or public items to make recommendations. CF mainly includes user-based collaborative filtering (U-CF) and item-based collaborative filtering (I-CF) [35]. U-CF assumes that

users have similar interests in certain projects, so they may have the same interests in other projects. According to this hypothesis, the user-based collaborative filtering method firstly calculates the user similarity, that is, it finds the nearest neighbors. CF calculates weighted average scores of products that are graded by several nearest neighbors of target user, and sets these average values as the scores graded by target user to generate a list of recommendations. In the process of searching for the nearest neighbors, the statistical calculation method is usually used to search for similar users of target user's, and the higher the similarity is, the closer the users will be [36]. The general similarity calculation methods include Cosine similarity and Pearson similarity [37]. For example, the Pearson similarity: The similarity calculation formula of user i and user j is as follows, I_{ij} represents the set of items that both users i and j have scored, and the $R_{i,p}$ is the score that user i grades item p, and $\overline{R_I}$ is the average score of all the items graded by i, and the $R_{j,p}$ is the score that user j grades item p, and $\overline{R_J}$ is the average score of all the items graded by j.

$$Sim_{ij}^{pearson} = \frac{\sum_{p \in I_{ij}} \left(R_{i,p} - \overline{R_I}\right)\left(R_{j,p} - \overline{R_J}\right)}{\sqrt{\sum_{p \in I_i} \left(R_{i,p} - \overline{R_I}\right)^2} \sqrt{\sum_{p \in I_j} \left(R_{j,p} - \overline{R_J}\right)^2}} \tag{1}$$

Considering the context information in the process of collaborative filtering recommendation fits in with the current MPRS application scenario, but it also makes the high-dimensional scoring matrix of "user-project" sparser, resulting in a larger error in the similarity calculation of neighboring users, and thus affecting the final quality of personalized service [38]. When calculating the nearest k neighbor sets of the target user, Kaleli [39] firstly combined dynamic difference of score and score similarity; then, based on the above information, he predicted the preference of the unevaluated items, and finally the top k scoring items were recommended to target users according to the ranking order. Winoto et al. studied the role of emotion in the film recommendation system, and pinpointed similar users through the emotional state submitted by users, and then proposed a collaborative filtering method based on emotion perception [40]. In order to make up for or avoid the problem of data sparseness and cold start of collaborative filtering, some scholars have proposed to combine multiple recommendation methods to achieve more realistic recommendation results by using a variety of mechanisms and hybrid collaborative filtering (Hybrid Collaborative Filtering, H-CF). Ben et al. [41] classified the hybrid collaborative methods into pre-fusion, medium-fusion, and post-fusion according to the stage and degree of fusion among methods in the contextual recommendation process. In order to address the problem of online news recommendation, Claypool et al. proposed a voting mechanism to integrate the prediction results based on content recommendation with that based on collaborative filtering recommendation [42]. Masoumeh proposed that recommending projects could be based on a linear combination of predictive scores, or evaluation of the credibility of different recommendation results, from which a list of recommendations could be selected [43]. Li et al. studied an individual privacy policy mechanism based on cluster recommendation, analyzed the privacy concerns in the user-based collaborative filtering recommendation process, and proposed a method of encrypting and anonymizing individual private information to protect users' privacy information [44].

In summary, the research of mobile personalized recommendation services based on privacy or context has received more and more attention from home and abroad. On one hand, in the big data era, users' interest mining needs to consider more contextual factors. Users ratings and different privacy concerns level require different personalized recommendation services, so the existing methods fail to carry out effective personalized recommendation services. On the other hand, collaborative filtering algorithms usually identify the similarity among users and their preferences based on users' historical behaviors, and has certain advantages in the actual personalized recommendation application. However, the calculation of the user rating provided by the existing methods in the recommendation process is too one-sided, and the psychological reasons for the differences in user ratings regarding different contexts are rarely analyzed, let alone the subjective privacy perceptions of users.

In this study, PC-MPRS not only consider the context, but also the privacy concerns, which is different from existing methods. It is a significant innovation to predict target users' preferences by reducing the privacy concerns. What's more, PC-MPRS provides users with more efficient mobile personalized recommendation services, reduces users' privacy concerns to stimulate users to continue to adopt MPRS, and finally promotes the healthy and sustainable development of M-commerce.

3. Mobile Personalized Recommendation Model Based on Privacy Concerns and Context Analysis

For privacy concerns, users often provide preference information in an anonymous manner. Therefore, by analyzing the tendency of privacy concerns instead of direct interest ratings, PC-MPRS protects privacy of users. Then, the nearest neighbor user set calculated by the intensity of privacy concerns is used for the personalized recommendation service. In addition, the long tail indicates that the cold start problem of the recommendation system is increasingly serious [1]. Because of the lack of historical score records, the collaborative filtering recommendation cannot find similar user sets for new users, nor can it recommend suitable products or services to target users. The PC-MPRS recommends products to new users based on context similarity. The context similarity is used to calculate nearest neighbor user set. If a new user is in a similar context to the group that has rated for a certain products/services which receive many favorable comments from the group, the new user is more likely to like these products/services. At the same time, a hybrid collaborative filtering method based on privacy concerns and context analysis is proposed, and it can alleviate the problem of data sparsity to a certain extent. The implementation framework of PC-MPRS is shown in Figure 1.

