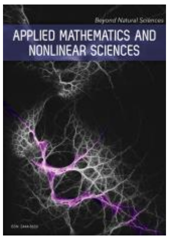
Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-19



Applied Mathematics and Nonlinear Sciences

https://www.sciendo.com

Optimization of product marketing and management path of cross-border e-commerce enterprises relying on big data technology

Yangxue Luo[1,†]

1. Chengdu Vocational & Technical College of Industry, Chengdu, Sichuan, 610000, China.

Submission Info

Communicated by Z. Sabir
Received December 20, 2023
Accepted December 27, 2023
Available online January 31, 2024

Abstract

Precision marketing is an intrinsic motivation for enterprises as a strategic consideration and guiding principle. In this paper, we first constructed a cross-border e-commerce precision marketing and management strategy based on big data technology. We mined user data and analyzed user behavior and characteristics. Moreover, the initial group division of users is carried out to realize the construction of user segmentation and user portrait, followed by the prediction of user purchasing behavior based on the Stacking algorithm and the use of a collaborative filtering algorithm to carry out accurate recommendations for different user groups. The effectiveness of the marketing management strategy is evaluated based on the level of customer value perception of Enterprise H. By using regression modeling, the impact of the marketing management method on customer loyalty and user purchase intention is investigated. The results show that the perceived level of each dimension of precision marketing is between (4,5.6), and the perceived risk is 3.657. The degree of explanation of the precision marketing model on the customer's willingness to buy is 78.8%, and the t-value significance is 0.005, which reaches a significant level, indicating that the marketing management model is effective. The purpose of this study is to provide practical marketing management suggestions for enterprises that can obtain and maintain competitive advantages in fierce market competition, which will promote enterprise performance improvement and stable growth.

Keywords: Big data technology; Stacking algorithm; User profiling; Collaborative filtering algorithm; Product marketing.
AMS 2010 codes: 97M50

†Corresponding author.
Email address: luoyangxue1988@163.com

ISSN 2444-8656
https://doi.org/10.2478/amns-2024-0191

1 Introduction

In the traditional marketing era, enterprises are not very clear about the needs of users, the marketer's thinking path is mainly from the product to the consumer, and the purpose of marketing promotion is mainly to show consumers the advantages of the product itself. The product-centered thinking mode does not need to consider the substantive needs and differences of consumers; as long as the product is good enough, there will be consumers to buy [1-2]. Nowadays is the era of the buyer's market; there are many kinds of products with the same function on the market, and consumers have many choices, which means that the marketing mode needs to be changed from the original marketing mode from the perspective of the product to the marketing mode from the perspective of the consumer [3].

With the development of the Internet and big data technology, the massive popularization of intelligent mobile terminal equipment, as long as a portable smartphone, people can obtain and read information anytime and anywhere without time and space constraints. Cell phones and other intelligent terminal devices make consumer behavior, location, body and other data become recordable and analyzable data, and at the same time, will produce a large amount of data, and the value of these data for business is huge [4-5]. Enterprises can acquire effective insights into users by mining and analyzing user data and predicting their future needs and behavioral decisions based on their past behavioral data analysis. The era of big data is leading to changes in enterprises' marketing methods and modes [6-7]. For enterprises, in the face of this era, it is not only necessary to keep up with the pace of product development, but also to keep up with the pace of marketing.

Choi, Y. J. et al. explored the relationship between international logistics and cross-border e-commerce trade based on panel data for the period 2000-2018, and the results showed that international logistics, in the long run, has a facilitating effect on e-commerce trade and international logistics in the short run of e-commerce has a negative effect on cross-border e-commerce trade [8]. Weltevreden, J. W. et al. investigated the cross-border e-commerce marketing strategy deployment and found that a growth-oriented strategy has a positive impact on e-retailers, and a customer-oriented strategy has a negative impact on e-retailers [9]. Wang, Y. et al. investigated supplier business management strategies and explored the service dynamics of cross-border e-commerce companies based on data from several cross-border e-commerce companies, emphasizing the importance of supply chain service capabilities for cross-border e-commerce development [10]. Yeolib. et al. studied customer trust in e-commerce networks and found through 150 empirical studies that network trust contributes to perceived service quality, customer loyalty, and repeat purchase intention and that network trust is critical to e-commerce marketing [11].

Chesney, T. et al. explored the impact of marketing information richness in e-commerce on constructing online trust and suggested that communication media with interactive nature helps to construct customers' trust and marketing information richness contributes to customers' online trust [12]. Bijmolt, T. H. A. et al. analyzed the drivers of consumers' experimentation with e-commerce based on research data for a comprehensive meta-analysis aimed at exploring the factors influencing consumers' online consumption and found that consumer habits, cultural traits and convenience of e-commerce significantly contribute to consumers' willingness to buy [13]. Karavdic, M. et al. deeply analyzed the impact of e-commerce development on export performance based on five in-depth interviews and a deep analysis of a sample of 340 exporters with data, and the results showed that specialized E-commerce marketing capabilities have a significant positive impact on improving the efficiency of enterprise sales and the export performance of enterprises [14]. Reza_Mousavi. et al. put forward some problems of e-commerce development for the current situation of cross-border e-commerce development and put forward a strategic plan for the future development of cross-border e-commerce based on the current situation [15].

This paper obtains user data through big data technology to establish the corresponding data analysis model, constructs a user feature project based on user feature data, segments users based on the behavioral preferences of different customers using the RFM model, and constructs a clear user portrait. Then, based on the Stacking algorithm to predict the user consumption behavior, for the user's consumption and shopping habits, the user preference information or commodity matching to achieve the user's accurate and personalized commodity recommendation. Finally, the customers' perception of the product value of H cross-border e-commerce company is analyzed, and the impact of cross-border e-commerce marketing based on big data on brand awareness, customer loyalty, and customers' willingness to close the deal is explored based on the regression analysis model, which verifies the validity of the marketing model.

2 Precision Marketing Optimization Strategies

For enterprises, by using the acquired big data and analyzing it, they can obtain potential consumer information and precise target market positioning so as to formulate marketing measures and interact with consumers, improve product competitiveness, and improve the quality of products and marketing, thus enhancing the core competitiveness of enterprises. It can be said that big data technology drives the further development of precision marketing, and the process of precision marketing becomes a business process based on the operation of big data technology.

