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A Study on the Influence of User Behavior Data on Brand Strategy in Mobile Computing Environment

Journal of Electrical Systems

Abstract: - Ordinary brand strategy can't attract users' attention and consumption psychology, in order to improve the brand's strategy, this paper firstly analyzes the consumer's behavior and the relationship between consumers and brand strategy, to obtain the psychology and behavior of consumers when they buy goods. Secondly, transfer learning algorithm is used to process the user behavior to make the data more complete and accurate. Finally, the neural network is used to predict the user behavior, so as to formulate a reasonable brand strategy. Analyzing the formulated brand strategy from various aspects such as conversion rate, market evaluation and user activity, the results show that the formulated brand strategy has a high conversion rate, increasing the conversion rate of the brand to 88%, so that the benefits of the enterprise can be improved, and the number of times the brand has been exposed is also higher, up to about 90 times. It can accurately locate the target users, attract the attention of users, and effectively interact with them, which improves the brand awareness in the mobile environment and promotes the positive development of the brand.

Keywords: brand strategy; transfer learning algorithm; neural network; user behavior; mobile environment

1. INTRODUCTION

In today's era, mobile computing technology and smart devices are developing rapidly and gradually being applied in various fields, changing people's living habits and consumption methods. As a result, users' behavioral preferences and consumption browsing have become important information in the market, influencing market demand and brands' marketing approaches [1-2]. In order to be able to better predict the behavior of users and formulate favorable brand strategies, a model for the analysis and prediction of user behavior is established to attract the consumption of target users based on the predicted results, and to accurately formulate the brand's strategy [3-4]. Brand strategy is the core factor of enterprise competition, and the long-term development and image of the brand is closely related, which directly affects the market position of the enterprise. Through the prediction and analysis of user behavior, we can identify the potential opportunities in the market, market trends and brand positioning and other factors, so as to better attract users to consume, grasp the direction of the market, adjust the marketing and promotion of the brand, and maximize the use of the brand [5].

This paper first analyzes the relationship between user behavior and brand strategy and user behavior to get the psychological process and motivation of user consumption. Secondly, in order to make the data more accurate and complete, migration learning is used to process the collected user behavior data and correct the wrong data, so as to facilitate the subsequent establishment of user behavior prediction model. Finally, the keyword extraction method is used to extract the user behavior data, and the Bayesian method is used to classify the data, and the classified results are sent to the neural network to achieve the prediction of user behavior, and a reasonable brand strategy is formulated based on the predicted results, so that the brand content is more targeted, the target users can be accurately located, the brand awareness and conversion rate is improved, and the

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attention of users is attracted to stimulate the user's awareness of purchasing and increase the motivation of the user. It stimulates the user's purchasing consciousness, improves the sales and performance of the enterprise, broadens the market channels of the enterprise, promotes the positive development of the enterprise, makes the enterprise more competitive in the market, and can master the wind direction and trend of the market.