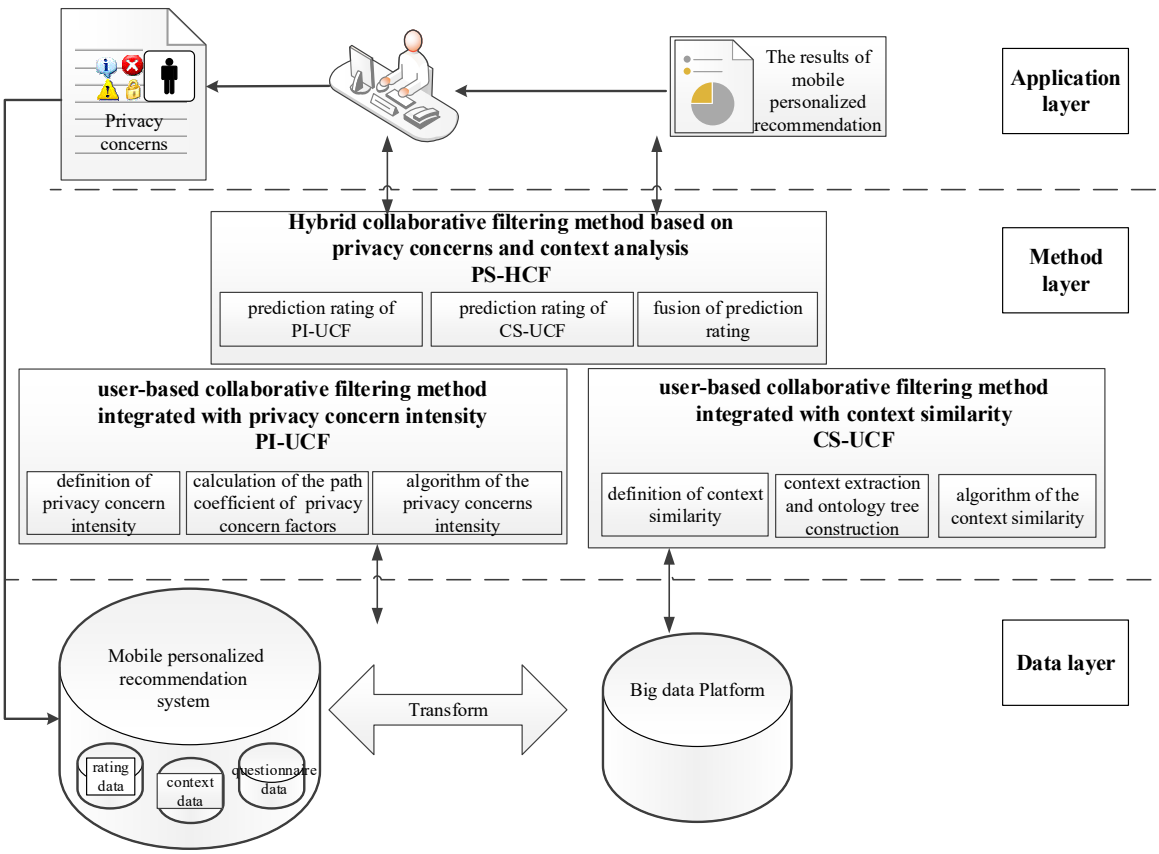

Figure 1. Operating mechanism of mobile personalized recommendation model based on privacy concerns and context analysis.

3.1. User-Based Collaborative Filtering Method Integrated with Privacy Concerns Intensity

Users' preference for goods or services has great differences under the influence of privacy concerns. The social attributes of individuals will affect the users' online behavior, so that people with similar privacy concerns will gather together. If this situation is not considered, users treat most of the influence factors of privacy concerns with the same or almost indistinguishable intensity, and it is impossible to find out which factors of privacy concerns will have a practical effect on the user's demand preference. Therefore, this paper proposes to use the privacy concerns intensity (PCI) to measure the difference between user's demand preferences under the constraints of privacy concerns. On this basis, Algorithm 1 constructs a new "user-privacy concerns intensity" preference matrix I, and then it calculates k nearest neighbor of new user based on the matrix I, and finally generates Top-N recommendation based on the privacy concerns intensity. At this point, each row of the matrix I represents the intensity vector of the influence factor of privacy concerns on user: $I_{u,p} = \left\{ i_{u,p} \middle| u \in U, p \in P, i_{u,p} \in [0,1] \right\}$ Among them, $i_{u,p}$ indicates the comprehensive intensity value of P, which is the influence intensity of user u on specific privacy concerns under the influence of six privacy concerns influencing factors. Algorithm 1 considers the importance of privacy concerns and protects the user's privacy by replacing the "user-rating" matrix with "user-privacy concerns intensity" matrix.

Algorithm 1 User-based collaborative filtering method integrated with privacy concerns intensity (PI-UCF).

Input: User U, *Service(R)S*, the rating matrix of "user-privacy concerns intensity".

Output: TOP-N recommendation service list and its rating.

Step1: It calculates the path coefficient of the influenced factors of privacy concerns based on structural equation model [15], and defines its absolute value as privacy concerns intensity I_{u,p_j}. The i_{u,p_j} means the value of users' preference, influenced by one of privacy concern factors (user's privacy tendency, internal locus of control, openness, extroversion, easygoingness, and social group influence), which has four dimensions (information collection, improper access, information error, and secondary use).

Step2: It defines the comprehensive intensity of a privacy concerns factor with four dimensions as $I_{U,P}$, and calculates the value according to Formula (2).

$$I_{U,P} = i_{u,p_j} + (\overline{i_u^p} - i_{u,p_i}) \times \left(\frac{i_{u,p_i} - \theta_1}{\theta_2 - \theta_1}\right)^2 \tag{2}$$

θ_1 and θ_2 are two constant thresholds. $\overline{i_u^p}$ is the average intensity of a privacy concerns factor with four dimensions. The Formula (2) uses square function to smooth differential influence degree in order to get better accuracy.

Step3: It defines the average intensity of six privacy concerns factor with four dimensions as $\overline{r_{u_i}^p}$ and is calculated as $\overline{r_{u_i}^p} = \frac{1}{N_p} \sum_{p \in P} r_{u_{i,p}}$ Then, according to Formula (3), the users' similarity is calculated based on privacy concerns intensity. N_p is defined as the size of $\left\{ r_{u_{i,p}} \right\}$

$$sim(u_i, u_j)_{privacy-pearson} = \frac{\sum_{p \in P_{u_i,u_j}} (r_{u_{i,p}} - \overline{r_{u_i}^p})(r_{u_{j,p}} - \overline{r_{u_j}^p})}{\left[\sum_{p \in P_{u_i,u_j}} (r_{u_{i,p}} - \overline{r_{u_i}})^2 \sum_{p \in P_{u_i,u_j}} (r_{u_{j,p}} - \overline{r_{u_j}})^2\right]^{1/2}} \tag{3}$$