Aiming at the characteristics of cross-border e-commerce, this paper formulates a cross-border e-commerce precision marketing management optimization strategy based on big data technology, which includes data processing, portrait analysis, user segmentation, recommendation algorithm research and other parts, and Figure 1 shows the cross-border e-commerce precision marketing management optimization scheme based on big data technology. Firstly, the data of e-commerce users' purchasing behavior is preprocessed to construct user characteristic engineering, and the users are segmented according to their preferences, needs and other consumption behaviors, and they are distinguished into different groups so as to improve the level of service and formulate marketing strategies to meet the needs of customers. Use big data technology to predict customer-level purchasing behavior based on a significant amount of customer-level transaction data. Users' needs are taken into account when providing them with accurate product recommendations based on their diverse and personalized characteristics.

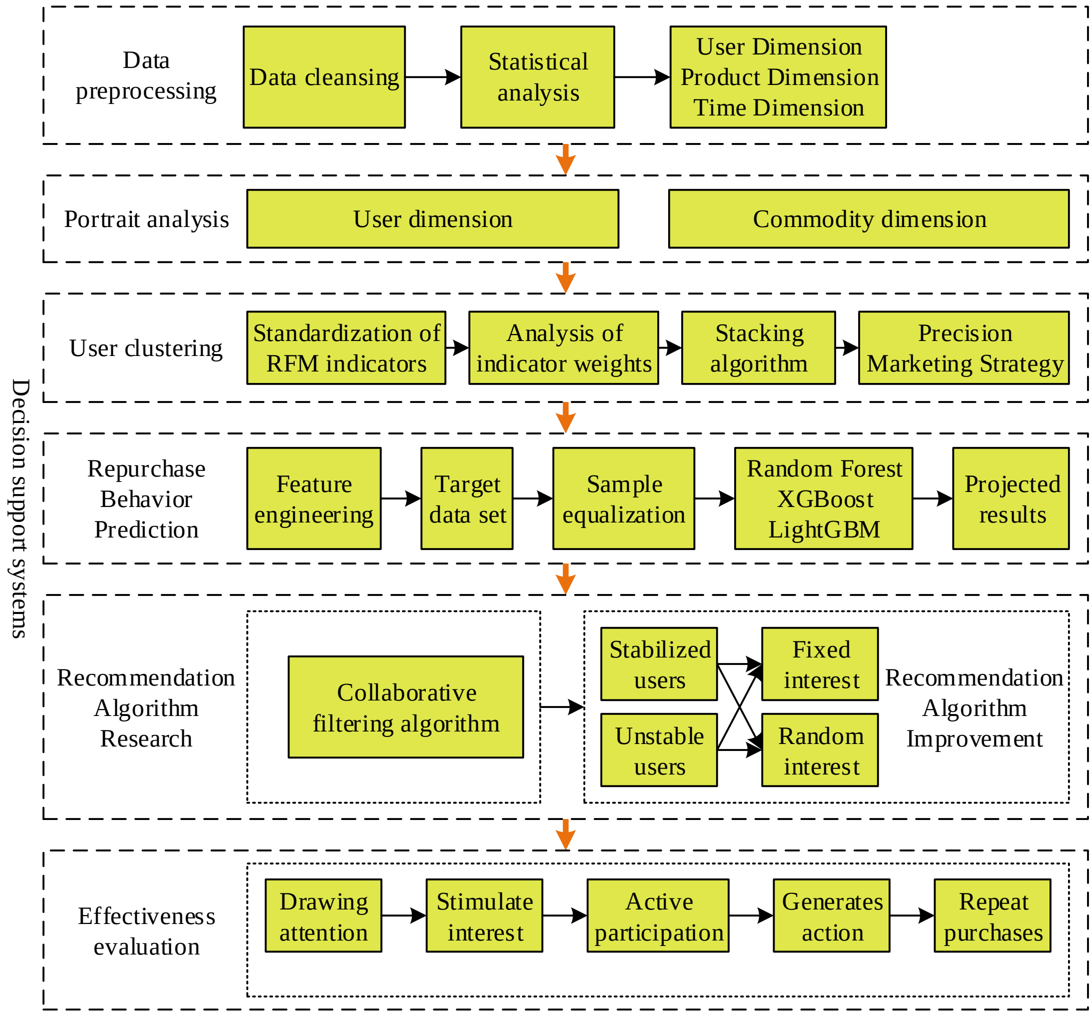


Figure 1. Product precision marketing plan

3 Methodology

3.1 Characteristics of user purchasing behavior

3.1.1 Construction of base features

User purchase behavior features mainly contain basic user information features, the total number of user views, clicks and other behaviors and the time interval between the occurrence of user behavior, the price of the purchased goods, the total number of comments and the rate of bad reviews and other basic features of commodity behavior, a total of 32 fields that can be directly extracted from the original data set, the specific features are shown below. Table 1 shows the explanation of the basic features.

Table 1. Basic characteristics explanation

Feature interpretation	Characteristic representation
The total number of times the user is viewed	X_1
User clicks the total number of items	X_2
The total number of times the user collects the goods	X_3
Users add to the total number of shopping carts	X_4
User delete the total number of shopping cart	X_5
The total number of times the user buys the goods	X_6
Total number of user behavior	X_7
Users have viewed several different kinds of goods	X_8
The user clicked several different kinds of goods	X_9
The user collects several different kinds of goods	X_{10}
The user has bought several different kinds of goods	X_{11}
The user bought several different kinds of goods	X_{12}
The average price of the goods purchased by the user	X_{13}
The average number of comments on items such as user browsing and clicking	$X_{14} \dots X_{19}$
The average difference rating of goods such as user browsing and clicking	$X_{20} \dots X_{25}$
The average number of comments on the average number of items such as user browsing and clicking	$X_{26} \dots X_{31}$
The average time interval for each purchase	X_{32}

3.1.2 Construction of Derived Features

In addition to the basic features, there are additional derived features that can be extracted by combining the original features two by two. First of all, the conversion rate is one of the indicators that can be mined for key information, and the conversion rate of purchase under different behaviors can be calculated through six different types of user behaviors. Additionally, the ratio of two basic features can be regarded as a new feature that can depict the influencing factors of users when shopping from the side. Table 2 shows the explanation of the derived features.

