

## Retraction

# Retracted: Consumer Behavior Based on Big Data and Cloud Computing and Construction of Customer Perception Mobile Terminal System

### Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] C. Yu, M. H. Shu, P. Ho, and J. Huang, "Consumer Behavior Based on Big Data and Cloud Computing and Construction of Customer Perception Mobile Terminal System," *Security and Communication Networks*, vol. 2022, Article ID 7531530, 11 pages, 2022.

## Research Article

# Consumer Behavior Based on Big Data and Cloud Computing and Construction of Customer Perception Mobile Terminal System

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The arrival of the era of big data has realized the transformation of people's production and lifestyle. At the same time, it also increases people's desire to consume, and the feedback behavior of consumers' comments and ratings is the feedback of users' experience in merchants' products, that is, the matching of products to consumer needs and preferences. When the product can reach the user's satisfaction level, the customer-aware mobile terminal system is constructed and optimized by using the advanced methods and technologies of big data information display and the principles and laws of the collaborative filtering algorithm in cloud computing. It ensures the ecological development of the consumer industry. Among them, in the experimental evaluation of the collaborative filtering recommendation algorithm, the mean absolute error (MAE) and root mean square error (RMSE) values of the SVD<sup>++</sup> algorithm are higher than those of the other three algorithm models, indicating that other algorithm models can effectively improve the accuracy of the recommendation algorithm. A cross-sectional comparative analysis of experimental results has shown that, as the number of neighbors increased, the MAE and RMSE values first decreased and then increased. When the number of neighbors  $N$  is 25, the MAE and RMSE reach the minimum value, so the optimal number of neighbors is 25. Therefore, it is very important to use the collaborative filtering algorithm to analyze and construct the consumer behavior and customer perception mobile terminal system.

## 1. Introduction

With the rapid development of the current era, consumers gradually have the awareness of post-consumer feedback and comments, and some open user comment platforms have emerged. User-generated content has emerged as the times require and has become an emerging development model, such as China's Dianping and Europe's Yelp platform. This type of platform is responsible for the management and operation of consumer-generated reviews and product reviews. In addition to writing reviews, consumers also browse review information and conduct social interactions. In this way, the study of user joining has become

the rule of the community to write and generate information so that users have a good experience. It is important to conduct consumer reviews to review domestic products in the market, follow new developments, analyze research, and conduct consumer reviews. It has promoted the positive development of the platform and helped the progress and innovation of the internet platform. In the development of the Internet UGC (User Generated Content) platform, the massive information accumulated gradually has made most of the user-generated content buried, making the value of the platform not fully highlighted. On the one hand, it makes it difficult for most merchants to be discovered by consumers, thus failing to obtain user

purchases and comments. On the other hand, the exploration of massive data cannot satisfy consumers who are pursuing high efficiency, thus affecting the user's experience of using the platform.

In the UGC platform, massive information is the treasure of the platform, and merchants and consumers generate feedback through information. Thus, the fundamental of operation and development is generated, and the ultimate goal is to obtain satisfactory information for users, thereby increasing user stickiness. At the same time, the development of the UGC platform needs to provide users with community interaction in addition to high-quality user-generated information. As a human need, social networking is widely used on the UGC platform. Social networks help the dissemination of platform information, promote users' experience of using the UGC platform, and increase the construction of a community atmosphere. How to use generated quality content, analytical special demand, current use, information progress distribution, increased user experience, promotion of old use and new use rate, and generated quality information is an important issue for platform development. This study has analyzed the influence of users' comment behavior on social network by studying the characteristics of users and merchants. Combined with the above research conclusions, the user's comment data on merchants have been integrated, a collaborative filtering recommendation algorithm has been constructed, and the target users have screened user groups with similar characteristics and taste preferences and analyzed the target user's social network. The social familiarity of users is calculated, and a collaborative filtering recommendation algorithm based on the social network is creatively constructed by integrating with the traditional user recommendation algorithm model. The combined calculation method is a kind of famous and commonly used calculation method, based on the historical action of the calculation, the favorable deviation of the calculation, and the promotion of the favorite products that can be used for parallel measurement. It is also common to say that people are happy with their purchases and that they are happy with the goods they buy. All the data in this article have come from the real data of the public comment platform, and the data characteristics have been mined by means of empirical analysis, which has a certain reference value and reference significance for the recommendation of the UGC Internet platform.

In the field of consumption, consumer behavior analysis and the establishment of a customer perception system are closely related to their interests. Among them, De Mooij has aimed to find out the similarities and differences between the three-dimensional models of national culture and consumption and help researchers choose a specific model or dimension for cross-cultural research [1]. Jin has aimed to examine the impact of leisure sports satisfaction on consumer behavior and lifestyle. The results of the study are as follows: physical well-being, social well-being, and

mental well-being have no significant effect on leisure sports satisfaction [2]. Choi has used the 2016 Food Consumer Behavior Survey data collected by the Korea Rural Economic Research Institute to analyze the value system of restaurant consumers in response to changing demands in the food service industry [3]. Hosseini and Ghalamkari research consisted of two parts. First, the content of user reviews has been analyzed by researchers to explore consumers' brand attitudes, purchasing decision processes, and consumer decision-making styles. In the second part, the content of brand posts is coded to examine the creative social media strategies used by these brands and measure their effectiveness [4]. Agnihotri and Bhattacharya have suggested that the poor institutional environment, frugal attitudes, and materialistic values have prompted consumers in emerging economies to indulge in unethical behavior [5]. However, the reason for the above research is that the number source is not clear because of the lack of collection of the numbers, and the research work was only conducted on the theory stage, and there is no practicality.