Step4: On the basis of Step3, it selects the k nearest neighbor users for u_i who has the most similar privacy concerns. Then, according to known ratings scored by the k nearest neighbor users, it predicts rating of target services by Formula (4).

$$r_{u,s}^{privacy-CF} = \overline{r_{u_i}^s} + \frac{\sum_{u_j \in U} sim(u_i, u_j)_{privacy-pearson} \times (r_{u_{j,s}} - \overline{r_{u_j}^s})}{\sum_{u_j \in U} \left| sim(u_i, u_j)_{privacy-pearson} \right|} \tag{4}$$

3.2. User-Based Collaborative Filtering Method Integrated with Context Similarity

The paper proposes a collaborative filtering method based on user integrated with context similarity (CS-UCF). It is based on the assumption that users who have similar preference patterns for some kinds of products under similarity context may have similar preferences for a new product or service. User's preferences in different contexts may be different, and similar user's preferences also vary with dynamic contexts. Therefore, this paper introduces the concept of "context similarity (CS)", uses the context information in collaborative filtering recommendation process, and calculates the context similarity among user context set. Then, this paper proposes CS-UCF to construct a set of similar contexts for the target users in the current context. CS-UCF combines the scoring information with the context information of users, and brings it into the unified collaborative filtering model to play its own strengths, so as to achieve complementary advantages and improve the prediction effect on the preferences of the target users.

3.2.1. The Calculation of Context Similarity

Context factors in recommendation process have important influence on user behaviors. Taking into account the complexity and dynamics of context in the mobile commerce environment, as well as the internal relationship among contexts, this paper proposes a context management model based on ontology. Based on the context ontology model, the MPRS context type can be subdivided into individual information, user devices information, user environment information, and so on. The context is formally defined and semantically expressed by a tree node, which is stored and updated through a tree data structure pattern. Each tree node represents a context factor. User and context-related definitions are as follows.

Definition 1. *u is the user with some characteristics in the electronic business platform. Users register a unique access account on the site with their individual information, and log into the website to engage in operations like visiting, browsing, and purchasing. This paper describes the user set as* $U = \{u_1, u_2, \cdots, u_N\}$.

Definition 2. $UserContext = (UPC, UEC, UDC)$. *UPC indicates user's basic information, such as* $UPC = (Backgroud, \mathrm{Relation})$. *Backgroud indicates user's age, gender, etc.* Relation *indicates user's interaction and intimacy, etc. UEC indicates user's device information, such as* $UEC = (Hardware, Software)$., *which includes hardware devices, software products, broadband, etc. UDC indicates user's environmental information, such as* $UDC = (DayTime, Location)$. *DayTime includes morning, afternoon, evening, and Location* indicates geographical location (home, company, etc.)

The main idea of Algorithm 2 (Context Similarity Algorithm, CSA) is that in order to improve the accuracy of finding similar user sets in collaborative filtering recommendation, this paper adopts context similarity calculation instead of user similarity calculation. At the same time, data structure of ontology tree is used to calculate the relationship among various contextual concepts, and users are clustered according to the context similarity. CSA algorithm does the recursive similarity calculation based on context data structure of ontology tree from the children node to the parent node, and to the root node. CSA calculates the similarity of the conceptual attributes among nodes in each layer, and finally compares the comprehensive similarity between the previous context level model with the current context level model.

Definition 3. *Assuming that a non-leaf node G in the current context ontology tree* CT_1, $G = \{G_1, G_2, \cdots, G_N\}$ *indicates N sub node of G. A non-leaf node G′ in the previous context ontology tree* CT_2, $G' = \left\{G'_1, G'_2, \cdots, G'_N\right\}$ *indicates N sub node of G. The calculation of similarity between G and G′ is listed as follows.*

$$CTSim(G, G') = \sum_{i=1}^{N} W_i \times Sim(G, G') \tag{5}$$

$\sum W_i = 1$, and W_i is the weight of the i-th sub node.

Then, the calculation method of string similarity based on Levenstein edit distance (Formula (6)) is used to calculate the similarity between context concepts G_i and G'_i.

$$Sim(G, G') = \max(0, \frac{\min(|G_i|, |G'_i| - ed(G_i, G'_i))}{\min(|G_i|, |G'_i|)}) \tag{6}$$

$ed(G_i, G'_i)$ is the Levenstein edit distance between G_i and G'_i.

Algorithm 2 Context similarity algorithm based on context ontology-tree (CSA).

Input: Context ontology tree CT_1 and CT_2.
Output: Context similarity $CTSim(G, G')$.
Step1: Initializing $CTSim(G, G') = 0$.
Step2: Judging whether the context concept G_i exists in CT_1. If it exists, jump to step 3, or end.
Step3: Judging whether the context concept G'_i exists in CT_2. If it exists, jump to step 4, or step 2.
Step4: Recursion calculation the comprehensive similarity between the G_i and G'_i in this two context ontology tree by $CTSim(G, G,) + = w_i \times Sim(G, G,)$.

CSA improves incidence relation of "user-product" in each class through context filtering before recommending, and improves the recommendation performance. At the same time, the user is clustered with context information. The purpose is to gather the "user-product" with similar context in a class to reduce the data noise.

3.2.2. User-Based Collaborative Filtering Method Integrated with Context Similarity

The superiority of traditional user-based collaborative filtering method depends on the K nearest neighbors' preferences. Algorithm 3 finds k nearest neighbors of a target user based on context analysis who have similar preferences in context, and use similarity user preferences to predict the preference of the target user to different services in a multi-dimensional context. Therefore, the rating matrix of user-service is transformed into a preference matrix of user-context to calculate user similarity based on context analysis. The construction of the preference matrix of user-context depends on the rating matrix of user-service and the correlation matrix of service-context. $R_{u,c}$ is used to represent the "user-context" preference matrix, and each row of the matrix represents the user's preference vector for various contexts, $R_{u,c} = \{r_{u,c} | u \in U, c \in C, r_{u,c} \in [0, 100]|\}$, and $r_{u,c}$ represents the user's preference value of u in a specific context c.

