

Study on Personalized Positioning and Prediction Model of Consumer Behavior in Digital Marketing

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Abstract: In today's digital era, consumer behavior has become one of the key factors for companies to formulate marketing strategies and implement personalized marketing. With the rapid advancement of the Internet and mobile technology, consumers' behavior patterns and preferences when purchasing products or services have become increasingly complex and variable. Traditional advertising channels can no longer meet the demand for interaction between companies and consumers, while digital marketing provides companies with more flexible and precise marketing methods. Therefore, researching the personalized positioning of consumer behavior in digital marketing and developing predictive models have important implications for the development of marketing strategies for enterprises.

Keywords: consumer behavior; digital marketing; personalized positioning; predictive modeling

1. Introduction

In digital marketing, the study and application of personalized positioning and predictive models have become industry hotspots. Personalized positioning refers to dividing consumers into different market segments based on their individual characteristics, historical behavior, and preferences, and providing customized marketing strategies and services for each group. Predictive modeling, on the other hand, utilizes historical data and statistical analysis methods to predict and simulate future consumer behavior, guiding companies in decision-making and resource allocation.

With the popularity of the Internet and mobile devices, consumers have increasingly diverse and convenient ways to access information and make purchases. They obtain information through search engines, social media, e-commerce platforms, and engage in purchasing behaviors on different channels. This multi-channel consumer behavior makes it difficult for companies to accurately grasp consumer preferences and behavior paths, thus requiring personalized positioning and predictive models to better understand and predict consumer behavior. The demand for personalized services and customized experiences among consumers is increasing. In a fiercely competitive market environment, companies need to attract and retain consumers through personalized marketing. Personalized positioning and predictive models can help companies better understand consumer needs and preferences, thereby providing more attractive products and services. The continuous development and application of new technologies such as big data and artificial intelligence provide strong technical support for the research of personalized positioning and predictive models. Companies can utilize big data analysis of consumer behavior and preferences, and use machine learning algorithms to construct personalized positioning and predictive models, thereby achieving precision marketing and intelligent decision-making.

Therefore, the study of personalized positioning and predictive models of consumer behavior in digital marketing has important theoretical significance and practical value. By deeply researching consumer behavior patterns and rules, constructing effective personalized positioning and predictive models can help companies better understand consumers, improve marketing efficiency, and achieve sustainable development[1].

2. Consumer Behavior Overview

2.1 Definition and Significance of Consumer Behavior

Consumer behavior refers to the psychological, emotional, and action manifestations that

consumers exhibit when purchasing products or services. This behavior is not merely a simple purchasing act but rather a result influenced by various factors, including individual characteristics, socio-cultural aspects, and economic environments. The study of consumer behavior is crucial for companies in formulating marketing strategies, improving product design, and enhancing service quality. By deeply analyzing consumers' purchase decision-making process, motivations, and behavioral characteristics, companies can accurately grasp consumer needs and trends, thereby adjusting product positioning, developing new products, and formulating targeted marketing strategies to enhance market competitiveness. Understanding consumers' purchasing psychology and behavioral characteristics allows companies to improve products and services based on consumer feedback and demands, thus enhancing product competitiveness and market share. By precisely targeting consumer groups, understanding their consumption behavior and preferences, companies can formulate targeted marketing strategies, reduce ineffective marketing investment, and increase marketing ROI (Return on Investment). Finally, by understanding consumers' purchasing behavior and consumption habits, governments and relevant departments can formulate relevant policies and regulations to protect consumers' legitimate rights and interests, maintain market order, and promote sustainable economic development.