Table 2. Derivative characteristics explanation

Angle of view	Feature interpretation	Characteristic representation
Conversion rate	User purchase total/user browsing (click, collect, plus purchase) total frequency	$X_{33} \dots X_{36}$
	The number of items purchased by the goods is viewed (click, collect, and purchase) the number of types	$X_{37} \dots X_{40}$
Ratio	The total number of actions per person/user behavior per user	$X_{41} \dots X_{46}$
	The number of items per user's behavior per user per user behavior	$X_{47} \dots X_{51}$

One of the new construction of the purchase conversion rate of the relevant indicators mainly to reflect each user in the browsing, clicking, favorites, plus purchase of each type of goods can be purchased after the possible probability of the goods, which can also reflect the side of the user for the degree of preference for this type of goods, the higher the rate of conversion, indicating that the higher the degree of popularity of the goods, the greater the possibility of being purchased; the new construction of the ratio of the relevant fields are used to reflect the degree of activity of the user's online purchases As well as the degree of picky about the goods, through the two-two ratio can be seen in the e-commerce platform users often appear in the type of behavior, but also through the user browsing, clicking, and other behaviors under the number of categories of goods and the ratio of the total number of times the user behavior to measure the user's loyalty to the store's merchandise, which can be a side reflection of the probability of whether the user will produce a repeat of the purchase of the commodity behavior.

3.1.3 Feature selection

There are many statistical methods for feature selection; in conjunction with this research problem, in order to better determine which indicators are important and which unimportant indicators should be eliminated, it will be intended to use the recursive feature elimination method; the basic idea is to train the baseline model several times, and after each round of training, eliminate the features with smaller weighting coefficients from the total set of features, and then carry out the next round of training of a new set of features, and so on for selecting the optimal features. To eliminate recursive features, the next step is to use the support vector machine as the benchmark model.

First a brief description of the support vector machine, assuming training set $\left\{\left(x_i, y_i\right)\right\}_{i=1}^{n}$, where $x_i \in \mathrm{R}^d, y_i \in \{0,1\}$, x_i is the ith sample of the training set, n is the sample size, and d is the total number of features. the SVM uses interval maximization to completely separate the binary classification of the sample dependent variable, it will be necessary to learn a hyperplane to separate, i.e., to solve for the unique solution of $\lambda \cdot x + m = 0$, which in turn will lead to the final problem optimization as follows:

$$\begin{gathered} \min \frac{1}{2}\|\lambda\|^2 + Z\sum_{i=1}^{n}\varphi_i \\ s.t. f\left(\lambda \cdot x_i + m\right) \geq 1 - \varphi_i, \varphi_i \geq 0 \end{gathered} \tag{1}$$

To simplify the problem of solving can be transformed into a dyadic problem of the algorithm:

$$\begin{gathered} \min \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_i\beta_j y_i y_j\left(x_i \cdot x_j\right) - \sum_{i=1}^{n}\beta_i \\ s.t. \sum_{i=1}^{n} y_i\beta_i = 0, 0 \leq \beta_i \leq Z \end{gathered} \tag{2}$$

where β_i is the Lagrange multiplier, is finally derived:

$$\lambda = \sum_{i=1}^{n}\beta_i y_i x_i, m = y_i - \sum_{i=1}^{n}\beta_i y_i\left(x_i \cdot x_j\right) \tag{3}$$

where each feature training score is based on:

$$\omega_i = \lambda_i^2 \tag{4}$$

The above operational process is repeated and Table 3 shows the 11 features selected in the final iteration.

Table 3. The data characteristics of the previous 11 of the importance of the algorithm selected

Serial number	Characteristic representation	Feature description
1	X_6	The total number of times the user buys the goods
2	X_7	Total number of user behavior
3	X_{13}	The average price of the goods purchased by the user
4	X_{19}	The average number of comments the user buys the goods
5	X_{25}	The average difference rating of the user's purchase of the goods
6	X_{32}	The average time interval for each purchase
7	X_{33}	User browsing rate
8	X_{34}	User clicks on the number of items
9	X_{37}	User browse for the type of product order
10	X_{38}	User clicks on the type of commodity order
11	X_{46}	The percentage of users' purchase behavior accounts for the number of total lines

As can be seen from the above table, the optimal 11 features selected by the algorithm are mainly the number of times the product is purchased, the price of the product, the number of reviews, the rate of bad reviews, and the total number of times of user behavior, the time interval between purchasing the product, and the rate of browsing and clicking on the change of the purchase rate also have a certain impact on the user's purchasing behavior.

3.2 User Segmentation and User Profiling

In this paper, the characteristics of the research object are fully considered, and an improved RFM model consisting of five consumption characteristics is proposed to segment users and construct a user portrait.

R_1 is the average consumption time, the average time interval between transactions by the user in a certain period of time.

F_1 is the frequency of consumption, the number of order transactions occurring within a certain period of time by the user.

M_1 is the consumption amount, the total amount of money consumed by the user in a certain period of time.

S is the duration of the user relationship, the time interval between the first transaction and the last transaction occurred by the user.

P is Repeat Purchase, the number of purchases of a category of goods that the user has purchased at most during the reference time.

The specific calculation of each indicator can be expressed as:

R_1 The formula for the calculation of the indicator is:

$$R_1 = \frac{T_{last\_time} - T_{first\_time}}{F_1} \tag{5}$$

Where T_{last_time} indicates the time of the user's last order transaction in the reference time period and T_{first_time} indicates the time of the user's first order transaction in the reference time period.

The formula for the M_1 indicator is:

$$M_1 = \sum_i^n M_i \tag{6}$$

where n indicates the total number of times the user consumed during the reference time period, and M_i indicates the amount of money the user consumed on a single occasion.

The formula for the S indicator is:

$$S = T_{last\_time} - T_{hfirst\_time} \tag{7}$$

where T_{hfirst_time} denotes the user's historical first transaction time.

