Research on Precision Marketing Strategy Based on Big Data Analysis Technology

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Abstract. With the advent of the big data era, the rapid advancement of information technology has profoundly transformed marketing models. In the context of intense market competition, enterprises increasingly rely on data analytics to gain deep insights into consumer behavior and to optimize the allocation of marketing resources. This paper systematically explores the theoretical framework and logical structure of precision marketing strategies based on big data analytics. First, it clarifies the definition, influencing factors, and decision-making process of consumer behavior, and constructs a behavioral research framework driven by data analysis. Second, by integrating the RFM model with the K-means clustering algorithm, this study analyzes the theoretical pathway of customer value identification and market segmentation. Third, differentiated marketing strategies are proposed across four dimensions: product, price, channel, and promotion. Research shows that big data technology not only provides theoretical support and methodological basis for precision marketing, but also promotes the transformation of marketing decision-making from experience-oriented to data-driven and intelligent decision-making. The theoretical model and strategic framework constructed in this paper provide scientific basis and practical reference for enterprises to maximize customer value and optimize resource allocation.

Keywords: Big data analysis, Precision marketing, RFM model, Clustering algorithm, Marketing

1 Introduction

With the rapid development of information technology and the popularity of the Internet, the global economic system is gradually entering the digital era with data as the core driving force [1]. The improvement of the generation, transmission and processing ability of massive data enables enterprises to understand the market dynamics and consumer demand in a wider scope and at a deeper level, thus promoting the fundamental transformation of marketing model. Traditional marketing is mainly based on empirical judgment and macro statistics, and it is difficult to accurately describe the characteristics of individual consumers. The rise of big data technology provides a new path for the scientific and intelligent marketing activities. Through data mining, machine learning and behavior modeling, enterprises can realize real-time monitoring and accurate

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prediction of consumer behavior, so as to formulate more targeted marketing strategies [2].

In this context, Precision Marketing, as an important product of the era of big data, has become the key direction to enhance the competitiveness of enterprises. The core of precision marketing is to identify consumer differences through data analysis and realize "delivering the right information to the right people at the right time and in the right way". This not only changed the logic of marketing, but also reshaped the relationship between enterprises and consumers. Enterprises no longer rely on one-way push marketing means, but realize user stratification, behavior prediction and personalized recommendation through data-driven analysis, thus improving the effectiveness of marketing and resource utilization.

For China market, with the development of Internet economy, mobile payment and social media, consumers' behaviors are increasingly digital, personalized and diversified. How to identify consumers' characteristics, capture potential demand and formulate targeted marketing strategies in a huge data environment has become an important issue that enterprises need to solve urgently. Therefore, the research on precision marketing based on big data analysis technology has both important theoretical significance and outstanding practical value.

Theoretically, this study is helpful to deepen the cross-integration of marketing and data science, and promote the development of traditional marketing theory towards intelligence, quantification and modeling; From a practical point of view, this study provides an operable reference path for enterprises to optimize marketing decisions, improve customer value and market response speed.

2 Construction of Big Data Technology Analysis Framework

2.1 Definition and classification of consumer behavior

Consumer behavior refers to all the activities and psychological reactions of individuals or groups in the process of obtaining, using and evaluating goods or services, and is one of the core objects of marketing research [3]. It not only covers the complete chain from demand germination, information collection, purchase decision, use experience to after-sales feedback, but also profoundly reflects the psychological changes and decision-making logic of consumers at all stages. Under the background of big data, the study of consumer behavior no longer relies on traditional means such as questionnaires and interviews, but through the collection and analysis of multi-source data such as online click stream, search records, social interaction and consumption logs, the dynamic tracking and quantitative research of behavior patterns is realized.

In the theoretical framework, consumer behavior can be roughly divided into two types: rational behavior and perceptual behavior [4].

(1) Rational consumption behavior focuses on the consideration of objective attributes of products. Consumers make rational evaluation mainly based on price, function, quality, service life and other indicators, and achieve maximum utility through data comparison. This kind of behavior usually has the characteristics of high stability and predictability, and is suitable for algorithm modeling and pattern recognition analysis.

(2) Perceptual consumption behavior is more influenced by personal feelings, attitudes, values and social and cultural factors. Consumers often make decisions based on subjective feelings such as brand image, social identity and emotional experience, which embodies the symbolic and self-expression functions of consumption. For example, through Sentiment Analysis, we can mine consumers' emotional attitudes and potential preferences from consumer comments and social media corpus, and provide decision-making basis for brand marketing.