The use of big data and cloud computing to analyze consumer behavior is a very innovative project. Among them, Huang and Ge research is based on the theory of planned behavior (TPB), introducing consumer cognitive state, product cognition, and incentive policy measures and constructing an influence mechanism model of electric vehicle purchase intention [6]. Zhang et al. have used evolutionary game models to study how environmental life cycle cost (E-LCC) control has affected the decision-making behavior of manufacturers [7]. Olaleye research has combined and extended the unified theory of acceptance and use of technology with the theory of trust and satisfaction to explain the usefulness of mobile applications to retail customers [8]. He et al. have constructed a duopoly pricing model and have captured consumer heterogeneity in two dimensions to study consumers' choice of vehicle adoption and electric vehicles [9]. Yu et al. have established a consumer purchase behavior research model of agricultural product traceability information based on the composite perspective of the product, consumer cognition, and consumer emotion [10]. However, because of the aforementioned scholars in the consumption area, the analysis of consumer behavior is progressing, and there is no general math for technology and consumer behavior analysis.

The innovation of this study is that this study has explored the data characteristics of Dianping users and merchants based on the business information data, user information data, and comment scoring data in the UGC platform Dianping. It has explored the spatial and temporal rules of business, user review behavior, and exploratory research on the impact of users and social relationships on users' willingness to consume and review behavior. It has explored the construction of users' social familiarity to quantify the familiarity of social attributes among users.

## 2. Consumer Behavior Based on Big Data

**2.1. Data Analysis of Dianping Platform Based on Consumer Behavior.** Dianping is a platform for users to share content generated by merchants, and users write ratings and evaluation content for merchants on the platform. Ratings are on a star system. The lowest score is 1 star, that is, 1 point, the highest 5 stars, 5 points, and the level of the score indicates the user's overall rating of the merchant [11]. The evaluation content includes text and pictures. It is necessary to record the user's dining experience in the form of text, and the number of words should not be less than 10 words. The content can include business environment, food taste, and personnel services. Users can choose to upload pictures taken during dining for intuitive evaluation and sharing. After the user generates a rating comment, the backend staff of the platform will review the rating content for 3–24 hours to ensure that the rating and comment content is authentic and effective. Its attraction method is shown in Figure 1.

Figure 1 shows that when the user browses the business information, on the one hand, he learns the situation of the business through the introduction information of the business interface and the pictures of the business's autobiography. On the other hand, the feedback and word-of-mouth of other users on the business situation are obtained through the user's overall rating of the business and the comments and pictures uploaded by the user [12, 13]. Information is provided for users to understand the business information platform. It provides a reference for offline consumption and forms comments and pictures, forming a virtuous circle. In addition, as a UGC platform, Dianping has strong social attributes, and users have a high degree of active participation and a large space for interaction. All data sources in this study are from real platform data, divided into two interrelated programs. One retrieves city merchant information data and merchant review data, and the other retrieves individual user information data and historical review data based on user IDs [14]. The two crawlers wrote more than 1,000 lines. Since the website not only blocks the IP but also slides the CAPTCHA screen every half hour to unlock the backend, the schematic diagram is shown in Figure 2.

As can be seen from Figure 2, through the dismantling of data analysis and mining requirements and the comparison of data using major user-generated content platforms, it is found that the dimensions and quality of the public comment data are in line with the requirements of this study and can be obtained through web crawling for scientific research [15, 16]. Therefore, this study has used the request library in Python to obtain the HTML of the web page, parsed the data through Xpath and re-regular expressions, and used the MySQL database to save the data in three separate tables "Shop," "Comment," and "Customer," which are the platform's business information and comments and the user's information, respectively, and connect the three tables in series according to the user ID, business ID, and comment ID. The specific idea is as follows: first traverse according to the business, crawl the basic information of the business and the comment information of the business, and then

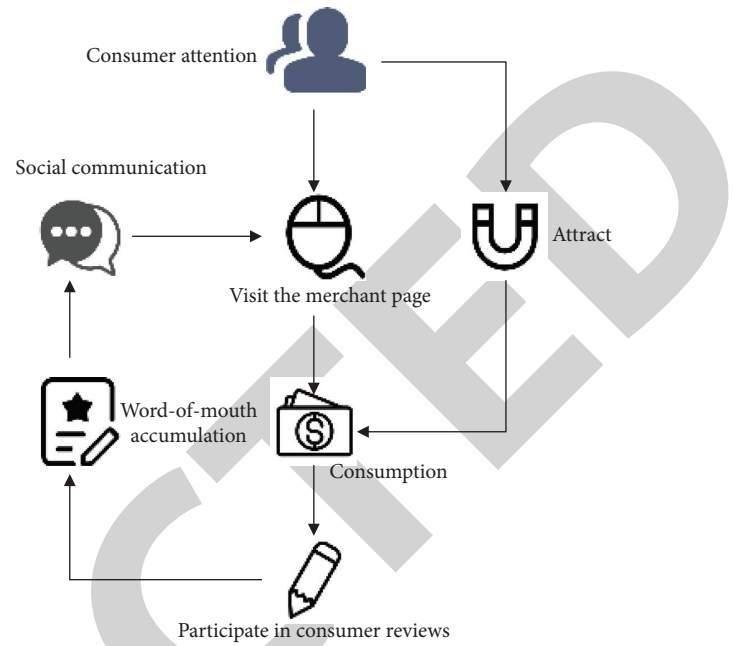


FIGURE 1: Dianping's user attraction methods.

according to the comment information, make a table list of the basic information of the user and the user IDs he is following/followed by and save it in the user table. Finally, it traverses according to the user and crawls all the comments of the user and the information of the corresponding business. After the above three steps, the completeness of the calculation is guaranteed so that the analysis is provided afterward, and the consistency is guaranteed. Its main point is Nanjing City, which has a limited capacity to accept orders from flat platforms, which is why the number of orders has been adjusted to 500 times/hour. Immediate use is not yet prosperous use, but if you use it for a long time, it will be confirmed that the IP progress is abnormal. Because of this recruitment proxy IP method, immediate use forwarding destination contact proxy, through proxy IP connection target, through proxy change input target IP. The schematic diagram of its proxy server is shown in Figure 3.