In the improved RFM model, the average order transaction time interval R_1 indicator is proposed to replace the recent consumption time R, so as to capture the customer's consumption habits and avoid the defect of the recent purchase time indicator with large randomness. The average order transaction time is more representative for loyal users with high consumption stickiness and high consumption frequency. User Relationship Duration Indicator S reflects the time span and continuous purchase trend of users using T-APP, i.e., the interval between the user's historical first consumption and the last consumption at the reference time. The repurchaseability indicator P indicator, on the other hand, portrays the degree of the user's dependence on a single item. Therefore, compared with the original RFM model, the improved model can more accurately portray the differences of the user groups studied in this paper, and more accurately identify the value of different categories of users.

3.3 User behavior prediction based on Stacking algorithm

After determining the base learner of the first layer of the Stacking integration algorithm, the training is started in the Python environment using the relevant code in accordance with the basic idea of the algorithm. The primary learner is used to obtain the secondary training set through cross-validation, and then it is applied to the meta-learner to make predictions on the final test set and then the model of the Stacking integration learning algorithm is evaluated next by using a number of metrics and ROC curves Prediction Effect. The first run is to get the confusion matrix Z6 of the predictive model of the algorithm, and Table 4 shows the results of the Stacking integrated algorithm for the prediction of user purchase behavior.

Table 4. The result of the algorithm for the user's purchase behavior

Category \ Prediction category	Positive sample (purchase)	Negative sample (not purchased)
Positive sample (purchase	1572	771
Negative sample (not purchased)	745	6456

The evaluation metrics of the model can be obtained based on the confusion matrix Z6 and Table 5 shows the evaluation metrics of the Stacking integration algorithm model.

Table 5. The evaluation index of the integrated algorithm model

	Accuracy rate P_1	Accuracy rate P_2	Recall rate R	F1-score	Support
$y=1$ ((Purchase))	84.12%	67.85%	67.10%	0.6747	2343
$y=0$ (Unpurchased)		89.33%	89.65%	0.8949	7201

From the above table, it can be concluded that the prediction accuracy P_1 of the Stacking integration algorithm model is as high as 84.12%, and the F1 score is 0.67, which can be seen by the value of these evaluation indexes, the heterogeneous integration learning algorithm prediction model is more accurate than the traditional single machine learning model and homogeneous integration, and the model is more effective.

3.4 Modeling of collaborative filtering algorithms

3.4.1 Stable Purchase Interest of Active Users $(\mathbf{I_A} \mid \mathbf{U_A})$ Recommendations

Figure 2 shows the schematic curve of the recommendation reward and punishment function for stable purchase interest of stable users. For products in $I_A \mid U_A$, the user's purchase interest remains stable and the purchase intention is high. Therefore, the main consideration of the recommendation for this type of user is the life cycle of the user's purchase of goods. In general, users are less likely to buy a product again after they have just purchased it. Over time, users need to be more likely to recommend the product when they are about to run out of it. Therefore, the product recommendation for this type of user is based on the User_CF algorithm, and by considering the relationship between the last purchase time of the product and the usage cycle, the time reward and punishment factor $\omega_\alpha\left(t^{ui}\right)$ based on no Ebbinghaus forgetting is constructed, and then the algorithm is improved. Specifically, let the life cycle of the product be T^i, the best time to buy again is αT^i, and α is the advance threshold period coefficient, $\alpha \in (0,1)$. When the recommended purchase time t^{ui} is within the first αT^i hours of the last purchase product $\left(t^{ui}_{last}\right)$ use cycle, the recommendation result of the product is given a penalty factor of ω_2, and when the recommended purchase time t^{ui} is after αT^i of the use cycle of the most recent purchase product and before the future purchase $\left(t^{ui}_{last+1}\right)$, the reward factor ω_1 is given to the recommendation result of the product, and the expression of the reward and punishment function is shown in equation (8).

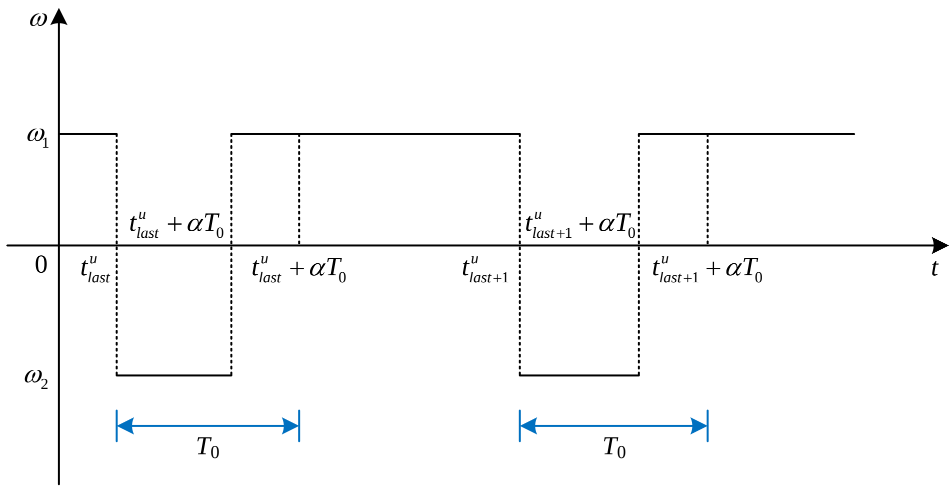


Figure 2. Diagram of punishment function to stabilize the user's stable purchase interest

Reward and punishment segmentation functions:

$$\omega_\alpha\left(t^{ui}\right)=\begin{cases}\omega_1, \alpha T^i \le t^{ui}-t^{ui}_{last} < t^{ui}_{last+1}-t^{ui}_{last}\\ \omega_2, 0 \le t^{ui}-t^{ui}_{last} < \alpha T^i\end{cases} \tag{8}$$

The cosine similarity is used to calculate the similarity between users, and the similarity between user u and user μ at moment t is calculated in Equation (9):

$$sim(u,\mu)_t=\frac{u_t * \mu_t}{\|u_t\| * \|\mu_t\|} \tag{9}$$

where u_t, μ_t denotes the purchase records of user u and user μ as of t moment.

