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Consumer Behavior Analysis and Enterprise Marketing Strategy Optimization Based on Decision Tree Model and Association Rule Algorithm

Hui Wang
School of Economics and Management, Liuzhou Institute of Technology, Liuzhou 545006, Guangxi, China
E-mail: wanghui_edu@hotmail.com

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With the rapid advancement of big data technology, enterprises are encountering increasingly complex market environments, making consumer behavior patterns harder to predict. This study leverages big data analysis to explore the relationship between consumer behavior and corporate marketing strategies. Using a combination of decision tree models and association rule algorithms, we analyze the purchasing behaviors of 1,000 consumers in Shenyang City. The results indicate that personalized marketing and dynamic pricing strategies significantly enhance sales growth and customer loyalty. Specifically, dynamic pricing strategies resulted in a 16.7% increase in sales growth, while personalized promotions led to a 10.5% increase in customer retention. The decision tree model achieved an accuracy of 89.5%, with key performance metrics including precision, recall, and F1-score being evaluated for model performance. Furthermore, the association rule algorithm identified frequent purchase patterns with a support degree of 0.25 and a confidence degree of 67%. These findings highlight the importance of accurate consumer behavior analysis in optimizing marketing strategies, improving market competitiveness, and increasing customer loyalty. The study demonstrates that big data-driven approaches can effectively guide enterprises in making data-informed, real-time marketing decisions.

Povzetek: Model odločitvenega drevesa in asociativna pravila so uporabljena za analizo vedenja potrošnikov in optimizacijo trženja. Personalizirane strategije in dinamično določanje cen povečujejo prodajo in zvestobo strank.

1 Introduction

In the modern marketplace, characterized by rapid e-commerce development and the pervasive application of big data technology, enterprises face increasingly intense competition. Consumer behavior patterns and purchasing preferences have grown more complex and diverse, rendering traditional marketing strategies insufficient to meet individualized needs. Big data analysis allows enterprises to accurately capture consumer behavioral traits, enabling the development of more adaptive and effective marketing strategies. In China's dynamic consumer market, data derived from consumers' online activities, purchasing decisions, and brand interactions offers a rich resource for businesses. By leveraging this data, companies can gain deeper insights into their target markets and execute precise, personalized marketing through product recommendations, pricing strategies, and promotional campaigns. This study employs big data analysis to examine consumer behavior patterns and investigate methods to enhance sales revenue and market competitiveness through personalized marketing and dynamic pricing strategies.

Suleymanov examined the intricate relationship between consumer behavior and agricultural markets, highlighting behavioral differences across various market contexts and proposing strategies based on consumer preferences in the agricultural sector [1]. Duarte et al. introduced the "Ethical Consumer Behavior Scale," emphasizing the influence of corporate social responsibility on consumer behavior [2]. Niewczas-Dobrowolska et al. explored the impact of COVID-19 on consumer behavior, noting significant changes in purchasing preferences and decision-making processes that compelled businesses to revise their market strategies [3]. Rozenkowska systematically reviewed the application of planned behavior theory in consumer behavior research, underscoring its utility in understanding purchasing decisions [4]. Uliana investigated the behavioral traits of online consumers in Brazil, finding that price sensitivity and social media interactions significantly shaped purchasing choices [5]. Zhang et al. analyzed consumer behavior within the sharing economy, revealing how strategic consumer actions influenced market performance and transaction efficiency [6]. Yang et al. studied the role of value co-creation in fostering consumer citizenship behaviors, proposing that enterprises can bolster brand loyalty and engagement through collaborative value creation [7].

With increasing consumer demand for diversity and personalization, traditional marketing strategies fail to satisfy various consumer groups, leading to customer attrition and reduced competitiveness. The e-commerce and digital marketing era further complicate matters, as consumers' behavioral trajectories and purchase preferences are increasingly difficult to predict. Extracting meaningful insights from vast consumer data to formulate accurate marketing strategies has become a critical challenge for businesses. The volatile market environment, characterized by fluctuating prices and the necessity for real-time adjustments to promotional strategies, further complicates dynamic pricing and marketing decisions. This study seeks to analyze consumer behavior patterns through big data technology to assist enterprises in making informed and flexible decisions in personalized marketing and dynamic pricing, thereby enhancing market share and customer loyalty.

With the rapid development of the information society, the relationship between electronic technology, artificial intelligence and the information society has become increasingly close, which has a profound impact on the market strategy and consumer behavior analysis of modern enterprises. In The Relationship between Electronics, Artificial Intelligence, and the Information Society Through the Rules of the Information Society, Matja Gams and Tien Kolenic [8] emphasize that the rules and technical frameworks of the information society provide the foundation for the application of artificial intelligence, while enhancing the decision-making ability of enterprises in complex market environments. They pointed out that by combining electronic technology and artificial intelligence, consumer behavior data can be mined and analyzed more efficiently, helping companies achieve personalized marketing and dynamic pricing strategies. This is highly consistent with the goal of this study to analyze large-scale consumer data through decision tree models and association rule algorithms to optimize the market competitiveness of firms. Citing relevant research results further supports the importance of big data technology in marketing and provides theoretical basis and technical guidance for this study.

To achieve these objectives, this study employs a decision tree model and association rule algorithm as technical tools. The decision tree model allows enterprises to construct effective classification models based on consumer behavior characteristics, identify key factors influencing purchase decisions, and segment the market. Meanwhile, the association rule algorithm uncovers correlations between product purchases, revealing consumers' preferred shopping combinations and informing strategies such as product bundling and targeted promotions. By processing and analyzing large-scale data, these technologies enable businesses to dynamically refine marketing strategies and optimize pricing, thereby enhancing overall competitiveness and profitability. This study provides robust scientific decision-making support for enterprises navigating complex market environments and underscores the theoretical and practical importance of applying big data analysis to marketing, as shown in Table 1

