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Strategies for Enhancing Customer Lifetime Value through Data Modeling

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Abstract: With the increasingly fierce social competition, customer lifetime value (CLV) is recognized as an important indicator to measure customer relationship and long-term value of enterprises. Through the method of improving CLV to maximize customer value and promote the sustainable development of enterprises. With the rapid development of big data technology, data modeling has become one of the best means to improve CLV. With data modeling as the core, this paper analyzes the means to improve the customer lifetime value by using accurate customer prediction, personalized marketing, loss prediction and other methods. This paper reviews the theoretical basis of customer lifetime value (CLV) and how to use data modeling to improve customer prediction accuracy and behavior analysis. This paper discusses the practical application of data modeling in customer segmentation, dynamic pricing, personalized recommendation and so on. This paper provides some guidance and reference methods for enterprises to use data modeling to enhance customer lifetime value.

Keywords: customer lifetime value (CLV); data modeling; personalized marketing

1. Introduction

Customer lifetime value (CLV) has become one of the important indicators of enterprise strategic decision-making in the current data-driven business environment. CLV is the net income created by a customer in the whole life cycle of business interaction with the enterprise. In the increasingly fierce market competition environment, in addition to looking for new potential customers, the company should also pay attention to existing customers and explore their potential value. How to maximize CLV has become a major challenge for the company's sales and customer relationship management. In recent years, the development and application of data modeling technology provides an effective new method to achieve this goal. Analyze and mine historical data through data modeling, predict customers' future actions according to their historical consumption records, times, preferred products and other behaviors, and carry out targeted customer management. Through data-based tactical measures such as accurate prediction, customer segmentation and personalized recommendation, enterprises can more effectively increase the customer's life cycle value and win in the market competition. This paper summarizes the theoretical basis of CLV, the calculation method of CLV and the application value of CLV, analyzes how to use data modeling to predict customer behavior, and implement personalized promotion to predict customer churn, in order to maximize CLV. This paper presents three feasible data modeling strategies to improve CLV: customer segmentation and behavior model analysis, dynamic pricing and promotion optimization, and cross channel marketing and personalized recommendation [1].

2. Theoretical Basis of Customer Lifetime Value (CLV)

Customer lifecycle value (CLV) refers to the total profit generated in the whole cycle of interaction between a customer and the company. It is a major business evaluation tool that can help enterprises estimate and predict the long-term value of customers, adjust sales strategies and allocate resources appropriately. CLV calculation is mainly based on the customer's past behavior records (such as purchase frequency, consumption amount, loyalty, etc.) and uses a specific prediction model to estimate the future return. The calculation formula of CLV is generally:

$$\mathrm{CLV} = \sum_{t=1}^{T} R_t/[(1+d)]^t \tag{1}$$

Where R_t is the customer's income or profit in the T period, t is the length of the customer's life cycle, and d is the discount rate. Another common CLV calculation formula is:

$$\mathrm{CLV} = (\mathrm{AOV} \times \mathrm{Freq} \times \mathrm{Lifespan})/(1+d) \tag{2}$$

Where AOV (average order value) is the average amount of each purchase, freq is the purchase frequency of the customer, and lifespan is the length of the customer's life cycle (that is, the customer's maintenance period). With the help of these two calculation formulas, enterprises can accurately measure the long-term value of customers and carry out reasonable marketing plans on this basis. The great value of CLV is that it can provide a tool to measure customer value, help enterprises identify the most valuable customers, and guide enterprises how to maintain and develop these customer relationships. The goal is to improve CLV, that is, to increase customer value by extending customer life cycle, increasing customer purchase frequency, reducing customer churn rate and other means. Therefore, enterprises need to use data modeling to optimize the customer life cycle at each stage, so as to obtain the highest customer lifetime value.

