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The Impact of Digital Marketing Campaign Strategies on Consumer Buying Intention

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Abstract: Consumer psychology and shopping motivation have been studied since ancient times, and their study has progressed with technological advancements. Today's companies can only imagine operating with digital marketing to effectively reach a broad audience and get valuable insights about customer behavior. Digital marketing campaigns are an excellent tool. However, conventional methods of assessing shoppers' propensity have limitations regarding accuracy and breadth of coverage. Aiming to overcome the drawbacks of existing methods, this paper offers a Machine Learning-based Consumer Buying Intention Analysis Method (ML-CBIAM). ML-CBIAM adopts machine learning algorithms to consumer data from online advertising efforts. It provides a more accurate and comprehensive understanding of customer habits and preferences by the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS). The simulated results show that the suggested technique for ML-CBIAM surpasses state-of-the-art methods in terms of accuracy and coverage. Furthermore, results from a small sample of simulations demonstrate that the ML-CBIAM can correctly forecast customer purchase intent for various digital marketing campaign techniques. All indexes of ML-CBIAM are better than those of Fuzzy, SVM, PCA and LDA. On average, ML-CBIAM has a click-through rate of 13.7%, a conversion rate of 3.3%, and a return on spending of 19.4%. Using ML-CBIAM, companies boost the success of their marketing initiatives, increase their profits, and enrich their connections with customers.

Keywords: consumer buying intention; digital marketing campaign; machine learning; ML-CBIAM

1 INTRODUCTION

The idea of a customer and what he wants to purchase has existed since ancient times. Barter systems, in which products were traded for one another, developed as one of the first forms of trade [1]. Time and the advent of money ultimately gave rise to consumerism. Modern materialism permeates many aspects of life, from personal choices to cultural norms [2]. The growing purchasing power of the Chinese middle class has made consumer spending a crucial factor in the country's economic development [3]. The Chinese consumer market is becoming savvier and more selective, favoring top-tier goods. The Chinese government has reduced taxes, provided subsidies, and invested in domestic consumption because it values consumer spending [4]. China has one of the most important e-commerce markets in the world, led by giants like Alibaba and JD.com [5, 6]. However, the Chinese consumer market has difficulties, such as a complicated regulatory framework and a fragmented market with wildly varying tastes among Chinese citizens in various parts of the country. Companies that want to thrive in this sector must understand consumer psychology and the motivations behind their purchases. Technology and data analytics have helped businesses better understand customers' habits and interests, resulting in more targeted advertising. Marketing tactics such as influencer marketing, social media marketing, and individualized marketing campaigns fall within this category [7].

For companies of all sizes and in every industry, digital marketing in China is now an integral part of the overall marketing strategy. China is the biggest and most profitable digital marketplace because of its massive population (over 1.4 billion) and widespread internet usage (over 900 million users). eMarketer predicts that by 2022, China's digital advertising expenditure will reach $110.12 billion, making it the world's second-largest market [8]. Due to the country's stringent internet rules and customer behavior, China's digital marketing environment is distinct. WeChat, Weibo, and Douyin (commonly known as TikTok) are the most widely used platforms for digital marketing in China, each with unique capabilities and user base [9, 10]. WeChat is a well-liked social media platform company, which used to engage with their clients through messaging, mini-programs, and WeChat Pay. It has more than one billion monthly active users. Weibo is a microblogging site with over 550 million monthly active users where brands can publish content, promote their products, and interact with their customers.

Traditional marketing in China has several obstacles that can only be solved with a strategy that can effectively understand people's buying intentions. ML-CBIAM is a strategy that can help companies learn more about their customers' habits to target their advertising better. ML-CBIAM creates a framework for analyzing customer behavior to determine what aspects of digital marketing in China are most effective in influencing consumers to make purchases online. In Part 4, authors demonstrate the performance of ML-CBIAM in detail. By comparing with existing methods such as fuzzy logic, support vector machines, etc., ML-CBIAM's performance on key metrics such as click-through rate, conversion rate, average order value, customer lifecycle value, and return on investment was validated. The advantages of ML-CBIAM point out its potential to improve the effectiveness of digital marketing.