2. RELARED WORDS

In predicting the impact of user behavior on brand strategy, Dai, T. et al. optimized the improved Cuckoo search with optimal parameters to predict user behavior. The factors affecting brand strategy are analyzed in terms of both self-factors and external factors, and the time-slicing method is used to predict user behavior so as to determine the brand's future strategy trend. Experiments show that the method can accurately predict user behavior and perceive the brand's future strategy trends [6]. Wu, C. et al. proposed a model for predicting brand trends based on user behavior, which learns user interests and purchasing behaviors from user behaviors with a certain degree of privacy. By learning users' consumption behaviors on different platforms, a reasonable brand strategy is formulated to attract users [7]. Su, Z. et al. designed a similarity metric based on the probability of users' historical behaviors, and based on the similarity method, a complex model of the user relationship network was built. The user degree and community information of the modeled network, as well as the number of shared ratings among users, are used along with the proposed similarity metric to design a prediction algorithm to derive future strategies and trends of the brand. Experiments have shown that the method is effective and can successfully improve the accuracy of ratings prediction [8]. Li, J. et al. firstly calculate the correlation of user behavior using the fusion layer in the neural network and develop a modeling of the correlation. Secondly, since the links that can be observed on a website are not dense enough, a new link loss function needs to be designed that preserves the topology of the website. Finally, a joint optimization function is designed to train two behavioral modeling tasks for mutual enhancement. The experimental results show that the proposed method is on average 6.21% better in consumer behavior prediction, which is a good guideline for the future strategies and trends of the brand [9]. Wang, T. et al. firstly proposed a multi-message interaction influence-driven mechanism for accurately predicting user's consumer behavior. Secondly, due to the complexity of users' consumption behavior and psychology, it is necessary to construct a neural network for predicting users' preferred brands and deriving brand trends [10]. Zhang, N. et al. proposed a prediction model for automatically annotating user behavior. The proposed prediction model for automatically annotating user behavior combines long and short-term memory networks and mining recognition methods to achieve the prediction of user consumption behavior. The performance of the model was evaluated based on experiments, and the results showed that the prediction model of automatically annotated user behavior can effectively identify behaviors and has good behavioral prediction performance, and the strategies and trends of brands were derived based on the predicted user behaviors [11]. Yan, M. et al. firstly extracted the trajectory information of users by analyzing the user's behavioral data, and used the way of moving the trajectory entropy to get the user's trajectory complexity. Secondly, a machine learning algorithm was used to classify the consumption behaviors of different users. Finally, according to the results of classification, the step threshold and weighting coefficients of the weighted Markov prediction model are optimized, and the mobility prediction is carried out for each user behavior, and the subsequent marketing direction of the brand is derived based on the results [12].

3. CONSUMER BEHAVIOR AND BRAND STRATEGY

3.1 Consumer behavior

The psychology and behavior expressed by consumers when they carry out consumption activities is consumer behavior, and the characteristics of consumer behavior usually include consumer interests, consumer habits, and values and personality. When consumers buy goods, their behavioral process generally includes seven stages, generating demand, forming purchase motives, collecting information about goods, preparing for purchase, selecting goods, using goods and evaluating the purchased goods [13-14].

Consumer behavior and psychology are easily affected by multiple factors such as consumer environment, consumer guidance and consumer shopping places, while enterprises often develop targeted marketing strategies based on consumer behavior and psychology, and studying consumer behavior can enhance the business efficiency and corporate visibility. So the enterprise will launch the study of consumer behavior, mainly from the following two aspects:

(1) Study the internal conditions of consumer purchase, including the psychological activities and personality psychological characteristics of consumers, as well as the factors that affect consumer psychology in the purchase process.

(2) To study the external conditions of consumer purchasing, including the social environment, the trend of consumption, commodity factors and shopping environment.

The analysis of consumer behavior and psychology from the above two aspects can facilitate the enhancement of the efficiency and popularity of enterprises and attract the attention of users.

3.2 The relationship between consumer behavior and brand strategy

When consumers buy goods, consumer psychology and motivation is the motivation to stimulate consumers to buy goods, consumers with different psychology and motivation to choose different brands. Currently more commonly used psychological motivation theories include: the need for self-expression and defense, the need for consistency, the need for attribution and categorization, the need for cues, the need for independence and reinforcement, the need for intimate and harmonious interpersonal relationships, and the need for imitation, so that in the development of the brand advertising and marketing strategy can be based on the above to develop positioning, and thus accurately locate to the customer [15-16].

And when choosing a brand, gender differences are also one of the influencing factors. Gender differences between men and women include cognitive differences, emotional and volitional differences. These differences are reflected in the consumer psychology can be expressed as.

(1) Whether in personal consumption or family consumption, women's consumption ability is higher than men's, according to the survey, urban women's purchasing ability is much higher than men.

(2) Since the quantity, color and packaging of female products are richer than that of men, the consumption demand of women is usually higher than that of men.

(3) Due to the difference in thinking styles between men and women, logical thinking ability is also different. Men's thinking logic is stronger, so when buying goods, they only choose what is needed and practical, and the selection time is shorter and quicker, while women's image thinking ability is stronger, so women spend more time selecting goods, pay more attention to the packaging and style of the goods, and like to choose the goods with beautiful style.

