Research Article

E-Commerce Personalized Recommendation Model Based on Semantic Sentiment

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The real economy has moved to online electronic market transactions as a result of the rapid development of Internet technology. Online shopping makes up a growing portion of transactions in China’s e-commerce market, and the number of users who are aware of online payment transactions on mobile phones is rising. Online shopping platforms like Taobao and JD.com, which are all exemplary online shopping platforms, are constantly emerging. However, because there is so much product information available when shopping online, it can be challenging for users to locate the information they need. Recently developed personalized recommender systems have successfully addressed this issue. The system can predict the user’s preferences through extensive data analysis, and it then pushes the predicted information to the user interface, greatly increasing the user’s purchasing efficiency and the advantages of e-commerce. As a result, in the modern era, research on the personalized recommendation model in e-commerce has become increasingly popular. In this study, semantic sentiment analysis—which is improved on the traditional semantic sentiment analysis algorithm—is introduced in the research of a personalized recommendation system, and 1000 users are chosen for an experimental study. On the user’s personalized product recommendation, the improved semantic sentiment analysis and other widely used personalized recommendation algorithms are compared. According to the survey results, the average transaction success rate is 71.3 percent, and the maximum search time is 1.74 milliseconds when collaborative filtering recommendation algorithm is used. Semantic sentiment analysis has reduced search times to a maximum of 1.42 milliseconds and increased transaction success rates to 87.9 percent. After the addition of semantic sentiment analysis, it is clear that the personalized recommendation system model has a higher accuracy in recommending the products that users have expressed an interest in, which can have a greater positive impact on e-commerce transactions.

1. Introduction

E-commerce based on network technology is becoming more and more prevalent in people’s lives as a result of the rapid development of network technology. Internet data are growing at a rate of 50% per year, according to the US Internet Data Center. With the advancement of computing technology on the Internet in recent years, big data has found extensive use across a number of industries. Every year, mobile traders’ dividends are on the decline. Personalized suggestions can successfully match enormous amounts of data, anticipate user preferences, and optimize pages, increasing business effectiveness. In order to determine the user’s characteristics and preferences, personalized recommendations involve gathering and analyzing the user’s historical personal data. The user is then presented with pertinent information and products based on their portrait, which is used to describe their preferences. But as more data become available, the personalized recommendation algorithms that are currently in use are progressively unable to meet the requirements of recommendation accuracy. Therefore, in the age of big data, thorough research on the personalized e-commerce, recommendation is crucial.
For the personalized recommendation system, more and more scholars are involved in this field and have made a series of related researches. Jing et al. proposed a personalized social image recommendation method based on the user-image-label model. In fact, it has been proved that this algorithm could make good use of tags, realizing a user-image-tag-based personalized recommendation system by classifying the content of images, thereby significantly improving the accuracy of personalized recommendation [1]. Aiming at the problem of information overload in current e-commerce, Zhang proposed an e-commerce recommendation system based on personalization. Based on the “shopping basket analysis” function of the Apriori algorithm, through the analysis of the customer’s buying and selling data, it was found that there were many interesting correlations between the products purchased by customers, so that users of e-commerce could shop more conveniently and quickly [2]. Pan and Zhang proposed a context-aware mobile e-commerce personalized recommendation model MTERec to address the sparseness and low accuracy of personalized recommendation data that integrate multiple social information in an e-commerce personalized recommendation model. It was concluded that the algorithm and model have higher customer satisfaction and recommendation accuracy than commonly used algorithms [3]. To overcome some common problems of personalized recommendation algorithms, such as low limitations and low accuracy, Lv proposed a personalized recommendation model based on incremental learning and continuous discrete attribute optimization and conducted related experiments. The obtained experimental results showed that the proposed improved algorithm had a good performance in classification accuracy and accuracy, and the accuracy of recommendation results based on other classification algorithms was significantly lower than this improved algorithm [4]. However, with the progress of the times, the variety of commodities is increasing and the information is increasing day by day. Therefore, a better personalized recommendation algorithm is needed to improve the accuracy of personalized recommendation to customers. In this regard, this paper introduces semantic sentiment analysis in the study of personalized recommendation model.