The novelty of the work presented in the document lies in the application of the Machine Learning-based Consumer Buying Intention Analysis Method (ML-CBIAM). This method addresses several knowledge gaps that previous articles in the field of digital marketing and consumer behavior analysis could not adequately address. ML-CBIAM aims to provide a more accurate and comprehensive understanding of customer habits and preferences. This is a clear advancement over conventional methods, which the authors argue have limitations regarding accuracy and breadth of coverage. The paper employs the TOPSIS method to analyze consumer buying intentions, which is not seen in digital marketing studies. This technique allows for a more thorough and precise assessment of digital marketing efforts, filling a gap in the existing literature. The authors conducted a simulation study using the Alibaba Cloud Tianchi dataset and Google Analytics, which is a novel approach. Given the unique characteristics of the Chinese digital marketing environment, the paper's focus on China provides novel insights into how digital marketing strategies can be optimized in this specific context, which is under-researched in the existing literature. ML-CBIAM creates a framework for analyzing customer behavior to determine the most effective aspects of digital marketing in China. This is a significant contribution as it offers a structured approach to understanding and predicting consumer behavior in the digital space; a more thorough and precise assessment of digital marketing efforts using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach for purchasing intention analysis. The TOPSIS method finds the highest and lowest scores in the purchase intention survey report, and then calculates the difference between your score and those two scores to get an objective assessment of your purchase intention. With the changes in digital marketing strategies on the Internet, coupled with the rapid development of the logistics industry, online shopping for consumers has become particularly convenient and fast. People's pace of life has accelerated, and many groups are more inclined to shop online.

The sections are arranged as follows: A review of the literature on different marketing tactics and customer purchasing intentions is presented in Section 2, which identifies gaps in the body of knowledge. The suggested ML-CBIAM is covered in Section 3, which intends to examine customer purchasing intention in digital marketing campaigns while overcoming the drawbacks of conventional marketing tactics. The simulation study and results of the suggested ML-CBIAM technique are shown in Section 4, along with example values, emphasizing how well it predicts customer purchasing intent. In its conclusion, Section 5 highlights the need for further study in this area and describes the potential use of the suggested strategy for assessing customer behavior in digital marketing efforts.

2 BACKGROUND AND LITERATURE SURVEY

The literature review shows how crucial it is for marketing tactics to comprehend customer behavior and purchasing intentions. It looks at various ideas and approaches for examining consumer purchasing behavior.

The impact of quality on customers' purchasing intentions between local and international cosmetic enterprises was examined by Faisal-E-Alam et al. [11]. The research used a survey-based methodology, and the suggested strategy focused on the variables influencing consumer behavior and purchase intention. With a preference ratio of 75% for international cosmetic companies and 25% for local cosmetic companies, the simulation findings showed that customers were more likely to buy from the former than the latter. This method is only analyzed for specific genders and items. It does not have a wide range of reference.

In 2020, Purwanto et al. looked at Indonesian non-Muslim customers' intentions to buy halal cuisine [12]. The research showed that variables including awareness, knowledge, attitudes, and behavior strongly affected customers' purchase intention for halal goods the suggested technique comprised an exploratory case study methodology. The simulation's findings indicated that non-Muslim Indonesian customers had a 70% preference for halal cuisine. This method is only analyzed for Indonesian non-Muslim customers' intentions. It does not have a wide range of reference.

The paradigm changes in consumer behavior toward green cosmetics studied by Sharma et al. in 2021 [13]. The suggested strategy used an empirical research approach and emphasized the elements of environmental awareness, health consciousness, and social responsibility that influence consumer behavior toward green cosmetics. According to the simulation findings, customers preferred green cosmetics items by 65%. The impact of mobile marketing, sales, and lifestyle on customers' impulsive purchasing behavior in online market places was examined by Ittaqullah et al. in 2020 [14]. The suggested strategy focused on the variables influencing customer impulsive purchase behavior, such as mobile marketing, discounts, and lifestyle, and employed a survey-based methodology. The simulation outcomes showed that, with a 40% preference ratio, mobile marketing had the most influence on impulsive purchasing behavior. The above are simulation results and are not for actual application scenarios.

In Bangalore, Jagadeesh Babu et al. examined how social media marketing affected millennials' purchasing decisions about cell phones [15]. The suggested technique used a survey-based methodology and emphasized the elements influencing millennials' purchasing decisions about cell phones, such as brand, price, and features. According to the simulation findings, social media marketing considerably (and to a preference ratio of 50%) affected millennials' purchasing decisions about cell phones.

An approach to assess the influence of brand awareness and social media content marketing on customer purchase decisions was put out by Ansari et al. [16]. With a simulation result of 85% accuracy, the research showed that brand awareness and social media content marketing significantly affect customer purchasing choices. The study should have considered how other variables can affect customer behavior.

