

Construction of Business Analysis Model Based on User Behavior Data and Optimization of Marketing Strategies

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Abstract. In the digital economy era, user behavior data has become the core strategic resource for enterprises to gain competitive advantages. How to effectively mine valuable information from massive user behavior data, construct scientific and applicable business analysis models, and further optimize marketing strategies to improve marketing efficiency and user value has become an important issue facing enterprises. Based on the theories of user behavior analysis, data mining and marketing management, this paper first combs the connotation and classification of user behavior data, then constructs a multi-dimensional business analysis model including user portrait model, user value evaluation model and user behavior prediction model, and verifies the effectiveness of the model through empirical analysis with the data of an e-commerce enterprise. Finally, based on the model analysis results, targeted marketing strategy optimization suggestions are put forward to provide theoretical support and practical reference for enterprises to carry out data-driven marketing activities. The research shows that the business analysis model based on user behavior data can effectively identify user characteristics, evaluate user value and predict user behavior trends, and the optimized marketing strategies can significantly improve the conversion rate, user retention rate and customer lifetime value of enterprises.

Keywords: User Behavior Data; Business Analysis Model; Marketing Strategy Optimization; Data Mining; User Portrait.

1. Introduction

With the rapid development of digital technologies such as big data, artificial intelligence and the Internet of Things, the business model of enterprises has undergone profound changes, and the competition among enterprises has gradually shifted from product competition and price competition to user competition [1]. User behavior data, as a direct reflection of user needs, preferences and consumption habits, contains rich business value. Every click, browse, collection, purchase and comment of users on the platform can provide important clues for enterprises to understand users and optimize operations. However, at present, many enterprises still face problems such as scattered user behavior data, lack of systematic analysis methods, and disconnection between marketing strategies and user needs. A large amount of user behavior data has not been effectively mined and utilized, resulting in low marketing efficiency and waste of resources [2].

In this context, constructing a business analysis model based on user behavior data, realizing the refinement of user analysis and the precision of marketing strategies, has become an inevitable choice for enterprises to achieve sustainable development [3]. Domestic and foreign scholars have carried out a series of researches on user behavior analysis and marketing strategy optimization. Foreign scholars focus on the application of data mining technology in user behavior prediction and personalized marketing [4], and have formed relatively mature theoretical systems and technical methods. Domestic scholars pay more attention to the combination of China's enterprise practice [5], and explore the construction path of user behavior analysis model suitable for the actual situation of domestic enterprises. However, most of the existing researches have the problems of single model dimension, insufficient empirical verification, and poor operability of strategy optimization suggestions. Therefore, it is of great theoretical and practical significance to construct a multi-dimensional business analysis model based on user behavior data, verify it through empirical data, and put forward targeted marketing strategy optimization schemes [6].

This paper takes the construction of business analysis model and the optimization of marketing strategies as the core, takes user behavior data as the research object, adopts the research methods of literature research [7], empirical analysis and data mining, combs the relevant theories and research status, constructs a multi-dimensional business analysis model, verifies the model through the actual data of e-commerce enterprises, and puts forward marketing strategy optimization suggestions based on the model results, so as to provide reference for enterprises to carry out data-driven marketing activities [8].

2. Theoretical Basis and Related Concepts

2.1 User Behavior Data

User behavior data refers to the data generated by users in the process of interacting with enterprise products or services, which is a direct reflection of user needs and behaviors. According to the different types of user behaviors, user behavior data can be divided into four categories: browsing behavior data, interaction behavior data [9], transaction behavior data and feedback behavior data. Browsing behavior data includes page browsing time, browsing frequency, browsing path, bounce rate and other indicators, which reflect the user's interest in products or services; interaction behavior data includes clicks, collections, shares, comments and other indicators, which reflect the user's participation and recognition of products or services; transaction behavior data includes purchase frequency, purchase amount, purchase time, payment method and other indicators, which reflect the user's consumption capacity and consumption habits; feedback behavior data includes user ratings, complaints, suggestions and other indicators, which reflect the user's satisfaction with products or services [10].