At the same time, there is also a certain correlation between consumers' personality and brand choice. Consumer decision-making pattern is a kind of habitual way of thinking and psychological trend when consumers buy goods, and it has a psychological coercive effect that consumers can not realize when they make purchasing decisions, and this kind of psychology will fundamentally dominate the decision-making behaviors of consumers, and the main patterns of consumer decision-making include: perfectionist type, economic and affordable type, brand cognition type, confused and indecisive type, careless and impulsive type, and loyal and habit type, and these patterns are reflected according to different personalities. These patterns are embodied in different people according to their personalities, and they also guide consumers' consumption psychology and behavior.

4. USER BEHAVIOR PREDICTION MODELING

4.1 Data collection and processing

In order to more accurately analyze and predict the psychology and behavior of consumers, it is necessary to collect consumer consumption data, usually offline questionnaires are used to collect consumer purchases, while online users browse the product situation and historical purchase data are collected to obtain the consumer's consumption behavior. However, the data collected in these ways may be incorrect or lost, so the data need to be processed [17-18].

Migration learning algorithms are used to process the collected data, filter the redundant data in the original data, and correct the erroneous data.

Let M represent the target data set and F represent the original data set, a samples are randomly selected from the original data set F and b samples are randomly selected from the target data set M, and the data of the two samples are merged together in the following equation:

$$H = MF\left\{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\right\} \tag{1}$$

where x_N represents the sample eigenvector and y_N represents the category of the sample.

Expanding the weights of the sample is processed to obtain Eq:

$$\begin{cases} w_i^1 = x_N \dfrac{1}{a} \\ w_i^1 = y_N \dfrac{1}{b} \end{cases} \tag{2}$$

where w_i^1 represents the weights of the data samples.

Let the number of trainings be i. The training of the collected data is carried out to produce the classifier:

$$h_t(x) : w_i^1 (x \to y) \tag{3}$$

where h_t represents the classifier.

The classifier $h_t(x)$ error classification for the original and target data sets is:

$$\varepsilon_f = H \frac{w_i^1 \left|h_t(x_i) - y_i\right|}{\sum_{i=1}^{a} w_i^1} \tag{4}$$

$$\varepsilon_t = \sum_{a+1}^{a+b} \frac{w_i^t \left|h_t(x_i) - y_i\right|}{\sum_{i=1}^{a+b} w_i^t}, \varepsilon_t < \frac{1}{2} \tag{5}$$

Where, ε_f represents the classification error of the original data set and ε_t represents the classification error of the target data set.

The parameters of data weights are given in the following equation:

$$\beta = \frac{1}{1+\sqrt{a/N}} b = \frac{\varepsilon_t}{1-\varepsilon_f} \tag{6}$$

where N represents the total number of data. The weights of the updated sample are as follows:

$$w_i^{t+1} = \begin{cases} w_i^t \beta^{-\left|h_t(x_i - y_i)\right|}, a+1 \le i \le a+b \\ w_i^t \beta^{\left|h_t(x_i - y_i)\right|}, 1 \le i \le a \end{cases} \tag{7}$$

After the sample weights are updated, the final output of the classifier is obtained:

$$H(x) = \begin{cases} 1, \sum\limits_{i=1} w_i^{t+1}\left(\frac{1}{\beta_t}\right) h_t(x) \ge \frac{1}{2}\sum\limits_{i=1}\left(\frac{1}{\beta_t}\right) \\ 0, other \end{cases} \tag{8}$$

According to the above equation, abnormal data and normal data in the collected data can be differentiated and processed, so as to realize the filtering of the data and effectively extract the defective data.

The proposed defective data is corrected to ensure that the collected data is complete and correct. The least squares regression method is used to repair the mutilated data to correct the data, and the objective function of the corrected data is:

$$\min E(\lambda) = H(x)\sum_{i=1}\left|W_i - H_i\vartheta\right| = \sum_{i=1}\left|v_i\right| \tag{9}$$

Where, W_i represents the sample of the residual data, ϑ represents the coefficient of the correction value, v_i represents the fitting error of the data, and H_i represents the indicator of the data residual.

