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Research on Consumer Behavior Patterns and Their Precision Marketing Strategies Based on Decision Tree Algorithms: A Case Study of Superstore Customer Data

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Abstract. With the rapid development of data-driven marketing, personalized and precision strategies have become essential tools for enterprises to enhance competitiveness. However, the deep mining of multidimensional consumer data in offline superstore scenarios still faces significant challenges. This study applies a decision tree algorithm to analyze consumer behavior patterns in four product categories—wine, candy, meat, and gold—based on customer consumption data from a supermarket. The findings indicate that income level is the core factor influencing consumption. Family structure also plays a differentiating role: childless families prefer wine; families with children spend more on confectionery; meat consumption is influenced by both income and number of children; and gold consumption is primarily driven by income. Accordingly, the study proposes precision marketing strategies such as promoting high-end wines to high-income childless families, recommending healthy candy options to families with children, and tailoring meat and gold promotions based on family structure. By shifting from single-variable to multifactor joint modeling, this study emphasizes the importance of family structure in consumer profiling and offers a cost-effective precision marketing solution using interpretable decision trees for traditional retail.

Keywords: decision tree algorithm, consumer behavior analysis, precision marketing, household structure, retail

1. Introduction

With the rapid development of data-driven marketing, personalized and precision marketing have become essential strategies for enterprises to enhance competitiveness and promote sustainable growth. By conducting meticulous customer profiling and accurately identifying consumer needs, enterprises can significantly improve customer experience and brand loyalty, thereby advancing organizational development. However, despite the accumulation of vast amounts of consumer data, many companies still face substantial challenges in transforming and applying this data to practical marketing activities. Enterprises often fail to fully leverage the potential of customer data, resulting in limited success in delivering accurate, personalized recommendations and customized services. Consequently, the effective utilization of data analysis tools to enhance the implementation of precision marketing has become a pressing issue in the current marketing landscape.

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In recent years, research on personalized and precision marketing has attracted increasing attention from both academia and industry. Scholars have proposed personalized recommendation systems based on BERT and the nearest neighbor algorithm, wherein the BERT model extracts semantic features from product descriptions and combines them with users' historical behavior data (e.g., clicks and purchase records) to achieve personalized product matching and improve user conversion rates.[1] The transfer learning framework proposed by Afrin et al. [2] successfully migrates historical product data into new product demand forecasts by constructing product differentiation indices (PDIs) and feature decoupling techniques, which has methodological implications for the cold-start consumer analysis in this study-when facing new supermarket openings or new category consumer data, we can learn from its domain adaptation idea to achieve knowledge transfer across stores/categories through quantifiable "consumer differentiation features". This has methodological implications for this study - when facing new supermarkets or new categories of consumer data, the idea of domain adaptation can be borrowed to realize cross-store/cross-category knowledge migration through quantifiable "consumer differentiation characteristics".[3] However, existing literature predominantly focuses on macro-level market analysis or single-factor studies, lacking joint analysis and personalized prediction using miniature models for multidimensional customer data. Moreover, shopping relevance specific to offline superstores is often overlooked. Additionally, most studies fail to conduct in-depth analyses of particular superstores or retail scenarios, resulting in a lack of targeted and effective precision marketing strategies. Therefore, leveraging decision tree algorithms to mine customer data can bridge the gap between the dynamics of offline retail environments and the complexity of multidimensional data, providing more targeted and practical personalized marketing solutions for the superstore sector.

Using customer purchase data from a superstore, this study analyzes consumer behavior patterns through a decision tree algorithm, aiming to uncover the preferences and decision-making patterns of consumers across different age groups and education levels. By conducting multidimensional joint analyses, the study identifies latent consumer needs to offer more precise marketing strategy recommendations for the superstore. Unlike traditional univariate analysis methods, this research harnesses the strengths of decision tree algorithms to delve deeper into customer data. Ultimately, it aims to provide more scientific and actionable strategies for superstores in precision marketing, foster the broader application of personalized marketing, and offer both theoretical and practical support for marketing innovation in the retail industry.