It can be seen from Figure 3 that the platform server has a limited carrying capacity, so the number of calls is adjusted to less than 500 times/hour. Even if it is not called frequently but used for a long time, it will still lead to malicious detection of the server, and it will be identified as an abnormal IP for sealing. This method of proxy IP immediately uses the proxy service and the IP connection target of the proxy service and changes the target of the service to the IP of the proxy service.

### 2.2. Collaborative Filtering Algorithm Based on Big Data.

In the user-based collaborative filtering recommendation algorithm, the similarity of users is calculated, and the ratings of two users for the same thing (such as a business) are generally analyzed. The main idea is that the closer the ratings of two users to the same thing and the more things with similar ratings, the more obvious the two users'

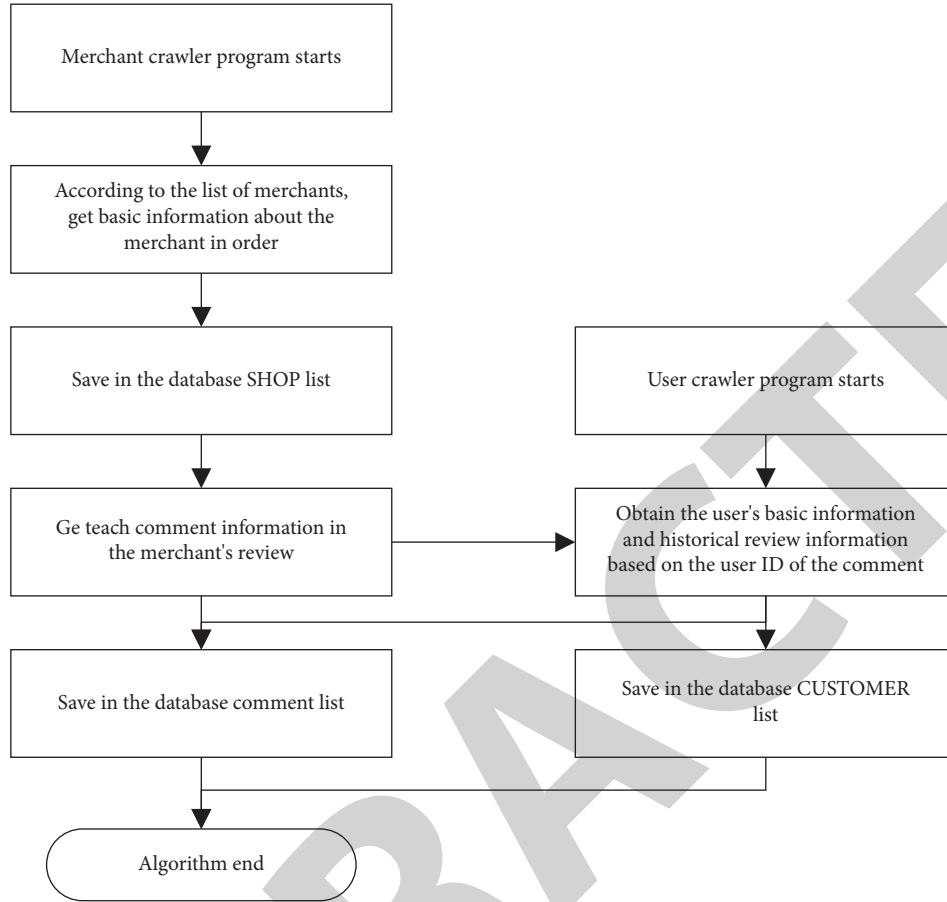


FIGURE 2: Schematic diagram of merchant crawler.

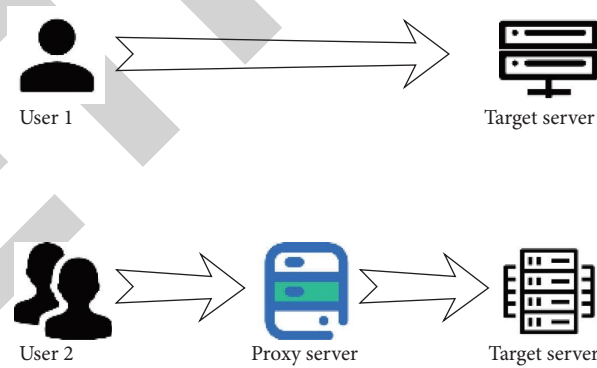


FIGURE 3: Schematic diagram of a proxy server.

preference for things and the higher the similarity of their interests [17]. An ITPC similarity calculation model that combines users, item average scores, and time factors is

proposed. The calculation method is shown in the following formula :

$$\text{sim\_ITPCC} = \frac{\sum_{j \in I_a \cap I_b} [(R_{a,j} * \bar{R}_a * \rho_M) - (R_{a,j} * \bar{R}_j * \rho_i)] [(R_{b,j} * \bar{R}_b * \rho_M) - (R_{b,j} * \bar{R}_j * \rho_i)]}{\sqrt{\sum_{j \in I_a} [(R_{a,j} * R_a * \rho_M) - (R_{a,j} * \bar{R}_a * \rho_M) - (R_{a,j} * R_j * \rho_i)]^2}} \quad (1)$$

where  $\bar{R}_a$  represents the average user rating. The specific calculation method is as follows, which is the average of all item ratings of user  $a$ :

$$\bar{R}_a = \text{avg} \left( \sum_{U \in R_a} R_{a,j} \right), \quad (2)$$

where  $\bar{R}_b$  represents the average score of the user's score, and the specific calculation method is as follows, which is the average of the scores of all items of the user  $b$ :