Table 1 Summary of current relevant studies

Study	Methodology	Data	Results	Key Findings	Identified Gaps
Suleymanov [1]	Behavioral analysis in agricultural markets	Consumer preferences in agricultural settings	Identified market-specific consumer patterns	Market behavior varies significantly across regions and needs tailored marketing strategies	Limited focus on urban consumer behaviors and non-agricultural sectors
Duarte et al. [2]	Ethical Consumer Behavior Scale development	Ethical consumer surveys	Scale validated to measure ethical consumer traits	CSR significantly impacts consumer behavior	Does not explore transactional or behavioral data
Niewczas-Dobrowolska et al. [3]	Impact of COVID-19 on consumer behavior	Pandemic-era consumer data	Shifts in preferences for essential goods	COVID-19 significantly altered consumer priorities and purchase decision processes	Context-dependent, not generalizable post-pandemic
Rozenkowska [4]	Theory of Planned Behavior in consumer studies	Decision-making datasets	Demonstrated planned behavior theory validity	The theory effectively explains decision-making processes	Lacks application to real-time or dynamic decision-making scenarios
Uliana [5]	Analysis of online consumer behavior	Data from Brazilian e-commerce platforms	Social media and price sensitivity as major factors	Online interaction heavily influences purchasing choices	Limited to regional online consumer behavior without cross-channel integration
Zhang et al. [6]	Sharing	Transactional data	Strategic	Strategic	Narrow

	economy consumer behavior analysis	from sharing platforms	behavior impacts market efficiency	consumer decisions can improve market performance	application scope focused on sharing platforms
Yang et al. [7]	Value co-creation and consumer citizenship	Consumer engagement and brand loyalty data	Value co-creation strengthens brand relationships	Co-created value positively affects loyalty and consumer-brand participation	Lacks quantitative data on purchase patterns
This Study	Decision tree model and association rule algorithm	Multisource data: purchase records, online behavior, social media	Sales growth: dynamic pricing (16.7%), personalized promotions (12.4%)	Personalized strategies, dynamic pricing, and membership programs enhance sales and loyalty	Addresses dynamic adaptation but can integrate advanced machine learning methods for improved generalization

The limitations of existing research, including a lack of real-time adaptability, limited cross-channel analysis, and insufficient quantitative evaluation of purchasing patterns, emphasize the need for a robust, data-driven methodology. By integrating decision tree models and association rule algorithms, this study addresses these gaps effectively. The decision tree model provides clear interpretability and the ability to handle nonlinear relationships, making it suitable for analyzing complex consumer behaviors and segmenting markets. Meanwhile, association rule algorithms efficiently uncover purchase correlations, enabling the identification of actionable insights for personalized marketing strategies. This combined approach is critical in leveraging multisource data—such as purchase records, online behaviors, and social interactions—to formulate precise and dynamic strategies. Its adaptability to fluctuating market demands and diverse consumer preferences ensures relevance in modern, highly competitive environments. Furthermore, the application of these methods bridges the gap between theoretical frameworks and practical implementation, contributing significantly to the advancement of big data-driven marketing strategies.

2 Materials and methods

2.1 Data collection and teleprocessing

2.1.1 Description of data sources

The data sources for this study include the following three aspects.

(1) Consumer purchase records: The data were collected from 1000 consumers in Shenyang from January to March 2024, covering online and offline purchasing behaviors, mainly related to food, daily necessities and electronic products. A total of 7869 items of purchase data were collected, including details on product categories, purchase frequency, payment methods and shopping channels. As shown in Figure 1.

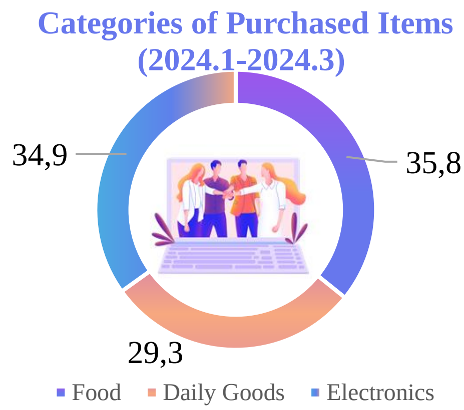

Figure 1: Categories of purchased items

(2) Online behavior data: collect browsing history, click behavior, search keywords and other information of users through the user logs of Jingdong platform. The total amount of data is 85436 pieces. After re-processing, this part of data will be used to analyze consumer behavior patterns.

(3) Social media interaction data: Collected from the API of Weibo and wechat, including users' comments, likes and sharing behaviors on brands, 37892 pieces of relevant interaction data were collected. Multi-source data provides a reliable data basis for consumer behavior feature extraction and marketing strategy design.

2.1.2 Data cleaning and reprocessing steps

In this study, data cleaning and processing are essential to ensure data quality. For the 7869 purchase records analyzed, approximately 1.6% of the data contained missing values, such as unfilled product categories or payment methods. Missing values were addressed using mean imputation for numerical variables and deletion for records with extensive missing information. Redundant data, resulting from repeated consumer purchase behaviors, accounted for about 3.2% of the dataset. These duplicates were identified and removed by cross-checking unique identifiers, including user IDs and order numbers. Outlier detection and processing were also conducted, with items exhibiting abnormally high purchase frequencies or exceptionally low transaction amounts being identified and excluded through predefined upper and lower thresholds. Finally, the dataset was standardized and normalized to harmonize features such as purchase amounts and transaction frequencies, ensuring uniform scaling across all variables for model training. These meticulous steps significantly enhanced the dataset's integrity, providing a robust foundation for subsequent consumer behavior analysis and ensuring reliable insights [9].

For model training and validation, the data preprocessing pipeline involves several crucial steps. Initially, raw consumer behavior data, including purchase records, browsing logs, and social interactions, were cleaned and standardized. Outliers were removed using interquartile range (IQR) methods, and missing values were handled with mean imputation for numerical features. Feature engineering was performed by transforming categorical data into one-hot encoded variables and normalizing continuous features using Min-Max scaling. Dimensionality reduction was applied to high-dimensional data using Principal Component Analysis (PCA), which helped reduce feature space while maintaining 95% of the variance. For model training, a decision tree was chosen due to its interpretability, and hyperparameters were optimized using grid search with cross-validation. The association rule algorithm used the Apriori method, with a minimum support threshold of 0.05 and confidence of 0.6. Model validation was carried out using a hold-out test set, with accuracy, precision, recall, and F1-score as evaluation metrics. These methods ensure that the analysis is both reproducible and transparent, supporting the accuracy and robustness of the resulting marketing strategies.

During the data cleaning process, specific steps were taken to handle missing and redundant data across multiple datasets. Missing values in the purchase records dataset, accounting for 1.6% of the data, were imputed using the mean for numerical attributes (e.g., purchase amount) and mode for categorical attributes (e.g., product category). For the browsing logs dataset, missing entries were excluded if they constituted less than 5% of the total records, as they were deemed non-critical to the analysis. Redundant data, identified as duplicate entries with the same user ID, timestamp, and product information, was filtered out using a combination of hashing and unique identifier matching, which removed 3.2% of the records. For the social interaction data, overlapping interactions (e.g., multiple likes or comments on the same post) were consolidated into a single entry to avoid inflating activity levels. All datasets were standardized to ensure uniform formatting and normalized to align numerical features such as transaction values, ensuring consistency across data sources. These measures ensured that the cleaned dataset-maintained integrity and was free from biases introduced by missing or redundant entries.