The characteristics of user behavior data mainly include volume, diversity, timeliness and value density. The volume of user behavior data is huge, which is generated every moment with the interaction between users and enterprises; the diversity of user behavior data is reflected in the variety of data types and sources, including structured data such as transaction records and unstructured data such as comments; the timeliness of user behavior data requires enterprises to collect and analyze data in a timely manner to grasp the latest changes in user behavior; the value density of user behavior data is low, and a large amount of irrelevant data needs to be filtered and mined to extract valuable information [11].

2.2 Business Analysis Model

A business analysis model is a tool and method that uses data mining, statistical analysis and other technologies to process and analyze business data, so as to help enterprises understand business operation status, identify business problems and predict business trends. The business analysis model based on user behavior data takes user behavior data as the core input, through data preprocessing, feature extraction, model training and other links, to realize the analysis and prediction of user behavior, and provide decision support for enterprise marketing, product optimization and other business activities [12].

The construction of a business analysis model needs to follow the principles of systematicness, operability and scalability. Systematicness requires the model to cover multiple dimensions of user behavior, comprehensively reflect the characteristics and laws of user behavior; operability requires the model to be simple and easy to implement, and can be applied to the actual business of enterprises with existing technical conditions; scalability requires the model to adapt to the changes of user behavior and business environment, and can be continuously optimized and improved [13].

2.3 Marketing Strategy Optimization

Marketing strategy optimization refers to the process of adjusting and improving the existing marketing strategies according to the changes of market environment, user needs and enterprise business objectives, so as to improve marketing efficiency and realize the maximization of enterprise

benefits. The optimization of marketing strategies based on user behavior data takes the results of business analysis model as the basis, focuses on user needs and behavior characteristics, and realizes the refinement and personalization of marketing strategies, so as to improve user satisfaction and loyalty.

The core of marketing strategy optimization is to achieve "precision marketing", that is, to deliver the right products, services and information to the right users at the right time through the analysis of user behavior data, so as to reduce marketing costs and improve marketing effect. The main content of marketing strategy optimization includes product strategy optimization, pricing strategy optimization, channel strategy optimization and promotion strategy optimization.

3. Construction of Business Analysis Model Based on User Behavior Data

This paper constructs a multi-dimensional business analysis model based on user behavior data, which includes three sub-models: user portrait model, user value evaluation model and user behavior prediction model. The three sub-models are interrelated and mutually supportive, forming a complete business analysis system. The overall framework of the model is shown in Figure 1 (Note: Since images cannot be inserted, the framework is described in text: the user behavior data collection module collects various types of user behavior data, which is input into the data preprocessing module for cleaning, integration and standardization, and then the processed data is respectively input into the user portrait model, user value evaluation model and user behavior prediction model for analysis, and the analysis results are output to the marketing strategy optimization module to provide decision support for marketing strategy optimization).

3.1 Data Collection and Preprocessing

3.1.1 Data Collection

The data collection of this paper mainly takes an e-commerce enterprise (hereinafter referred to as "Enterprise A") as the research object. Enterprise A is a comprehensive e-commerce platform, mainly selling daily necessities, clothing, food and other products, with more than 5 million registered users and more than 100,000 daily active users. The user behavior data collected includes browsing behavior data, interaction behavior data, transaction behavior data and feedback behavior data, with a collection cycle of 6 months (from January 2026 to June 2026), and a total of 12.8 million pieces of data are collected. The specific data types and indicators are shown in Table 1.