Set the correction error parameter φ_i and the repair value ξ as follows:

$$\begin{cases} \varphi_i = \dfrac{\left|v_i\right| + v_i}{2} \\ \xi = \dfrac{\left|v_i\right| - v_i}{2} \end{cases} \tag{10}$$

The absolute and actual values of the fitting errors are as follows:

$$\begin{cases} \left|v_i\right| = \varphi_i + \xi \\ v_i = \varphi_i - \xi \end{cases} \tag{11}$$

where $\left|v_i\right|$ represents the absolute value of the fitting error for the mutilated data.

From this, a repair model $\min E(\varphi, \xi)$ for the data can be derived as follows:

$$\min E(\varphi, \xi) = \sum_{i=1}\left(\varphi_i + \xi_i\right) \tag{12}$$

Based on the above process, the collected data can be repaired and incorrect data can be corrected to get accurate and complete data.

4.2 Prediction of user behavior and branding strategy

4.2.1 User behavior analysis

The user behavior prediction model is established based on the corrected user behavior data, in order to predict the user's future consumption behavior, determine the market trend, and formulate accurate brand marketing strategies [19-20].

The user behavior prediction model first analyzes user behavior through behavioral data, and user behavior analysis is shown in Figure 1. The essence of clarifying the analysis goal is to determine the purpose of analyzing user behavior, and to clarify the problems that need to be solved as well as the psychology of the user's purchase of goods. The collected data are processed and analyzed to summarize the behavior and psychology of user consumption. Analyze the users' consumption behavior by using the established model to get the motivation and psychology of the users when purchasing goods. Evaluate the user's consumption behavior and psychology analyzed by the model, assess the performance and accuracy of the model, and give the obtained data to the relevant staff or use it as the data basis for predicting the user's consumption behavior [21].

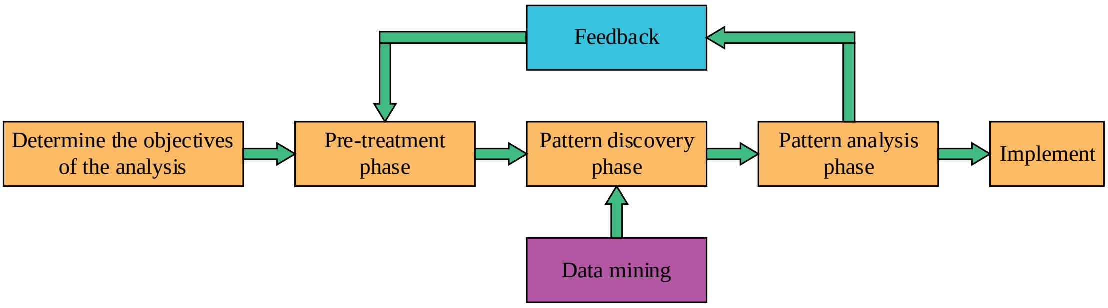

Figure 1 User behavior analysis

4.2.2 Keyword extraction

Keyword extraction method refers to the way of extracting frequently occurring words and information through statistical methods, which is commonly used in machine learning, including the maximum entropy model, genetic algorithm and support vector machine and other models are also gradually applied to the keyword extraction technology, Figure 2 shows the keyword extraction process. After obtaining the analysis of the user's consumption behavior, the keyword extraction technique is used to extract the relevant motives and behaviors of the user's consumption, which facilitates the subsequent prediction.