2. Literature review

Personalized marketing addresses consumers' individual needs, preferences, and behaviors to deliver customized products, services, and communications. In contemporary marketing practice, personalized strategies have proven effective in increasing consumer satisfaction, enhancing brand loyalty, and improving conversion rates and sales performance. While existing research demonstrates substantial success in personalized marketing within e-commerce and social media platforms, challenges persist in its application to brick-and-mortar retail environments. Recent reviews of machine learning applications in sales forecasting [4] highlight that decision trees and ensemble methods excel in handling heterogeneous consumer data, particularly when demographic factors (e.g., income, family structure) influence purchasing patterns. This aligns with the present study's focus on leveraging interpretable models for precision marketing in offline retail [5]. Kim [6] used machine learning algorithms to predict the poverty status of Costa Rican households in her study, demonstrating the potential of decision tree algorithms in handling complex socioeconomic

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data. Her study not only reveals the significant effect of education level on poverty status, but also emphasizes the advantages of decision trees in dealing with heterogeneous datasets and missing values. This got me thinking about whether decision tree algorithms can also be used in retail environments to support personalized marketing in offline retailing by analyzing consumer behavioral data and revealing the impact of factors such as family structure and income level on consumption patterns [7].

Recent advances in deep learning have shown promising results in e-commerce recommendations through pre-trained language models [8], yet these methods primarily focus on textual product features rather than structured household demographics. This gap highlights the need for interpretable algorithms that can bridge online-offline consumer profiling [6]. İbrahim Halil Efendioğlu and Yakup Durmaz, in their study The Impact of Perceptions of Social Media Advertisements on Advertising Value, Brand Awareness, and Brand Associations: Research on Generation Y Instagram Users, found that young consumers prioritize the entertainment and usefulness of advertisements. For instance, the click-through rate of a “Weekend Family Package” advertisement can be increased by 30% when aligned with a user’s purchasing history—such as frequent snack purchases. This finding indicates that personalized content tailored to users’ needs can significantly boost their consumption willingness [8]. Natallia Kokash and Leonid Makhnist, in Using Decision Trees for Interpretable Supervised Clustering, proposed the use of decision trees for "interpretable clustering." This method categorizes customers into segments such as the "high-value weekend segment" (spending over 200 RMB on weekends) and the "low-priced weekday segment." Such segmentation enables superstores to implement time-sensitive discount strategies that take customer clustering into account.[9] In a similar vein, Khan et al. [3] demonstrated the effectiveness of decision trees in predicting irrigation water requirements, achieving high accuracy rates. Their study supports the use of decision trees for their interpretability and accuracy in forecasting, which aligns with the goals of precision marketing in retail environments [10]. Similarly, Liping Yang, Xiaxia Niu, and Jun Wu, in their work RF-LightGBM: A Comprehensive Probabilistic Ensemble Way to Predict Customer Repurchase Behavior in Community E-commerce, proposed an integrated model combining Random Forest and LightGBM. Their model predicts user repurchase probability and increases user retention rates on community e-commerce platforms by 15%, particularly by targeting high-potential users through tailored coupon strategies. This approach balances clustering accuracy with business interpretability and supports dynamic pricing [4].

Karb, Tristan, et al., in A Network-Based Transfer Learning Approach to Improve Sales Forecasting of New Products, emphasized that the food retail industry relies heavily on data-driven methods such as machine learning and time-series models for sales forecasting. However, traditional models often struggle to predict demand for newly launched products or new users due to the lack of historical data. As a solution, the authors proposed a transfer learning framework that transfers historical sales patterns of similar products to new items, reducing prediction errors by more than 20% [11]. Batool Madani and Hussam Alshraideh, in Predicting Consumer Purchasing Decision in the Online Food Delivery Industry, applied the C4.5 algorithm to discover that users with an "Order Convenience Score > 2" and a "Taste Score > 2" have a 95% repurchase rate. This insight provides direct guidance for supermarkets to optimize delivery services—for example, by shortening delivery radii and strengthening quality control [2].

However, most existing studies focus primarily on transactional data, such as purchase amounts and frequencies, while overlooking contextual data relevant to offline retail environments. Factors such as family structure, income level, and responsiveness to promotions are dynamic and can influence consumer preferences over time. Yet, most current models adopt static approaches, lacking

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the flexibility to capture evolving consumer behaviors in offline scenarios. In order to fill the gaps in existing research, several studies have begun to explore new approaches to multidimensional consumer data. For example, García-Gil et al. proposed a Smart Data-driven Decision Tree Integration approach (SD DeTE), which effectively improves data quality and diversity by combining random discretization (RD), principal component analysis (PCA), and clustering-based random over-sampling (ROS) to efficiently generate smart datasets under a distributed computing framework and improve the performance of integrated learning. This approach provides new ideas for retailers to deal with multidimensional consumer data, which helps to identify and predict consumer purchasing behavior more accurately [12].