2.2 Factors Influencing Consumer Behavior

Consumer behavior is influenced by various factors, including individual characteristics, socio-cultural factors, psychological factors, and economic environments. The complexity and diversity of consumer behavior make the influencing factors broad and complex. Individual characteristics include age, gender, education level, occupation, etc. Different individual characteristics will have different effects on consumers' purchase decisions and behaviors. For example, young people may pay more attention to the fashion and personalization of products, while older people may pay more attention to the practicality and quality of products. Socio-cultural factors include cultural values, social customs, traditional habits, etc. Different cultural backgrounds and social environments will affect consumers' consumption concepts and behaviors. For example, in some Eastern cultures, people may pay more attention to etiquette and face, while in some Western cultures, people may pay more attention to individuality and freedom. Psychological factors include individuals' cognition, emotions, attitudes, motivations, etc. These factors will affect consumers' perception, evaluation, and selection of products or services. For example, consumers' purchase decisions may be influenced by factors such as brand image, product packaging, and advertising. Finally, economic environments include factors such as inflation, income levels, employment conditions, etc. The state of the economy will affect consumers' consumption ability and willingness to purchase. For example, in times of economic downturn, consumers may consume more cautiously and rationally, while in times of economic prosperity, consumers may consume more aggressively and boldly.[2]

2.3 The Impact of Digital Marketing on Consumer Behavior

Digital marketing has profoundly impacted consumer behavior, covering various aspects such as the purchase decision-making process, consumption habits, brand loyalty, and more. Through the Internet and mobile devices, consumers can access the necessary product information anytime, anywhere, compare prices and performance of different products, thus making more rational purchase decisions. Moreover, digital marketing provides consumers with various payment and delivery methods, meeting personalized shopping needs, enhancing the convenience and comfort of shopping. Through channels such as social media and e-commerce platforms, consumers can interact directly with brands and merchants, participate in product reviews, share shopping experiences, participate in promotional activities, etc., strengthening emotional connections and interactive experiences between consumers and brands. This interactivity and participation not only enhance consumers' brand recognition and loyalty but also provide valuable user feedback and market information for companies. Additionally, in the era of digital marketing, consumers are more inclined to search, compare, and purchase products online, and even make purchasing decisions and transactions directly through social media and e-commerce platforms, changing both consumer shopping habits and traditional retail formats and supply chains significantly. Finally, through big data analysis and personalized recommendation algorithms, companies can recommend personalized products and services to consumers based on their historical purchase behavior and preferences, providing customized shopping experiences and enhancing consumer satisfaction and loyalty. This personalized positioning and service also bring greater market competitiveness and business value to companies.

3. Personalized Positioning and Predictive Model Overview

3.1 Concept and Principles of Personalized Positioning

As one of the essential strategies in digital marketing, personalized positioning aims to divide consumers into different market segments based on their individual characteristics, historical behaviors, and preferences, providing tailored marketing strategies and services for each group. Its core concept lies in precise marketing based on consumer differences to meet their personalized needs and expectations. Personalized positioning, relying on technologies like big data and artificial intelligence, collects, analyzes, and explores vast consumer data to reveal their behavioral patterns, preferences, and demands. These data may include purchase history, browsing records, click behaviors, social interactions, and more. By conducting in-depth analysis, hidden consumer needs and potential behavioral patterns can be discovered. Based on individual characteristics and behavioral traits, consumers are segmented into different market segments[3]. This segmentation can be based on characteristics such as age, gender, location, interests, purchasing power, or behavioral traits such as purchasing preferences, lifestyles, and social circles. Through market segmentation, companies can more accurately grasp the needs and preferences of different consumer groups and tailor marketing strategies accordingly. Personalized positioning, based on individualized marketing strategies, provides customized products and services for different market segments. This personalized service may include personalized product recommendations, customized promotional activities, personalized communication, and customer service. Through personalized positioning, companies can enhance the accuracy of products and the degree of service personalization, thus increasing consumer satisfaction and loyalty.

3.2 Types and Application Fields of Predictive Models

Predictive models are crucial tools in digital marketing, aiming to predict and simulate future consumer behavior using historical data and statistical analysis methods, guiding companies in decision-making and resource allocation. Predictive models mainly include various types such as classification models, regression models, clustering models, and time series models, each with its specific application fields and advantages. Classification models are commonly used predictive models, mainly applied to divide consumers into different categories or groups. Through classification models, companies can segment consumers into different market segments based on their individual characteristics and behavioral traits, achieving precise marketing and personalized services. Classification models are commonly used in customer segmentation, product positioning, market segmentation, providing essential decision support for companies. Regression models are another common predictive model used to predict the values of continuous variables. Through regression models, companies can predict future sales, market shares, product demand, and other continuous variables based on historical data and statistical analysis methods, guiding production plans and sales strategies. Regression models are commonly used in sales forecasting, demand forecasting, price optimization, providing essential market forecasting and planning basis for companies. Clustering models are predictive models used to discover potential patterns and groups in data, mainly applied to aggregate similar consumer groups to discover potential market segments and consumer groups. Through clustering models, companies can better understand consumers' purchasing preferences, behavioral patterns, and demand characteristics, providing essential market insights and decision support for personalized marketing and product customization. Finally, time series models are predictive models used to predict time series data, mainly applied to analyze and predict trends, cycles, and seasonality in time series data. Through time series models, companies can predict future sales trends, market demand, and seasonal sales fluctuations, adjusting sales strategies and production plans to improve market responsiveness and resource utilization efficiency.