Semantic and sentiment analysis is a branch of natural language processing, which can analyze and classify the sentiment of text through machine learning. There are also many related studies in this field. To address the Twitter-related sentiment analysis problem, Gupta I proposed a very general but novel transfer method to improve the performance of handling lexical modifier negation during SWN score computation, and the effectiveness of the proposed method was experimentally demonstrated [5]. Ramanathan and Meyyappan applied contextual semantic sentiment analysis to examine people’s personalities based on his or her tweets and proposed three methods for evaluating tweets. And through experimental research, 51.46% of tweets changed their mood because of cooccurrence words [6]. Vo et al. investigated how to use multilayered architectures to understand the nature of emotion representations and proposed a model that used a mixture of semantic and syntactic components to capture semantic and emotional information. Experimental results showed that the model achieved an appropriate level of detail and rich representational capabilities [7]. Based on the limited and complex contextual information of microblogs, Wang et al. proposed a bidirectional long short-term memory (BiLSTM) network with emotional semantic enhancement with a multthead attention mechanism model (EBILSTM-MH) for sentiment analysis. Finally, the effectiveness of the model was proved by experiments [8]. More and more scholars have made research on this, and it can be seen that the research of semantic sentiment analysis has been paid more and more attention. In addition to its own advantages, this paper introduces the semantic sentiment analysis algorithm and applies it to the personalized recommendation model of e-commerce to achieve better recommendation effect.

In the research on personalized recommendation, in addition to studying the semantic sentiment analysis algorithm and improving it, in order to compare the pros and cons of the improved semantic sentiment analysis algorithm model, other common e-commerce personalized recommendation algorithms are also studied, and the differences in the implementation results of the algorithms are analyzed and compared. In the experimental survey of 1,000 selected users, the results show that when using the common collaborative filtering recommendation algorithm, the maximum transaction success rate is only 71.3%. After using the improved semantic sentiment analysis algorithm, the maximum transaction success rate reached 87.9%. In contrast, the improved semantic sentiment analysis algorithm is used in the personalized recommendation model to obtain higher business benefits, which brings new progress to the future development of e-commerce.

2. E-Commerce Personalized Recommendation Algorithm

2.1. E-Commerce Personalized Recommendation System

2.1.1. Definitions. There are many concepts of personalized suggestions based on e-commerce, but the concept given by Resnick and Varian in 1997 is more commonly used at present. Through the use of e-commerce networks, product information and opinions are presented to customers, and users are assisted in choosing what products to buy, or imitating marketers to assist customers in the purchase process [9]. So far, the system has been used in many applications. And with the continuous development of electronic information technology, such as daily necessities, clothing, books, and travel destinations, all use the system for services.

2.1.2. Function. In general, the role of the e-commerce personalized recommendation system is to collect customer information, obtain the customer’s possible interests and preferences according to the algorithm, and recommend it in the customer’s browsing interface. To put it simply, just like
when Taobao is usually opened, the system will present the products you may need to buy on the main page without any input from the customer. Relevant studies have shown that after using the e-commerce personalized recommendation system, the sales of goods can be increased by 2% to 8% [10].

2.1.3. Composition of the System. Generally speaking, the main part of an e-commerce personalized recommendation system is composed of three modules, namely the input data module, the personalized recommendation algorithm module, and the final recommendation output module.

The personalized recommendation system must first obtain the input information of the customer before entering the data. The input information can be either explicit or implicit, wherein the displayed input data are the relevant information filled in by the client on the system, such as phone number, region, as well as the product search records and evaluations on the client. The most effective of these are search records and review content. The implicit output refers to the information such as the browsing time and browsing content of a product when the customer usually browses the product.

The personalized recommendation algorithm module processes the acquired customer information. The algorithm model is used to analyze the input information and output the results to obtain the customer’s interests and preferences and the products they may want to buy. Finally, the obtained results are fed back to the customer through the recommendation output module and sent to the customer’s browsing interface.

Among the three models, the most critical is the recommendation algorithm model. The accuracy of the output results in the algorithm model directly affects the customer’s feeling and the success or failure of the transaction. In the current personalized recommendation algorithm, the most commonly used algorithm modes are collaborative filtering recommendation algorithm, association rule-based recommendation algorithm, content-based recommendation algorithm, and even collaborative filtering and content-based recommendation algorithm [11]. In the following article, only the collaborative filtering recommendation algorithm is explained and analyzed.