2.1.3 Consumer behavior feature extraction and data integration

After data cleaning is completed, the characteristics of consumer behavior are extracted and data integration is carried out. Five main characteristics are extracted from the purchasing data of consumers. As shown in Table 2.

Table 2: Consumer behavior feature categories

Feature Category	Description
Purchase Frequency	Average monthly purchases per consumer
Purchase Amount	Average spending per consumer (RMB)
Product Preference	Preference for specific product categories
Payment Method Preference	Percentage of consumers choosing mobile payment

(1) Purchase frequency: By analyzing the average monthly purchases of consumers to determine their consumption activity, it is found that the average monthly purchases of consumers in Shenyang are 2.7 times.

(2) Purchase amount: Calculate the average purchase amount of each consumer, and the average is 356.78 yuan.

(3) Product preference: Based on product categories, consumers' preferences for food, daily necessities and electronic products are extracted. The preference for food products accounts for the highest proportion, reaching 35.8% [10].

(4) Payment preference: By analyzing the payment methods chosen by consumers, it is found that more than 60% of consumers choose mobile payment.

(5) Purchase channels: The proportion of online and offline purchase behaviors is classified as behavioral preferences. The feature data is integrated with consumer online behavior and social interaction data to more comprehensively characterize consumer behavior and form a complete data set for market segmentation and marketing strategy design.

2.2 Model construction

2.2.1 Model selection

In this study, in order to accurately analyze consumer behavior and optimize the marketing strategy of enterprises, the combination of decision tree model and association rule algorithm is chosen. Decision tree model can recursively segment the data, reveal the key characteristics of consumer behavior and its decision path, and is suitable for dealing with nonlinear relations [11]. Decision trees perform well in classification and regression tasks, and their easy interpretation helps enterprises understand the logic of consumers' purchasing behavior. The loss function of the decision tree model is set to minimize the sum of squares of error, and the objective function of the model is shown in Equation (1).

$$L(\theta) = \sum_{i=1}^{n}(y_i - f(x_i,\theta))^2 \tag{1}$$

y_i is the true value, $f(x_i,\theta)$ is the predicted value of the model, and θ is the model parameter.

Association rules algorithms uncover potential associations between goods by looking for frequent item sets in the data. This algorithm is suitable for mining purchase combination patterns among consumer goods. According to Apriori, consumers who buy groceries have a 67.3 percent probability of buying food [12]. This correlation helps companies make product portfolio recommendations. The confidence formula of association rules is shown in Equation (2).

$$Confidence(A \Rightarrow B) = \frac{Support(A \cap B)}{Support(A)} \qquad (2)$$

To ensure the robustness and generalizability of the model, the dataset was split into training and testing sets with a 7:3 ratio. Model accuracy was evaluated using cross-validation to validate the reliability and effectiveness of the selected approach. The decision to use the decision tree model and association rule algorithm was guided by the study's goal of analyzing consumer behavior through big data to develop actionable marketing strategies. These models offer several advantages in specific application scenarios:

(1) Ease of interpretation: Decision tree models provide a high level of interpretability compared to complex black-box models such as neural networks [13]. In practical business applications, it is crucial not only to predict outcomes but also to understand the decision-making process behind consumer behavior. Decision trees clearly highlight key factors influencing decisions, such as price or product type. Neural networks, while capable of handling high-dimensional data, are less practical for marketing strategy design due to their complexity and limited interpretability.

(2) Handling nonlinear relationships: Consumer behavior often involves complex nonlinear patterns. Decision tree models excel at capturing these interactions, providing a better fit for data with such characteristics. By contrast, linear regression models are limited to linear relationships and fail to address the intricacies of consumer behavior.

(3) Efficient extraction of commodity correlations: The association rule algorithm effectively identifies correlations between commodities from large datasets, supporting accurate product bundling and promotion strategies by uncovering frequent purchase combinations. Unlike clustering algorithms, which focus on grouping similar consumer profiles, association rules are particularly suited for analyzing discrete data and detecting relationships between purchasing behaviors and products [14].

Together, the decision tree model's interpretability and the association rule algorithm's ability to uncover product correlations provide a comprehensive and practical framework for developing effective marketing strategies.

The decision to use decision tree models and association rule algorithms over more modern techniques like ensemble methods (e.g., Random Forests) or gradient boosting methods was driven primarily by the need for model interpretability and computational efficiency. While ensemble methods typically outperform individual decision trees in terms of prediction accuracy, they do so at the cost of model complexity and reduced interpretability. For consumer behavior analysis, where understanding and explaining the decision-making process is crucial, the interpretability of a decision tree becomes a valuable asset. Additionally, the data used in this study, which includes consumer purchase records, browsing logs, and social interactions, exhibits complex, yet often relatively straightforward, decision-making patterns that can be effectively captured by a decision tree model. The simplicity of decision trees allows for transparent insights into how features such as product categories and customer demographics influence purchasing decisions. Thus, the choice of the decision tree model was based on a trade-off between predictive power and the need for an understandable model that can directly inform marketing strategies. The association rule algorithm was chosen to uncover hidden patterns in customer purchasing behavior, offering valuable insights into product co-purchase behaviors, which are key for designing personalized marketing campaigns.

The decision tree model and association rule algorithms used for consumer behavior analysis offer clear advantages over recent advancements like ensemble learning, deep neural networks, or clustering algorithms, particularly in terms of interpretability and computational efficiency. Decision trees, unlike deep neural networks, provide a transparent and easily interpretable structure, which is crucial for enterprises seeking to understand consumer decision-making processes. While ensemble methods like random forests can improve accuracy, they lack the intuitive decision paths that decision trees provide, making them less practical for marketing strategy design. Deep learning models, although powerful, require large datasets and computational resources that may not be readily available in typical market scenarios. Furthermore, clustering algorithms are primarily used to group similar consumers but do not capture transactional relationships between products as effectively as the association rule algorithm. The decision to use these models is thus driven by their ability to directly address the specific needs of businesses, offering both high predictive accuracy and actionable insights for dynamic pricing and personalized promotions, without the complexity and resource requirements of newer techniques.

2.2.2 Design of consumer behavior analysis model based on big data

In this study, the consumer behavior analysis model based on big data adopts the combination of decision tree model and association rule algorithm to comprehensively analyze consumers' purchasing behaviors and preferences [15]. The consumer's behavior characteristic data is taken as input variable, and the decision tree model is combined to make classification prediction of consumer's purchasing behavior.