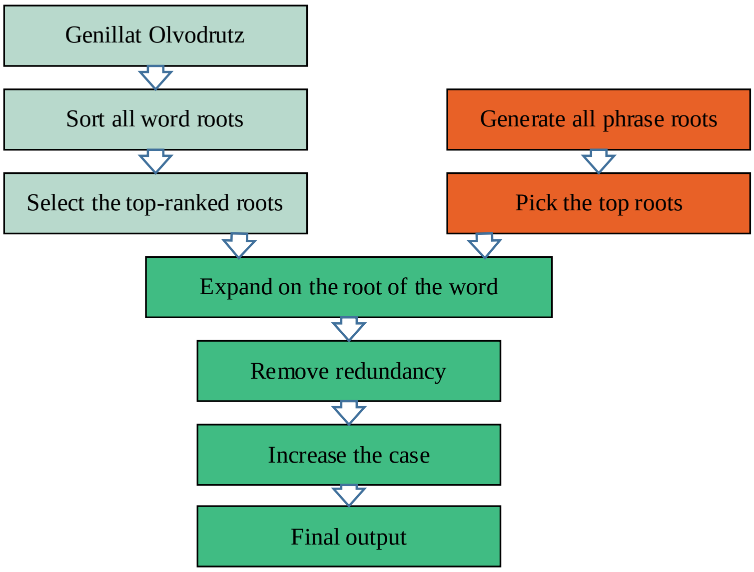

Figure 2 Keyword extraction

Before extracting the keywords to the user behavior, the characteristics of the keyword information as well as the phrase characteristics are considered and the phrases of the user behavior are ranked by using the KL scattering method of the single point state, and the KL scattering is defined as follows:

$$D(p\|q)=\sum_{x}p(x)\log\frac{p(x)}{q(x)} \tag{13}$$

The point-state KL scatter is defined as follows:

$$\delta_{\omega}(p\|q)=p(\omega)\log\frac{p(\omega)}{q(\omega)} \tag{14}$$

According to the above equation to achieve the extraction of keywords of user behavior, and using Bayesian classification method to expand the classification of the extracted keywords to complete the generalization of user behavior.

The obtained keywords are represented by $W_1,W_2,\cdots,W_n$, where the word frequency of $W_1 \sim W_n$ gradually decreases, and the Bayesian formula is used to classify the keywords as follows:

$$P(C_i|X)=\frac{\prod_{k=1}^{n}P(W_k|C_i)P(C_i)}{P(X)} \tag{15}$$

where C_i represents the class with the highest a posteriori probability.

4.2.3 Output of forecast results

Based on the classified user behavior keywords, neural network technique is used to predict the user's behavior. In neural network, each neural unit model is modeling a biological neuron, which is singularly composed of multiple inputs x_i, $i=1,2,\cdots,n$ and one output y. The intermediate states are represented by the weights of the input data and the values of the outputs:

$$y_j(t)=f\left(\sum_{i=1}^{n}w_{ji}x_i-\theta_j\right) \tag{16}$$

where w_{ji} represents the weights between neural unit i and unit j, θ_j represents the threshold of neural unit j, $f()$ represents the excitation function, and x_i represents the input.

The keywords are inputted into the neural network to start the prediction of the user's behavior, and the neural network process is shown in Figure 3. Let the unit connection weight from the input layer to the hidden layer be V_{hi}, the threshold value of the hidden layer unit be θ_i, the connection weight from the hidden layer to the output unit be w_{ij}, and the net value of the output unit be V_j. The keywords of the user's behavior will be inputted into the input layer and passed from the input layer to the hidden layer.