Dangi et al. conceptualized a framework to examine customer purchasing patterns and intentions for organic food [17]. The paradigm emphasized several social, psychological, and demographic variables that affect consumer behavior. The suggested framework has yet to undergo an empirical study. Ali et al. examined the effect of pricing tactics on consumers' buying choices in 2021 [18]. The suggested approach quantitatively examines the connection between various pricing methods and customer behavior. With a simulation result of 80% accuracy, the research demonstrated that pricing tactics significantly affect customer behavior. Although the study has yet to be exhaustive, it only took a small number of pricing options into account.

Empirical research on the effectiveness of social media marketing initiatives in maintaining long-term online customers in the online fashion retail sector was put up by Wang et al. [19]. With a simulation result of 75% accuracy, the researchers examined the effects of several social media marketing methods on customer behavior. They discovered that they had a considerable impact on consumer retention. However, the study's narrow emphasis on the online fashion retail business made its conclusions less generalizable.

A strategy to examine the impact of social media marketing, word-of-mouth, and the efficacy of advertising on brand awareness and purchase intention was put out by Maria et al. [20]. With a simulation result of 90% accuracy, the research indicated that all three variables significantly affect customer behavior. The study only looked at a few variables and skipped over the effects of extraneous variables like economic and political ones.

The literature review covered research on customer behavior and purchase intent in many situations, including the effects of quality, halal foods, eco-friendly cosmetics, social media marketing, and pricing tactics. Further research is required to address the issues and gaps in the existing literature and provide marketers with valuable ideas to enhance their strategies and boost sales. Better personalization is one way machine learning is changing how your brand engages customers, but it is not the only way. Artificial intelligence and machine learning can also be used to better automate your marketing efforts and significantly improve customer engagement.

3 PROPOSED MACHINE LEARNING-BASED CONSUMER BUYING INTENTION ANALYSIS METHOD

A system was created to research and forecast clients' online purchasing patterns. The architectural scheme separates the system into three subsystems: consumer knowledge acquisition, information service, and real-time consumer behavior prediction. The primary purpose of the knowledge provision subsystem's customer knowledge gathering subsystem is to send newly information to forecast behavior among consumers. The knowledge service subsystem's primary duties include storing and organizing the knowledge that the customer acquisition subsystem has acquired and providing ongoing cognitive assistance to the consumer behavior forecasting subsystem. The real-time customer behavior forecast subsystem finishes the real-time consumer behavior forecasting by the information in the information base by analyzing the goods that consumers are now browsing during their visit. The architecture of the proposed ML-CBIAM is shown in Fig. 1.