2.2. Collaborative Filtering Recommendation Algorithm

2.2.1. Algorithm Theory. In 1992, some researchers proposed a collaborative filtering recommendation model for filtering information and recommending news [12]. The collaborative filtering recommendation algorithm can well solve some problems in search engines, such as too single retrieval, and the collaborative filtering recommendation algorithm is based on machine learning. The main idea of this algorithm is if customers A and B have common hobbies, when customer A buys or frequently browses a certain product, then it is inferred that the product is also attractive for customer B to purchase. The collaborative filtering algorithm generally generates a recommendation matrix. Before generating the matrix, the algorithm compares the customer’s historical purchase or browsing data and calculates the similarity. The principle diagram of this algorithm is shown in Figure 1.

There are many kinds of collaborative filtering algorithms, and there are three commonly used ones, namely model-based collaborative filtering algorithm, item-based collaborative filtering algorithm, and user-based collaborative filtering algorithm [13].

2.2.2. The Basic Principle of the Algorithm. There are three main steps in the process of implementing the collaborative filtering recommendation algorithm. First, the user information is collected, then the similarity is calculated, and finally the recommendation list is generated.

(1) Collection of User Information. This step is to mine the data and obtain the customer rating data set required to generate the corresponding rating matrix, where the rating matrix is shown in Table 1.

(2) Similarity Calculation. The so-called similarity calculation is actually a measure of the similarity between two objects. The commonly used calculation methods are Pearson correlation coefficient, cosine similarity, and corrected cosine similarity [14].

Regarding the calculation of cosine similarity, its calculation process is to set the scores of two customers as a vector and then find the cosine value of the two vectors. The similarity of these two vectors keeps increasing because their cosines get smaller. Formula (1) is the calculation formula:

\[
\text{sim}(a, b) = \cos(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{||\vec{a}|| \cdot ||\vec{b}||}
\]  

In the formula, \(a, b\) is the vector set by the two user rating data.

The Pearson correlation coefficient can be used to judge whether the ratings of a product by different customers are on the same straight line. It improves the calculation method of cosine similarity. The Pearson correlation coefficient can be used to calculate the similarity of the same item between every two groups. The calculation formula is as

\[
\text{sim}(n, m) = \frac{\sum_{k \in I_{nm}}(S_{n,k} - \bar{S}_n)(S_{m,k} - \bar{S}_m)}{\sqrt{\sum_{k \in I_{nm}}(S_{n,k} - \bar{S}_n)^2 \sum_{k \in I_{nm}}(S_{m,k} - \bar{S}_m)^2}}
\]  

In the formula, \(I_{nm}\) indicates the items that customers \(n\) and \(m\) jointly participate in scoring; \(S_{n,k}\) is the rating of item \(k\) by customer \(n\); \(S_n\) is the average score of customer \(n\)’s project rating; \(S_{m^{-}}\) is the average score of customer \(m\)’s rating for the item.

However, due to the different evaluation criteria of different users, regarding the issue of cosine similarity,
scholars have proposed an improved cosine similarity on this basis. Since the traditional cosine similarity calculation method only considers the similarity of i vector dimensions and ignores the difference of different dimensions in each dimension, the calculation method of cosine similarity is improved. When calculating the similarity, the sample mean of this group is subtracted from each component, and the calculation formula is as follows:

$$sim(n,m) = \frac{\sum_{k \in I_{m}} (S_{n,k} - \bar{S}_n) (S_{m,k} - \bar{S}_m)}{\sqrt{\sum_{k \in I_{m}} (S_{n,k} - \bar{S}_n)^2} \sqrt{\sum_{k \in I_{m}} (S_{m,k} - \bar{S}_m)^2}}$$  

(3) Generation of Recommendation List. After obtaining the similarity between users through the previous process, the similarity in ascending order is sorted, and finally the target users are selected according to the sorting, and the corresponding personalized recommendation list can be generated.

2.2.3. Evaluation Indicators

(1) User Satisfaction. An important indicator of the final recommendation effect of a personalized recommendation system is user satisfaction. The degree of user’s approval of the system’s recommendation results can be measured by satisfaction. Generally speaking, satisfaction can be calculated from the data of users’ browsing, purchasing, and evaluation behaviors in major shopping platforms. Its calculation formula is as follows:

$$PR = \frac{|P(o)|}{|R(o)|}$$  

(4) Diversity. The essence of diversity is to consider the needs of consumers, in order to improve the user experience, meet the needs of users for different products, and increase their operating efficiency. Therefore, the recommender system needs to recommend many kinds of products to users, such as vegetables, meat, and fruits. The diversity evaluation indicators of the recommendation system include recommendation list diversity and average diversity.