Therefore, under the framework of big data analysis, the definition and classification of consumer behavior is not only the starting point of theoretical analysis, but also the basis for the establishment of precision marketing model. Through the parallel study of rational and perceptual behavior, enterprises can portray consumers' portraits more comprehensively and realize the panoramic insight of consumers driven by data.

2.2 Analysis of Influencing Factors of Consumer Behavior

The formation of consumer behavior is influenced by many factors, including individual psychological and physiological characteristics, as well as external environmental variables such as society, culture, economy and technology. Traditional theory usually divides it into two categories: internal factors and external factors. In the era of big data, emerging factors such as information environment and algorithm intervention have also become important variables affecting consumer behavior [5].

2.2.1 Internal factors. Including motivation, demand, personality traits, lifestyle and values, etc., is the internal core that drives consumers' actions. Different motives (practicality, hedonism and social identity) will lead to different behaviors of consumers in the same market situation; Personalized data analysis technology (clustering and portrait modeling) can effectively identify these differences and provide data basis for subsequent market segmentation.

2.2.2 External factors. Due to different social and cultural background, family environment, group influence and economic conditions, they influence consumers' purchase decisions through social norms, cultural identity and information dissemination. In social media, the guiding effect of "KOL" and "network celebrities" on group consumption intention has become an important research content of enterprise big data marketing analysis.

2.2.3 Technology and information environment factors. With the popularity of artificial intelligence, recommendation algorithms and intelligent terminals, technical variables have become a new dimension that affects consumer behavior. Through the analysis and prediction of users' historical behavior data, algorithmic recommendation mechanism shapes consumers' cognitive and choice paths, and makes algorithmic decision-making gradually replace autonomous search as the main consumption trigger mechanism. At present, privacy protection, information security and data transparency are also imperceptibly affecting consumers' trust and purchase intention.

Therefore, the influencing factors of consumer behavior are multidimensional, dynamic and computable in the big data environment. Through the structural modeling and weight analysis of these factors, enterprises can grasp the decision logic of consumers more accurately and provide scientific basis for precision marketing.

2.3 Consumer decision-making process model

Consumer decision-making process is a complete psychological and behavioral path from identifying problems to post-purchase evaluation when consumers face purchasing needs, and it is an important basis for making marketing strategies. The traditional model usually includes five stages: problem identification, information collection, scheme evaluation, purchase decision and post-purchase feedback. Under the big data analysis technology, this process has evolved from a linear and static model to a dynamic and data-driven closed-loop decision-making system.

2.3.1 Problem identification stage. When consumers are aware of unmet needs due to internal needs or external stimuli, the behavior chain is triggered. Through the analysis of data such as search keywords, browsing behavior and interest tags, enterprises can capture potential demand signals in advance and realize pre-marketing

2.3.2 Information collection stage. Consumers use search engines, e-commerce platforms, social media and other channels to obtain product information. Big data analysis can record its access frequency, residence time and interaction behavior, and provide training samples for building personalized recommendation systems.

2.3.3 Scheme evaluation stage. Consumers compare and analyze different products, and comprehensively consider price, word of mouth and function. Behavioral data such as collection, comparison and evaluation reading at this stage provide an important basis for enterprises to implement differentiated marketing.

2.3.4 Purchase decision-making stage. Consumers finally choose and complete the purchase. Enterprises can calculate the conversion probability through the forecasting model, and implement hierarchical pricing or preferential policies according to the user's value level, thus improving the transaction rate.

2.3.5 Post-purchase feedback stage. Consumer evaluation, repurchase rate and return behavior constitute the key data sources for enterprises to optimize their service and marketing strategies. Through the machine learning model, customer satisfaction and churn risk can be predicted, forming a closed loop of "data analysis-strategy adjustment-user retention".

By tracking and modeling the whole process of consumer decision-making, enterprises can build an intelligent analysis system of precision marketing, realize the transformation from empirical judgment to data-driven, and enhance the scientific and sustainable marketing activities.

3 Construction of Precision Marketing Model Based on Big Data

3.1 Thinking of model construction

In the era of big data, corporate marketing decisions have gradually changed from experience-oriented to data-driven orientation. The core goal of precision marketing model is to identify the characteristics and behavior laws of different consumer groups through big data analysis technology and realize personalized marketing strategy formulation. On the basis of combing consumer behavior theory and data mining methods, this paper constructs a precision marketing model framework with "data collection-feature extraction-customer grouping-value evaluation-strategy formulation" as the main line [6].