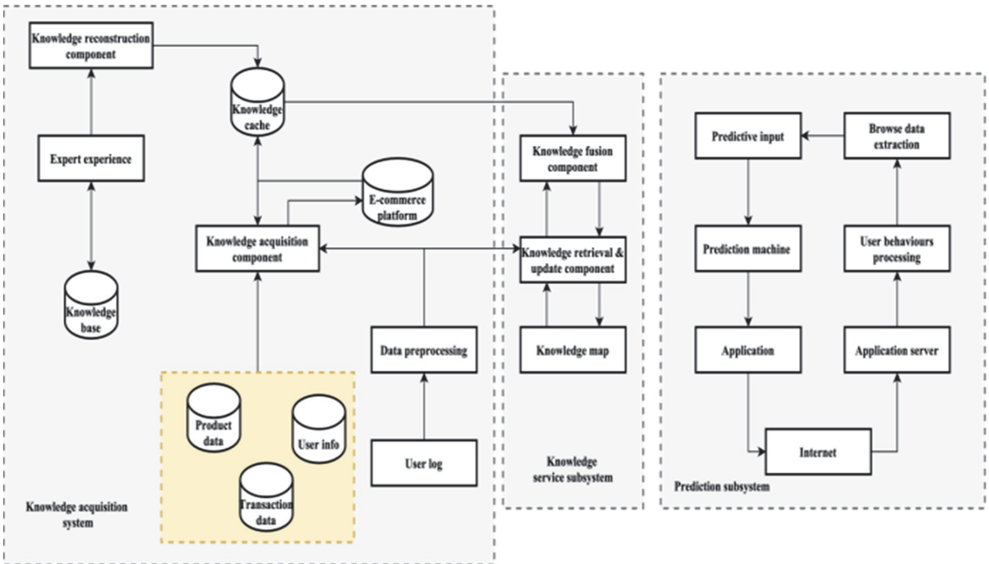

Figure 1 Architecture of the proposed ML-CBIAM

The ML-CBIAM system comprises three primary subsystem blocks, namely the knowledge acquisition system, the knowledge service subsystem, and the prediction subsystem. The knowledge acquisition system is responsible for acquiring and processing data from diverse sources, including user information, transaction data, product data, and user logs, which is the knowledge acquisition system. The present block encompasses a knowledge reconstruction element that transforms the obtained information into a structured format and archives it in the knowledge cache. This block encompasses both the expertise gained through experience and the acquisition of knowledge, thereby contributing to the expansion of domain-specific knowledge within the knowledge base.

The knowledge service subsystem is tasked with the provision of diverse knowledge services, which encompass knowledge fusion, retrieval, and update, as well as knowledge mapping. The component responsible for merging information from various sources to produce novel insights and suggestions is known as the knowledge fusion component. The component responsible for retrieving and updating the knowledge base in response to user queries is the knowledge retrieval and update component. The knowledge map offers a comprehensive view of the knowledge repository, facilitating the identification of knowledge lacunae and prospective avenues for enhancement.

The prediction subsystem utilizes a predictive input that is obtained from user behavior and browsing data to facilitate the training of the prediction machine. Subsequently, the application server employs the trained machine to generate prognostications and furnish individualized suggestions to the user. This block encompasses the e-commerce platform and the internet, both of which facilitate e-commerce transactions and enable system access from any location worldwide. The data preprocessing module is utilized to preprocess the data prior to its input into the system.

There are many factors that affect the purchasing behavior of consumers; the main factors are personal factors, social factors, cultural factors, and psychological factors. Their direct influence on consumer purchase is different, and their identification is also different. Payment safety and confidentiality are crucial challenges in Internet marketing from a technological perspective. Business security is presently one of the key elements influencing e-commerce growth and is essential to all facets of online buying. Theoretically, consumers' positive attitudes and behaviors toward online shopping can be affected by safeguards such as preventing the disclosure or theft of private trade information, database anonymity, fraud avoidance, secure functioning of online transactions structures, buyer recognition, credit, electronic signature confirmation, antifraud, and merchant security when collecting cash. The model is expanded upon and coupled with other principles to better forecast and account for customer purchasing behavior. Fig. 2 illustrates the development of a broadly extended online customer purchase intention paradigm using the perceived danger principle, perceived trust principle, and innovation dissemination technique.