3. Research design

This study aims to analyze customer data from a superstore and construct consumer behavioral profiles using a decision tree approach to inform the development of personalized marketing strategies. Drawing on customer transaction data provided by the superstore, the study will examine purchasing behaviors across various product categories and identify key influencing factors through the application of a decision tree model. The dataset comprises basic demographic information (e.g., age, gender, income) as well as consumption behavior metrics (e.g., purchase amount, purchase frequency, product category), totaling 75,308 records.

User profiling refers to the process of modeling consumer characteristics through data analysis. In this study, consumers will be categorized into distinct behavioral groups, and detailed profiles will be generated for each group using a combination of cluster analysis and decision tree modeling. A decision tree is a classification model structured as a tree, in which the dataset is recursively partitioned into smaller subsets. Each internal node represents a decision rule based on a specific feature, while each leaf node corresponds to a classification outcome.

The core principle of decision tree algorithms is to maximize the purity of each category by selecting optimal features for splitting, typically using criteria such as information gain or the Gini index. In this study, a classification tree will be constructed using the Gini index to select the most informative features. The Gini index, which measures the impurity of a probability distribution, is formally defined in:

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and Regression Trees. Wadsworth. Aouad et al. [7] showed that decision trees can improve the accuracy and interpretability of market segmentation by optimizing the choice of split points. This approach demonstrates good computational efficiency when dealing with large-scale datasets and provides a practical solution for personalized marketing in retail environments. By combining market segmentation and response modeling, decision trees can more accurately capture differences in consumer behavior to support precision marketing strategies.[13] Likewise, Moulay et al. [14] proposed a machine learning approach combining supervised and unsupervised learning for automatic detection and classification of anomalies in mobile networks. Their study shows that decision trees not only categorize data efficiently, but also help network administrators to quickly diagnose and solve network problems through explanatory modeling. By combining the explanatory nature of decision trees with the flexibility of clustering algorithms, this approach provides an automated solution that identifies the root causes of network performance problems. This is consistent with our research goal of analyzing consumer behavior patterns through decision tree models and providing support for precision marketing.[14]

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4. Portrait study of household consumption patterns

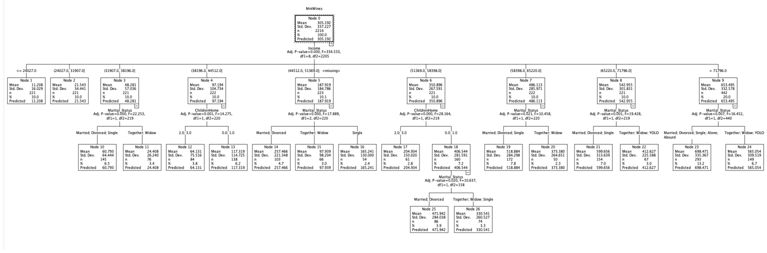

Figure 1: Decision tree analysis of consumption and consumer characteristics wine

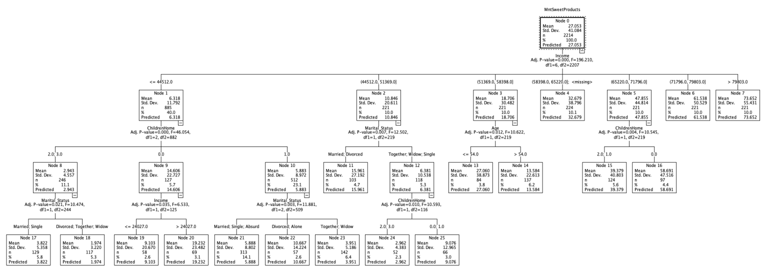

Figure 2: Decision tree analysis of consumption and consumer characteristics candy