The recommendation list diversity formula is

$$Diversity = 1 - \frac{\sum_{n,m \in R(v), i,j \neq k} j^S(n,m)}{(1/2)|R(v)||(|R(v)| - 1)}$$  

In the formula, $PR$ is the total number of products that users have purchased or frequently browsed; $R(o)$ is the number of products recommended to users.

(2) Prediction Accuracy. The so-called prediction accuracy is the accuracy of the information content recommended to users. Generally speaking, before making a correct prediction, the training set and the test set are sorted out, and then the machine learning algorithm is used to generate a recommendation prediction model of behavior and interest according to the user’s preferences. The final step is to compare the actual results with the test results and observe the differences. The prediction accuracy is usually calculated using mean absolute error (MAE) and root mean square error (RMSE), which are calculated as follows.

The RMSE is

$$RMSE = \sqrt{\frac{\sum_{v \in T} (S_m - \hat{S}_m)^2}{|T|}}$$  

The MAE is

$$MAE = \frac{\sum_{v \in T} |S_m - \hat{S}_m|}{|T|}$$  

In the formula, $S_m$ is the actual score of the item $n$ by the user $v$; $\hat{S}_m$ is the predicted score of the item $n$ by the user $v$; $|T|$ is the total number of evaluations of the product.

(3) Coverage. Coverage is a measure of the recommendation performance of a recommender system when there are few sales in the market. It is the ratio of the product derived by the recommendation algorithm to all the items in the test set, where the greater the number of recommended items, the better the recommendation algorithm. The calculation formula of coverage rate is

$$Coverage = \frac{|U_{set} \cap R(V)|}{|Q|}$$  

In the formula, $U$ is the set of all user data; $Q$ is the set of items; $R(V)$ is the set of all the items recommended by the personalized recommendation system to the user.
The average diversity formula is

\[
\text{Diversity} = \frac{1}{|U|} \sum_{v \in U} \text{Diversity}(R(v)).
\]  

(9)

In the formula: \( s(n, m) \) is the similarity of items \( n \) and \( m \); \( U \) is the set composed of users; \( R(V) \) is calculated user recommendation list.

(5) Novelty. Novelty metrics are about showing users something they have never seen or heard of in order to arouse their interest. The novelty metric measures the average popularity of an item, and its freshness decreases as the product’s popularity increases.

(6) Real-Time. The real-time nature of the recommendation system is that the products recommended to users must be real-time. If there is no timeliness, it will not bring better results. For example, when buying a certain mobile phone, consumers will always buy mobile phone accessories together, and the system should push relevant content immediately, instead of recommending accessories based on consumers’ purchasing behavior after a few days.

2.3. Semantic Sentiment Resolve

2.3.1. Emotions. Generally speaking, when users consume on electronic platforms, they are easily controlled by emotions, so it is necessary to consider the emotions of users if they want to make effective recommendations to users. For humans, emotions can be a good reflection of people’s intuitive experience of certain things and the behavioral feedback people make. People’s own needs and attitudes towards objective things are the factors that affect emotional changes, and they mainly have four functions: adaptation, communication, motivation, and organization. Many scholars have researched many models. Some researchers have proposed an ontology-based opinion perception framework EOSentiMiner [15], and some researchers have proposed a concept of emotional space including four basic emotions and defined the correspondence between happiness and anger and the correspondence between relaxation and fear as the concept of opposite emotions. The schematic diagram of its two-dimensional emotional space is shown in Figure 2.

Each emotion can be transferred to other emotions. So in this paper, emotions are represented in the form of two-tuples, and each parameter has the following definitions.

Emotion \( \alpha_a \):

\[
\alpha_a = [x_a, y_a],
\]

\[
x_a = \left\{ x | x \in R, 1 \geq x \geq -1 \right\};
\]

\[
y_a = \left\{ y | y \in R, 1 \geq y \geq -1 \right\}.
\]  

(10)

Among them, when \( y = -1 \), it represents sadness, and when \( y = 1 \), it represents happiness.