3. The Role of Data Modeling in CLV Promotion

3.1. Accurate Customer Prediction and Behavior Analysis

Through data modeling, enterprises can use past behavior data to predict consumers' future purchase behavior, purchase frequency, consumption amount, etc., and serve as a reference for enterprise customer management and marketing strategy formulation. Use data modeling to deeply mine the connotation behind customer data and achieve accurate customer prediction. Enterprises can collect and analyze consumer basic data, transaction records, favorite items, consumption habits and other data, and build an individualized behavior database for each consumer. Through machine learning algorithms (classification and regression, decision tree, neural network, etc.), analyze massive data to understand customers' consumption behavior. Through cluster analysis, identify high-quality customer groups and loss risk customer groups. According to the customer's previous consumption history, it can predict the customer's possible consumption pattern and consumption amount, help the enterprise optimize the asset structure and establish a more scientific marketing plan. Through accurate customer behavior prediction, enterprises can prevent customers who may generate a lot of value in the future by early identifying and taking corresponding measures, and judge whether this consumer group should invest more in the cost of market promotion. Using user behavior analysis, we can identify the key factors that affect consumers' purchase decisions, such as seasonal demand, the effect of promotional activities, etc., to help guide commodity marketing and pricing strategies. Data modeling can not only effectively predict the short-term response of consumers, but also tap deep insight into the long-term value of consumers. By comprehensively considering the customer life cycle and future consumption status, enterprises can improve the customer lifetime value according to accurate prediction and maximize the long-term benefits of each customer. And constantly adjust the strategy according to the regular tracking of customer behavior changes to ensure that the maximum value of customers can be obtained in each period [2].

3.2. Personalized Marketing and Product Recommendation

Through data modeling, enterprises can provide personalized marketing promotion and product recommendation services. By analyzing a large number of data and information of customers, each customer can obtain targeted advertising and recommended products for them, which will stimulate customer satisfaction, strengthen their loyalty and increase their purchase times. The key point is to create targeted advertising by analyzing customers' historical behaviors and interests. By using the methods of shopping history, website browsing data and social network communication, the machine learning algorithm can accurately grasp the needs and preferences of users. Through data modeling, enterprises can continue to segment customer groups, divide them into different categories, and formulate unique marketing plans according to the characteristics of different categories. For high-end users, enterprises can take certain promotional activities and loyalty rewards; For new customers or prospective customers, they can be stimulated by preferential prices, free products and other incentives to meet their needs and generate purchase behavior. Personalized recommendation is one of the key steps. It relies on data modeling to mine the customer's information to invest in the products that the customer is most interested in. Through the customer's purchase history, interest labels, paths and other information, the recommendation system can timely recommend relevant products to customers, improving the possibility of cross selling and supplementary sales. Build a model based on the historical behavior data of users, so as to push highly targeted products or audio-visual materials to users, which will help significantly improve the conversion consumption rate of customers and enhance user stickiness. At the enterprise level, accurate personalized marketing and recommendation is an effective way for enterprises to help them increase sales, improve customer loyalty, reduce customer churn, and effectively enhance the customer's life cycle value. Using the personalized marketing model of data model, enterprises can provide products and services that meet customer expectations from the perspective of customer needs, so as to optimize customer experience. This refined marketing method may be either a one-time profit or an effective accumulation of customers' long-term dependence, and ultimately achieve the rise of CLV.

3.3. Churn Prediction and Customer Retention

Churn prediction and customer retention are two important factors that determine customer lifetime value (CLV). The company can predict the potential churn customers by using data modeling method, and prevent churn on the basis of its effective strategy, so as to obtain the maximum customer lifecycle value. The application of churn prediction model can obtain information from the historical behavior, consumption frequency, interaction log and other aspects of customers, find the customers that may lose, and remind the company of the possible loss of customers. However, the establishment of churn prediction model often uses machine learning methods such as logical regression, decision tree and support vector machine. These machine learning methods find out the characteristics related to churn according to the historical behavior of customers. If consumers do not buy goods or participate in promotions for a long time, or consumers do not contact the company frequently, this may be a sign of loss. The model based on the training data set can determine the risk index of each customer churn, and send an alarm to the company when the high-risk customers are evaluated, so as to intervene in the churn. It is not enough to worry about the possible loss of customers. It is also important to maintain existing customers. By using big data research, we can understand what factors are beneficial to retaining customers, and then according to the research results, we can customize corresponding measures to strengthen customer relations, such as improving customer experience, personalized recommendation of products and rapid response to customer needs, which can improve customer satisfaction and reduce the possibility of loss. Through the methods of churn rate and customer retention, it helps enterprises to improve customer survival. Using data model can not only help enterprises identify potential churn customer groups, but also provide effective solutions to help enterprises grow in the long term. When the churn rate decreases and customer retention increases, enterprises can achieve relatively stable revenue increase and high-value CLV [3].