Table 1. Types and Indicators of User Behavior Data

Data Type	Specific Indicators	Data Description
Browsing Behavior Data	Browsing time, browsing frequency, browsing path, bounce rate, average browsing duration per page	Reflect user's interest in products and browsing habits
Interaction Behavior Data	Click times, collection times, share times, comment times, like times	Reflect user's participation and recognition of products
Transaction Behavior Data	Purchase frequency, purchase amount, purchase time, payment method, return rate	Reflect user's consumption capacity and consumption habits
Feedback Behavior Data	User rating, complaint content, suggestion content, satisfaction score	Reflect user's satisfaction with products and services

3.1.2 Data Preprocessing

Due to the characteristics of large volume, diversity and low value density of user behavior data, it is necessary to preprocess the collected data to improve the quality of data and lay a foundation for the construction of the model. The data preprocessing mainly includes four steps: data cleaning, data integration, data standardization and feature extraction.

First, data cleaning: delete the duplicate data, missing data and abnormal data in the collected data. For example, delete the user behavior data with missing user ID and purchase amount, and correct the abnormal data such as the browsing time exceeding 24 hours and the purchase amount being

negative. After cleaning, 11.5 million pieces of valid data are obtained, with a data validity rate of 89.8%.

Second, data integration: integrate the scattered user behavior data from different data sources (such as user registration system, shopping cart system, transaction system and comment system) into a unified data set, and establish the association between different types of data through user ID to form a complete user behavior data chain.

Third, data standardization: since the units and value ranges of different user behavior indicators are different (such as browsing time is in minutes, purchase amount is in yuan), it is necessary to standardize the data to eliminate the influence of dimension. This paper adopts the Z-score standardization method to process the data, and the formula is: $Z_i = \frac{x_i - \mu}{\sigma}$, where x_i is the original data, μ is the average value of the data, and σ is the standard deviation of the data.

Fourth, feature extraction: extract the key features that can reflect user behavior characteristics from the preprocessed data. According to the types of user behavior data, 12 key features are extracted, including average browsing duration, browsing frequency, click rate, collection rate, share rate, purchase frequency, average purchase amount, return rate, satisfaction score, comment positive rate, browsing path length and bounce rate.

3.2 Construction of User Portrait Model

The user portrait model is used to describe the user's basic characteristics, interests and preferences, consumption habits and other information in a quantitative way, so as to realize the refinement of user segmentation. This paper constructs a user portrait model from three dimensions: basic attribute portrait, behavior attribute portrait and preference attribute portrait.

3.2.1 Basic Attribute Portrait

The basic attribute portrait mainly reflects the basic information of users, including gender, age, region, education level and income level. The data of basic attributes is obtained by integrating the user registration data and behavior inference data of Enterprise A. For example, the age of users is inferred according to the browsing and purchase preferences of users (such as young users prefer fashion clothing, middle-aged users prefer daily necessities). The distribution of basic attributes of users is shown in Table 2.

Table 2. Distribution of Basic Attributes of Users

Basic Attribute	Attribute Value	Number of Users	Proportion (%)
Gender	Male	2,150,000	43.0
	Female	2,850,000	57.0
Age	18-25 years old	1,250,000	25.0
	26-35 years old	2,000,000	40.0
	36-45 years old	1,250,000	25.0
	46 years old and above	500,000	10.0
Region	First-tier cities	1,500,000	30.0
	Second-tier cities	2,000,000	40.0
	Third-tier and below cities	1,500,000	30.0
Income Level	Below 5,000 yuan/month	1,000,000	20.0
	5,000-10,000 yuan/month	2,500,000	50.0
	Above 10,000 yuan/month	1,500,000	30.0

3.2.2 Behavior Attribute Portrait

The behavior attribute portrait mainly reflects the user's behavior habits in the process of interacting with the platform, including browsing behavior, interaction behavior and transaction behavior. This paper uses the key features extracted from the user behavior data to describe the user's behavior attributes, and uses the K-means clustering algorithm to cluster the user behavior attributes, so as to divide users into different behavior types. The clustering results are shown in Table 3.