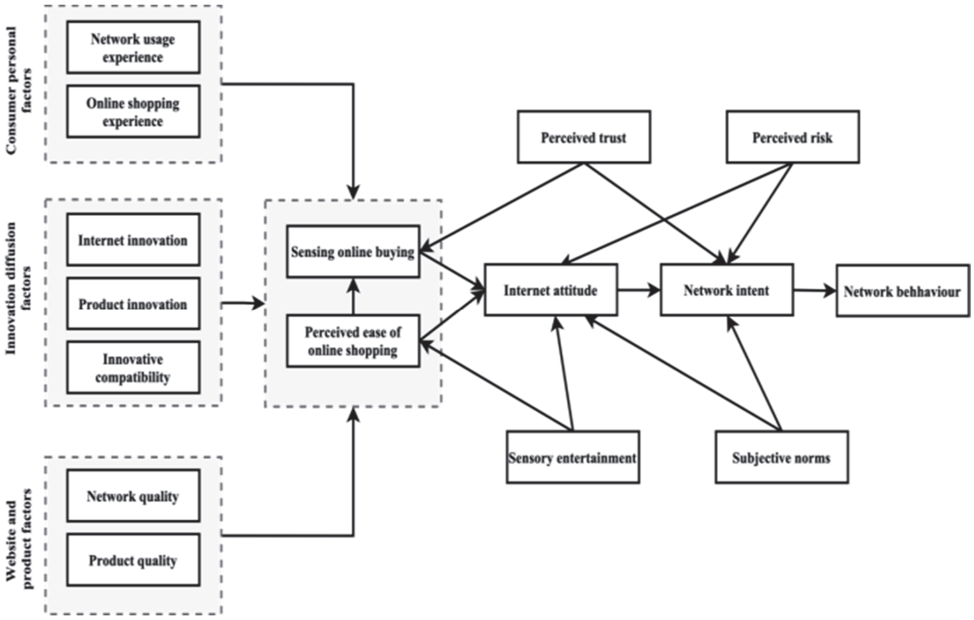

Figure 2 Affecting factors of consumer buying intention

A multivariate statistical analysis technique is a combined analysis of different factors affecting consumer buying intention. Consumer buying preferences adopt quantitative analytic characteristics to determine the overall level of choice, the relative weight given to various product characteristics in customer preferences, and the usefulness each feature group provides to customers. The conjoint evaluation determines preference ratings, weights, and attractiveness scores by asking customers to assess a few product identities. Despite not being created with advertising studies in mind, it has evolved into one of the most widely used methods for studying customers because of its distinct benefits. The following keywords are often used while using the conjoint evaluation method:

(1) Attributes: A product or service's key characteristics or indications influencing customer behavior. Online commodities pricing and purchase evaluations are group-buying items' characteristics.

(2) Attribute Level: Product characteristics have varied values, and the level of the attribute price might be below 100 yuan, 100- 200 yuan, and so on.

(3) Complete Profiles: Full biographies are all service and product-level configurations.

(4) Utility Purposes: Utility functions define the utility value assigned to each customer profile, which in layman's words, means the influence on consumer behavior preference.

(5) Weights' Relative Importance: When customers make buying choices, the relative significance of weights defines the influence of product or service features on their purchasing decisions.

(6) Internal consistency: The degree of correlation between the user evaluation and prediction tools demonstrates the dependability of the survey findings.

(7) Simulation of Maximum Validity: The highest utility simulation model, the most often used market segment simulation model, believes that customers would always buy the most elevated value goods or services and make choices when purchasing them.

3.1 Cost Modeling

The proposed model focuses on the multiproduct purchasing decision-making system under fixed demand. The demand hypothesis is straightforward. The yearly fixed need frequency of product x is considered D_x, the entire replenishment cycle of each firm to be T, and the joint replenishing frequency of commodity x to be C_x. The buy cycle inventory cost is written as h_x, and the associated formula is shown in Eq. (1).

$$I_{c(h)} = \frac{1}{2}\sum_{x=0}^{m-1} C_x \cdot T \cdot D_x \cdot h_x \tag{1}$$

Eq. (2) can calculate the corresponding ordering expenses, including primary and secondary costs. The direct purchasing cost is the fixed expense incurred for each transaction. This cost is unrelated to the consolidation of joint orders. The variable cost must have factored into the additional buying expense in each supplementary (s) ordering operation.

$$V_{c(h)} = \frac{S_x}{T} + \sum_{x=0}^{m-1} \frac{S_x}{C_x \cdot T} \tag{2}$$

The replenishment cycle is T, and the commodity is C_x. Then, the overall expense of the JPR model is equal to the sum of the inventory expenses and procurement cost, which can be stated in Eq. (3).

$$T_{c(T,\,C)} = I_{c(h)} + V_{c(h)} \tag{3}$$

The inventory cost and variable cost are denoted $I_{c(h)}$ and $V_{c(h)}$. With the assistance of mobile Internet infrastructure and big data evaluation, the digital marketing scenario is more complicated and ever-changing, and client requirements are more dispersed and arbitrary. This issue is more relevant to real-world circumstances. The unpredictability of actual demand includes a shortage cost ($O_{c(h)}$) to account for this uncertainty. Nonetheless, this problem requires certain presumptions, namely that the demand in the digital advertising mode is autonomous, equally dispersed, and subject to a Gaussian distribution and that the maximal level of stock recurring investment in the observational time is shown in Eq. (4).

$$R_x = D_x\left(C_x \cdot T + L_x\right) + Z_x\sqrt{\infty_x\left(C_x \cdot T + L_x\right)} \tag{4}$$

The dispersion time is D_x, the commodity cost is C_x, the replenishment time is T the maximum distribution level is L_x, the dispersion function is Z_x, and the coefficient is ∞_x . Based on this supposition, the $O_{c(h)}$ expense is computed using Eq. (5).

$$O_{c(h)} = \frac{1}{C_x \cdot T}\infty_x\sqrt{C_x \cdot T + L_x}\left(f\left(Z_x\right) - Z_x\left(1 - F\left(Z_x\right)\right)\right) \tag{5}$$

where $f(Z_x)$ is the accumulated dispersion expression of the need for product x, and $F(Z_x)$ is the likelihood density, the demand for product is x. The replenishment time is T, the commodity is C_x, the maximum distribution level is L_x, and the coefficient is ∞_x. The total expense of the approach consists of the sum of the procurement cost, the stock storage cost, and the shortfall expense.