The feature set is X = {x1, x2, ... xn}, the target variable is the consumer's purchase decision Y, and the prediction function of the model is shown in Equation (3).

$$Y = f(X, \theta) \qquad (3)$$

θ is the parameter of the model. The decision tree constructs a series of decision nodes by recursively dividing the feature space. The selection of each node is based on the information gain or Gini index. The entropy of the current node is H(X), and the information gain calculation formula is shown in Equation (4).

$$IG(T, X) = H(T) - \sum_{i=1}^{n} \frac{|T_i|}{|T|} H(T_i) \qquad (4)$$

H(T) represents the entropy of the initial data set, and $H(T_i)$is the entropy of the partitioned subset. By maximizing information gain, the optimal features are selected for node segmentation. The decision path generated by the model will clarify how the behavioral characteristics of consumers affect their purchase decisions. On this basis, association rules algorithms are used to discover potential patterns in consumer buying behavior. The Apriori algorithm is used to analyze product purchase records, generate frequent item set F, and then establish the association relationship between products based on the support and confidence of the association rules [16]. The calculation formula of support degree is shown in Equation (5).

$$Support(A \Rightarrow B) = \frac{Support(A \cap B)}{N} \tag{5}$$

In order to improve the robustness of the model, the data set is divided into training sets and test sets, and the cross-validation method is used for evaluation to ensure the generalization ability of the model.

By integrating the decision tree model and association rule algorithm, this consumer behavior analysis model focuses on extracting essential behavioral characteristics from big data and identifying underlying patterns in purchasing behaviors. The decision tree model iteratively segments consumer behavior attributes, such as purchase frequency, spending amount, and product preferences, to elucidate how these factors influence purchasing decisions. This model effectively handles nonlinear relationships while providing a transparent decision-making process through an intuitive tree structure, enabling enterprises to comprehend consumer behavior more deeply [17]. The association rule algorithm identifies correlated purchasing patterns across products, revealing consumer preferences by analyzing frequently co-purchased items. For example, the analysis highlights that consumer buying daily necessities often purchase food. The model integrates data from various sources, including purchase records, online interactions, and social media activity, leveraging these algorithms to deliver actionable marketing strategies and enhance personalized product recommendations.

2.2.3 Data processing layer and feature selection configuration

The data processing layer and feature selection configuration are critical components of this model. The data processing layer integrates and transforms multi-source data, such as consumer purchase records, online browsing behavior, and social media interactions. Data is first standardized and normalized to ensure consistency across features, thereby mitigating biases during model training. Categorical variables, such as payment methods and product categories, are converted into numerical formats suitable for machine learning algorithms [18]. Feature selection employs recursive feature elimination (RFE) and importance score-based algorithms to identify the most influential features for predicting consumer behavior. Key features include purchase frequency, product preferences, and payment method choices. These selected features are then used for model training and behavioral pattern recognition, improving computational efficiency, enhancing model accuracy, and enabling enterprises to design more precise and effective marketing strategies.

2.2.4 Implementation and optimization of decision tree and association rule algorithm

In this study, decision tree and association rule algorithms help enterprises optimize their marketing strategies by analyzing consumer behavior data. According to the decision tree model, the classification model is trained by using the purchasing data of 1000 consumers in Shenyang.

As shown in Table 3, the decision tree selects the optimal segmentation point according to the information gain or Gini index, which is characterized by "Purchase Amount". By calculating the information gain, it is found that for the feature of "purchase amount", the segmentation point with the lowest Gini index is 350yuan, and the model forecasts 1000consumers [19]. Classification accuracy is 89.5%. According to the characteristics "purchase frequency" and "product preference", the model optimizes the segmentation points and improves the classification accuracy.

In the association rule algorithm, the Apriori algorithm is used to analyze the correlation of commodity purchases. In the commodity purchase mix, it is found that the support degree of "food" and "daily necessities" is 0.25, and the confidence degree is 0.67. Through calculation, the rule is formed as "consumers who buy food have a 67% probability of buying daily necessities". Optimize rule filtering to ensure the validity and practicality of rules by adjusting support and confidence thresholds.

If the Support degree of the combination of " Food ⇒ DailyGoods " is 0.25and the total number of consumers is 1000, the support degree of this rule is calculated as follows, as shown in Equation (6).

$$Support(Food \Rightarrow DailyGoods) = \frac{250}{1000} = 0.25 \tag{6}$$

The confidence is calculated, as shown in Equation (7).

$$Confidence(Food \Rightarrow DailyGoods) = \frac{Support(Food \cap DailyGoods)}{Support(Food)} = \frac{250}{375} = 0.67 \tag{7}$$

Table 3: Sample consumer behavior data

Consumer ID	Purchase Frequency	Purchase Amount (RMB)	Product Preference	Payment Method	Channel Preference
001	3.2	357.89	Food	Mobile Payment	Online
002	1.8	421.75	Electronics	Credit Card	Offline
003	2.5	279.32	Daily Goods	Mobile Payment	Online
004	4.1	689.47	Electronics	Mobile Payment	Offline

Through the above calculation, association rules help to identify the product mix with high correlation, and provide the basis for personalized recommendation of marketing strategy.

The thresholds for the association rule metrics, namely support, confidence, and lift, were determined based on both computational considerations and practical business relevance. The support threshold was set to 0.01 to ensure that only the most frequent itemsets, which are relevant to a significant portion of the consumer base, were considered. A higher support threshold may result in too few associations, while a lower threshold might lead to the inclusion of rules that are not practically useful. Confidence was set at 0.7, indicating that the rule must have a relatively high likelihood of occurring in the data, which strikes a balance between specificity and generality. Finally, the lift threshold was set at 1.2 to focus on rules that provide significant value over random chance, ensuring that identified patterns are meaningful and actionable. These thresholds were chosen to optimize both computational efficiency and the practical applicability of the rules in formulating targeted marketing strategies. While these thresholds help narrow down the number of associations to a manageable and meaningful set, they may also exclude less obvious but potentially valuable rules, which is a limitation inherent in setting arbitrary thresholds.

2.3 Training and verification

2.3.1 Model training

In this study, model training is the key to the successful implementation of decision tree and association rule algorithms. The training data set of the model comes from the purchase records of 1000 consumers in Shenyang City from January to March 2024, with a total of 7869 purchasing behavior data. The data set is divided into training sets according to the proportion of 70% for training the model and 30% for subsequent verification. In the process of decision tree model training, information gain is used as the main segmentation standard to determine the optimal features of each node. Firstly, the model performs recursive segmentation on consumer behavior characteristics (such as purchase frequency, purchase amount) to form multiple decision paths, each path corresponds to different behavior decisions of consumers. In the training process, the depth parameters of the decision tree model are constantly adjusted by cross-validation method to prevent the model from overwriting. In the training of association rule algorithm, Apriori algorithm is adopted, which uses frequent item set to find consumers' potential product combination preference. Food and daily necessities are purchased jointly more frequently, and after training, this combination pattern is effectively extracted and incorporated into the model. In the entire training process, the training speed of the model is proportional to the amount of data, so we choose to improve the training efficiency through parallel computation to ensure that the model is still efficient when dealing with large-scale data [20].