$$\bar{R}_b = \text{avg} \left( \sum_{U \in R_b} R_{b,j} \right), \quad (3)$$

where  $\bar{R}_j$  represents the average of the item scores, and the specific calculation formula is as follows, which is the average of the scores of all the corpse items that have scored the item  $j$ :

$$\bar{R}_j = \text{avg} \left( \sum_{I \in R_j} R_{a,j} \right). \quad (4)$$

The combination of the average user score and the average item score uses the correlation of full-text contextual information to fully learn the relationship between users' information in different dimensions.  $\rho_u$  is the user's long-term time factor, and the calculation formula is as follows:

$$\rho_M = \exp \left( \frac{T_e^u - T_s^u}{T_e^u} \right), \quad (5)$$

where  $T_e^u$  and  $T_s^u$  are the last and first time when user  $u$  provides ratings, respectively. Among them,  $\rho_i$  is the long-term time factor of the project, and the calculation method is as follows:

$$\rho_i = \exp \left( -\frac{T_e^i - T_s^i}{T_e^i} \right), \quad (6)$$

where  $\bar{R}_a$  and  $\bar{R}_b$  are the time when the item  $i$  is rated for the last time and the first time, respectively. The above findings learn long-term user preferences and item popularity by integrating types with factorized features to address sparsity and decay.

**2.2.1. Research on the URP Model of User Rating Preference Difference.** In order to improve the user's preference for the geographical environment, the similarity effect between the number of individuals and the amount of variation is reduced. The specific calculation method of URP is modeled as shown in the following formula:

$$\text{URP}(a, b) = \cos(|\bar{R}_a - \bar{R}_b|), \quad (7)$$

where  $\bar{R}_a$  and  $\bar{R}_b$  represent the average ratings of user  $a$  and user  $b$ , respectively, and the coefficients of variation of user  $a$  and user  $b$  ratings, respectively. In the application of the URP model in this study, it can be calculated directly using the information in the user item rating matrix. The objective weight is given as a normalized measure to measure the

user's rating behavior preference, which eliminates the influence of different users due to different rating preferences [18]. The specific calculation method of the coefficient of variation (CV) is shown in the following formula:

$$\text{CV}_a = \frac{\text{Var}_a}{\bar{R}_a}, \quad (8)$$

where  $\text{Var}_a$  is the score variance of user  $a$ , and the calculation formula is shown in the following formula:

$$\text{Var}_a = \frac{\sum_{j \in I_a} (R_{a,j} - R_a)^2}{|I_a|}, \quad (9)$$

where  $|I_a|$  represents the number of items rated by user  $a$ .

### 2.2.2. ITPCR Collaborative Filtering Optimization Algorithm.

When only user similarity is considered, the user's personal rating preference is ignored. When only considering the difference in user rating behavior preference and when the average ratings of users  $a$  and  $b$  are the same, the value of URP is 1. The rating preferences of user  $a$  and user  $b$  will be considered the same. It does not take into account the number of items scored by users and the time of scoring [19]. Therefore, this study has adopted the weighted similarity obtained by the adaptive combination of user similarity and user rating preference difference as the similarity between user  $a$  and target user  $b$  and finally named it  $\text{sim\_ITPCR}$  and used it to predict the rating of user  $b$ . The calculation formula is shown in the following formula:

$$\text{sim\_ITPCR} = a \text{sim\_ITPCC} + (1 - a) \text{URP}, \quad (10)$$

where  $a$  and  $(1 - a)$  also ensure that the ITPCR similarity measurement method takes into account the differences in user rating behavior preferences and normalizes the high-rating effect and low-rating effect of each user.

According to the steps of the collaborative filtering recommendation algorithm, by calculating the ITPCR similarity between other users (such as (b)) and the target user  $a$  and arranging them in order from high to low, the nearest neighbor user set NN of user  $a$  is obtained, and the final score prediction is obtained:

$$\hat{R}_{a,j} = \bar{R}_a + \frac{\sum_{b \in \text{NN}} \text{ITPCR}_{(a,b)} (R_{b,j} - R_b)}{\sum_{b \in \text{NN}} |\text{ITPCR}_{(a,b)}|}, \quad (11)$$

where  $b$  represents a user in the nearest-neighbor user-level set of  $a$ .

**2.2.3. Normalized Modeling of User Behavior Difference Coefficients RD and TD.** Using the same method to calculate the similarity, the traditional similarity measurement method is shown in the following formula:

$$\text{sim\_PCC} = \frac{\sum_{j \in I_a \cap I_b} (R_{a,j} - R_a)(R_{b,j} - R_b)}{\sqrt{\sum_{j \in I_a} (R_{a,j} - R_a)^2}}, \quad (12)$$

where  $j \in I_a \cap I_b$  represents the item set that has scored both item  $a$  and item  $b$ , and  $R_{a,j}$  and  $R_{b,j}$  represent the rating of item  $j$  by user  $a$  and user  $b$ , respectively. Different users have different rating scales. For the same item, different ratings of different users may represent the same degree of preference. For the traditional PCC similarity calculation, only the shortcomings of co-rating items are considered. This study introduces the difference between user ratings and the average user rating. The ratio of user rating preference difference is modeled, which not only takes into account the user's non-co-rating items but also measures the user rating preference difference in a more comprehensive and standard dimension [20]. The user rating preference difference coefficient (RD) calculation formula is shown in the following formula:

$$RD = \sum_{j \in I_a \cap I_b} \frac{2|R_{a,j} - R_{b,j}|}{|\bar{R}_a + \bar{R}_b|}. \quad (13)$$