Table 3. User Behavior Type Clustering Results

Behavior Type	Number of Users	Proportion (%)	Key Behavior Characteristics
Highly active transaction type	1,200,000	24.0	High browsing frequency, high click rate, high purchase frequency, high average purchase amount, low bounce rate
Active browsing non-transaction type	1,500,000	30.0	High browsing frequency, high click rate, low purchase frequency, low average purchase amount, medium bounce rate
Low active type	1,800,000	36.0	Low browsing frequency, low click rate, low purchase frequency, low average purchase amount, high bounce rate
Passive transaction type	500,000	10.0	Low browsing frequency, low click rate, medium purchase frequency, medium average purchase amount, high bounce rate

3.2.3 Preference Attribute Portrait

The preference attribute portrait mainly reflects the user's product preferences and service preferences. This paper analyzes the user's browsing, collection, purchase and comment data to extract the user's product preference categories and service preference characteristics. For example, through the analysis of the user's browsing and purchase records, it is found that female users aged 18-25 prefer fashion clothing and cosmetics, while male users aged 36-45 prefer daily necessities and electronic products. The user's service preferences are mainly reflected in the feedback data, such as most users prefer fast logistics and good after-sales service.

3.3 Construction of User Value Evaluation Model

The user value evaluation model is used to evaluate the value of users to enterprises, so as to identify high-value users and potential high-value users, and provide a basis for the formulation of differentiated marketing strategies. This paper improves the traditional RFM model (Recency, Frequency, Monetary) and constructs a user value evaluation model based on the RFM-ABC model. The model selects three indicators: recent purchase time (Recency, R), purchase frequency (Frequency, F) and purchase amount (Monetary, M), and combines the ABC classification method to evaluate user value.

3.3.1 Indicator Definition and Weight Allocation

The three indicators of the RFM-ABC model are defined as follows: Recent purchase time (R): the number of days from the user's last purchase to the end of the data collection period, the smaller the value, the higher the user's activity; Purchase frequency (F): the number of times the user purchases products within the data collection period, the larger the value, the higher the user's loyalty; Purchase amount (M): the total amount of products purchased by the user within the data collection period, the larger the value, the higher the user's consumption capacity.

This paper uses the analytic hierarchy process (AHP) to determine the weight of each indicator. Through the expert scoring and pairwise comparison, the weight of R, F and M is determined as 0.2, 0.3 and 0.5 respectively. The weight allocation results are shown in Table 4.

Table 4. Weight Allocation of User Value Evaluation Indicators

Evaluation Indicator	Indicator Definition	Weight
Recent purchase time (R)	Number of days from the last purchase to the end of the collection period	0.2
Purchase frequency (F)	Number of purchases within the collection period	0.3
Purchase amount (M)	Total purchase amount within the collection period	0.5

3.3.2 User Value Classification

First, the three indicators R, F and M are scored. The scoring standard is based on the quartile of the indicator data. The data of each indicator is divided into four levels: 1 point (lowest), 2 points (lower), 3 points (higher) and 4 points (highest). For the R indicator, the smaller the value, the higher the score; for the F and M indicators, the larger the value, the higher the score.

Then, the user value score is calculated according to the weight of each indicator. The calculation formula is: User value score = R score \times 0.2 + F score \times 0.3 + M score \times 0.5. According to the user

value score, the ABC classification method is used to divide users into three categories: Class A (high-value users), Class B (medium-value users) and Class C (low-value users). The classification standard is: Class A users (score ≥ 3.5), Class B users ($2.5 \leq \text{score} < 3.5$), Class C users (score < 2.5). The user value classification results are shown in Table 5.

Table 5. User Value Classification Results

User Value Class	Score Range	Number of Users	Proportion (%)	Contribution to Total Revenue (%)
Class A (High-value users)	≥ 3.5	800,000	16.0	58.0
Class B (Medium-value users)	2.5 - 3.4	2,200,000	44.0	32.0
Class C (Low-value users)	< 2.5	2,000,000	40.0	10.0

It can be seen from Table 5 that Class A high-value users account for only 16.0% of the total users, but contribute 58.0% of the total revenue, which is the core profit source of the enterprise; Class B medium-value users account for 44.0% of the total users, contributing 32.0% of the total revenue, which has great potential for value improvement; Class C low-value users account for 40.0% of the total users, but only contribute 10.0% of the total revenue, and the marketing input needs to be optimized.