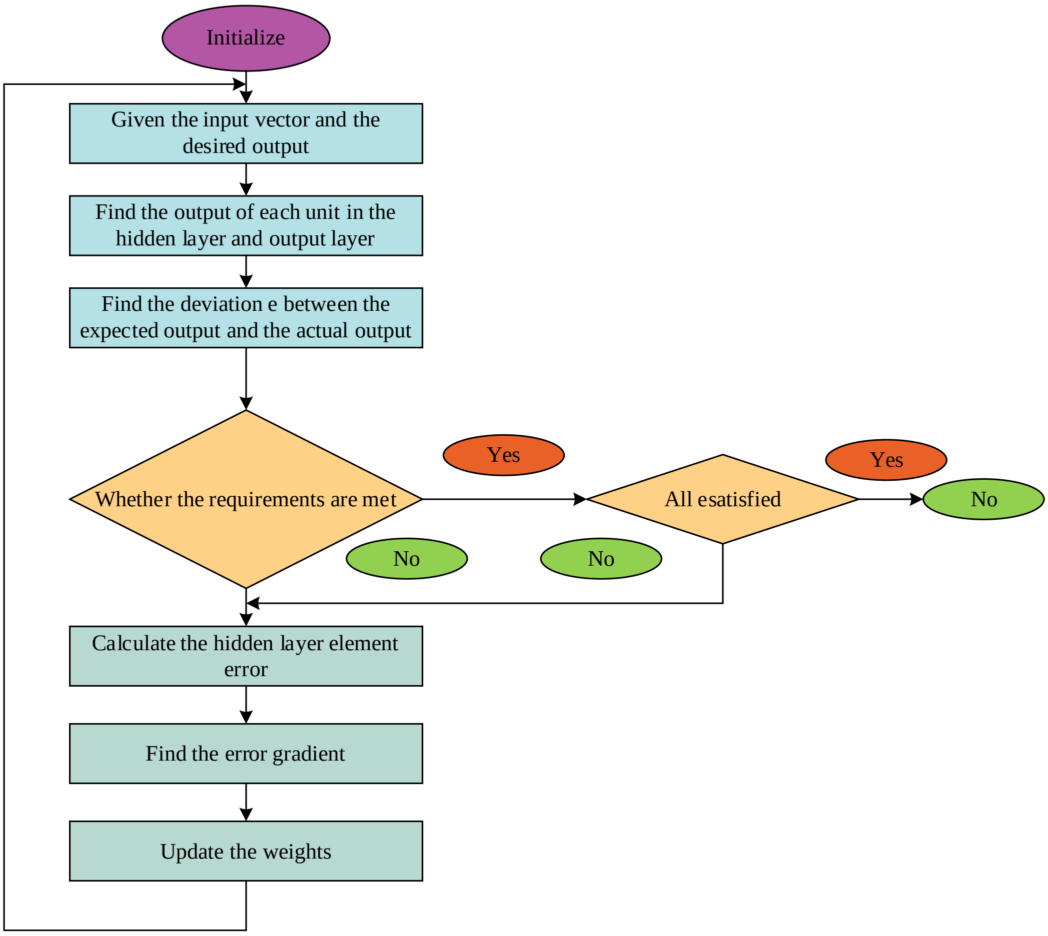

Figure 3 Neural network process

The excitation function is used to calculate the actual output value of the node in the hidden layer unit $o = f(wx)$, where f represents the neural activation function and the derivative of the excitation function is:

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{17}$$

$$f'(x) = \lambda f(x)\left[1 - f(x)\right] \tag{18}$$

As the keywords are fed into the neural network to produce the output, a corresponding error occurs, and the sum of squared output unit errors is as follows:

$$E^{(p)} = \frac{1}{2}\sum_{l=0}^{m-1}\left(d_l^{(p)} - y_l^{(p)}\right)^2 \tag{19}$$

When all the data is entered once, the total error obtained is as follows:

$$E_A = \sum_{p=1}^{P} E^{(p)} = \frac{1}{2}\sum_{p=1}^{P}\sum_{l=0}^{m-1}\left(d_l^{(p)} - y_l^{(p)}\right)^2 \tag{20}$$

Using w_{sq} to represent the weight of any connection of the network, the error is corrected to be correct according to the gradient descent method as follows:

$$\Delta w_{sq} = -\eta \frac{\partial E_A}{\partial w_{sq}} \tag{21}$$

The error correction for the output layer is:

$$w_{kl}\left(n_0+1\right) = w_{kl}\left(n_0\right) - \eta \frac{\partial E_A}{\partial w_{kl}} \tag{22}$$

$$\frac{\partial E_A}{\partial w_{kl}} = -\sum_{p=1}^{P}\left(d_l^{(p)} - y_l^{(p)}\right)y_l^{(p)}\left(1-y_l^{(p)}\right)x_k^{(p)} = -\sum_{p=1}^{P}\delta_{kl}^{(p)}x_k^{(p)} \tag{23}$$

Eq. $\delta_{kl}^{(p)} = \sum_{p=1}^{P}\left(d_l^{(p)} - y_l^{(p)}\right)y_l^{(p)}\left(1-y_l^{(p)}\right)$.

Then the modified value of the weights of each connection in the model is calculated, and the input data samples are learned, if the number reaches a predetermined number, jump to the next step, otherwise return to the incentive function. According to the weight correction formula to amend the weight of each layer, according to the new weights to calculate the input and output again, and use the model to predict the user behavior, get the predicted results.