3.3. Hybrid Collaborative Filtering Recommendation Method based on Fusion of Prediction Rating

The fusion of predictive ratings essentially means that a collaborative filtering method should be considered multi-dimensional information. The information that alleviates data sparsity and cold start problems to a certain extent, is divided into two categories, namely, privacy concerns information and context information. This paper proposes the user-based collaborative filtering method integrated with privacy concerns intensity (PI-UCF) in Section 3.1, and the user-based collaborative filtering method integrated with context similarity (CS-UCF) in Section 3.2, and put forward PS-HCF, which combines the PI-UCF and the CS-UCF in the prediction rating stage. Specific process: The prediction rating of target user in PI-UCF is converted into a hundred points system, and then a mixed user rating is generated by linear weighting (see Formula (10)) with the prediction score of target user proposed in CS-UCF, and a Top-N recommendation is generated according to the score.

Algorithm 3 User-based collaborative filtering method integrated with context similarity (CS-UCF).

Input: Context C, Internet User u, Recommend services *Service(R)*, rating matrix of "user-service" and the correlation matrix of "service-context".

Output: TOP-N recommend services and their scores.

Step1: Calculating the user's average preference for a certain context:

$$r_{u,c} = \frac{1}{\left|S_{u,c}\right|} \sum\nolimits_{s \in S_{u,c}} r_{u,s,c} \tag{7}$$

$S_{u,c} = \{s \left| s \in S, r_{u,s} \neq null, sc = 1 \right|\}$, $\left|S_{u,c}\right|$ is the number of elements contained in $S_{u,c}$, $r_{u,s,c}$ represents the preference value of user u to service s in context C. It constructs "user-context" two-dimension preference matrix.

Step2: Calling the context similarity calculation method (CSA) proposed in Algorithm2 to calculate the similarity between contexts in $(C)_{ij}$.

Step3: After building the new "user-context" matrix, an improved method based on context similarity is proposed.

$$sim(u_i, u_j)_{context-pearson} = \frac{\sum_{c \in C} (r_{u_{i,c}} - \overline{r_{u_i}^c})(r_{u_{j,c}} - \overline{r_{u_j}^c})}{\left[\sum_{c \in C} (r_{u_{i,c}} - \overline{r_{u_i}})^2 \sum_{c \in C} (r_{u_{j,c}} - \overline{r_{u_j}})^2\right]^{\frac{1}{2}}} \tag{8}$$

$\overline{r_{u_i}^c}$ represents the average preference of user u_i for contexts related to services. It uses similarity $sim(u_i, u_j)_{context-pearson}$ to select k nearest neighbors for user u_i.

Step4: Finding the nearest neighbor set of the target user u_i under Context c_i. Since user's preferences are closely related to context, the paper first obtains the similarity between c_i and c_j based on step 2. Then, find the nearest neighbor sets of u_i under the influence of context c_i and c_j respectively. In the end, the nearest neighbor users under Context c_j are merged into the nearest neighbor set under Context c_i.

$N_j = \left\{N_{j,c_1}, N_{j,c_2}, \cdots, N_{j,c_k}\right\}, 1 \leq j \leq Num(U)$ is used to represent the nearest neighbor set. $c_1, c_2, \cdots, c_k$ is the k context. $Num(U)$ is the total number of users. N_{j,c_i} is the similarity user set of user j under the influence of the context c_i.

Step5: Using the user preferences of k nearest neighbors obtained in step 4, the prediction score $r_{u_{i,s}}$ of potential user is calculated by Formula (9).

$$r_{u,s}^{context-CF} = \overline{r_{u_i}^s} + \frac{\sum_{u_j \in U} sim(u_i, u_j)_{context-pearson} \times (r_{u_{j,s}} - \overline{r_{u_j}^s})}{\sum_{u_j \in U} \left|sim(u_i, u_j)_{context-pearson}\right|} \tag{9}$$

$$r_{u,s} = \alpha \times r_{u,s}^{\text{privacy}-CF} + (1 - \alpha) \times r_{u,s}^{context-CF} \tag{10}$$

The parameter α is used to balance the importance between PI-UCF and CS-UCF. When $\alpha = 0$ or 1, the fusion of prediction rating method becomes PI-UCF or CS-UCF. In this paper, the dynamic adaptation of the recommender service is used to determine the value of α.

4. Experiment and Analysis

4.1. Data Set

4.1.1. Simulated Data Set

This paper extracts 400 sample sets from questionnaire survey data [15]. The total number of survey data is 421, and its descriptive statistical analysis is listed in Table 1. On the basis of the data generation process and the analysis of user network behavior according to the literature [45], a simulated data set is constructed by constituting a series of reasonable context generation rules and user behavior generation rules. Simulated data set is used as the input data source of the mobile personalized recommendation system. The simulation of the data set is described as follows.

(1) User data set. The dataset size is 400, mainly including the user's unique ID, ID Card, Occupation, Address, Birthday, etc.
(2) Service data set. The dataset size is 100, and service attributes includes service identity (SID), service type, service name, service description, etc.
(3) The matrix of "user-privacy concerns intensity". This paper processes the sample data set of questionnaires and constructs the "user-privacy concerns intensity" matrix (400 × 6).
(4) The matrix of "user-service behavior" (400 × 100). When the user adopts the personalized recommendation service, the behavior variable value is 1, otherwise the user's behavior variable value is 0.
(5) The context data set. Five types are selected, such as time, device, location, sentiment, activity status.

Table 1. Descriptive statistical analysis of survey data.