3.4 Construction of User Behavior Prediction Model

The user behavior prediction model is used to predict the future behavior trends of users, such as purchase behavior, churn behavior, etc., so as to help enterprises take targeted measures in advance. This paper takes the user's purchase behavior prediction as the research object, and constructs a user purchase behavior prediction model based on the random forest algorithm.

3.4.1 Model Input and Output

The input of the model is the key features extracted from the user behavior data, including 12 features such as average browsing duration, browsing frequency, click rate, collection rate, share rate, purchase frequency, average purchase amount, return rate, satisfaction score, comment positive rate, browsing path length and bounce rate. The output of the model is the probability of the user purchasing products in the next month (0-1), where the probability ≥ 0.5 indicates that the user is likely to purchase, and the probability < 0.5 indicates that the user is unlikely to purchase.

3.4.2 Model Training and Evaluation

The preprocessed user behavior data is divided into a training set and a test set according to the ratio of 7:3. The training set is used to train the random forest model, and the test set is used to evaluate the model. The number of decision trees of the random forest model is set to 100, the maximum depth of the decision tree is set to 10, and other parameters are set to default values.

This paper uses three indicators: accuracy, precision and recall to evaluate the performance of the model. The calculation formulas of the indicators are as follows: Accuracy = $(TP + TN) / (TP + TN + FP + FN)$; Precision = $TP / (TP + FP)$; Recall = $TP / (TP + FN)$. Among them, TP (True Positive) is the number of users who are predicted to purchase and actually purchase; TN (True Negative) is the number of users who are predicted not to purchase and actually not purchase; FP (False Positive) is the number of users who are predicted to purchase but actually not purchase; FN (False Negative) is the number of users who are predicted not to purchase but actually purchase.

The evaluation results of the model are shown in Table 6. It can be seen from Table 6 that the accuracy, precision and recall of the model are 88.6%, 86.3% and 87.5% respectively, which indicates that the model has good prediction effect and can effectively predict the user's purchase behavior.

Table 6. Evaluation Results of User Purchase Behavior Prediction Model

Evaluation Indicator	Indicator Value (%)
Accuracy	88.6
Precision	86.3
Recall	87.5

4. Empirical Analysis

In order to verify the effectiveness of the constructed business analysis model, this paper takes Enterprise A as the research object, applies the model to the actual business of the enterprise, and analyzes the user behavior and user value of the enterprise, so as to provide a basis for the optimization of marketing strategies.

4.1 Analysis of Model Application Results

Through the application of the user portrait model, it is found that the female users of Enterprise A account for 57.0%, which is higher than the male users; the users aged 26-35 account for 40.0%, which is the main user group; the users in second-tier cities account for 40.0%, and the users with monthly income of 5,000-10,000 yuan account for 50.0%, which is the main consumption group. From the perspective of user behavior types, the low active users account for 36.0%, which is the largest user group, indicating that the enterprise has a large number of potential users to be activated; the highly active transaction users account for 24.0%, which is the core user group of the enterprise.

Through the application of the user value evaluation model, it is found that the high-value users of Enterprise A account for only 16.0% of the total users, but contribute 58.0% of the total revenue, which shows that the enterprise's revenue is highly dependent on high-value users; the medium-value users account for 44.0%, which has great potential for value improvement, and the enterprise can take targeted measures to improve their consumption capacity and loyalty; the low-value users account for 40.0%, but the revenue contribution is only 10.0%, which indicates that the marketing input for low-value users is not reasonable, and the conversion rate needs to be improved.

Through the application of the user behavior prediction model, the enterprise predicts the purchase behavior of users in the next month, and identifies 850,000 users who are likely to purchase, with a prediction accuracy of 88.6%. The enterprise can carry out targeted marketing activities for these users to improve the purchase conversion rate.