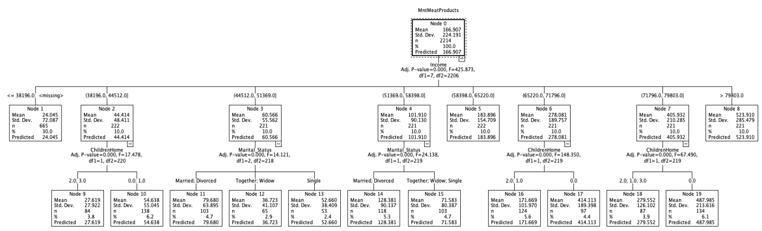

Figure 3: Decision tree analysis of consumption and consumer characteristics meat

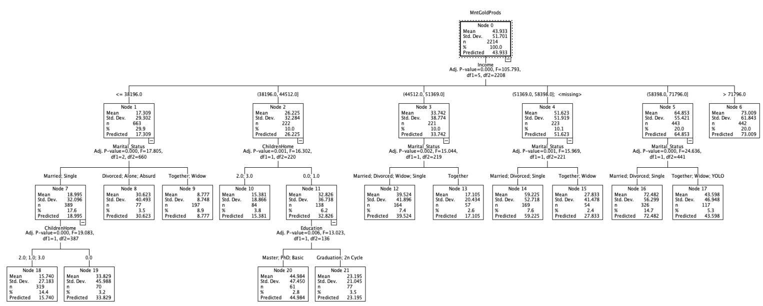

Figure 4: Decision tree analysis of consumption and consumer characteristics gold

4.1. Wine consumption patterns and marketing strategies

4.1.1. Portrait of wine consumption patterns

Consumers’ primary motivations for purchasing wine typically include personal enjoyment, family dinners, social gatherings with friends, business banquets, and holiday gifting. These motivations are

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closely tied to individual lifestyle preferences, social interactions, and ceremonial occasions. Influenced by the growing emphasis on healthy living, wines that are low in alcohol content, organically produced, or free of additives are increasingly favored, particularly among high-income and highly educated consumers.

According to the decision tree analysis, wine consumption is closely associated with income level, family structure, and educational background. Specifically, higher income correlates with greater wine purchases. Even among consumers with similar incomes, childless households tend to spend significantly more on wine. This is attributed to greater expenditures on socializing and self-enjoyment, as these families are more inclined toward a high-quality lifestyle and more willing to invest in premium wines. Additionally, highly educated consumers exhibit relatively higher wine expenditures, reflecting a preference for quality and brand recognition.

4.1.2. Wine marketing strategy

To target core consumer segments—namely high-income, highly educated, and childless households—marketing strategies should emphasize the low-alcohol, natural, and additive-free attributes of wine products. These attributes should be communicated through compelling brand narratives, cultural associations, and health-conscious messaging to establish emotional connections and reinforce the link between wine consumption and a refined lifestyle. By implementing refined user segmentation, marketers can adopt a tiered pricing strategy, recommending product series that align with the income and educational levels of different consumer groups. This approach helps enhance user loyalty and encourages repeat purchases.

4.2. Confectionery consumption patterns and marketing strategies

4.2.1. Portrait of candy consumption pattern

Parents primarily purchase confectionery products as daily snacks, holiday treats, gifts for social occasions, or as a nostalgic indulgence rooted in their own childhood experiences. In recent years, growing parental concern for children's nutrition has led to the rising popularity of low-sugar, additive-free, and nutrient-enhanced candies. Additionally, confectionery products continue to play a central role in festive celebrations such as Chinese New Year, Valentine’s Day, and Christmas.

Decision tree analysis reveals a distinctly family-oriented consumption pattern: families with children, especially those with only one child, are the main consumers of sweets. At comparable income levels, single-child families demonstrate the highest purchasing power for candy. In contrast, families with multiple children often exhibit lower candy consumption, likely due to more distributed budget constraints or heightened parental efforts to limit sugar intake. Furthermore, higher-income families tend to spend more on candy, indicating a greater willingness to purchase higher-quality, health-conscious snack products for their children.