So, let the probability that user u purchases item i at moment t be $\tilde{R}^t_{ui}$. The computational equation is given in (10):

$$\tilde{R}^t_{ui}=\sum\nolimits_{\substack{\mu\in U_A\\ \mu\in I_A|U_A}} q^t_{\mu i} * sim(u,\mu)_t + x_{ui}\omega_\alpha\left(t^{ui}\right)+\left(1-x_{ui}\right)\overline{\omega_\alpha\left(t^{\mu i}\right)} \tag{10}$$

where $q^t_{\mu i}$ is the cumulative purchase of good i by user μ at moment t, $sim(u,\mu)_t$ is the similarity between user μ and user u at moment t, $\omega_\alpha\left(t^{ui}\right)$ denotes the time reward and punishment factor of user u for purchasing good i, $\overline{\omega_\alpha\left(t^{\mu i}\right)}$ denotes the average of time reward and punishment factor of user μ for purchasing good i, and x is a 0-1 variable, viz:

$$x_{ui}=\begin{cases}1 & \text{If user } u \text{ ever purchases good } i\\ 0 & \text{Other}\end{cases} \tag{11}$$

$$\overline{\omega_\alpha\left(t^{\mu i}\right)}=\frac{\sum_{\substack{\mu\neq u\\ \mu\neq U_A}} x_{\mu i}\omega_\alpha\left(t^{\mu i}\right)}{\sum_{\substack{\mu\neq u\\ \mu\in U_A}} x_{\mu i}} \tag{12}$$

3.4.2 Randomized Purchasing Interests of Active Users $\left(\mathbf{I_B} \mid \mathbf{U_A}\right)$ Recommendations

The overall interest of such users remains stable, but their willingness to purchase goods of random interest is high. Therefore, the method of recommending goods to such users is to combine the User_CF algorithm with the goods single sales heat index (goods single sales heat is a kind of index based on the sales volume in a single sale of goods, the higher the single sales volume, the greater the sales heat index). So, t moment to user u recommended to buy goods i is calculated as in Equation (13):

$$\tilde{R}_{ui}^t=\sum_{\substack{\mu\in U_A\\ i\in I_B|U_A}} q_{\mu i}^t\left(1-sim(u,\mu)_t\right)+\tau_i^t \tag{13}$$

where $q_{\mu i}^t$ is the cumulative purchase of commodity i by user μ at moment t, $sim(u,\mu)_t$ is the similarity between user μ and user u at moment t, and τ_i^t is the single hot selling index of commodity i before moment t. The expression for the single hot selling index of commodity i is given in (14):

$$\tau_i^t=\frac{c_{\max}^{it}-\min\sum_{j\in I_B|U_A} c_{\max}^{jt}}{\max\sum_{j\in I_B|U_A} c_{\max}^{jt}-\min\sum_{j\in I_B|U_A} c_{\max}^{jt}} \tag{14}$$

Where $c_{\max}^{it}$ is the maximum sales volume of a single sale of commodity i as of the moment t. $\max\sum_{j\in I_B|U_A} c_{\max}^{jt}$ indicates the maximum sales volume of a single sale of goods belonging to $I_B \mid U_A$, and $\min\sum_{j\in I_B|U_A} c_{\min}^{jt}$ indicates the minimum sales volume of a single sale of goods belonging to $I_B \mid U_A$.

3.4.3 Stabilized Purchasing Interests of Inactive Users $\left(\mathbf{I_A} \mid \mathbf{U_B}\right)$ Recommendations

The Ebbinghaus curve is used to show the improved schematic curve of the reward and punishment function in Figure 3. These users, unlike stable users, are prone to changing their interests over time. Therefore, the recommendation method for this type of user uses the Item_CF algorithm while considering the usage cycle of the item to construct the improved reward and punishment factor based on the Ebbinghaus forgetting curve law of the user's interest $\omega_b\left(t^{ui}\right)$. Specifically, when the recommended purchase moment is within the first αT^i times of the usage cycle of the most recently purchased item, a time penalty factor is added to the recommendation result for the item, which changes with the improved Ebbinghaus curve. When the recommended purchase moment is after αT^i the last purchase cycle and before the future purchase, a time reward factor is added to the recommendation result of the product, and again, the reward factor varies according to the improved Ebbinghaus curve. The expression of the improved Ebbinghaus curve-based reward and punishment function is shown in (15):

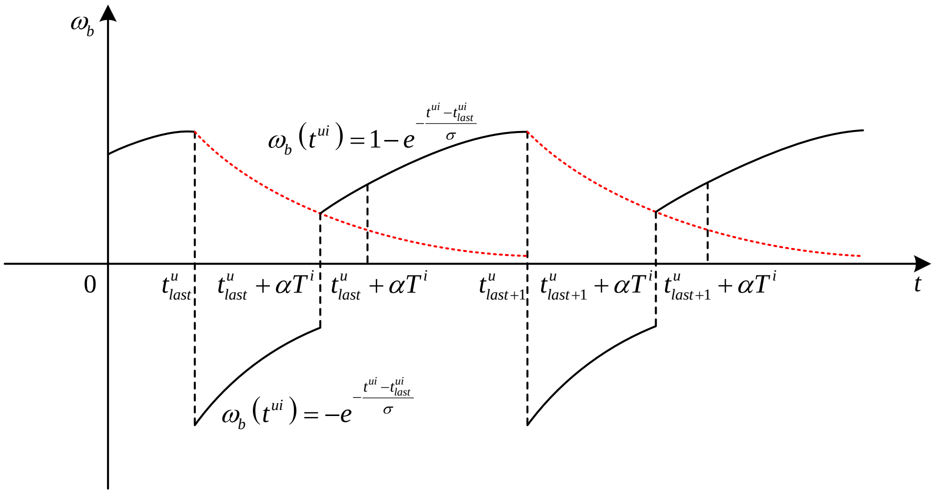


Figure 3. Improved diagram of reward and punishment function based on Ebbinghaus curve

$$\omega_b\left(t^{ui}\right)\begin{cases}1-e^{-\frac{t^{ui}-t^{ui}_{last}}{\sigma}}, & \alpha T^i < t^{ui}-t^{ui}_{last} < t^{ui}_{last+1}-t^{ui}_{last} \\ -e^{-\frac{t^{ui}-t^{ui}_{last}}{\sigma}}, & 0 < t^{ui}-t^{ui}_{last} < \alpha T^i\end{cases} \tag{15}$$

where σ is the forgetting rate.