Emotional intensity \( y_b \):

\[
y_b = x_b^2 + y_b^2.
\]  

(11)

Emotional angle \( \theta \):

\[
\theta = \arctan^y_{x^a}.
\]  

(12)

These definitions can be used to express the strength and weakness of emotions with functions, and the expression formula is

\[
\delta(\alpha_1 + \alpha_2) = \alpha_{1+2}
\]

\[
= [x_1 + y_1] + [x_2 + y_2]
\]

\[
= [x_1 + x_2, y_1 + y_2].
\]  

(13)

The emotional component is defined as

\[
\mu_i \equiv \begin{cases} 1, & x_1 + x_2 > 1 \text{ or } y_1 + y_2 > 1, \\ \mu_i, & x_1 + x_2 \leq 1 \text{ or } y_1 + y_2 \leq 1. \end{cases}
\]  

(14)

2.3.2. Recommendation Strategies and Motivations. Emotional motivation theory can describe the process of emotional activity, which has been widely confirmed and applied [16]. In this paper, this theory is introduced into the personalized recommendation system, and formula (15) can be used to express the satisfaction degree of each commodity to the customer’s needs:

\[
P_i(t) = \frac{1}{\exp(-E_i(t) - R_i) - 1}
\]  

(15)

In the formula, \( P_i(t) \) is the satisfaction degree of the \( i \)th demand at time \( t \); \( E_i(t) \) is the satisfied amount of the \( i \)th demand at time \( t \); \( R_i \) is the expectation of the \( i \)th demand.
When the difference between the amount to be satisfied and the expectation is larger, it means that the degree of user satisfaction is higher, and conversely, the smaller the difference is, the lower the degree of user satisfaction is.

People of different ages have different emphasis on commodities, and people of different ages have different emphasis on the quality, price, beauty, and other aspects of commodities. At the same time, the gender of the customer and the mood at the time also affect the choice of goods. Female users are more likely to consider products that are more aesthetically pleasing, while male users are more likely to value the practicality of products. In this regard, it is necessary to consider various factors of the product and the user itself when recommending products, so that users can obtain a more satisfactory experience.

For users, what kind of product they choose will observe the price, quality, and appearance of the product according to their emotions. When users are in a relaxed or happy situation, they will be more interested in warm-colored products. At this time, the weight of warm-colored products recommended by the recommendation system should be greater than that of cool-colored products. For customers who are sad or fearful, the system should increase the weight of recommending cool-colored products such as black and gray.

2.3.3. Recommendation Model Based on Semantic Sentiment.

The semantic sentiment recommendation model used in this paper is shown in Figure 3. Compared with the common semantic sentiment analysis model, the model has some improvements on the original basis. The parallel rule mining algorithm is introduced, and the Apriori algorithm is adopted. Frequent large itemsets are obtained to form recommendation results [17].

3. Personalized Recommendation Experiment Investigation and Data Resolve

3.1. Experimental Process. The experimental object of this paper is to randomly select 1,000 users from an e-commerce platform to conduct a push survey. The age of the 1,000 users is distributed between 20 and 50 years old. In the experimental investigation, the traditional semantic sentiment analysis model, the collaborative filtering recommendation model, and the improved semantic sentiment analysis model were used for experimental push. And the time spent by the surveyed users to search for the products they need and the number of successful transactions were recorded.

The first is the effect comparison between the traditional semantic sentiment analysis model and the improved model. In this experiment, Gabor and SVM are used to recognize expressions [18], and the program is written by VC++ and MATLAB. Compared with traditional algorithms, the recommendation results obtained by the semantic emotion algorithm considering customer emotions are more user-friendly and closer to users’ expectations.

The second is to use the collaborative filtering recommendation algorithm for recommendation investigation. The algorithm collects 5 data packets in the e-commerce platform database for information search, and each data packet has 50,000 data [19]. The experimental parameters are shown in Table 2.

3.2. Experimental Data and Resolve. The data emphasizing on different attributes of commodities at different ages are shown in Table 3.

As can be seen from the above table, young people in their 20s and 30s are more concerned about the brand and appearance of products, accounting for 89.5%. While middle-aged people focus on the quality of products, accounting for 92.3%. And the elderly in their 40s and 50s are chasing the practicality and cheapness of products, accounting for 96.4%. It can be seen from this that people of different ages have different emphasis on products. Therefore, when designing a personalized recommendation model, the relationship between the nature of the product and the age of the user should be considered to achieve more accurate product recommendation.

According to the previous description of this paper, the user’s emotions are represented by numerical values, and the experimental results of the traditional semantic emotion model and the improved semantic emotion analysis model can be compared, and Figure 4 can be obtained.