The model comprehensively uses RFM (Recency, Frequency, Monetary) model, K-means clustering algorithm and association rule analysis, and provides scientific decision support for enterprises by quantifying customer characteristics, dividing customer types and refining marketing rules.

3.2 Quantitative model of customer value: RFM model

3.2.1 Model definition. RFM model is a classic model to measure the customer's value and loyalty. Its core idea is to evaluate the customer's value contribution to the enterprise through three dimensions: customer's last purchase Recency, purchase Frequency and purchase Monetary [7].

Suppose there are n customers in the sample set, and the feature vector of each customer i is:

$$\mathrm{X_i} = (\mathrm{R_i}, F_i, M_i), i = 1,2,...,n \tag{1}$$

Where: Ri: Time interval from the last purchase of the customer (days);

Fi: the number of purchases during the observation period;

Mi: Total consumption during the observation period.

R value is negatively correlated with customer activity, while F and M value are positively correlated with customer value. For the convenience of analysis, the variables are standardized:

$$\mathrm{R}_i^{'} = \frac{R_i - \min(R)}{\max(R) - \min(R)'}, \mathrm{F}_i^{'} = \frac{F_i - \min(F)}{\max(F) - \min(F)'}, \mathrm{M}_i^{'} = \frac{M_i - \min(M)}{\max(M) - \min(M)'} \tag{2}$$

Obtain a standardized feature vector:

$$X_i^{'} = (R_i^{'}, F_i^{'}, M_i^{'}) \tag{3}$$

3.2.2 Customer value score. According to the strategic objectives of the enterprise, each dimension can be empowered to get a comprehensive customer value score:

$$S_i = w_R(1 - R_i^{'}) + w_F F_i^{'} + w_M M_i^{'}, w_R + w_F + w_M = 1 \tag{4}$$

Where w_R, w_F, w_M are the weights of each dimension.

3.3 Customer clustering model: K-means clustering algorithm

3.3.1 Algorithm principle. K-means algorithm is an unsupervised learning method, which is used to divide n samples into K independent categories make the similarity between samples of the same category maximum and the difference between samples of different categories minimum. Let the sample set be $X = \{x_1^{'}, x_2^{'}, ..., x_n^{'}\}$, then the clustering objective function is defined as:

$$\mathrm{J} = \sum_{k=1}^{K} \sum_{x_i^{'} \in C_k} \| x_i^{'} - \mu_k \|^2 \tag{5}$$

Wherein, C_k is k clusters; μ_k: the central vector of the cluster C_k.

The iterative process of the algorithm is as follows:

(a)randomly initializing k cluster centers;

(b)Assign the sample points to the nearest cluster center;

(c)Update the center of each cluster as the average value of samples within the cluster:

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i^{'} \in C_k} x_i^{'} \tag{6}$$

(d)Repeat steps (b)–(c) until the objective function J converges.

3.3.2 Improvement of weighted distance. In order to enhance the business interpretation of the model, a weight vector $w = (w_R, w_F, w_M)$ can be introduced in the feature dimension, and the clustering distance function is:

$$\mathrm{d}(\mathrm{x}_\mathrm{i}^{\mathrm{l}}, \mu_\mathrm{k}) = \sqrt{\sum_{\mathrm{j}=1}^{3} \mathrm{w_j} \, (\mathrm{x}_{\mathrm{ij}}^{\mathrm{l}} - \mu_{\mathrm{kj}})^2} \tag{7}$$

By adjusting the weight, the model can better reflect the focus of enterprises on different customer attributes, thus improving the business relevance of clustering.

3.3.3 Evaluation of clustering results. The clustering results can be evaluated by the contour coefficient:

$$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \tag{8}$$

Where: $a(i)$: the average distance from the sample to other samples in the same cluster;

$b(i)$: The average distance from the sample to the nearest cluster.

The range of s(i) is [-1,1], and the larger the value, the better the clustering effect.