Therefore, the user rating time difference coefficient is modeled according to the following formula :

$$TD = \sum_{j \in I_a \cap I_b} \frac{2|T_{a,j} - T_{b,j}|}{|T_a + T_b|}, \quad (14)$$

where  $\bar{T}_a$  and  $\bar{T}_b$ , respectively, represent the average time of user  $a$  and user  $b$  to score the item, respectively, and the calculation method is as follows:

$$\begin{aligned} T_a &= \text{avg} \left( \sum_{U \in R_a} T_{a,j} \right), \\ T_b &= \text{avg} \left( \sum_{U \in R_b} T_{b,j} \right). \end{aligned} \quad (15)$$

Combined with the exponential function, the similarity improvement coefficient  $P$  is constructed. The calculation formula of the improvement coefficient  $P$  is shown in the following formula:

$$P = 2 * \left[ 1 - \frac{1}{1 + e^{-[\beta RD + (1-\beta)TD]}} \right]. \quad (16)$$

According to Formula (16),  $P$  has a weakening effect on the traditional similarity PCC,  $P \in (0, 1]$ , and the larger the RD and TD, the smaller the  $P$  value, and the smaller the RD and TD, the larger the  $P$  value. Among them,  $\beta$  and  $(1 - \beta)$  also ensure that the coefficient takes into account the user's rating behavior preference surprise and time factors and normalizes it and normalizes the high-rating effect and low-rating effect of each user.  $P$  and the traditional similarity  $\text{sim\_pcc}$  are fused to obtain the final similarity  $\text{sim\_IMPCC}$ , which is shown in the following formula:

$$\text{sim\_ImPCC} = \text{sim\_PCC} * P. \quad (17)$$

According to the steps of the collaborative filtering recommendation algorithm, the nearest neighbor user set NN of user  $a$  is obtained by calculating the IMPCC similarity

of other users (such as (b)) and the target user  $a$  and arranging them in descending order, and the final score prediction is obtained:

$$\hat{R}_{a,j} = \bar{R}_a + \frac{\sum_{b \in \text{NN}} \text{IMPCC}_{(a,b)} (R_{b,i} - \bar{R}_b)}{\sum_{b \in \text{NN}} |\text{IMPCC}_{(a,b)}|}, \quad (18)$$

where  $b$  represents the users in the nearest neighbor user-level set of  $a$ , and the specific value of the number of nearest neighbors  $n$  is demonstrated in the chapter on the optimal value of the latter  $n$ .

### 3. Consumer Behavior Based on Big Data and Cloud Computing

#### 3.1. Collaborative Filtering Algorithm

**3.1.1. The Value of the Parameter  $\alpha$  in the Collaborative Filtering Algorithm.** Aiming at the influence of the value of parameter  $\alpha$  on the global similarity  $\text{sim\_ITPCR}$ , the next step is to carry out variable experimental research on parameter  $\alpha$ , the value range is  $[0,1]$ , and the step size is 0.1. The influence of parameter  $\alpha$  on the prediction accuracy of this algorithm is shown in Figure 4:

As shown in Figure 4, through the parametric variable experiment of the weight factor  $\alpha$  on the MovieLens-1M dataset, it can be found that when  $\alpha = 0.5$ , both the MAE and RMSE achieve the minimum value. Therefore, the optimal value of the parameter weight factor  $\alpha$  in this algorithm is 0.5.

**3.1.2. The Value of the Parameter  $\beta$  in the Collaborative Filtering Algorithm.** In view of the influence of the value of the parameter  $\beta$  on the global similarity  $\text{sim\_IMPCC}$ , the variable experimental research on the parameter  $\beta$  is carried out next, the value interval is  $[0,1]$ , the step size is 0.1, and the experiments are carried out on the MovieLens-1M data set, respectively. The effect of parameter  $\beta$  on the prediction accuracy of this algorithm is shown in Figure 5.

As shown in Figure 5, through the parametric experiment of the weight factor  $\beta$  on the MovieLens-1M dataset, it can be found that when  $\beta = 0.6$ , both MAE and RMSE achieve the minimum value. Therefore, the optimal value of the parameter weight factor  $\beta$  in this algorithm is 0.6.

**3.1.3. Experimental Evaluation of Collaborative Filtering Recommendation Algorithm Based on ITPCR Similarity Calculation.** In order to evaluate the performance of the collaborative filtering recommendation algorithm based on the ITPCR similarity calculation proposed in this study, the following representative models were selected as the comparison method in the comparative experiment. It includes three collaborative filtering recommendation algorithms based on SVD++, LTO, and IPWR similarity calculation methods [21]. It is shown in Tables 1 and 2.

Tables 1 and 2 show the comparison results of each algorithm on the MovieLens-1M dataset. The MAE and RMSE values of the SVD++ algorithm are higher than those