4.2.2. Candy marketing strategy

To appeal to family-oriented consumers, marketing strategies should emphasize themes of family bonding and the health-conscious nature of modern candy products. Packaging should be visually appealing to children while also addressing parents’ nutritional concerns by highlighting low-sugar, additive-free options. For families with multiple children, introducing value-packed family combination sets can enhance affordability and appeal. Launching DIY candy kits can further strengthen the parent-child connection by offering interactive, co-creative experiences. These

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strategies foster emotional engagement, enhance the overall enjoyment of the product, and increase purchase intent.

4.3. Meat consumption patterns and marketing strategies

4.3.1. Portrait of meat consumption patterns

Meat is a staple component of the household diet, and its consumption is primarily influenced by income level, family structure, health consciousness, and dietary habits. Key motivations for meat purchases include daily family meals, social banquets and gatherings, and fitness-related diets. In recent years, consumer demand has shifted toward healthier and safer meat options, resulting in the growing popularity of organic, low-fat, high-protein meats, as well as ready-to-cook and prepared meat products.

According to the decision tree analysis, meat consumption patterns are characterized by the following trends: higher income levels are associated with increased meat purchases, and high-income households are more inclined to select premium-quality meat products such as organic pork and beef. At the same income level, households with no children or only one child tend to consume more meat than those with multiple children. This difference is attributed to budget diversification in larger families, where spending must be balanced across a wider range of food categories. Moreover, middle-aged and married consumers represent the primary demographic for meat consumption, driven by the need for family-oriented meals and a preference for purchasing meat in larger quantities.

4.3.2. Meat marketing strategy

To address the diverse needs of various consumer groups, marketing strategies should focus on themes such as “family nutrition” and “quality assurance” to build trust and meet varying expectations regarding meat products. For middle-income families and households with multiple children, bundled value packs or family-size combination deals can be introduced to reduce the purchasing threshold and encourage greater volume purchases. Conversely, for high-income households, single-person households, and families with no or few children, marketing efforts should highlight the premium quality, nutritional benefits, and convenience of meat products. In addition, expanding a multi-channel sales network—including online platforms, in-store promotions, and community-based retailing—will help strengthen brand visibility and enhance promotional effectiveness across different consumer segments.

4.4. Gold consumption pattern portrait and marketing strategy

4.4.1. Gold consumption pattern portrait

The primary motivations for gold consumption include investment purposes, status display, traditional wedding customs, and holiday gift-giving. High-income consumers often view gold as part of their diversified asset portfolio, whereas middle-income consumers tend to purchase gold jewelry for significant life events such as weddings, childbirth, and anniversaries. In recent years, the demand for light luxury and customizable gold jewelry among younger consumers has been rising, contributing to the diversification of the gold market.

According to decision tree analysis, gold consumption is predominantly influenced by income level—higher-income individuals demonstrate greater willingness to purchase investment-grade

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gold bars and branded jewelry. Marital status also plays a role, with married consumers more likely to buy gold for anniversaries, holidays, and other celebratory occasions. In addition, educational attainment significantly impacts consumption behavior; highly educated consumers are more inclined to invest in gold and tend to emphasize brand reputation, design aesthetics, and artisanal craftsmanship.

4.4.2. Gold marketing strategy

Marketing efforts targeting high-income and highly educated consumers should focus on gold's investment value, while also highlighting the cultural significance and brand heritage associated with gold products. Through storytelling, brands can communicate the unique blend of traditional craftsmanship and modern innovation, appealing to consumers' pursuit of exclusivity and quality. For young consumers, offering customizable and fashionable gold products can enhance emotional resonance and brand loyalty. By employing refined user segmentation, marketing messages can be tailored more precisely to different consumer profiles, thereby improving conversion rates and user retention.

4.5. Differences in household consumption

The decision tree analysis reveals significant differences in consumer behavior across various product categories, highlighting income as the most influential factor in the consumption of wine, meat, sweets, and gold. Regardless of the product type, income consistently emerges as the primary determinant of purchasing behavior.