The cosine similarity is used to calculate the correlation between goods as in Equation (16):

$$sim(i,j)_t = \frac{i_t * j_t}{\|i_t\| * \|j_t\|} \tag{16}$$

Where, i_t, j_t denotes the sales record of item i and item j at the moment t and before.

Then the recommendation algorithm equation for user u to purchase item i is as follows:

$$\tilde{R}^t_{ui} = \sum\nolimits_{j\in I_A|U_B} q^t_{uj} * sim(i,j)_t + x\omega_b\left(t^{ui}\right) + (1-x)\overline{\omega_b\left(t^{\mu i}\right)} \tag{17}$$

where q^t_{uj} is the cumulative purchase of each good j by user u at moment t, $sim(i,j)_t$ is the similarity of good i and good j at moment t, $\omega_b\left(t^{ui}\right)$ the time reward-penalty factor for user u purchasing good i, $\overline{\omega_b}\left(t^{\mu i}\right)$ the average over the time reward-penalty factor for user μ purchasing good i, and x is a 0-1 variable, i.e.:

$$x = \begin{cases}1 & \text{If user } u \text{ ever purchases good } i \\ 0 & \text{Other}\end{cases} \tag{18}$$

3.4.4 Randomized Purchasing Interests of Inactive Users $\left(\mathbf{I_B} \mid \mathbf{U_B}\right)$ Recommendations

The overall interest performance of this type of users is unstable, and the randomness of the performance is more apparent for goods with a random purchase interest. Therefore, the recommendation method for the random purchase interest of this type of users is to recommend the goods with higher total sales heat index in combination with Item_CF algorithm, the expression is shown in (19):

$$\tilde{R}_{ui}^{t} = \sum_{j \in I_B | U_B} q_{uj}^{t} * \left(1 - sim(i, j)_t\right) + \varphi_i^t \tag{19}$$

where q_{uj}^{t} is the cumulative purchase of item j by user u at moment t, $sim(i, j)_t$ is the similarity between item i and item j at moment t, and φ_i^t is the heat index of the total sales of item i as of moment t, whose expression is shown in (20):

$$\varphi_i^t = \frac{c^{it} - \min \sum_{j \in I_B | U_B} c^{jt}}{\max \sum_{j \in I_B | U_B} c^{jt} - \min \sum_{j \in I_B | U_B} c^{jt}} \tag{20}$$

Where C^{it} denotes the total number of sales of item i at and before moment t. $\max \sum_{j \in I_B | U_B} C^{jt}$ denotes the total number of sales for all commodities belonging to the largest sales total in $I_B | U_B$, and $\min \sum_{j \in I_B | U_B} C^{jt}$ denotes the total number of sales for all commodities belonging to the smallest sales total in $I_B | U_B$.

4 Results and discussion

4.1 Customer Perceived Value Analysis

This paper takes H cross-border e-commerce company as an example to study the customer's perception of H cross-border e-commerce company's products so as to verify the effectiveness of the high marketing model. This paper adopts a 1-8 scale to measure the customer's perceived situation, and the data are all from the backend data of the web user's rating feedback on H cross-border e-commerce company's products. Table 6 shows the customer's perceived value. From the survey, it can be seen that the very small value of all the observed variables is 1, and the very large value is 7, indicating that the degree of recognition and importance for each indicator varies greatly among different respondents. The mean value of most of the indicators exceeds 4.5, indicating that the respondents show a more favorable attitude towards the perception of the precision marketing model, and the marketing effect is better. The skewness and kurtosis coefficients of each index are close to 0, the maximum value of the skewness coefficient is 0.087, and the maximum value of the kurtosis coefficient is 0.304, which is smaller than the critical value, thus indicating that the fluctuation of the respondents' ratings is small.

Among them, the scores of precision marketing dimensions are between (4,5.6), the customer perceived value is above 5 points, and the perceived risk index is 3.657, which indicates that customers think that Company H's products have low risk, high perceived value, and good effect of precision marketing.

Table 6. Customer perception value

		Min	Max	Mean	Error	Degree of bias	kurtosis
Precision marketing	Immediacy	1	7	5.595	1.309	-0.319	0.0665
	Pertinency	1	7	4.724	1.421	-0.539	-0.052
	Interactivity	1	7	5.382	1.330	-0.929	0.008
	Fun	1	7	4.996	1.299	-0.545	0.160
	Profitability	1	7	4.027	1.833	-0.114	-0.140
Customer perception value	Perceptual utility	1	7	5.857	1.025	-0.419	0.304
	Perceptual emotion	1	7	5.480	1.231	-0.150	0.046
	Perceived brand	1	7	5.194	1.424	-0.067	0.053
	Perceived trust	1	7	5.124	1.352	-0.042	0.277
Perceived risk	Customer perception risk	1	7	3.657	1.459	0.087	-0.113

4.2 Analysis of the impact of product marketing on awareness, customer loyalty

As an example to study the effectiveness of Company H’s precision marketing approach, this paper uses a regression analysis model to do regression analysis of precision marketing and Company H’s brand awareness and customer loyalty. The regression analysis of precision marketing and total customer value is shown in Table 7. In precision marketing, the regression coefficients of the dimensions of information immediacy, relevance, interactivity, fun, profitability and customer loyalty are between 078 and 1.75, and all of them have high significance levels, which shows that the dimensions of precision marketing have a positive impact on customer loyalty. The study of cross-border e-commerce shopping behavior based on big data shows that the regression coefficients of information immediacy, relevance, interactivity, interestingness, profitability and brand awareness in precision marketing are between 0.125 and 0.594, and all have a high level of significance, so that the dimensions of precision marketing can positively affect brand awareness. It can be seen that in cross-border e-commerce marketing, enterprises can enhance customers’ shopping experience in terms of products and services by providing accurate, instant, and interesting shopping information, and at the same time, can promote the enhancement of cross-border e-commerce enterprise image and product awareness.

In precision marketing, the regression coefficients of information immediacy, relevance, interactivity, interestingness, profitability and brand awareness are between (0.662, 1.748), and all of them are highly significant, so the dimensions of precision marketing can positively affect brand awareness, and the accuracy, relevance, interestingness, interactivity and profitability of the marketing information can promote the user’s understanding of the brand and enhance the marketing Effectiveness.