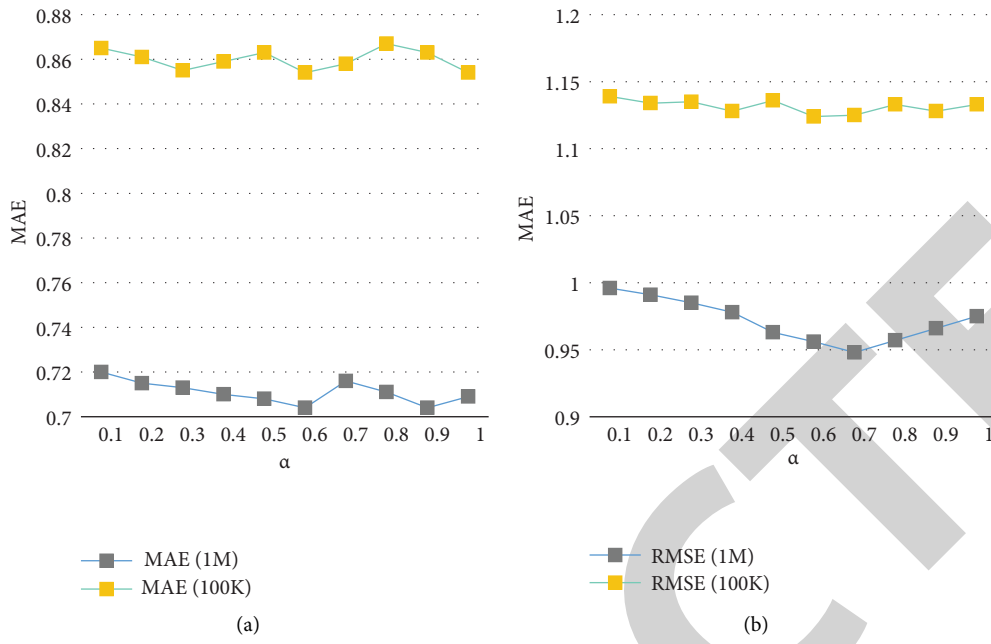


FIGURE 4: Statistical graph of the effect of  $\alpha$  on the prediction accuracy of this algorithm. (a). The effect of  $\alpha$  on MAE (b). The effect of  $\alpha$  on RMSE.

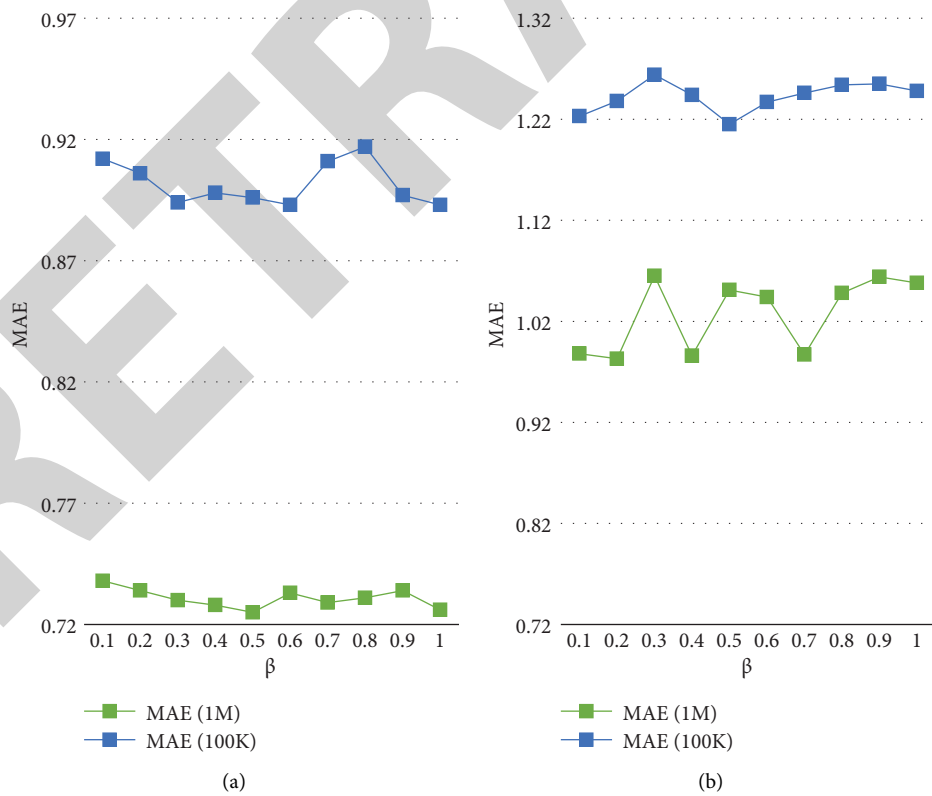


FIGURE 5: Statistical graph of the effect of  $\beta$  on the prediction accuracy of this algorithm. (a). The effect of  $\beta$  on MAE (b). The effect of  $\beta$  on RMSE.



TABLE 1: ITPCR-1M-MAE.

Number of neighbors (MAE)	5	10	15	20
SVD <sup>++</sup>	0.763	0.756	0.756	0.725
LTO	0.735	0.734	0.735	0.739
Ipwr	0.744	0.735	0.723	0.742
ITPWR	0.722	0.716	0.714	0.729

TABLE 2: ITPCR-1M-RMSE.

Neighbors (RMSE)	5	10	15	20
SVD <sup>+</sup>	1.007	0.999	0.993	0.99
LTO	1.001	0.995	0.993	0.99
Ipwr	1.004	0.989	0.983	0.961
ITPWR	0.975	0.966	0.964	0.958

TABLE 3: ITPCR minimum MAE and RMSE values.

Evaluation metrics	SVD <sup>++</sup>	LTO	IPWR	The proposed algorithm
MAE	0.745	0.524	0.728	0.797
RMSE	0.987	0.685	0.986	0.978
MAE	0.896	0.575	0.829	0.887
RMSE	1.135	1.322	1.56	1.697

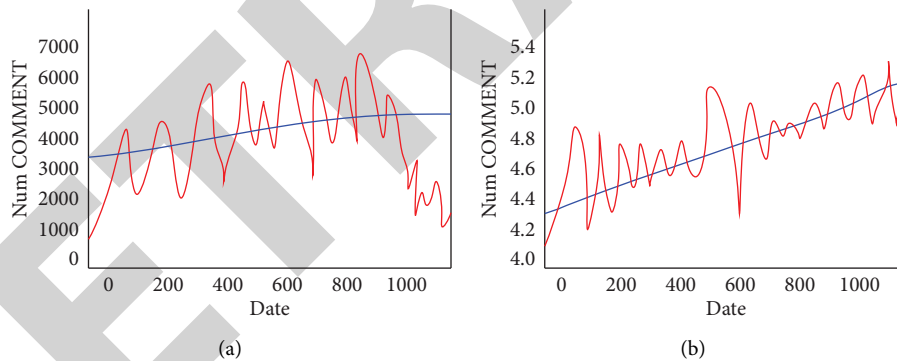


FIGURE 6: Platform development trend forecast. (a) The number of comments that change with the date. (b) The average of rating that change with the date.

of the other three algorithm models, indicating that other algorithm models can effectively improve the recommendation accuracy of the recommendation algorithm. Through the horizontal comparative analysis of the experimental results, it can be seen that, as the number of neighbors increases, the values of MAE and RMSE first decrease and then increase. When the number of neighbors  $N$  is 25, MAE and RMSE achieve the minimum value, so the optimal number of neighbors is 25.