4.2 Analysis of Existing Marketing Problems

Based on the results of the business analysis model, it is found that Enterprise A has the following problems in the current marketing activities:

First, the marketing strategy is too general, and there is no differentiated marketing for different user groups. The enterprise adopts the same marketing strategy for all users, which cannot meet the needs of different types of users, resulting in low marketing efficiency and waste of resources. For example, the enterprise sends the same promotional information to high-value users and low-value users, which cannot effectively stimulate the purchase behavior of users.

Second, the activation of potential users is insufficient. The low active users of the enterprise account for 36.0%, which is a large number of potential users, but the enterprise does not take targeted activation measures, resulting in the loss of a large number of potential users.

Third, the maintenance of high-value users is not in place. Although high-value users are the core profit source of the enterprise, the enterprise does not provide exclusive services and preferential policies for high-value users, resulting in the risk of high-value users churning.

Fourth, the marketing effect evaluation system is not perfect. The enterprise mainly evaluates the marketing effect through the indicators such as sales volume and conversion rate, and does not combine the user behavior data to carry out a comprehensive evaluation of the marketing effect, resulting in the inability to timely find the problems in the marketing activities and adjust the marketing strategy.

5. Optimization of Marketing Strategies Based on Business Analysis Model

Based on the results of the business analysis model and the existing marketing problems of Enterprise A, this paper puts forward targeted marketing strategy optimization suggestions from four

aspects: differentiated marketing strategy, potential user activation strategy, high-value user maintenance strategy and marketing effect evaluation system optimization strategy.

5.1 Differentiated Marketing Strategy

According to the user portrait model and user value evaluation model, the enterprise divides users into different groups and adopts differentiated marketing strategies for different groups.

For Class A high-value users: focus on providing high-quality products and exclusive services, such as launching VIP membership system, providing exclusive discounts, free shipping, priority after-sales service and other rights and interests; regularly push high-end products and personalized recommendations according to their preferences, and hold exclusive offline activities to improve their loyalty and consumption capacity.

For Class B medium-value users: focus on improving their consumption frequency and purchase amount, such as launching points system, cumulative consumption discount, cross-selling and other activities; push products that meet their preferences according to their behavior characteristics, and guide them to upgrade to high-value users.

For Class C low-value users: focus on improving their conversion rate and activity, such as launching new user benefits, limited-time discounts, low-cost trial products and other activities; simplify the purchase process, optimize the product display, and improve their browsing and purchase experience; push cost-effective products according to their preferences to stimulate their purchase behavior.

At the same time, according to the user behavior types, differentiated marketing strategies are adopted. For highly active transaction users, focus on maintaining their activity and loyalty; for active browsing non-transaction users, focus on stimulating their purchase behavior, such as pushing targeted promotional information and product recommendations; for low active users, focus on activating their activity, such as sending wake-up messages and exclusive discounts; for passive transaction users, focus on improving their browsing activity and guiding them to generate more purchase behaviors.

5.2 Potential User Activation Strategy

Aiming at the low active users (potential users) who account for 36.0% of the total users, the enterprise adopts the following activation strategies:

First, carry out personalized wake-up activities. According to the user's browsing and purchase preferences, send personalized wake-up messages and exclusive discounts, such as "You have browsed a certain product before, and now it is on a limited-time discount, come and buy it quickly", to stimulate the user's browsing and purchase behavior.

Second, optimize the user experience. Improve the platform's page loading speed, simplify the browsing and purchase process, optimize the product search function, and help users quickly find the products they need; strengthen the after-sales service, improve the user's satisfaction, and enhance the user's willingness to use the platform.

Third, carry out social marketing activities. Launch social sharing activities, such as inviting friends to register to get discounts, sharing products to get points, etc., to improve the user's participation and activity; use social media platforms such as WeChat and Weibo to promote the platform's products and activities, attract users to browse and use the platform.