3.4 Association rule model: analysis of consumer combination behavior

In order to identify the potential association between different products or services, this study uses Apriori algorithm to mine strong association rules in transaction data. Let the commodity set be $\mathrm{I} = \{i_1, i_2, ..., i_m\}$, the transaction set be $T = \{t_1, t_2, ..., t_n\}$, and the item set be $X \subseteq I$, and its support can be defined as:

$$\mathrm{supp}(X) = \frac{|\{t \in T | X \subseteq t\}|}{|T|} \tag{9}$$

Confidence:

$$\mathrm{conf}(X \Rightarrow Y) = \frac{\mathrm{supp}(X \cup Y)}{\mathrm{supp}(X)} \tag{10}$$

Lift:

$$\mathrm{lift}(X \Rightarrow Y) = \frac{\mathrm{conf}(X \Rightarrow Y)}{\mathrm{supp}(Y)} \tag{11}$$

By setting thresholds min and confmin, association rules with statistical significance for enterprise marketing decisions can be screened out to guide product mix and cross-selling strategies.

3.5 Model synthesis and strategy mapping

Through RFM index quantification, K-means cluster analysis and association rule mining, a complete closed loop from customer identification to strategy formulation can be realized. Clustering results can usually be divided into the following customer groups (Table 1):

Table 1. Customer Type and Differentiated Marketing Strategy Design

Customer type	Characteristic expression	marketing strategy
High-value customers	R (small), F (high), M (high)	Customized services, membership rights upgrades, exclusive offers

Customer type	Characteristic expression	marketing strategy
Potential customers	R (middle), F (middle), M (high)	Value-added incentives, secondary transformation, and recommended rewards
General customer	R (middle), F (low), M (middle)	Content marketing, price concessions
Loss of risk customers	R (high), F (low), M (low)	Wake-up marketing, targeted push
New customers	No historical transactions.	Cold Start Recommend and Guide Experience Activities
Short Title	Short title of article	History

4 Precision marketing strategy design based on model results

4.1 Logical basis of precision marketing strategy

The essence of precision marketing strategy is to realize the transformation of enterprise marketing from "product-centered" to "customer-centered" through big data analysis technology. Its core logic is: identifying consumer behavior rules through data model → scientifically dividing consumer groups → formulating differentiated marketing strategies accordingly, so as to optimize resource allocation and maximize customer value [8].

In the second part of the model construction, RFM model is used to quantify customer value, K-means clustering algorithm is used to identify customer characteristics differences, and association rule model is used to discover potential purchase connections. Through the theoretical analysis of the model mechanism, this study reveals the formation path of precision marketing strategy from the logical level. [9] The design idea of precision marketing strategy is systematically discussed, and a reasoning framework from model results to marketing strategy is constructed. Through the interpretation of the results of the data model, enterprises can clearly define the value characteristics and behavior patterns of different consumer groups, so as to formulate more targeted strategies in products, prices, channels and promotion.

4.2 Strategic basis of customer segmentation and market positioning

4.2.1 Customer segmentation based on model logic. Theoretically, RFM model reflects customer activity and value contribution through three indicators: recent consumption time (R), consumption frequency (F) and consumption amount (M). Mapping the results of RFM model into three-dimensional space, different customer points will naturally form a number of feature clustering areas, and the function of K-means clustering algorithm is to identify these clustering features, thus completing the automatic division of customer groups. The corresponding relationships of various customers in model characteristics, value orientation and strategic direction are shown in Table 2.

Table 2. Customer Type and Precision Marketing Strategy Mapping

Customer type	Model feature representation	Theoretical value orientation	Strategic direction
High-value customers	R (small), F (high), M (high)	High loyalty and frequent repurchase	Retention and appreciation
Potential customers	R (middle), F (middle), M (high)	Great room for growth	Cultivation and encouragement
General customer	R (middle), F (low), M (middle)	Medium value	Guide consumption
Loss of risk customers	R (high), F (low), M (low)	Low repurchase rate	Awakening and retaining
New customers	No historical transactions.	High uncertainty	Guidance and experience

It can be seen from Table 2 that different types of customers have significant differences in R, F and M dimensions: high-value customers are characterized by high frequency, high amount and low R value, representing the core income groups of enterprises; Although the purchase frequency of potential customers is low, the consumption amount is high, which has great room for growth; However, the risk customers with high R value, low F value and insufficient repurchase rate need to be reactivated by awakening marketing and emotional retention strategy.