In order to understand the comparative effect of this experiment more intuitively, this study presents the experimental results in the form of a table. Table 3 shows the MAE and RMSE values of the improved algorithm when the number of neighbors is different.

As can be seen from Table 3, as the number of nearest neighbors  $N$  changes, the values of MAE and RMSE both show a trend of decreasing first and then increasing. Only when  $N = 25$  do these two values reach the minimum value.

**3.2. Time Dimension Consumer Behavior.** Considering the time span of the data, the quality of merchants and the degree of user satisfaction are not static, so it is necessary to observe the trend of some indicators concerned in this study over time, which can reflect the development trend of platform popularity and service quality [22]. In order to maintain “physical attributes” in the core facility, it is possible to analyze the processing time on a smooth platform and to

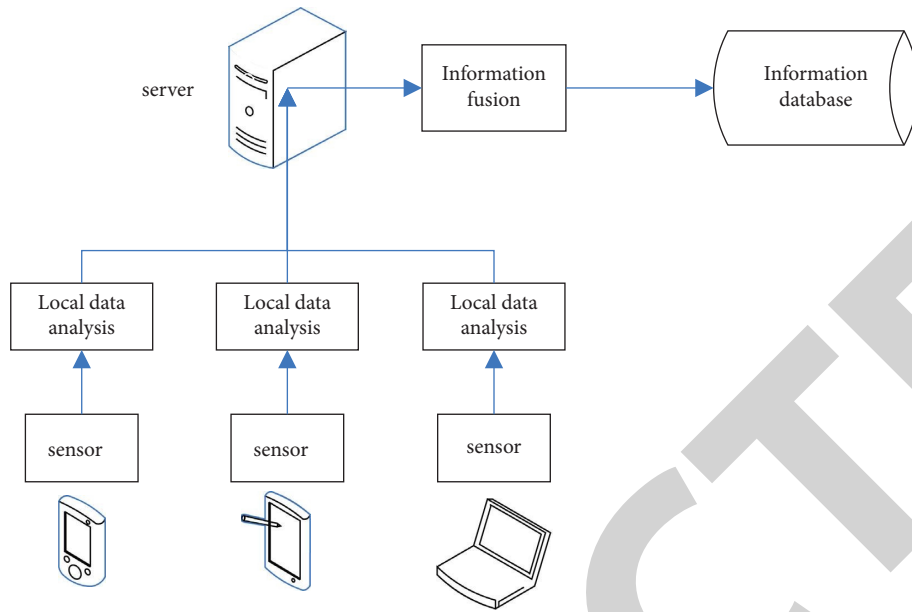


FIGURE 7: Mobile terminal data collection application framework.

eliminate the problem of quality change of the merchant so that the guarantee is established. It is shown in Figure 6.

As can be seen from Figure 6(a), the number of daily comments fluctuates greatly over time, but generally shows an obvious upward trend, indicating that the popularity of the platform is gradually increasing, and users' willingness to comment increases. In a large general city with a 400–800 range, the wave nature needs to be increased. Figure 6(b) shows the trend of the average daily rating, in which the average rating and rating variance have a slight upward and downward trend over time, indicating that, with the development of the platform, consumers' evaluation of food delivery services has generally improved, and the number of evaluations has increased. The difference is also decreasing, which may be reflected in the gradual improvement of the service quality of the platform.

#### 4. Construction of Mobile Terminal System Based on Big Data Customer Perception

**4.1. Data Analysis of Mobile Terminal Customers.** In terms of mobile terminal user context data collection, this study applies it to the realization of mobile terminal data collection, and the frame structure is shown in Figure 7.

In Figure 7, the information collection layer is mainly composed of a group of mobile devices carried by the user. After the context information is collected by the mobile sensing device, it is sent to the server through local analysis on the mobile terminal. The preliminarily processed mobile terminal data can improve the standardization and effectiveness of the data to a certain extent and also have better security to prevent the leakage of private data.

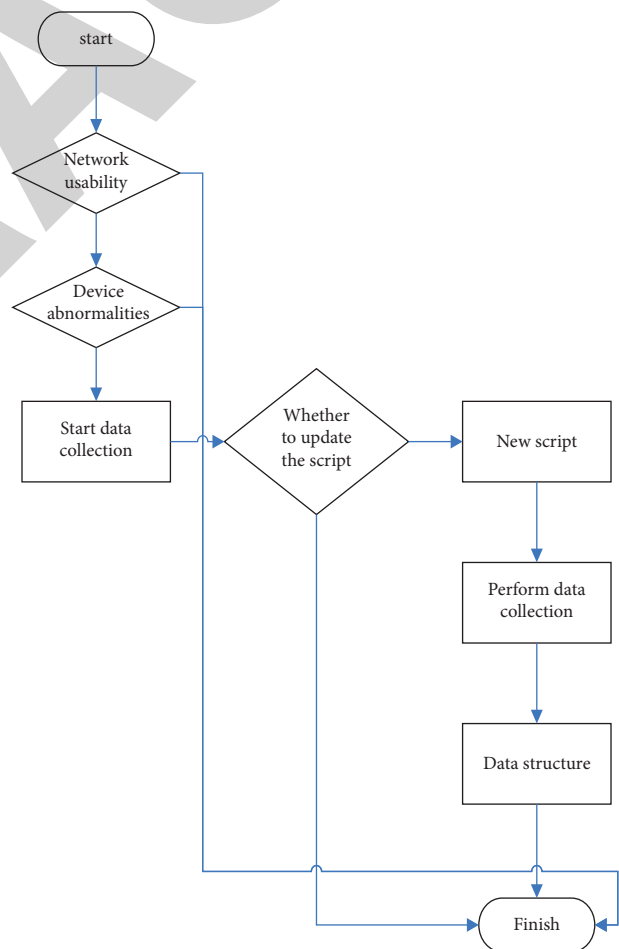


FIGURE 8: Timed data acquisition process.