According to the above process to complete the prediction of the user's consumption behavior, according to the predicted behavior of the enterprise to determine the market trend and direction, the development of appropriate marketing strategies and means to attract the attention of users, improve the efficiency of the enterprise.

5. THE IMPACT OF USER DATA ON BRANDS IN THE MOBILE ENVIRONMENT

5.1 Conversion Rate Analysis

Conversion rate analysis is a key performance indicator to measure the effectiveness of brand marketing, which is used to measure the proportion of success in brand marketing activities from the initial brand to reach the desired value. The higher the conversion rate, proving that the formulation of the brand strategy is more user-specific, attracting a large number of users to pay attention to the brand, as a way to improve the performance and efficiency of the enterprise and increase the competitiveness of the enterprise, the formulation of the brand strategy to start the conversion rate test, Table 1 shows the results of the conversion rate.

It can be seen that the conversion rate of the brand is high, the brand advertisement set in the search engine, there are 1,000 visits, the number of purchases reached 900, the conversion rate is 90%, in the media advertisement, the number of visits is 950, the conversion rate is 86%. In video marketing, the number of visits was at 860, with 810 purchases of the brand and a conversion rate of 89%, with an average conversion rate of around 88%. It proves that the brand strategy can accurately locate the target users, and can clear show the advantages and unique features of the brand, which inspires the users to buy. And when the user purchases, it provides a smooth purchase process to enhance the user's experience and builds up the user's trust, which helps to improve the user's purchase confidence and retention rate.

Table 1 Conversion rate results

Events	**Views**	**Number of people who completed the purchase**	**Conversion rate**
Search engine advertising	1000	900	90%

Media advertising	950	800	86%
Content marketing	970	900	88%
Offline events	850	800	88%
Video marketing	860	810	89%

5.2 Brand Exposure Count Test

The brand exposure number test is generally used to measure the degree of attraction of the developed brand marketing strategy to the users and whether it can be perceived and recognized by the consumers. In general, the higher the number of brand exposure, proving that the developed brand marketing strategy can meet the psychological expectations of users and can be known by more people. The brand's popularity is improved, and the enterprise's marketing activities have a certain effect, which improves the stickiness of product users and increases the enterprise's benefits and its own competitiveness. Tests on the brand strategy developed based on the prediction results were launched, and the results of the brand exposure test are shown in Figure 4. The number of brand exposure is very high at different user numbers, around 80 times at 100 to 200 users, and around 90 times at 300 to 400 users, which proves that the brand strategy based on the results of the predicted user behavior model is effective, the content is attractive and can capture the interests and needs of users, and effectively interacts with users and attracts their interest and competitiveness. Effectively interacting with users, it attracts a large number of users to pay attention to the brand, and generates desire and motivation to buy the brand, enhances the user experience, strengthens the user's loyalty and activity to the brand, improves the competitiveness of the enterprise and its share in the market, and brings stable customer resources and long-term success to the brand.