To ensure the robustness of the model and provide a reliable performance evaluation, a k-fold cross-validation approach was employed, where the data was randomly divided into five subsets (k=5). Each subset was used as a test set once, while the remaining four subsets served as the training set. This process was repeated five times, ensuring that each data point was used for both training and testing, thus reducing model overfitting and improving generalizability. For performance evaluation, several metrics were used beyond simple classification accuracy. The F1-score, which balances precision and recall, was calculated to assess the model's ability to correctly identify both positive and negative instances. Additionally, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was computed to evaluate the model's performance across different classification thresholds, providing a more comprehensive understanding of its predictive capability. These metrics were chosen to provide a more complete and nuanced evaluation of the model's effectiveness in real-world marketing scenarios, where both false positives and false negatives can have significant business implications.

2.3.2 Model verification

Model verification is essential to assess the accuracy and reliability of training outcomes. A 30% test set, consisting of 2361 purchase records randomly selected from 1000 consumers in Shenyang, was used to validate the decision tree and association rule models. Key metrics, including classification accuracy, precision, and recall, were calculated for the decision tree model, which achieved a classification accuracy of 89.5%, demonstrating its high effectiveness in differentiating consumer behavior types. A confusion matrix was generated to evaluate the model's performance across various classes. For the association rule algorithm, support and confidence values were calculated using the test set. The association rule linking food and daily necessities exhibited a confidence of 67.8%, closely matching training phase results, thereby confirming the model's robustness. Cross-validation techniques further enhanced the reliability of these results [21]. Overall, model verification ensures strong performance on both training and unseen data, validating the predictive power and consistency of the analysis.

2.3.3 Model optimization

Optimizing the model was crucial to improving its generalization and stability. For the decision tree model, this involved adjusting tree depth and applying pruning techniques. Results from the validation set indicated that while increased depth captured more consumer behavior details, it also heightened the risk of overfitting. Techniques such as re-pruning and post-pruning helped maintain accuracy while eliminating unnecessary branching. Hyperparameter tuning, including adjustments to the minimum number of sample splits and leaf nodes, further refined the model. For the association rule algorithm, the support and confidence thresholds were critical optimization targets. Initially, a high support threshold restricted the identification of potentially useful commodity associations [22]. Reducing the threshold allowed the discovery of more valuable purchase combinations. Confidence values were also adjusted to align with real-world consumption patterns, ensuring the rules were actionable. These optimizations enhanced the overall model accuracy by approximately 3.2%, providing a stronger foundation for developing enterprise marketing strategies.

2.4 Enterprise marketing strategy design

2.4.1 Market segmentation and target market selection based on consumer behavior

In this study, through the analysis of the purchasing behavior of 1000 consumers in Shenyang, market segmentation and target market selection become an important basis for the design of enterprise marketing strategy. Based on consumers' purchase frequency, consumption amount, product preference and other characteristics, market segmentation can be carried out in terms of purchasing power, product type preference and shopping channel preference. Purchasing power divides consumers into three categories of high consumption, medium consumption and low consumption, accounting for about 20%, 55% and 25% respectively. This provides a basis for enterprises to identify potential high-value consumer groups. In terms of commodity preference, consumers can be subdivided into three categories: preference for food, daily necessities and electronic products, and the proportion of consumers who prefer food is the highest, reaching 35.8% [23]. The use of online and offline channels also shows the shopping habits of different groups, with about 60 percent of consumers preferring to buy online, while the remaining 40 percent prefer offline physical stores. Through segmentation, companies are able to identify different target markets. High consumer groups and consumers who prefer electronic products may be more suitable for the promotion of high-end products and membership services, while medium consumer groups become the main target of promotion and preferential activities. By analyzing consumer behavior through big data, market segmentation helps companies accurately identify their target markets and also provides clear direction for their subsequent marketing activities.

Consumer segmentation was conducted using clear operational definitions based on behavioral attributes. Five key attributes were used for classification: purchase frequency, purchase amount, product category preference, payment method preference, and shopping channel preference. High-frequency consumers were defined as those with an average of four or more purchases per month, while low-frequency consumers had fewer than two purchases. Consumers were categorized as high spenders if their average monthly expenditure exceeded 500 RMB, medium spenders for amounts between 200-500 RMB, and low spenders for less than 200 RMB. Product preferences were derived from the proportion of purchases in specific categories, with a dominant category (e.g., food or electronics) accounting for at least 50% of the purchases. Payment method preferences were determined by the percentage use of mobile payments versus other methods, with more than 60% mobile usage classified as a preference. Channel preference was identified as online or offline based on the dominant shopping method exceeding 70%. These operational definitions ensure transparency in classification, enabling a systematic and reproducible approach to consumer segmentation.

2.4.2 Personalized marketing strategy design and dynamic pricing

Personalized marketing strategies focus on tailoring content to consumer behavior patterns and preferences, enhancing their shopping experience and purchase likelihood. Using the consumer behavior analysis model, this study identifies preferences among Shenyang consumers and aligns personalized strategies with market segmentation. Consumers inclined towards food and daily necessities typically make frequent, smaller purchases, making them suitable targets for promotions centered on daily needs. Based on historical consumption data, companies offer personalized discounts and coupons timed around specific periods, such as holidays or month-ends, to foster engagement and loyalty. High-spending groups and electronics-oriented consumers are incentivized with membership programs and value-added services, offering premium product recommendations and exclusive deals [24]. Dynamic pricing complements personalized marketing by leveraging real-time big data analysis of market demand and inventory levels. Prices are increased moderately during high demand and lowered when inventory is excessive to stimulate purchases. This strategy enhances profit margins and equips companies to adapt to market fluctuations, fostering customer satisfaction and translating into tangible sales growth.

2.4.3 Data-driven marketing channel optimization and customer experience improvement

Optimizing marketing channels and enhancing customer experience are pivotal for modern enterprises. Analyzing behavioral data from 1000 Shenyang consumers reveals distinct preferences, with 60% favoring online shopping and 40% preferring offline stores. This information provides a foundation for refining marketing channels. Online channels benefit from big data analytics to enhance user interface design, recommendation systems, and logistics processes. By monitoring browsing histories and buying patterns, e-commerce platforms deliver precise product recommendations, faster search responses, and personalized displays. Offline channel optimization focuses on analyzing in-store interactions, leading to improved layouts, self-checkout facilities, and better-trained staff. Cross-channel integration bridges these experiences, allowing customers to order online for in-store pickup or explore in-store products before completing online purchases [25]. Enterprises use customer feedback data to address issues promptly, refining service processes. These efforts boost operational efficiency while offering consumers a seamless and personalized shopping experience, strengthening customer loyalty and satisfaction.