From the comparison of the two charts in Figure 4, the products recommended by the traditional semantic sentiment analysis model cannot be very close to the customer’s emotional value; that is, it cannot accurately recommend the customer’s expected product under a certain emotion. After the introduction of the association rule mining algorithm, the sentiments contained in the products recommended by the semantic emotion algorithm model are closer to the customer’s emotional value, and the recommended products meet the needs of the users at that time.

Figure 5 shows the comparison of the recommendation effect before and after the improvement of the semantic emotion recommendation model. It can be seen from Figure 5 that the transaction success rate and the user’s browsing rate of products are both better with the improved algorithm model, which can increase the transaction success rate by 11.8% at most. It can be seen that the semantic emotion algorithm model after the introduction of the association rule mining algorithm can more accurately recommend the required products to users on the e-commerce platform. However, the results of the two recommendation models did not change much for people in the higher age group between 40 and 50 years old, and the online shopping rate was also very low. It can be seen that the elderly seldom conduct e-commerce transactions, and the products they need are more practical and cheap. Therefore, the personalized recommendation of e-commerce needs to be related to the age group and needs of users.

Through the comparison, it is concluded that the improved sentiment semantic analysis algorithm can improve the recommendation efficiency. In order to further explore the personalized recommendation effect of the algorithm, the improved semantic sentiment analysis algorithm is compared with the collaborative filtering recommendation
algorithm commonly used in personalized recommendation models. During the experiment, the user’s browsing time and satisfaction degree under the two algorithms are recorded. The experimental data are shown in Figure 6.

Satisfaction is evaluated according to the user’s rating of the recommended products. As can be seen from Figure 6, compared with the products recommended by the collaborative filtering recommendation algorithm, the users selected in the experiment are more satisfied with the products recommended by the personalized recommendation system based on the semantic emotion model. The highest satisfaction level for users in the age group of 30 to 35 years old reaches 0.9. At the same time, the time for users to browse products has been improved. The average browsing
Figure 5: Comparison of model recommendation results before and after improvement.

Figure 6: Product personalized recommendation effect.

Figure 7: Experimental results of transaction volume of e-commerce platform.
time in group B differs by about 5 s. The increase in the browsing time of products also proves that the recommended products are more attractive to users and more in line with their current inner needs.

By observing Figure 7, when a user searches for the same product, the traditional collaborative filtering recommendation algorithm model always takes more time than the improved semantic emotional recommendation algorithm model. When the amount of search information is 500, the time spent by the traditional collaborative filtering recommendation algorithm model is 1.74 ms, while the time spent by the improved semantic emotion recommendation algorithm model is 1.42 ms. At the same time, from the perspective of transaction success rate, the collaborative filtering recommendation algorithm model has continued to improve. However, the improved semantic emotional recommendation algorithm model has better effect, and the maximum transaction success rate reaches 87.9%, which greatly improves the benefits of the e-commerce platform and further facilitates e-commerce transactions.

4. Conclusion

In order to further improve the recommendation effect of the personalized recommendation system, this paper improves the traditional semantic emotional recommendation algorithm model. The parallel rule mining algorithm is introduced to make the products recommended by the system to the user more in line with customer needs, and the improved semantic emotion recommendation algorithm model is compared with the commonly used collaborative filtering recommendation algorithm model. From the above experimental results, the following can be concluded:

(1) Both the traditional semantic emotion recommendation template and the improved semantic emotion recommendation template can effectively improve the recommendation accuracy. However, the products recommended by the improved recommendation model more accurately meet the current inner needs of users and achieve a better product recommendation effect.

(2) Both the commonly used collaborative filtering recommendation algorithm model and the improved semantic emotion recommendation algorithm model can shorten the time that customers take to search for products. However, the traditional recommendation algorithm model is less effective, and it is difficult for customers to quickly find the product information they want when using the traditional push model. The improved semantic emotional recommendation algorithm model can accurately recommend customer needs and product information and quickly push it to customers, which can well meet the timeliness of products, greatly increase the number of product transactions, and thus gain more e-commerce benefits.

However, in the experimental investigation of this paper, the algorithmic recommendation model also exposed other shortcomings, such as not being able to make accurate personalized recommendations for people of different ages, and the complexity of algorithm steps. Therefore, there is still a lot of research space for personalized recommendation based on semantic sentiment analysis, and it still has important research significance in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors do not have any possible conflicts of interest.

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