Beyond income, family structure plays a crucial role, particularly in the consumption of sweets and meat. Households with children are more likely to purchase sweets, driven by needs related to daily snacks, holiday treats, or rewards. In contrast, when it comes to meat consumption, families with multiple children tend to spend less, likely due to the need for broader budget allocation across diverse food categories and a greater focus on nutritional balance. Wine consumption, by comparison, is markedly higher among households without children, potentially reflecting a lifestyle that prioritizes social engagement and personal enjoyment. Inversely, sweets consumption is strongly associated with households with children, indicating distinct household expenditure patterns driven by family needs. Interestingly, gold consumption is largely unaffected by the number of children in a household. Instead, it is primarily driven by income level and educational background, reflecting motivations such as investment, status display, and symbolic consumption tied to life events. These findings point to diverging consumption preferences: wine and gold are predominantly favored by higher-income groups as lifestyle and investment goods, whereas meat and confectionery see more substantial demand among middle-income households, where practical and family-oriented consumption needs are more prominent.

Supermarkets can personalize their marketing strategies by drawing consumer profiles based on these characteristics. For example, a wine promotion targeting high-income families without children or a candy promotion targeting families with children. Meanwhile, gold sales can focus more on investment and status marketing, while meat products can focus on family meal culture.

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5. Conclusions and discussion

5.1. Research findings

Based on the decision tree model, this study analyzes consumer expenditures on four commodity categories—wine, candy, meat, and gold—considering variables such as age, education, income, marital status, and number of children. The results reveal significant differences in spending patterns across various family structures and income levels. These findings echo the results of Raden Johannes and Andry Alamsyah, who successfully predicted footwear sales on an Indonesian e-commerce platform using a decision tree approach, further validating the effectiveness and applicability of decision tree algorithms in analyzing consumer behavior.[15] These findings are consistent with the advancements in decision tree algorithms, such as the Max-Cut decision tree proposed by Bodine and Hochbaum, which enhances classification accuracy and computational efficiency. This underscores the effectiveness of decision tree models in analyzing complex consumer behavior patterns.[16] Income emerges as the core determinant of consumption: high-income, childless families tend to favor wine; families with children primarily purchase candy; meat consumption is influenced by both income and the number of children; and gold consumption is predominantly driven by income level. Family structure also significantly shapes purchasing behavior. By conducting multivariate analysis with a focus on family profiles, this study provides data-driven insights to support personalized marketing strategies.

5.2. Theoretical contributions

First, this study shifts from single-variable analyses to a multifactor synthesis approach. Unlike previous literature that often focuses on a single variable or limited dimensions (e.g., Predicting Consumer Purchasing Decisions in the Online Food Delivery Industry), this paper employs a decision tree model to analyze consumer behavior from multiple perspectives—including age, education, income, marital status, and number of children. By constructing a framework centered on the “family unit,” the study addresses the limitations of analyses based on single factors.

Second, the introduction of the “family structure” variable enhances the consumer behavioral profile. Traditional consumer behavior research mainly emphasizes individual characteristics such as age and income. This study, however, incorporates the number of children to analyze behavior at the family level, revealing distinct consumption patterns across different family types. This addition enriches the consumer portrait and lays the foundation for more precise and targeted marketing strategies.

Finally, decision tree modeling is integrated with the practical adaptability of precision marketing scenarios. Unlike existing studies that rely heavily on complex algorithms—such as RF-LightGBM integration models—this paper highlights the interpretability of the decision tree model, which directly translates consumer behavior patterns into actionable marketing strategies. For example, superstores can use the model to tailor wine discount coupons or high-end tasting events to specific family profiles. This approach lowers the barriers to applying algorithmic models in traditional retail and offers small and medium-sized enterprises a cost-effective, business-relevant precision marketing solution.

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5.3. Implications for practice

Firstly, when designing marketing strategies, enterprises should consider consumers' family structure—such as marital status, presence of children, and number of children—to develop targeted marketing programs and deliver precise product recommendations. For example, promoting wines to high-income families without children, while offering family-sized candy packages and discounted meat bundles to families with multiple children, can enhance marketing effectiveness.

Secondly, this study shifts the marketing focus from the traditional individual perspective to a family-centered approach. By treating the family as the core unit of precision marketing, it encourages a transformation from individual-based marketing pathways toward a new paradigm that emphasizes personalized marketing centered on family structure.

5.4. Research limitations and prospects

The consumer purchase data used in this study is sourced from a single superstore, which presents certain limitations in terms of generalizability. Therefore, consumption patterns may vary under different circumstances and should be analyzed accordingly.

Future research could incorporate multi-source data, combining online and offline consumer information, to further enrich consumer behavioral profiles and enhance the accuracy and applicability of the findings.

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