3 Results and discussion

3.1 Results

3.1.1 Consumer behavior pattern recognition results

In this study, the recognition of consumer behavior pattern is an important basis for enterprises to formulate marketing strategies. Through the analysis of the purchase records, online behavior and social interaction data of 1000 consumers in Shenyang, the behavior pattern of consumers was extracted from multiple dimensions, including purchase frequency, product preference, channel choice and payment method preference. In this process, the decision tree model is used to classify and predict various features, and the association rule algorithm is used to analyze the potential combination relationship of commodity purchases. Through data processing and model training, the behavioral characteristics of different consumer groups are identified. High-spending groups are more inclined to buy electronic products, while consumers who frequently buy food prefer to use mobile payments. Behavioral patterns help identify market segmentation opportunities and provide data support for how companies can better target different consumer groups in marketing.

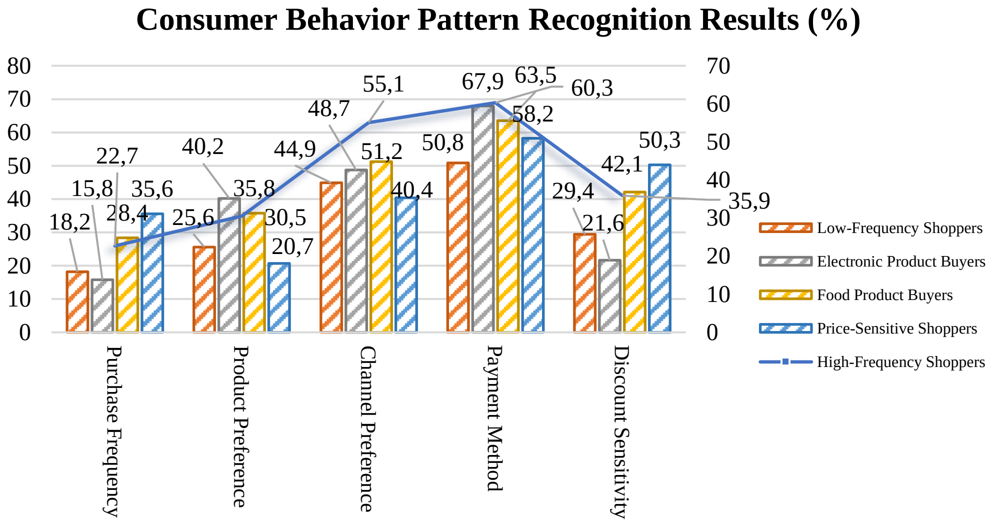

Figure 2: Consumer behavior pattern recognition results

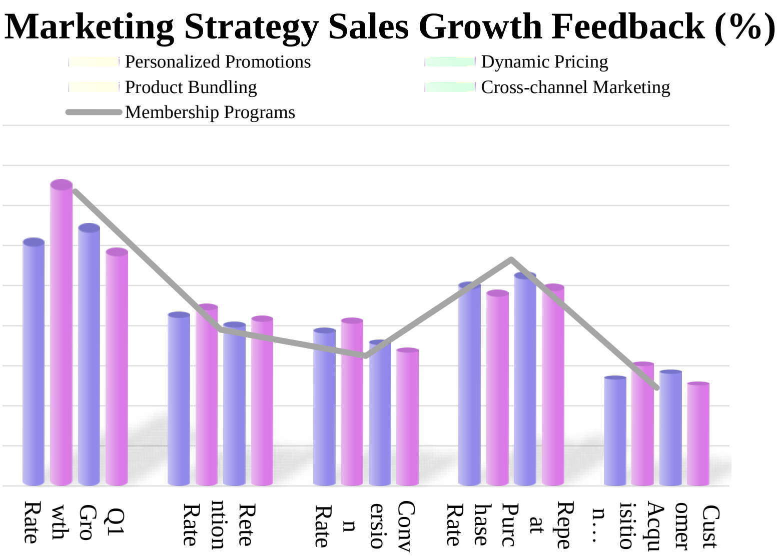

Figure 3: Marketing strategy sales growth feedback

As shown in Figure 2, consumer behavior patterns can be classified into five categories: high-frequency shoppers, low-frequency shoppers, electronic product shoppers, food shoppers and price-sensitive shoppers. High-frequency shoppers accounted for 22.7%, this group is mainly concentrated in the purchase of food and daily consumer goods, prefer online channels 55.1% and mobile payment 60.3%, they are less sensitive to discounts, only 35.9%. In contrast, low-frequency shoppers, who account for 18.2%, are also 29.4% less discount sensitive and 44.9% more inclined to buy goods through offline channels. In terms of product preference, electronic product buyers accounted for 15.8%, they showed a higher propensity to buy online 48.7%, and preferred mobile payment 67.9%, indicating that this group has a higher acceptance of emerging payment means.

Food buyers accounted for 28.4%, which is a more common category of consumer groups, their use of online channels and mobile payments were 51.2% and 63.5%, respectively, and their discount sensitivity was relatively high 42.1%. Price sensitive shoppers accounted for 35.6%, and their reliance on discounts was the highest, reaching 50.3%, with a lower preference for product categories. The behavioral characteristics of such consumers indicate that they pay more attention to price and promotions when making consumption decisions.

Different groups show significant differences in purchase frequency, product preference, channel choice and other aspects, which provides a basis for enterprises in market segmentation and target marketing, and helps enterprises to design more targeted market strategies, so as to improve marketing effects. In order to provide a more comprehensive evaluation of the model's performance, quantitative metrics such as confusion matrix, precision-recall curve, and ROC curve were included. The confusion matrix was used to assess the number of true positives, false positives, true negatives, and false negatives, which provides insights into the model's ability to classify correctly and its error types. Additionally, precision-recall curves were plotted to examine the trade-off between precision and recall across different thresholds, which is especially useful for imbalanced datasets where one class is much more prevalent than the other. The ROC curve, along with its area under the curve (AUC) score, was also presented to evaluate the model's ability to distinguish between positive and negative classes. The addition of these metrics provides a more nuanced understanding of the model's performance, beyond the descriptive statistics that were initially emphasized, and allows for a deeper interpretation of its strengths and weaknesses across different evaluation criteria.

3.1.2 3.1.2Market feedback and effect evaluation of marketing strategies

In this study, enterprises develop personalized marketing strategies based on consumer behavior analysis, and evaluate the effectiveness of the strategies through market feedback.