4. Improve the Data Modeling Strategy of CLV

4.1. Customer Segmentation and Behavior Mode Analysis

Refined customer segmentation and analysis of customer behavior are effective ways to improve customer life cycle CLV. Through in-depth analysis of customer data, enterprises can identify different attributes of different customer segments, and then formulate targeted sales strategies to maximize long-term revenue. Customer segmentation refers to dividing customers into segments based on characteristics such as transaction frequency, amount, and purchase preferences. (such as transaction frequency, transaction amount, purchase preference, etc.). Typical clustering methods include RFM model (i.e., recency, frequency, monetary) and K-means clustering method. The customer segmentation process of RFM model is shown in Figure 1.

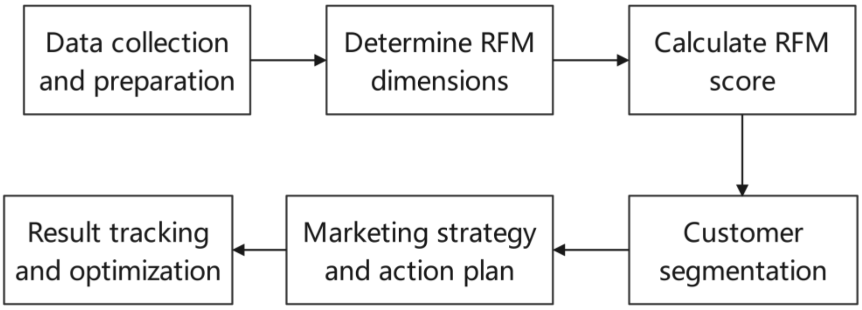

Figure 1. Customer segmentation process of RFM model.

After further analysis of user behavior information by RFM model, users can be classified according to their recency, frequency and money, such as high-end users, low activity users and users who are likely to lose. For example, in an e-commerce platform, the platform uses this method to distinguish user groups. By observing the last purchase time, purchase frequency and purchase amount of customers, the platform divides its users into "high-end customers", "medium and high-end customers" and "low-end customers". For high-end users, businesses retain users by offering preferential services, preferential policies and other measures; For middle and high-end users, merchants can stimulate them to increase their consumption amount by formulating promotional activities and providing personalized product push for them; For low-end users, merchants stimulate users' next consumption by issuing coupons and strengthening interaction with users [4].

4.2. Dynamic Pricing and Promotion Optimization

Dynamic product pricing and promotion activities are also one of the more effective ways to improve CLV. Through data modeling, enterprises can dynamically and flexibly formulate product prices and promotion policies for different markets, different customers and different competitive environments, so as to obtain the highest revenue and the highest customer long-term value [5]. The dynamic pricing and promotion optimization process is shown in Figure 2.

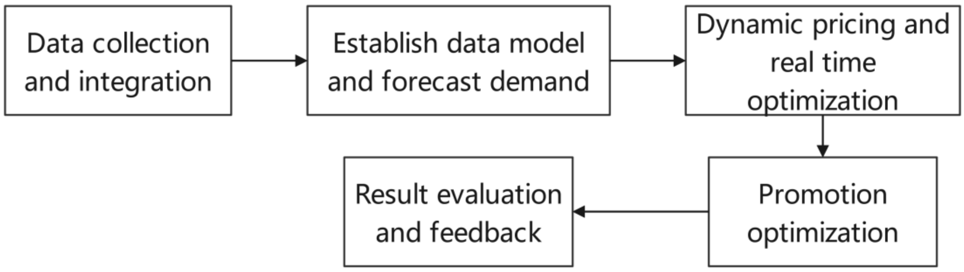

Figure 2. Dynamic pricing and promotion optimization process.

Taking a tourism reservation platform as an example, the platform uses dynamic pricing strategy to adjust prices according to demand fluctuations, customer purchase behavior and market competition. Key data before and after dynamic pricing and promotion optimization are shown in Table 1.

Table 1. Key data before and after dynamic pricing and promotion optimization.