3.3 Application Cases of Personalized Positioning and Predictive Models in Digital Marketing

In the field of digital marketing, there are abundant application cases of personalized positioning and predictive models. Taking an online retail company as an example, let's elaborate on its application of personalized positioning and predictive models. Assume our company is an online retailer mainly selling clothing and accessories products. To increase sales and customer satisfaction, we have adopted strategies of personalized positioning and predictive models. Firstly, we utilize big data analysis of consumers' historical purchase behavior and preferences to segment them into different market segments. By analyzing data such as purchase frequency, purchase amount, and preferred product

categories, we identified some obvious purchasing patterns and behavioral characteristics, such as:

High-frequency purchasers: These users frequently purchase products on our website, are sensitive to new products and promotions.

High-value customers: Although these customers do not purchase frequently, their purchase amounts are significant, and they demand high-quality products and services.

Potential returning customers: These customers have previously purchased our products but have not made a purchase recently, potentially losing interest or encountering issues. Based on the above market segmentation results, we can develop personalized marketing strategies for different consumer groups. For example, for high-frequency purchasers, we can enhance new product promotion and promotional activities; for high-value customers, we can provide customized services and exclusive discounts; for potential returning customers, we can re-engage them through email marketing and customer care programs. **Application of Predictive Models:** We utilize predictive models to forecast future sales trends and customer demands. Through time series models and regression models, we can analyze historical sales data and market conditions to predict key indicators such as future sales, product demand, market share, etc. For example, we can use time series models to analyze trends and seasonal fluctuations in historical sales data to predict sales and demand for the next few quarters. Additionally, we can use regression models to analyze the relationship between product sales and promotional activities, seasonal factors, and competitive factors, thereby formulating corresponding sales strategies and promotion plans[4].

4. Consumer Behavior Data Collection and Processing

4.1 Methods and Tools for Data Collection

The collection and processing of consumer behavior data are crucial in digital marketing, providing essential insights into consumer behavior and preferences for businesses. Businesses can collect data through proprietary channels, including their websites, mobile applications, and offline stores. By embedding data collection tools on websites or applications, companies can track consumer browsing behaviors, search behaviors, click behaviors, etc., to obtain a wealth of behavioral data. Additionally, online surveys, user registration information, customer feedback, etc., are also important channels for collecting consumer behavior data. Furthermore, companies can collect data through third-party data providers. Third-party data providers typically have vast data resources and professional data analysis capabilities, offering companies richer and more diverse data information. For example, market research companies provide market research data, consumer survey data, etc.; data companies provide consumer purchase data, offline consumption data, etc. Companies can purchase these data services to obtain more comprehensive consumer behavior data. Moreover, companies can also collect data through social media platforms. Social media platforms are not only important places for consumer communication and interaction but also crucial channels for obtaining consumer behavior data. By monitoring user behaviors, comments, shares, etc., on social media, companies can understand consumer interests, social circles, product preferences, etc., providing references for personalized marketing and product positioning. Finally, data processing is an important part of consumer behavior data collection. The massive amount of collected data needs to undergo a series of processing steps such as cleaning, organizing, and analysis to be transformed into useful information and insights. Data processing tools such as data mining software, statistical analysis software, and artificial intelligence algorithms can help companies process big data, discover patterns and trends in data, and provide decision support for businesses[5].