Table 7. Precision marketing and customer value regression analysis

	Independent variable	Non-normal coefficient		Normal factor	T	Sig.
		B	Standard error	Beta		
Customer loyalty	Immediacy	0.780	0.054	0.125	7.687	0
	Pertinency	1.748	0.029	0.594	44.435	0
	Interactivity	0.806	0.046	0.256	17.490	0
	Fun	0.882	0.056	0.307	10.678	0
	Profitability	0.913	0.036	0.184	22.777	0
Brand awareness	Immediacy	0.662	0.069	0.118	7.665	0
	Pertinency	1.731	0.037	0.604	44.407	0
	Interactivity	0.807	0.029	0.285	17.499	0
	Fun	0.680	0.054	0.125	7.687	0
	Profitability	1.748	0.029	0.594	44.435	0

4.3 Analysis of e-commerce enterprises' product marketing and customers' purchase intention

4.3.1 Correlation analysis

In this study, Pearson's correlation coefficient was used to describe the relationship between the variables. Correlation analysis was conducted for each factor of precision marketing, each factor of customer perceived value, consumer trust and consumer purchase intention. Table 8 shows the results of the correlation analysis of each variable.

Precision marketing has a significant correlation with each dimension, including customer perceived value, consumer trust, and purchase intention. The correlation between precision marketing and customer perceived value, consumer purchase intention, and consumer trust is significant. The perceived value of customers greatly influences consumer trust and purchase intention. Consumer trust has a significant positive impact on consumer purchase intention.

Precision marketing immediacy and consumer trust have a weak correlation, and their correlation is only significant at the 0.05 level. Moreover, the correlation between precision marketing targeting, interactivity and consumer trust is significant at the 0.01 level, and it is a strong correlation, which indicates that consumer trust is mainly influenced by precision marketing targeting and interactivity, and the influence of immediacy is weaker.

Table 8. Shows the correlation analysis of variables

	JS	ZD	HD	SY	QW	QG	PP	XR	YY
JS	1								
ZD	0.388**	1							
HD	0.407**	0.276**	1						
QW	0.408**	0.876**	0.355**	1					
SY	0.456**	0.857**	0.356**	0.357**	1				
QG	0.889**	0.469**	0.450**	0.478**	0.405**	1			
PP	0.407**	0.566**	0.297**	0.668**	0.409**	0.427**	1		
XR	0.386*	0.764**	0.523**	0.467**	0.408**	0.427**	0.527**	1	
YY	0.586**	0.489**	0.378**	0.596**	0.408**	0.626**	0.595**	0.638**	1

Note: JS, ZD, HD, SY, QW, QG, PP, XR, and YY denote information immediacy, information relevance, information interactivity, information fun, information profitability, perceived utility value, perceived emotional value, perceived brand value, trust, and willingness to buy, respectively.

4.3.2 Regression Analysis of Perceived Customer Value by Precision Marketing

A regression analysis is performed to determine whether precision marketing has a positive impact on customer-perceived value after taking precision marketing and customer-perceived value as overall variables. Secondly, regression analysis was conducted to verify the positive impact of precision marketing on customer-perceived value across different dimensions of precision marketing and customer perception. The regression analysis results for precision marketing and customer-perceived value can be found in Table 9.

Precision marketing and customer perception value were both analyzed as a group of variables in the regression analysis. The adjusted R^2 is 0.658, indicating that precision marketing explains 65.8 % of the overall variation in customer perceived value, which is a good level of explanation. The t-value of precision marketing has a significance probability of 0.000, which is less than 0.001 and has reached the significant level, and the F-value statistic is 551.039, which has a significance probability of 0.000, which is less than 0.001 and has reached the significant level, which indicates that precision marketing has a positive effect on customer perceived value has been verified. Precision marketing and customer perceived value were separately divided into dimensions for regression analysis, and its significance level was 0.000, less than 0.001, indicating that the regression equation was well-fitted and the linear relationship was significant, reaching the desired level. The t-value significance probability of each dimension of precision marketing reached a significant level, indicating that the immediacy, relevance, and interactivity of precision marketing all have a positive effect on the experiential value in perceived value.

Table 9. Results of the regression analysis of accurate marketing and customer perception value

Independent variable	Non-normal coefficient		Normal factor	t	Sig.	R^2 Tune up	F	Significant f value changes
	Beta	SD	Beta					
Constants	0.396	0.138		2.837	0.007	0.658	551.039	0.000
Precision marketing	0.849	0.037	0.815	23.476	0			
Immediacy	0.038	0.028	0.035	1.108	0.27	0.787	340.838	0.000
Pertinency	0.747	0.029	0.836	27.479	0			
Interactivity	0.108	0.028	0.116	3.658	0			
Fun	0.753	0.0564	0.498	27.688	0			
Profitability	0.108	0.047	0.196	3.689	0			

4.3.3 Regression analysis of customer perceived value on purchase intention

Both precision marketing and customer perceived value are taken as overall variables to do regression analysis, and Table 10 shows the regression analysis of customer perceived value on purchase intention. The adjusted R^2 is 0.529, indicating that the degree of explanation of customer perceived value on purchase intention reaches 52.9%, with a good level of explanation. The t-value of customer perceived value has a significance probability of 0.000, which is less than 0.001 and reaches a significant level, and the F-value statistic is 321.987, whose significance probability is 0.000, which is less than 0.001 and also reaches a significance level, which indicates that the customer perceived value has a positive effect on purchase intention. Regression analysis of perceived value on willingness to buy shows that the adjusted R^2 is 0.549, indicating that these variables can explain 54.9 % of the overall variance, which is a good explanation. The f-value statistic is 112.864, with a significance level of 0.000. t-value probability of significance of all dimensions of the perceived value of the customer reaches the level of significance, which indicates that basic value, experiential value, and social value all have a positive effect on willingness to buy, which is less than 0.001. Value all have a positive effect on purchase intention.