Index	Before transformation (2020)	After transformation (2023)	Growth rate
Annual revenue (US $100 million)	100	120	+20%
Repurchase rate	45%	60%	+33%
Average order amount (AOV)	50	55	+10%
Promotion conversion rate	10%	18%	+80%
CLV (USD)	200	250	+25%

The platform uses the model of machine learning to predict the demand change of the product in a certain period of time according to the previous transaction records, the behavior characteristics of consumers and the price of competitors, and then makes corresponding adjustments according to the demand change. For example, in the peak tourism season, it uses its algorithm to predict that the demand will increase, so it increases the room and air ticket prices. When it is in a relatively weak state, it is necessary to reduce the price to attract more consumers to buy. In addition, the marketing optimization technology is used to improve the customer's life cycle value, and the a/b test method is used to compare the effects of different marketing measures and customize the exclusive benefits of different target customers. For example, provide exclusive discounts and rewards for high-level customers; For potential new customers, attractive discounts and coupons are provided to stimulate customers' purchase behavior. Use its past transaction data to accurately show the best discount to consumers, and improve the conversion rate and repurchase rate of customers. Use flexible price scheme and marketing strategy to improve customer lifetime value; Precise promotion and personalized discount can improve the contribution ability of repeat customers and boost long-term customers.

4.3. Cross Channel Marketing and Personalized Recommendation System

Improve CLV with cross channel marketing and personalized recommendation system. Through data modeling, enterprises can combine customer information from multiple channels to provide customers with unique and smooth experience, so as to enhance their long-term value. Therefore, it is necessary to provide customers with integrated and complementary services between all contacts (such as website, social media, mobile app, e-mail, etc.) to ensure that customers get a consistent experience in different contact points, so as to enhance customer loyalty. Through the data model, organizations can aggregate the information received from various channels into a unified consumer portrait, which can be used to support the marketing strategy across multiple channels. This not only improves the consumer experience, but also realizes the improvement of precision marketing and sales. For example, Amazon, as one of the world's largest e-commerce enterprises, has established an omni channel marketing and personalized recommendation system using data models [6]. Key data before and after the implementation of cross channel marketing and personalized recommendation system are shown in Table 2.

Table 2. Key data before and after the implementation of cross channel marketing and personalized recommendation system.

Index	Before transformation (2020)	After transformation (2023)	Growth rate
Annual revenue (US $100 million)	150	180	+20%
Repurchase rate	50%	70%	+40%
Customer stickiness (weekly activity rate)	30%	50%	+67%
Order conversion rate	15%	25%	+66%
CLV (USD)	300	380	+26.67%

In addition to capturing the user behavior data held by the e-commerce platform, Amazon also combines the data information collected by its mobile app, Alexa and various Amazon intelligent devices (such as Kindle or echo) to establish a user portrait. This enables it to push personalized products and advertising to all touchpoints. For example, when a user browses a new smart home product through Amazon website, he can not only receive advertising information about the product in his mobile app, but also get some suggestions related to it through Alexa, as well as the notice of discount for the product. In addition, Amazon's improved personalized recommender, relying on in-depth learning and collaborative filtering technology, continues to improve personalized accuracy, and predicts potential product demand by mining early shopping, browsing, commenting, and search behavior data. Therefore, when a customer buys an e-book, the recommender will recommend similar books according to his preference for books or recommend matching related devices (such as e-book readers or accessories) according to his other interests. Such personalized suggestions not only make it easier for consumers to generate purchase behavior, but also enhance the possibility of re purchase and further promote the improvement of CLV.

5. Conclusion

In the digital business environment, improving customer lifetime value (CLV) has become a necessary factor for enterprise success. Enterprises can accurately predict consumer behavior based on data modeling, achieve targeted marketing programs, and maximize the long-term value of customers by estimating the loss risk and customer retention measures. With the continuous progress of technology, data model plays an increasingly important role in improving CLV. Enterprises can better carry out targeted consumer prediction and personalized recommendation to enhance customer loyalty to enterprises, reduce the loss rate, and improve the effect of sales strategy. In the long run, with the application of technologies such as artificial intelligence and machine learning, the impact of data model on customer management will be further strengthened to help enterprises achieve more efficient and sustainable market success. Therefore, enterprises should increase the investment in data model and take data model as the main method to improve CLV, so as to help enterprises move towards long-term business success.

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