4.2 Data Processing and Cleaning

In the collection and processing of consumer behavior data, data processing and cleaning are essential steps. In the era of big data, companies often face massive amounts of data, which may contain noise, missing values, or inconsistent information, thus requiring data processing and cleaning to improve data quality and usability. Data cleaning refers to the process of identifying and dealing with noise, errors, and outliers in the data. This includes operations such as deduplication, noise reduction, error correction, missing value filling, etc. For example, removing duplicate data records, correcting erroneous data entries, filling missing values using interpolation, etc. Data cleaning can improve data quality and accuracy, avoiding analysis biases and incorrect conclusions caused by data quality issues. Data organization and transformation involve formatting and adjusting data to make it

more effectively analyzable and processable. This includes operations such as format conversion, unit conversion, date formatting, etc. For example, unifying different date formats into a consistent format, converting data from different units into a uniform unit, etc. Data organization and transformation can make the data more standardized and consistent, enhancing data usability and analyzability. Data integration and merging involve integrating and merging data from different data sources to obtain more comprehensive and complete data. This includes operations such as associating and merging data from different data tables or databases. For example, associating user behavior data with basic user information to obtain more detailed user profiles and behavior analysis. Data integration and merging can provide more comprehensive and multidimensional data information, offering more possibilities for in-depth analysis and exploration. Finally, data quality assessment and monitoring involve evaluating and monitoring the quality of cleaned and organized data to ensure data quality and reliability. This includes operations such as statistical analysis, anomaly detection, quality metric evaluation, etc. For example, checking data distributions, identifying outliers, evaluating data completeness and consistency, etc. Through data quality assessment and monitoring, data quality issues can be detected promptly, and corresponding measures can be taken for handling and improvement to ensure data quality and credibility.

5. Consumer Behavior Prediction Model Construction

5.1 Theoretical Foundations of Prediction Model Construction

The construction of consumer behavior prediction models relies on various theoretical foundations, encompassing statistics, data mining, machine learning, and behavioral economics. Firstly, statistics provide fundamental analytical tools and methods for prediction models, using techniques such as regression analysis and time series analysis to reveal relationships and trends among variables. Data mining technology extracts valuable information from large-scale datasets, offering a rich data foundation for model construction. Machine learning, especially supervised and unsupervised learning, achieves precise predictions of consumer behavior through algorithm training and pattern recognition. Supervised learning uses labeled data to train models, such as classification and regression models, to predict future consumer purchase behaviors and preferences. Unsupervised learning identifies potential patterns and behavioral characteristics within consumer groups through clustering algorithms, aiding businesses in market segmentation and personalized marketing.

Behavioral economics provides critical theoretical support for prediction models, emphasizing psychological and behavioral factors in consumer decision-making processes. Behavioral economics theories reveal irrational consumer behaviors in various contexts, such as loss aversion, anchoring effects, and social influences, which need to be considered when constructing prediction models. Incorporating insights from behavioral economics into models allows for more accurate simulation and prediction of actual consumer behavior.

Moreover, the construction of prediction models necessitates considering key steps such as data preprocessing and feature engineering. Data preprocessing involves data cleaning, missing value handling, and outlier detection to ensure data quality and consistency. Feature engineering transforms and extracts raw data to generate features that can enhance model performance. This step is crucial as the quality of features directly impacts the predictive accuracy of the model.

Lastly, model evaluation and optimization are essential components of constructing consumer behavior prediction models. Using evaluation metrics such as cross-validation, accuracy, recall, and F1 score, the performance of the model can be measured, allowing for necessary adjustments and optimizations. The iterative process of model optimization, including parameter tuning and model selection, continuously improves the model's predictive capability and robustness.

5.2 Steps and Process of Prediction Model Construction

Constructing a consumer behavior prediction model is a complex and systematic process involving several key steps and workflows. The process begins with clearly defining the prediction goal, where businesses need to specify the particular consumer behavior to be predicted, such as purchase intention, customer churn, or product demand. Next, data collection and preprocessing involve gathering relevant consumer behavior data from various channels like online transaction records, user browsing behavior, and social media interactions. Following data collection, data preprocessing includes cleaning the data, handling missing values and outliers, and standardizing the data to ensure quality and consistency.