Table 10. The regression analysis of customer perception value to purchase intention

Independent variable	Non-normal coefficient		Normal factor	t	Sig.	R^2 Tune up	F	Significant f value changes
	Beta	SD	Beta					
Constants	0.478	0.184	--	2.440	0.000	0.529	321.987	0.000
Customer perception	0.531	321.988	0.252	4.063	0.000			
Perceptual utility	0.255	0.049	0.242	4.057	0.000	0.549	112.864	0.000
Perceptual emotion	0.442	0.041	0.385	8.574	0.000			
Perceived brand	0.282	0.056	0.253	5.013	0.000			
Perceived trust	0.554	0.064	0.298	5.967	0.000			

4.3.4 Regression analysis of precision marketing on purchase intention

Taking precision marketing as an overall variable and doing regression analysis, it can be seen that Table 11 shows the results of regression analysis of precision marketing on purchase intention. The adjusted R^2 is 0.788, which indicates that the degree of explanation of precision marketing on purchase intention is 78.8%, which is a high level of explanation. The t-value significance probability of precision marketing is 0.005, which is less than 0.05 and reaches the significance level, and the F-value statistic is 1179.67, and its significance probability is 0.000, which also reaches the significance level. The regression analysis of precision marketing by dimension shows that the adjusted R^2 is 0.739, indicating that these variables can explain 73.9% of the overall variation, and the explanatory effect is average. The F-value statistic is 72.913, and its significance level is 0.000, which indicates that the regression equation fits well, the linear relationship is significant, and it reaches the desired level. The significant t-value significance probability for each dimension of precision marketing indicates that purchase intention is positively influenced by immediacy, relevance, and interactivity.

Table 11. Results in the regression analysis of the purchase intention of precision marketing

Variable	Nonnormalized coefficient		Normalization factor	T	Sig.	R^2 Tune up	F	Significant f value changes
	Beta	SD	Beta					
Constants	0.671	0.244	--	2.802	0.009	0.788	179.67	0.000
Precision marketing	0.825	0.069	0.620	13.404	0.005			
Immediacy	0.408	0.062	0.424	8.064	0.000	0.739	72.913	0.000
Pertinency	0.282	0.050	0.290	6.011	0.003			
Interactivity	0.125	0.052	0.132	2.650	0.002			
Fun	0.464	0.035	0.186	5.789	0.000			
Profitability	0.864	0.056	0.278	9.575	0.000			

5 Conclusion

This paper constructs a precision marketing management model based on big data technology, takes Company H as an example to study the customer's perceived value under the precision marketing model, and explores the impact of the precision marketing model on customer loyalty, purchase intention and product awareness based on regression analysis model. The main conclusions are as follows:

The scores of the dimensions of precision marketing are between (4, 5.6), the customers' perceived value is above 5 points, and the perceived risk index is 3.657, which indicates that the customers recognize the value of Company H's products in this marketing mode, the level of perceived value is high, and the level of perceived risk is small.

The regression coefficients of precision marketing information immediacy, relevance, interactivity, fun, profitability and customer loyalty are between 078 and 1.75, and the regression coefficients with customer loyalty are between 0.125 and 0.594, which are all significantly positive, indicating that this product marketing mode has a significant promotion effect on brand awareness and customer loyalty.

The degree of explanation of precision marketing on purchase intention is 78.8%, which is a high level of explanation. The t-value significance probability of precision marketing is 0.005, which is less than 0.05 and reaches a significant level, indicating that this product marketing model has significant marketing on customer purchase intention, and the precision marketing model based on big data can promote customer purchase intention. Based on the research, it has been concluded that the precision marketing model based on big data constructed in this paper is effective.

References

[1] Bao, Y., Cheng, X., & Zarifis, A. (2022). Exploring the impact of country-of-origin image and purchase intention in cross-border e-commerce. Journal of global information management.

[2] Ramirez, F. J., Parra-Requena, G., Ruiz-Ortega, M. J., & Garcia-Villaverde, P. M. (2018). From external information to marketing innovation: the mediating role of product and organizational innovation. Journal of Business & Industrial Marketing, 33(1), 00-00.

[3] Javier Ramirez, F., Parra-Requena, G., Ruiz-Ortega, M. J., & Garcia-Villaverde, P. M. (2018). From external information to marketing innovation: the mediating role of product and organizational innovation. The Journal of Business & Industrial Marketing, 33(5), 693-705.

[4] Feng, Z., & Chen, M. (2022). Platformance-based cross-border import retail e-commerce service quality evaluation using an artificial neural network analysis. Journal of global information management.

[5] Ju, M., Jin, J. L., & Zhou, K. Z. (2018). How can international ventures utilize marketing capability in emerging markets? its contingent effect on new product development:. Journal of International Marketing, 26(4), 1-17.

[6] Elia, S., Giuffrida, M., Mariani, M. M., & Bresciani, S. (2021). Resources and digital export: an rbv perspective on the role of digital technologies and capabilities in cross-border e-commerce. Journal of Business Research, 132(2), 158-169.

[7] A, D. T., B, E. R. N., & C, U. V. (2021). The indirect effect of online marketing capabilities on the international performance of e-commerce smes. International Business Review, 31(3).

[8] He, Y., Wu, R., & Choi, Y. J. (2021). International logistics and cross-border e-commerce trade: who matters whom?. Sustainability, 13(4), 1745.

[9] Goldman, S. P., Herk, H. V., Verhagen, T., & Weltevreden, J. W. (2020). Strategic orientations and digital marketing tactics in cross-border e-commerce: comparing developed and emerging markets. International Small Business Journal.

[10] Wang, Y., Jia, F., Schoenherr, T., Gong, Y., & Chen, L. (2019). Cross-border e-commerce firms as supply chain integrators: the management of three flows. Industrial Marketing Management.

[11] Peterson, Robert, A., Kim, & Yeolib. (2017). A meta-analysis of online trust relationships in e-commerce. Journal of Interactive Marketing.

[12] Chesney, T., Chuah, S. H., Dobele, A., & Hoffman, R. (2017). Information richness and trust in v-commerce: implications for services marketing. Journal of Services Marketing, 31(3).

[13] Zerbini, C., Maestripieri, S., Luceri, B., & Bijmolt, T. H. A. (2022). Drivers of consumer adoption of e-commerce: a meta-analysis. International journal of research in marketing.

[14] Gregory, G. D., Ngo, L. V., & Karavdic, M. (2017). Developing e-commerce marketing capabilities and efficiencies for enhanced performance in business-to-business export ventures. Industrial Marketing Management, 78(APR.), 146-157.

[15] Hazarika, B., & Reza_Mousavi. (2021). Review of cross-border e-commerce and directions for future research. Journal of Global Information Management.