4.2.2 Logical deduction of market positioning. Based on the results of customer segmentation, the goal of market positioning is to determine the target groups that enterprises should focus on serving. Theoretically, the positioning decision of precision marketing should follow the following three principles:

(a)Value priority principle: give priority to serving high-value customers and maximize revenue;

(b)The principle of tapping potential: pay attention to the growing customer groups and form a sustainable market;

(c)The principle of cost efficiency: optimize the marketing investment structure under the condition of limited resources.

Therefore, this paper further introduces the multi-objective optimization model for dynamic analysis and weight allocation of different strategy combinations. Let the comprehensive utility function of enterprises in marketing strategy be:

$$\max \mathrm{U} = \mathrm{w}_1\mathrm{P}_\mathrm{r} + \mathrm{w}_2\mathrm{P}_\mathrm{p} + \mathrm{w}_3\mathrm{P}_\mathrm{c} + \mathrm{w}_4\mathrm{P}_\mathrm{m} \tag{12}$$

where: $\mathrm{P}_\mathrm{r}, \mathrm{P}_\mathrm{p}, \mathrm{P}_\mathrm{c}$ and P_m respectively represent product innovation income, price acceptance, channel reach efficiency and promotion conversion rate, and w_i is the weight of each strategic dimension.

4.3 Differentiated Precision Marketing Strategy Design

Based on the logic of customer segmentation and positioning, precision marketing strategy should embody the principle of differentiation and personalization. Combined with the 4P theory of marketing (Product, Price, channel Place, Promotion), this paper puts forward the following strategic framework from the perspective of model logic.

4.3.1 Product strategy. High-value customer groups based on F and M dimensions in RFM model have stable consumption behavior and clear preferences. Enterprises should aim at "high-value customer maintenance" and adopt differentiated product strategies;

(a)Launch customized products and exclusive services for members;

(b)Providing high value-added functions or value-added services;

(c)Enhance emotional connection with brand stories and cultural identity.

For potential customers, personalized recommendation and product portfolio design can guide them to change from one-time purchase to long-term repurchase.

4.3.2 Price strategy. K-means clustering results show that there are differences in price sensitivity among different customer groups. Theoretically, enterprises can design hierarchical pricing mechanism:

$$P_i = P_0(1 - \alpha_k), \quad i \in C_k \tag{13}$$

Where P_0 is the benchmark price and α_k is the discount coefficient of the corresponding customer group.

High-value customers focus on value-added experience, and the price can be relatively stable; Low-value or price-sensitive customers can increase the conversion rate through coupons, time-limited discounts, etc.

4.3.3 Channel strategy. Based on the big data analysis framework, diversification of consumer contacts is the key to marketing strategy design. The following principles should be followed in channel optimization:

(a)Data-driven principle: configure channel weights according to customer behavior paths (online/offline, mobile /PC);

(b)Consistency principle: keep online and offline marketing content consistent with brand image;

(c)Convenience principle: improve the efficiency of customer contact and feedback, and optimize the buying experience.

4.3.4 Promotion strategy. The optimization of promotion strategy should be based on the prediction model of consumer behavior. According to the timeliness characteristics of R dimension, customers can be divided into three categories: highly active, moderately active and potential loss.

For highly active customers, we should focus on loyalty programs, points system and VIP activities to enhance long-term retention. For potential customers, time-limited discounts, holiday marketing and social fission activities should be adopted to stimulate transformation. For customers at risk of churn, we should build a Churn Prediction Model based on historical interactive data and similar user behaviors, and wake them up through targeted push and re-marketing advertisements.

5 Conclusion

Based on big data analysis technology, this study systematically discusses the theoretical basis and construction path of precision marketing strategy. Through the analysis of consumer behavior characteristics and the introduction of RFM model, this paper reveals the important role of big data in customer value identification, market segmentation and marketing decision-making from the theoretical level. Research shows that big data not only changes the way enterprises get information and gain insight into the market, but also promotes the transformation of marketing concept from experience-oriented to scientific decision-making. The precision marketing framework based on data analysis put forward in this paper emphasizes the marketing concept of customer-centered, data-driven and intelligence-oriented, which provides theoretical reference for enterprises to enhance their competitiveness in a complex and changeable market environment. Although the research can't be empirically verified due to data constraints, the model and strategic ideas constructed are universally applicable in theory, which lays a solid foundation for subsequent empirical research and enterprise practice. In the future, with the continuous maturity of artificial intelligence, machine learning and privacy computing, precision marketing will further realize intelligent, personalized and sustainable development, and its theoretical research will continue to deepen and improve.

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