Characteristics	Questionnaire Item	Frequency	Percentage (%)
Sex	Male	205	48.69
	Female	216	51.31
Age	Less than 18 years old	89	21.14
	18–24 years old	228	54.15
	25–34 years old	57	13.54
	Over 35 years old	47	11.16
Educational background	High school or below	23	5.46
	Junior college	75	17.82
	Undergraduate	218	51.81
	Master degree or above	105	24.91
Occupation	student	254	60.24
	Public institutions/civil servants	20	4.78
	Professional technicians (doctors, lawyers, etc.)	48	11.43
	Enterprise staff	85	20.14
	Self-employed worker/freelancer	9	2.22
	Others	5	1.19
Experience of usage of M-commerce service	Less than 1 years	53	12.63
	2 or 3 years	107	25.43
	4 or 5 years	191	45.39
	More than 6 years	70	16.55

4.1.2. Benchmark Datasets

Users' privacy concerns are usually related to context and sentiment orientation. This paper uses MovieLens as an experimental benchmark dataset to compare several methods. The data set includes not only user and project (movie) information, but also the user's emotional information at that time. MovieLens data sets contain context, such as geographic location, comment time, and emotional tendencies. MovieLens is divided into training data set and testing data set. The training data set has 4,544,409 records, which include scores made by 105,137 users to 25,058 films regarding 16 kinds of emotional influences. The testing data set collects 19,506 records, which includes scores made by 160 users to 3396 films regarding the effect of 16 kinds of emotional influences. The user takes five points as the step size, while the range of score is [0,100]. Because the addition of emotion in data dimension makes the dataset sparser, it is difficult to calculate user similarity through few movie rating data. After many tests, this paper finally determines that each user needs to score at least 150 movies in MovieLens, and at least 20 same movies are scored by these users ($|Mcc'|\min = \min\_corated\_num = 20$). Then, 3300 users, 2,578,325 scores, and 6,548 movies are selected.

4.2. Evaluation Metrics

At present, *P@R*, *MAP*, and *DOA* indicators are used to measure the fit between user's preferences and ranking of results. *P@R* represents the correlation between the top *R* goods/services in the recommended list and the user's real preference.

$$P@R = \frac{\textit{The}\text{ number of Top } - \text{R recommendation service including R services in the test set}}{R} \tag{11}$$

MAP (Mean Average Precision) can measure the average accuracy of algorithm in ranking of user search results. It is introduced into collaborative recommendation method to evaluate the accuracy of the proposed method in recommending related items.

$$MAP = \frac{1}{|c|}\sum_{i=1}^{|c|}\frac{1}{|R_i|}\sum_{j=1}^{|R_i|}\frac{j}{r_{ij}} \tag{12}$$

DOA (Degree of Agreement) is also one of the evaluation indicators to measure the ordering accuracy of the recommendation.

$$DOA_{U_j} = \frac{\sum\limits_{(i\in T_{U_j}, k\in NW_{U_j})} check\_order_{U_j}(I_i, I_k)}{\left|T_{U_i}\right| * \left|NW_{U_j}\right|} \tag{13}$$

$$check\_order_{U_j}(I_i, I_k) = \begin{cases} 1, predict\_rank_{I_i} \geq predict\_rank_{I_k} \\ 0, otherwise \end{cases} \tag{14}$$

$predict\_rank_{I_i}$ is the predicted position of I_i in the recommended list.

4.3. The Analysis of Experimental Results

4.3.1. Analysis of Factors Affecting Privacy Concerns and Measurement of Privacy Concerns Intensity

Firstly, the analysis module of privacy concerns is embedded in personalized recommendation systems, that is, when registering in website, users should fill out the questionnaire on the influence factors of users' privacy concerns in personalized recommendation services. Secondly, this paper calculates each hypothesis path coefficient based on the structural equation model, and analyzes the overall path of the questionnaire data. Finally, the paper uses the AMOS17.0 software to verify whether the relationship between the variables is significant, and Figure 2 is the path coefficient of the adaption model.

The above questionnaire results are expressed in numerical data, which is used as a part of the data set for the user-based collaborative filtering method integrated with privacy concerns intensity (PI-UCF) in Section 3.1.

This paper sets some reference values for the fitness index to evaluate whether the model is reasonable, such as $\chi 2/df < 3$, RMSEA < 0.08, GFI > 0.90, CFI > 0.90, AGFI > 0.80, and so on [46]. If the above conditions are met at the same time, it means that the model fits well and the path coefficient can reflect the actual data.

As shown in Table 2, each fitness index meets the reference value requirements, so the data in this study is ideal for the fitting degree of the model.

Table 2. Fitness index of model.

Fitness Index	χ2/df	GFI	AGFI	CFI	NFI	NNFI	RMSEA
reference value	<3	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
actual value	1.87	0.912	0.875	0.947	0.921	0.958	0.046

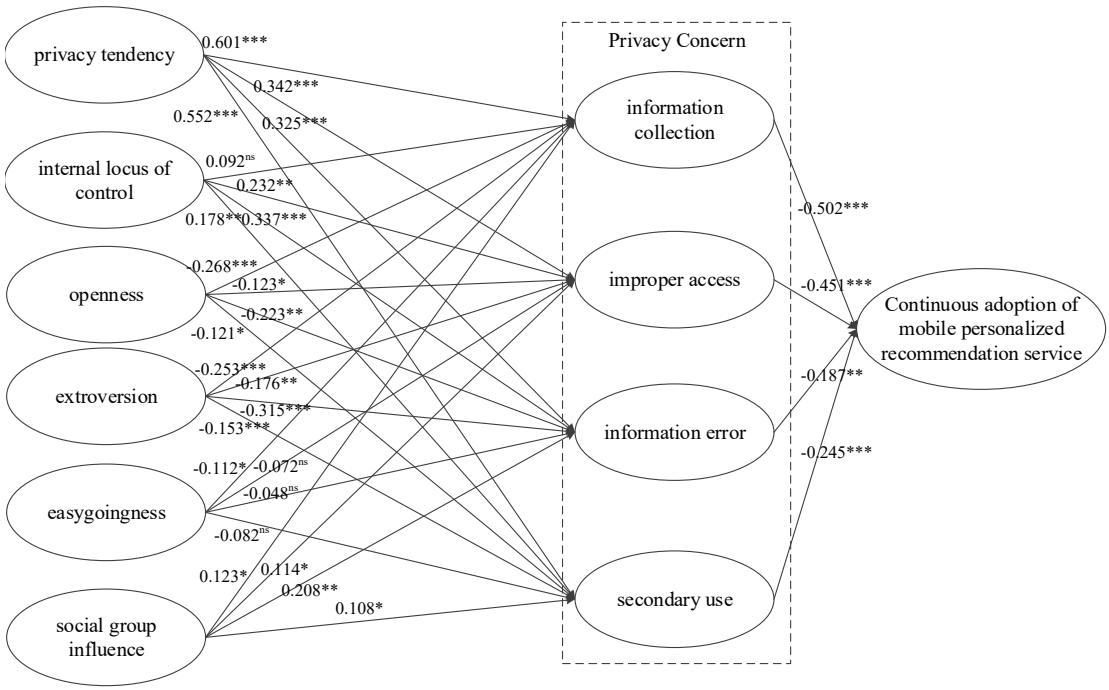

Figure 2. Analysis of factors affecting privacy concerns based on structural equation modelling. *** indicates significant level $P < 0.001$; ** indicates significant level $P < 0.01$; * indicates significant level $P < 0.05$; ns indicates $P > 0.05$.