After data preparation, the next phase is feature engineering, where raw data is transformed and extracted to generate features that improve model performance. Feature engineering involves feature selection, transformation, and construction to uncover potential patterns and relationships within the data. Subsequently, model selection and training involve choosing appropriate model algorithms based on prediction goals and data characteristics, such as linear regression, decision trees, random forests, or neural networks. The preprocessed data is fed into the model for training, where algorithms learn patterns and trends within the data to generate preliminary prediction models.

Once training is complete, model evaluation and validation take place. Various metrics such as cross-validation, accuracy, recall, and F1 score are used to assess model performance, ensuring high predictive accuracy and generalization capability. Based on evaluation results, model parameters may need adjustment, or different algorithms may be selected to optimize performance. After completing model evaluation, the optimized prediction model is deployed into actual business scenarios to predict consumer behavior in real-time and adjust marketing strategies accordingly.

Post-deployment, continuous monitoring and maintenance of the model are essential to track its performance in real-world applications. Any issues, such as performance degradation or changes in data distribution, must be promptly addressed. Regular updates to the model and data are necessary to maintain accuracy and effectiveness, ensuring the model consistently delivers reliable predictions.

Each step of this process requires rigorous and scientific methods to ensure the prediction model's validity and practicality. Through systematic steps and workflows, businesses can construct efficient consumer behavior prediction models, providing robust support for precise marketing, enhancing market competitiveness, and improving business performance.

5.3 Prediction Model Evaluation and Optimization

In the process of constructing consumer behavior prediction models, evaluation and optimization are critical steps that directly affect the model's practical application and predictive accuracy. The primary task of model evaluation is to verify the accuracy and stability of the model. To achieve this, data is typically divided into training and test sets. The model is trained on the training set and then validated on the test set. Model evaluation metrics are diverse, including but not limited to accuracy, recall, precision, and F1 score. These metrics collectively reflect the model's performance in various aspects.

During the model evaluation phase, cross-validation is a commonly used method. It involves dividing the dataset into multiple subsets and performing training and testing on each subset to assess the model's stability and generalization ability. Cross-validation helps to avoid overfitting to specific data and improves the model's predictive accuracy on new data.

If the model's performance is unsatisfactory during the evaluation process, optimization is necessary. The optimization process involves several aspects, such as feature engineering, model parameter tuning, and algorithm selection. Feature engineering is a key optimization step that significantly enhances the model's predictive ability by selecting and constructing features strongly correlated with the predictions. Additionally, tuning the model's hyperparameters is crucial. Hyperparameter tuning is usually conducted using methods like grid search or random search to find the optimal parameter combination, thereby improving the model's predictive performance.

When selecting a model algorithm, it is essential to consider the specific prediction task and the characteristics of the data. Different algorithms, such as regression models, decision trees, random forests, support vector machines, and neural networks, may need to be tried. Each algorithm has its advantages and limitations, and comparing their performance helps in selecting the most suitable model for the current task.

During the evaluation and optimization process, avoiding overfitting and underfitting is an important consideration. Overfitting occurs when a model performs well on the training data but poorly on the test data, while underfitting happens when a model performs poorly even on the training data. These issues can be addressed by adjusting the model's complexity, increasing the training data volume, or improving feature engineering.

Once the model has been optimized and meets the performance standards, the next step is deployment and monitoring. In practical applications, continuous monitoring of the model's predictive performance is necessary, especially when the data environment changes. Timely updates to the model and data are essential to ensure the model continues to provide accurate predictions.

6. Conclusion

This paper comprehensively explores the importance of consumer behavior in digital marketing and its related research. Firstly, through an overview of consumer behavior, we deeply understand its definition, influencing factors, and the impact of digital marketing on it. Secondly, the application cases of personalized positioning and predictive models demonstrate how precise marketing and market prediction are achieved through big data analysis and predictive models in practice. Additionally, the detailed elaboration of consumer behavior data collection and processing reveals the importance of data in digital marketing and the key steps of data processing. Through an in-depth discussion of the above content, we profoundly recognize the significance of consumer behavior to businesses and understand how to achieve more effective digital marketing strategies through personalized positioning, predictive models, data processing, and other means. In the digital age, a deep understanding of consumer behavior and the application of scientific methods for data collection, analysis, and processing will help businesses better grasp market trends, improve market competitiveness, and achieve sustainable development.

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