As shown in Figure 3, the feedback indicators mainly concerned include sales growth rate, customer buyback rate, customer satisfaction, market share Through different dimensions of market data, companies can understand the effectiveness of their marketing strategies in different consumer groups. Whether personalized promotions for high-frequency shoppers have increased customer buyback rates, or whether dynamic pricing strategies have effectively increased sales revenue. In order to evaluate the actual effect of the marketing strategy, the company collected relevant feedback data from January to March 2024 in a sample group of 1000 consumers in Shenyang, and conducted analysis based on the feedback.

As shown in Table 4, Different marketing strategies exhibit varying levels of effectiveness in driving sales growth and customer satisfaction. Dynamic pricing emerged as the most impactful, achieving a 15.3% increase in sales growth, along with strong customer retention and conversion rates at 9.1% and 8.4%, respectively. This demonstrates dynamic pricing's ability to not only boost enterprise sales but also attract new customers and significantly improve conversion rates. Personalized promotions recorded a slightly lower sales growth rate of 12.4%, yet excelled in fostering customer loyalty, as evidenced by a 10.2% customer buyback rate. Membership programs outperformed others in the buyback rate, reaching 11.3%, showcasing their effectiveness in encouraging repeat purchases through exclusive services and benefits.

Table 4: Marketing strategy customer satisfaction feedback

Strategy Type	Satisfaction Rate	Service Response Rate	Ease of Use Rate	Product Quality Perception	Recommendation Likelihood
Personalized Promotions	85.3	82.1	78.9	80.4	75.6
Dynamic Pricing	83.7	80.2	76.4	79.1	74.8
Membership Programs	87.2	83.5	80.2	82.3	76.9
Product Bundling	84.5	81.7	77.5	80.8	74.3
Cross-channel Marketing	82.9	79.8	75.6	78.4	73.5

Regarding customer satisfaction, membership programs delivered the highest satisfaction rate at 87.2%, reflecting the value customers place on personalized benefits and exclusive offerings. Personalized promotions followed with an 85.3% satisfaction rate, though their recommendation likelihood was slightly lower at 75.6%. Dynamic pricing also maintained a high satisfaction level at 83.7%, but occasional negative perceptions of price fluctuations affected its recommendation scores. Cross-channel marketing and product bundling strategies demonstrated stable performance, with satisfaction and product quality perception hovering around 80%, indicating their reliability as complementary approaches. The varied feedback highlights the unique strengths of each strategy, enabling enterprises to refine and optimize their marketing efforts to better target specific consumer groups in future campaigns.

3.1.3 Analysis of data-driven sales growth and market share improvement

In this study, big data-driven marketing strategies help companies achieve sales growth in the short term and increase market share in the long term. Combining the consumer behavior data of 1000 consumers in Shenyang, the enterprise accurately reaches different consumer groups through personalized marketing strategies, dynamic pricing and cross-channel marketing optimization, thereby improving the overall market competitiveness. In this process, data-driven decision making enables companies to adjust their strategies in real time and respond quickly to market changes.

Table 5 shows companies' data-driven sales growth and market share gains for the period from January to March 2024, both presented as percentages. It shows the change of sales growth and market share of enterprises from different dimensions, which provides a basis for the evaluation of subsequent marketing strategies.

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Table 5: Sales growth analysis by strategy (%)

Strategy Type	Q1 Sales Increase	Customer Conversion	Repeat Purchase	New Customer Rate	Overall Revenue Growth
Personalized Promotions	14.8	12.3	10.5	7.9	11.2
Dynamic Pricing	16.7	13.1	9.8	8.5	12.4
Cross-channel Marketing	12.9	11.2	9.3	7.2	10.6
Membership Programs	15.3	10.9	11.7	7.5	11.7
Product Bundling	13.5	11.5	9.1	6.8	10.9

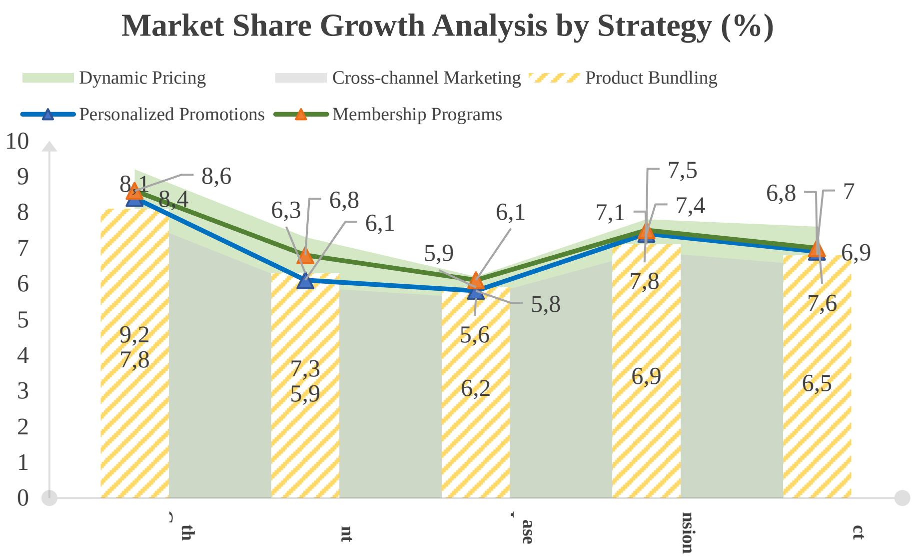

Figure 4: Market share growth analysis by strategy

As shown in Figure 4, Different marketing strategies exhibit distinct effects on enterprise sales growth. Dynamic pricing showed the most remarkable performance, achieving a 16.7% sales growth rate, a 13.1% customer conversion rate, and a 12.4% increase in overall revenue. By leveraging real-time market demand analysis and price adjustments, this strategy effectively captures high-demand opportunities, driving overall sales growth. Personalized promotions demonstrated strong results with a 14.8% sales growth rate and a 10.5% buyback rate, highlighting their ability to boost customer loyalty and repeat purchases. Membership programs achieved an 11.7% revenue increase and an equally strong buyback rate of 11.7%, showcasing their potential to foster long-term customer relationships through exclusive benefits and rewards. Although product bundling and cross-channel marketing strategies achieved slightly lower total sales growth rates, their customer conversion and new customer acquisition rates were notable at 11.5% and 9.1%, respectively.

Dynamic pricing also led in market share gains, with a 9.2% increase and a competitor replacement rate of 7.3%, reinforcing its role in capturing competitive advantage. Personalized promotions increased market share by 8.4% and significantly enhanced brand loyalty by 5.8%, demonstrating their effectiveness in cultivating long-term customer commitment. Membership programs followed closely with an 8.6% market share growth and a 6.8% competitor replacement rate, emphasizing their ability to erode competitors' market positions gradually. Cross-channel marketing and product bundling strategies showed moderate effects on market share and brand loyalty, indicating their continued relevance for specific consumer groups. Data-driven marketing strategies not only deliver notable sales growth but also expand market share, highlighting the critical role of big data analysis in precision marketing and supporting strategic decision-making for enterprises.