4.3.2. Comparison of Hybrid Collaborative Filtering Recommendation Method Based on Fusion of Prediction Rating with Different α

In this paper, the prediction rating of target user by PI-UCF ($\alpha = 1.0$) is weighted with the prediction rating of target user by CS-UCF ($\alpha = 0.0$) to implement a hybrid collaborative filtering recommendation method PS-HCF based on fusion of prediction rating. The weighting coefficient α represents the importance of these two algorithms. The compared results of PS-HCF with different α in the *MAP*, *DOA*, *P@10*, and *P@5* ranking evaluation indicators, are shown in Tables 3 and 4. This experiment sets $\alpha = 0.0, 0.2, 0.4, 0.6, 0.8, 1.0,\ k = 10, 20, 30, 50$. The comparison of the results in multiple groups experiments shows that the sorting accuracy of the PS-HCF is high, and the relation between the value α and the order accuracy are nonlinearly increasing and decreasing, and the performance of PS-HCF is the best when $\alpha = 0.6$.

Table 3. Comparison of hybrid collaborative filtering recommendation method based on fusion of prediction rating with different α (*P@R*).

PS-HCF	P@5(k = 10,20,30,50)				P@10(k = 10,20,30,50)			
	10	20	30	50	10	20	30	50
0.0	0.66	0.71	0.73	0.76	0.64	0.67	0.71	0.72
0.2	0.68	0.74	0.75	0.77	0.67	0.70	0.72	0.74
0.4	0.71	0.75	0.78	0.77	0.69	0.72	0.73	0.75
0.6 (cut-off point)	0.72	0.76	0.79	0.80	0.70	0.73	0.74	0.76
0.8	0.71	0.74	0.76	0.78	0.68	0.72	0.73	0.74
1.0	0.67	0.71	0.73	0.76	0.66	0.70	0.71	0.73

Table 4. Comparison of hybrid collaborative filtering recommendation method based on fusion of prediction rating with different α (MAP, DOA).

PS-HCF	MAP (k = 10,20,30,50)				DOA (n Selects 20–80%,30–70%, 40–60%,50–50%)			
	10	20	30	50	20–80%	30–70%	40–60%	50–50%
0.0	0.69	0.73	0.76	0.78	0.75	0.78	0.80	0.81
0.2	0.72	0.75	0.78	0.79	0.77	0.80	0.82	0.82
0.4	0.73	0.76	0.79	0.80	0.78	0.81	0.83	0.83
0.6 (cut-off point)	0.74	0.77	0.80	0.81	0.79	0.81	0.83	0.84
0.8	0.72	0.76	0.78	0.80	0.78	0.80	0.82	0.83
1.0	0.70	0.74	0.77	0.79	0.76	0.79	0.81	0.82

4.3.3. Comparison of the Recommendation Performances of CS-UCF, PI-UCF, PS-HCF, S-UCF, and UCF

In order to verify the impact of context, emotional tendencies, and privacy concerns on personalized recommendation services, this paper compares some kinds of collaborative filtering recommendation methods that incorporate the above information. Firstly, the collaborative filtering algorithm based on user integrated sentiment (S-UCF) is compared with the traditional user-based collaborative filtering method UCF. The weights are set to $\alpha = 0.6$, and the evaluation indexes are *P@10* and *P@5*. Although the overall performance of S-UCF is better than that of UCF, its indexes are lower than that of UCF when KNN is 15 and 20. On the one hand, the complexity of user's sentiment makes S-UCF deviate when user preferences are calculated. On the other hand, the sparsity problem of actual data is serious. Especially when the emotional information is introduced, the user-network service matrix is sparser, leading to a lack of score data support for the user similarity calculation based on sentiment analysis. However, the user-based collaborative filtering approach combined with context analysis is better than the UCF. Because it firstly uses context to cluster users, narrowing the construction scope of the nearest neighbor set. CS-UCF validates that the introduction of context can improve the accuracy of user preference analysis, thus enhancing the recommendation performance of collaborative filtering. The detailed experimental results are shown in Figure 3.