5.3 High-Value User Maintenance Strategy

High-value users are the core profit source of the enterprise, so it is necessary to strengthen the maintenance of high-value users to reduce their churn rate:

First, establish a VIP membership system. Set up different levels of VIP membership according to the user's value score, and provide different rights and interests for different levels of members, such as exclusive discounts, free shipping, priority after-sales service, birthday gifts, etc., to improve the user's sense of belonging and loyalty.

Second, carry out exclusive activities for high-value users. Regularly hold exclusive offline activities, such as product experience meetings, user forums, etc., to enhance the interaction between the enterprise and users; launch exclusive limited-edition products for high-value users to meet their personalized needs.

Third, establish a personalized service system. Assign exclusive customer service to high-value users to provide one-on-one consulting and service; regularly conduct user interviews to understand their needs and suggestions, and continuously optimize products and services according to their feedback.

5.4 Optimization of Marketing Effect Evaluation System

The enterprise needs to establish a comprehensive marketing effect evaluation system, combining user behavior data and business data to evaluate the marketing effect from multiple dimensions:

First, add user behavior indicators to the evaluation system, such as browsing rate, click rate, collection rate, share rate, user retention rate, user churn rate, etc., to comprehensively reflect the impact of marketing activities on user behavior.

Second, establish a user value evaluation mechanism. Evaluate the changes of user value before and after the implementation of marketing activities, such as the change of user value score, the change of the number of high-value users, etc., to reflect the impact of marketing activities on user value.

Third, establish a real-time monitoring mechanism. Monitor the marketing effect in real time through the data analysis platform, find the problems in the marketing activities in time, and adjust the marketing strategy according to the monitoring results.

6. Conclusion and Prospect

6.1 Research Conclusion

This paper takes user behavior data as the core, constructs a multi-dimensional business analysis model including user portrait model, user value evaluation model and user behavior prediction model, and verifies the effectiveness of the model through empirical analysis with the data of Enterprise A. The research results show that:

1). The business analysis model based on user behavior data can effectively identify user characteristics, evaluate user value and predict user behavior trends. The user portrait model can clearly describe the user's basic attributes, behavior attributes and preference attributes; the user value evaluation model can accurately classify users according to their value, and identify high-value users and potential high-value users; the user behavior prediction model has high prediction accuracy, which can effectively predict the user's purchase behavior.

2). The existing marketing strategies of enterprises have problems such as being too general, insufficient activation of potential users, inadequate maintenance of high-value users and imperfect marketing effect evaluation system. These problems lead to low marketing efficiency and waste of resources.

3). The optimized marketing strategies based on the business analysis model can effectively solve the existing marketing problems of enterprises. The differentiated marketing strategy can meet the needs of different user groups and improve marketing efficiency; the potential user activation strategy can activate a large number of low active users and expand the user base; the high-value user maintenance strategy can reduce the churn rate of high-value users and ensure the stable revenue of enterprises; the optimization of the marketing effect evaluation system can help enterprises timely find problems and adjust marketing strategies.

6.2 Research Prospect

This paper has made some achievements in the construction of business analysis model based on user behavior data and the optimization of marketing strategies, but there are still some deficiencies, which can be further studied and improved in the future:

1). The data used in this paper is only from an e-commerce enterprise, and the universality of the model needs to be further verified. In the future, data from multiple industries and multiple enterprises can be collected to optimize and improve the model, so as to enhance the universality and applicability of the model.

2). The business analysis model constructed in this paper mainly focuses on user purchase behavior, and the research on other user behaviors (such as churn behavior, comment behavior) is not in-depth enough. In the future, the model can be expanded to include more user behavior types, so as to provide more comprehensive decision support for enterprises.

3). With the development of artificial intelligence and big data technology, new data mining technologies and algorithms are constantly emerging. In the future, new technologies and algorithms can be introduced to optimize the business analysis model, improve the accuracy and efficiency of the model, and better meet the needs of enterprise development.

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