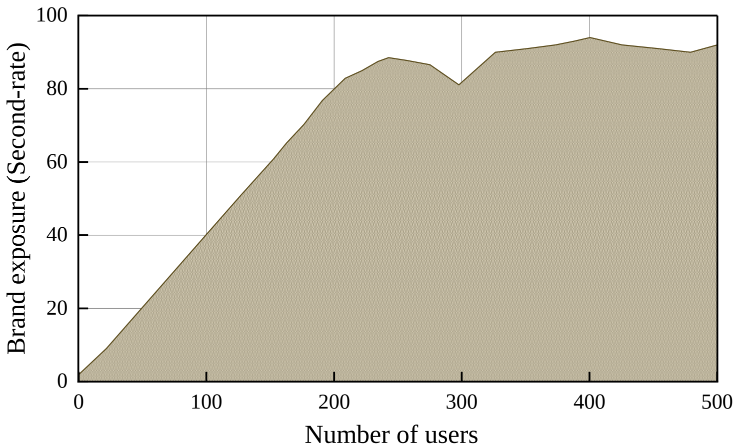

Figure 4 Brand exposure test

5.3 Evaluation of the effectiveness of marketing strategy development

Marketing strategy development assessment results are used to measure whether the developed brand strategy appears to have a positive response in the market and attracts the attention and engagement of consumers. The more positive the assessment results of market strategy development, the more the brand proves to be recognized in the market, has a positive response in the market, increases the sales and performance of the company, and attracts more users to participate in the purchase. Customers are more satisfied with the brand and have a strong adhesion, so the developed brand strategy is tested, and Table 2 shows the results of the assessment of market strategy development. It can be seen that after the development of brand strategy through the predicted user behavior, the market effect of the brand has been substantially improved, increasing the brand awareness from the original 35% to 90%, so that more consumers recognize the brand and attract the attention of consumers, which will increase the customer rate from 32% to 89%, and improve the sales of the company, which increased the original sales to 91%, and improve the efficiency of the company. This can prove that the improved brand strategy is more targeted, starting from the user's consumer behavior and psychology, to enhance the user's desire to buy, to ensure a stable customer base and market share, to expand the influence of the enterprise, so that the brand can obtain new customers, to broaden the sales channels, so that the enterprise is more competitive in the market, and to fully grasp the winds and trends of the market.

Table 2 Market strategy formulation evaluation effect

Metrics	Evaluation criteria	Performance before formulation	Performance after formulation
Brand awareness	Whether the brand mention rate has increased	35%	90%
Market share	Whether the market share has increased	25%	55%
Sales	Whether the sales performance has increased	50%	91%
Customer satisfaction	Whether the customer feedback is positive	50 score	92 score
Website page views	Whether the page views and clicks have increased	20%	89%
Customer retention rate	Whether the customer retention rate has increased	30%	85%
Customer growth rate	Whether the number of customers has increased	32%	89%
Brand influence	Whether the positive brand influence has increased	25%	88%
Media influence	Whether the brand's influence in the media has increased	10%	85%

6. MODEL MEAN SQUARE ERROR TEST

The mean square error test is generally used to measure whether the results predicted by the model are consistent with the actual observations and whether the predicted results are in error. Usually, the lower the value of the mean square error, proving that the results predicted by the model and the actual results are more similar, or even almost the same, the model can adequately predict the user's consumer behavior and psychology, for the subsequent development of brand strategy has a better effect. Therefore, the mean square error of the prediction model is tested, and the results of the root mean square error test are shown in Table 3. Due to the establishment of the model, the user behavior data collected before the data filtering and correction, reduce the data errors and loss of data, improve the availability of data. Therefore, the mean square error of the model is low, the mean square error of the first test is 0.013, the second is 0.011, and the third mean square error is 0.012. Going down in order, the error of each time is very close to 0, and the error is large. It can accurately predict the user's future consumption behavior, assist the brand to develop reasonable strategies and means to improve the brand's customer traffic, so that the brand has a high degree of competitiveness and can be actively developed.

Table 3 Root mean square error test

Frequency	Root mean square error
1	0.013
2	0.011
3	0.012
4	0.013
5	0.015
6	0.012

7. CONCLUSION

In this paper, the influence of brand strategy on consumer behavior is obtained by analyzing the behavior of consumers and the relationship between consumers and brands. The migration learning algorithm is used to filter and correct the collected user behavior data to make the data accurate and complete, so as to facilitate the establishment of subsequent models. A user behavior prediction model is established to predict user behavior through the collected data, so as to formulate a reasonable brand strategy based on the behavior. It was found that the formulated branding strategy was more effective and improved the conversion rate of purchase, making the conversion rate 88%, which improved the efficiency and performance of the company, and the market evaluation was also more effective. The brand advertisement set up in search engine had 1000 visits and the number of purchases reached 900, in media advertisement, the number of visits was 950, and in video marketing, the number of visits was at 860, which improved the user's viscosity and activity. The error of the constructed prediction model is minimized to 0.011, which broadens the sales channel of the enterprise and makes it more competitive. With the current development and progress of science and technology, the way to develop brand strategy based on user behavior will be widely used, which not only meets the needs of users, but also aids in the positive development of enterprises.

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