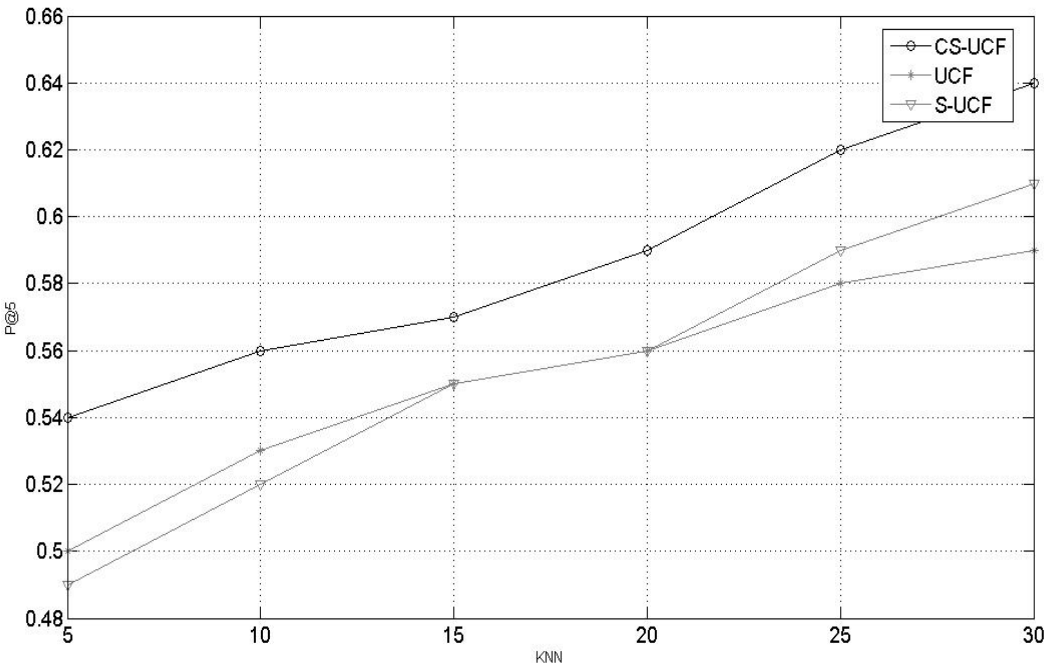

Figure 3. The accuracy of recommendation of CS-UCF, S-UCF and UCF in simulated data set.

In addition, the user-based collaborative filtering method PI-UCF, which is integrated with privacy concerns, is superior to the traditional UCF and CS-UCF. Because of obtaining the privacy concerns intensity of each user when adopting MPRS, to a certain extent, the "user clustering" is realized by privacy concerns, and the quality of recommendation is improved. It also shows that it is very meaningful to introduce privacy concerns intensity into collaborative filtering recommendation. Finally, comparing with CS-UCF, PI-UCF, S-UCF, and UCF, the PS-HCF method integrated with privacy concerns and context analysis is the best. Therefore, the integration of PI-UCF and CS-UCF to forecast rating for target users at the recommended stage can improve the overall performance of the mobile personalized recommendation system. The specific experimental results are shown in Figure 4.

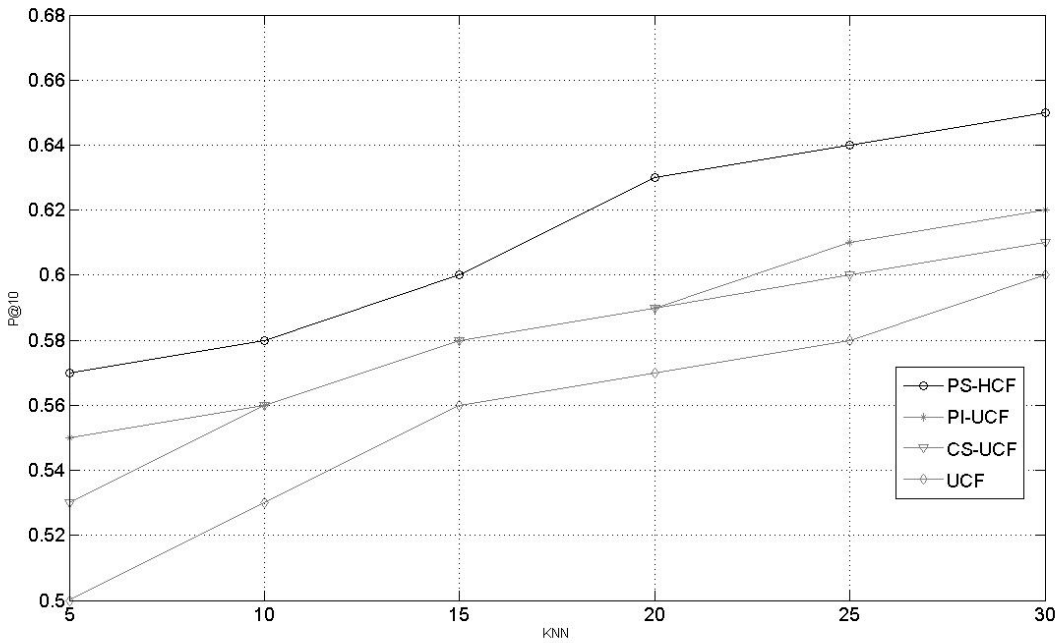

Figure 4. The accuracy of recommendation of PS-HCF, PI-UCF, CS-UCF, and UCF in simulated data set.

In this paper, the standard dataset MovieLens is used to further test the recommended performance of PS-HCF, PI-UCF, CS-UCF, and UCF methods. The MovieLens is divided into training data set and testing data set. It adopts mean absolute error (MAE) index to compare the advantages and disadvantages of the above methods. The lower the MAE is, the better the recommendation is. The nearest neighbor set KNN is $k = 50, 100, 150, 200, 250, 300$. The experimental results are shown in Figure 5. It can be seen that the PS-HCF in this standard dataset also achieves good prediction results. At the same time, the MAE value is lower than that of several other collaborative filtering methods, that is, the PS-HCF accuracy is higher than the other methods, and when the nearest neighbor number is 300, the recommendation accuracy of the PS-HCF is the highest.

At the same time, this paper uses MovieLens as the standard data set, and selects four algorithms, namely PS-HCF, PI-UCF, CS-UCF, and UCF, to compare and analyze the correlation of the recommended sorting on the DOA index. The results are shown in Table 5. The privacy concerns intensity annotated takes contextual factors such as emotion, time, and position into consideration. The experimental results show that the PS-HCF method proposed in this paper has the maximum DOA value on four different sets of data. It indicates that the goods/services and these orders recommended by the PS-HCF are more consistent with the actual requirements of the user, and the recommendation method of considering the privacy concerns intensity and the comprehensive context information in personalized recommendation service can improve the quality of recommendation service.