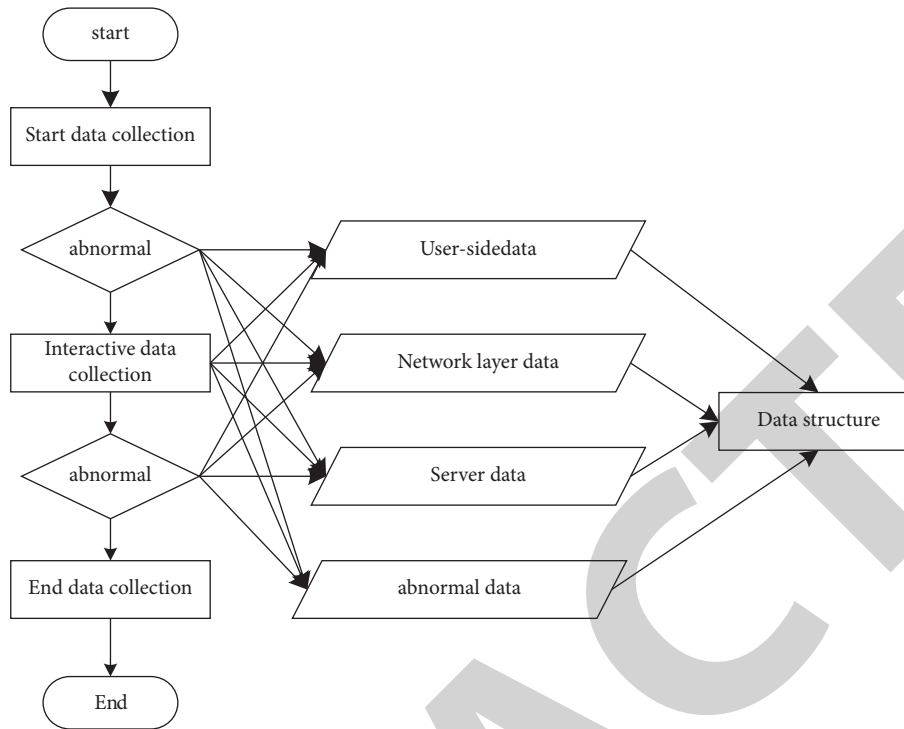


FIGURE 9: Service interaction data collection process.

#### 4.2. Mobile Terminal Timing Data and Service Interaction Data Collection

**4.2.1. Timing Data Collection.** For general context information such as location, temperature, network bandwidth, and device type, due to its variability, multiple collections are required to accurately calibrate the user's context. Therefore, since the frequency of such contextual information changes is relatively low, regular contextual information can be collected by regularly triggering data collection tasks at a certain frequency. The flowchart of the timing data acquisition method is shown in Figure 8.

**4.2.2. Service Interaction Data Collection.** Service interaction data collection is an interactive information collection method that is carried out at the same time as the user's consumption behavior. The context information collected by the service interaction data collection method is mainly divided into user-side context data, network-layer context data, and server-side context data, including the time of requesting the service, the category of goods or services, and user evaluations. The collection process is shown in Figure 9.

As can be seen from Figure 9, the process of service interaction data collection runs through the entire user consumption behavior cycle: when the user makes a consumption request, the server starts the data collection task. This stage mainly collects consumer behavior start time information and user-side data. In the process of consumption behavior, the server continues to collect interactive data. At this stage, the context information of the client, server, and network layers will be collected at the same

time. When the user's consumption behavior ends, in addition to the above three context, information will be recorded, and the specific ending time will be collected. If an exception occurs during the entire service interaction data collection process, the abnormal data information will also be recorded, structured and stored together with other data.

## 5. Conclusions

Based on big data and cloud computing technology, this paper has studied the current consumer behavior and the construction of customer perception mobile terminal systems. In the analysis of consumers, on the one hand, the influence of human attributes on consumer behavior is studied, such as commenting and rating behavior. On the other hand, the influence of social and social network consumer behavior is deeply studied. Then, the above two research studies have been integrated to improve the human-based recommendation algorithm and system to ensure that suitable content is recommended to target users in the massive generated data, which can improve the user experience and solve the problem of information overload caused by the development of the platform. In the research on the customer perception mobile terminal system, two major parts, the timing data collection process and the service interaction data collection process, have been studied. And the data collection framework has been studied, combined with the collaborative filtering algorithm to improve the accuracy and effectiveness of user behavior prediction. However, there are still some shortcomings in this study. Due to the problems of data sparsity and cold start

that have always existed in collaborative filtering algorithms, this study has made neighbor collection based on user familiarity, thereby reducing the weak sparsity problem. And in the current research, scholars have paid more attention to the consumer behavior of rating and review content, while in real usage scenarios, users have paid more attention to subjective experience and the perspective of review content and review pictures when using the product.

### Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to sensitivity and data use agreement.

### Disclosure

The authors confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

### Conflicts of Interest

The authors declare that there are no potential conflicts of interests in our paper.

### Authors' Contributions

All authors have seen the manuscript and approved to submit to your journal.

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