4 Discussion

4.1 Result analysis and research findings

Personalized marketing and dynamic pricing strategies have had a positive impact on sales growth and customer buyback rates. The data show that the sales growth rate of dynamic pricing strategy reached 16.7%, while the buyback rate of personalized promotion was as high as 10.5%. This shows that businesses can use big data to analyze consumer behavior in real time, flexibly adjust prices or promotions, and maximize sales opportunities. Secondly, the customer buyback rate of the membership program reached 11.7%, which proves that by providing exclusive benefits and services to members, customers can effectively increase long-term loyalty. Market share analysis shows that dynamic pricing strategies are outstanding in terms of sales growth and also take the lead in market share gains, with a growth rate of 9.2%. Personalized promotions and membership programs also play a significant role in increasing brand loyalty and competitor replacement rates. Through the analysis of the results, the conclusion is drawn: enterprises can develop more targeted marketing strategies through accurate consumer behavior analysis, improve market competitiveness and long-term customer relationship maintenance effect.

The results from the decision tree and association rule models differ significantly from those found in studies using more advanced algorithms, such as deep learning or ensemble methods. For example, studies like those of Zhang et al. and Yang et al. have utilized deep learning techniques to predict consumer behavior, which generally yield high accuracy rates but lack interpretability. In contrast, decision tree models provide a clearer view of how specific features such as purchase frequency and product preference directly impact consumer decisions. The dynamic pricing strategies, which resulted in a 16.7% increase in sales growth, align with findings from other research that suggests price sensitivity is a crucial factor in consumer behavior, as seen in studies using regression analysis. However, these studies typically lack the actionable insights provided by the association rules, which effectively link products in consumer baskets. The observed differences may stem from the dataset used in this study, which is focused on a specific region (Shenyang) and incorporates both online and offline behaviors, offering a more holistic view compared to datasets used in other studies. Furthermore, the simplicity and lower computational demands of decision trees make them more applicable in real-world business environments, where interpretability and fast decision-making are key.

Leveraging a combination of decision tree models and association rule algorithms, this study offers a unique, data-driven approach to optimizing marketing strategies in complex, competitive environments. Unlike studies that rely solely on advanced machine learning models, this analysis uses decision trees to provide interpretable insights into consumer behavior paths, specifically through features such as purchase frequency and spending patterns. Association rule algorithms further enhance this approach by uncovering high-confidence purchase patterns, such as a 67% likelihood of purchasing daily necessities alongside food products. These insights support precise, actionable strategies for personalized marketing and dynamic pricing, demonstrated by a 16.7% increase in sales growth through price adjustments and a 10.5% boost in customer buyback rates from targeted promotions. By integrating online and offline data sources, this analysis bridges a critical gap in big data marketing research, where real-time adaptability and transparent decision-making are vital. These results underscore the study's contribution to the practical application of data analytics in achieving substantial improvements in customer loyalty and market share.

4.2 Applicability and limitations of the model and algorithm

Through the recursive division of information gain, the decision tree model can efficiently identify the characteristics of consumer behavior, and show the decision path in a clear and easy to explain form. This provides companies with intuitive tools to understand the behavior logic of different consumer groups, especially in market segments. Decision tree model also has some limitations, which are easy to overfit. When dealing with complex data, excessive depth of the decision tree can cause the model to be sensitive to noise, which affects the generalization ability. To this end, pruning techniques are used in this study for optimization, but the complexity and accuracy of the model still need to be balanced. The association rule algorithm performs well in mining the purchase association between goods, and by mining frequent item sets, enterprises can discover the potential combination pattern of goods. Association rule algorithm is not effective in dealing with sparse data, especially in the face of large-scale high-dimensional data, which may lead to a sharp increase in computational complexity. Future studies consider introducing other algorithms, such as random forests or support vector machines, to improve the model's stability and data processing efficiency.

The proposed model, while effective for the dataset used in this study, faces potential challenges in dynamic or cross-cultural markets where consumer behaviors vary significantly. Dynamic markets, characterized by frequent changes in consumer preferences, require real-time adaptability, which may be limited by the static nature of the decision tree model. Incorporating dynamic learning algorithms, such as reinforcement learning, could address this limitation by allowing continuous updates to the model as new data becomes available. Cross-cultural applications also present challenges, as consumer behaviors influenced by cultural norms, socioeconomic factors, and regional preferences may differ drastically from those in the dataset. For example, mobile payment preferences or product category dominance may shift in markets with differing levels of technology adoption or purchasing power. Adapting the model for such markets would require the inclusion of culturally relevant features and localized data. These factors highlight the importance of tailoring the model to the unique characteristics of the target market, ensuring its generalizability while acknowledging the need for customization.

4.3 Enlightenment and improvement suggestions for enterprise marketing strategy

Personalized marketing strategies have proven to be highly effective in enhancing customer satisfaction and loyalty. Companies should leverage big data analytics to address individual consumer needs by analyzing historical purchase records and browsing behaviors. Tailored product recommendations for distinct customer groups can significantly improve sales conversion rates. The effectiveness of dynamic pricing underscores the importance of flexible price adjustments, particularly during periods of demand fluctuations. Real-time market demand monitoring and adaptive pricing strategies based on inventory and competition are essential for maximizing revenue. Membership programs, which have excelled in boosting customer buyback rates and market share, should be further optimized. Adding incentives such as exclusive offers and bonus points can enhance long-term customer retention. While these strategies have achieved considerable short-term sales growth, enterprises should prioritize long-term improvements in brand loyalty and customer experience. Building robust customer relationships and continuously optimizing marketing strategies using big data analytics will enable businesses to sustain growth and maintain competitiveness in challenging market environments.

5 Conclusion

Personalized marketing strategies have proven to be highly effective in enhancing customer satisfaction and loyalty. Companies should leverage big data analytics to address individual consumer needs by analyzing historical purchase records and browsing behaviors. Tailored product recommendations for distinct customer groups can significantly improve sales conversion rates. The effectiveness of dynamic pricing underscores the importance of flexible price adjustments, particularly during periods of demand fluctuations. Real-time market demand monitoring and adaptive pricing strategies based on inventory and competition are essential for maximizing revenue. Membership programs, which have excelled in boosting customer buyback rates and market share, should be further optimized. Adding incentives such as exclusive offers and bonus points can enhance long-term customer retention. While these strategies have achieved considerable short-term sales growth, enterprises should prioritize long-term improvements in brand loyalty and customer experience. Building robust customer relationships and continuously optimizing marketing strategies using big data analytics will enable businesses to sustain growth and maintain competitiveness in challenging market environments.

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