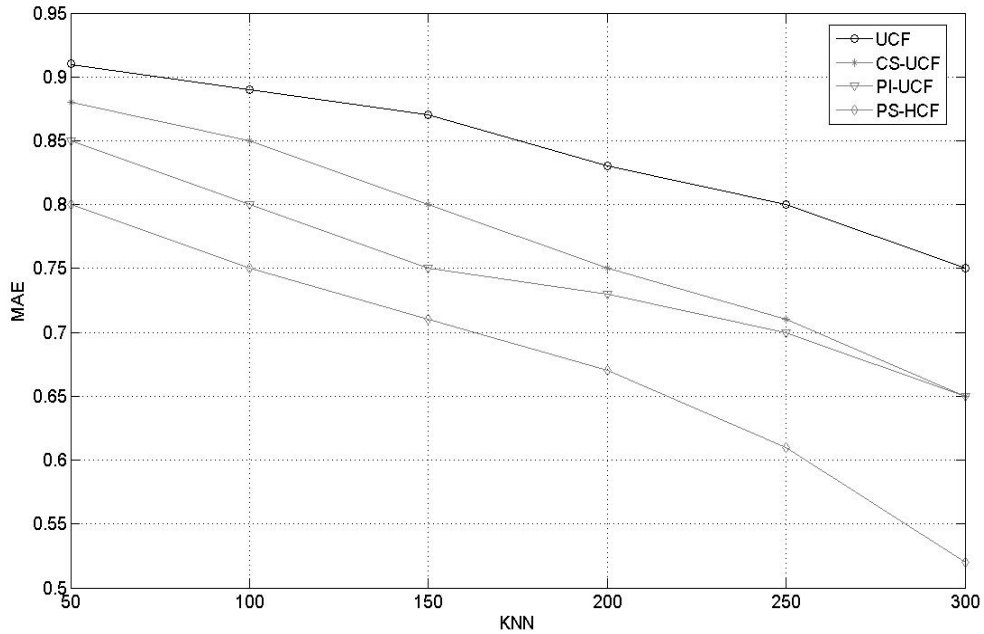

Figure 5. The MAE comparison of PS-HCF, PI-UCF, CS-UCF, and UCF in benchmark datasets.

Table 5. Contrasting results of different methods (DOA %).

Alg.\Split	20–80%	30–70%	40–60%	50–50%
CS-UCF	70.2	68.2	66.2	63.3
UCF	73.1	71.3	69.5	66.2
PI-UCF	78.3	77.5	73.5	68.8
PS-HCF	86.4	84.2	81.3	79.8

5. Discussion

Research cognitive process of users' privacy concerns in MPRS, including the composition of privacy concerns; influence elements of privacy concerns, and how to measure the relationship between these elements. This paper mainly studies the theory of privacy concerns and the theory of rational behavior, and based on the above theory to build MPRS adoption behavior theory model oriented to user privacy concerns. First of all, the paper summarizes six influencing factors of privacy concerns from the perspective of the user to users' privacy tendency, users' internal control, openness, extraversion, agreeableness, and social groups influence. After that, the paper develops the scale of independent variables and dependent variables, and defines these variables. On this basis, the paper researches the influence of each factor on the privacy concerns, and deeply analyzes user's intensity of privacy concerns, psychology of privacy preference, and network behavior. Second, empirical results show that the user privacy tendency, internal locus of control, and social groups have significant positive influence in privacy concerns about information collection, misuse, improper access, and secondary use. It also shows that user's openness, agreeableness, and extraversion have significant negative influence in the above four dimensions of privacy concerns, which have significant negative influence in adoption behavior intention of MPRS. Finally, the paper proposes a mobile personalized recommendation model based on privacy concerns and context analysis. It uses "privacy concerns intensity" to find neighbors set, and uses the known rating to predict the score of the target users. After that, the paper makes the "user-goods/services" clustering by using context similarity calculation method, which makes each subclass of "user-goods/services" have similar context. Then, a novel collaborative filtering recommendation algorithm is proposed, combining the user's privacy concern

and the context similarity, which solves problems such as data sparse in mobile recommendation, and reduces the degree of users' privacy concerns.

On the one hand, from the perspective of the sustainable development of mobile commerce, this paper studies the privacy concern impact mechanism and mobile recommendation method for mobile personalized recommendation service. It improves the control of users on the disclosure, distribution, and use of personal information, and combination of technical method research and empirical research expands the current research paradigm of mobile personalized recommendation under privacy concerns. On the other hand, this paper uses management and information discipline-crossing theory, such as privacy concern, data mining to carry out research. It is a new attempt to combine the field of personalized recommendation with the research of user privacy concern, which also complements and enriches the current academic methods and theoretical research of privacy protection in mobile commerce.

6. Conclusions and Future Work

With the wide application of MPRS in mobile commerce, how to protect the privacy of users while using MPRS, and how to obtain the fine-grained requirements of the users in the complex context are outstanding. Mobile personalized recommendation technology considering privacy concerns and context is ready to come out. Since MPRS predicts target users' interests and accurately recommends services to meet user's actual psychological needs, it can help users to complete cognitive decision-making. Therefore, this paper proposes a recommendation model based on subjective privacy perception and objective recommendation technology. The main conclusions are as follows:

(1) Since the preferences of target users are often similar to that of users who have common privacy concerns, this paper uses six influence factors of privacy concerns to calculate the comprehensive user's similarity. Then, a user collaborative filtering method incorporating privacy concerns intensity is proposed.
(2) It can better obtain users' interests and match the users' preference behaviors by learning in the complex context. It also can effectively alleviate the problems of collaborative filtering data sparsity and cold start by deeply mining context. Therefore, this paper proposes a user-based collaborative filtering method incorporating context similarity.
(3) Finally, mobile personalized recommendation services combining privacy factors with context information can reflect the actual needs of the user and meet the practical application, and alleviate the problems related to the privacy concerns in MPRS and the collaborative filtering methods.

Although this paper has put forward privacy concern and context analysis methods to improve the prediction accuracy of mobile personalized recommendations in the mobile e-commerce, some limitations also need to be pointed out. On the one hand, privacy concerns regarding complex mobile commerce context affect users' consumption intention, and the context similarity algorithm based on context ontology-tree may not be adaptive to user dynamic preference, which will lower the quality of recommendations. On the other hand, in the process of designing a mobile recommendation service, we have not proposed the privacy protection policy for customer privacy concern issues. Therefore, the follow-up study of this research will further use data mining methods to extract dynamic user context preferences, on which collaborative filtering recommend method will propose to be based. At the same time, in view of the importance of privacy protection, research of personalized recommendation services will be carried out in the future from the perspective of user privacy disclosure control, privacy preference, and so on.

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