3.2 Digital Marketing Strategies

Digital marketing campaigns can substantially affect consumer intent to purchase because businesses need to communicate with the target audience and influence how to make purchases. Here are a few ways digital marketing initiatives can impact consumer intent to purchase: They boost brand recognition by exposing the brand and its products to a larger audience. This prompts consumers to evaluate the brand when making purchase decisions.

Personalization: Using consumer data and targeting methods, digital marketing campaigns can send personalized communications to consumers, increasing their brand interaction and intent to buy.

Social substantiation: it is a significant factor in buying decisions. Digital marketing campaigns that employ user-generated content and evaluations can instil confidence and trustworthiness in the company, thereby increasing consumer intent to purchase. The time-honored brands that have been handed down not only allow the new generation to experience and identify with the unbounded knowledge of ancient people, but also provide economic value that can ensure the survival of future generations [27].

Influence of Influencers: Influencer advertising has become an increasingly common approach to digital advertising because it can effectively connect with the audiences it wants to reach. When an influencer endorses an item or service, it can significantly affect consumer intent to purchase because their fans view them as a reliable source of information.

Convenience: Digital advertising efforts can provide consumers with convenient purchase choices, such as ordering via the internet and shipment, which makes buying something simpler and more alluring.

3.3 Impact of Digital Marketing

Several marketing approaches can be used to figure out how digital marketing campaign methods affect consumers' plans to buy. The Attention, Interest, Desire, and Action (AIDA) model is one of these. The Consumer Choice-Making Process concept is another one. It has five steps: recognizing the problem, looking for information, weighing the pros and cons of different options, making a purchase choice, and evaluating the purchase after it has been made.

Using these models, it can get the following expressions for how digital marketing campaign tactics affect consumers' plans to buy:

Attention: Social media ads, optimization for search engines, and email marketing are all ways digital marketing efforts can get customers' interest. Eq. (6) can explain awareness:

$$A = f\left(SMA, SEO, EM\right) \tag{6}$$

where A is the amount of attention, SMA is how well digital advertisement works, SEO is how well the optimization of search engines works, and EM is how well email marketing works. The link between these factors is shown by f.

Interest: People must be curious once they know about a product or service. This can be done with strategies like content marketing, promoting through influential people, and focused ads. The expression of interest can be written by Eq. (7).

$$I = f\left(CM, IM, TA\right) \tag{7}$$

where I is the amount of attention, CM is how well content marketing works, IM is how well influencer marketing works and TA is how well-targeted advertising works. The function f shows the link between these factors.

People must want the goods or services before buying them. This can be done with strategies like advertising that makes people want to buy, social proof, and special deals. The consumer's wants are expressed in Eq. (8).

$$D = f\left(PA, SP, EO\right) \tag{8}$$

where D is the amount of desire, PA is how well advertising makes people want something, SP is how well social proof works and EO is how well exclusive offers work. The function f shows the link between these factors.

Action: Lastly, customers must move by buying something. This can be done with strategies like tracking, personalized deals, and making it easier to check out. The action can be written using Eq. (9).

$$Ac = f\left(RT, PO, SCP\right) \tag{9}$$

where Ac is the amount of action, RT is how well retargeting works, PO is how well custom deals work, and SCP is how well-streamlined checkout procedures work. The function f shows the link between these factors.

Putting these formulae together can make a complete model of how digital marketing campaign methods affect consumers' buying plans, as shown in Eq. (10).

$$BI = f\left(SMA, SEO, EM, CM, IM, TA, PA, SP, EO, RT, PO, SCP\right) \tag{10}$$

where BI is the degree to which a customer plans to buy; the complicated link between all the factors in the AIDA and Consumer Decision-Making Process frameworks is shown by function f.

3.4 Model Design and Application

Shopping via the Internet is an interaction between buyers and sellers in an online setting. The consumer is the central part of the market, and the consumer is the most critical factor in whether a business will stay in business and grow. The consumer's desire is a significant factor in how a company decides which advertising approach to use. It is the main reason a business chooses its marketing approach. So, the characteristics of customers and e-merchants, the two leading players in online commerce, will always affect whether they can do e-commerce or purchase goods with each other. Most people shop online because buying in person is more accessible and takes less time. The online shopping behavior of consumers from the Alibaba Cloud Tianchi dataset or Google Analytics is shown in Fig. 3.

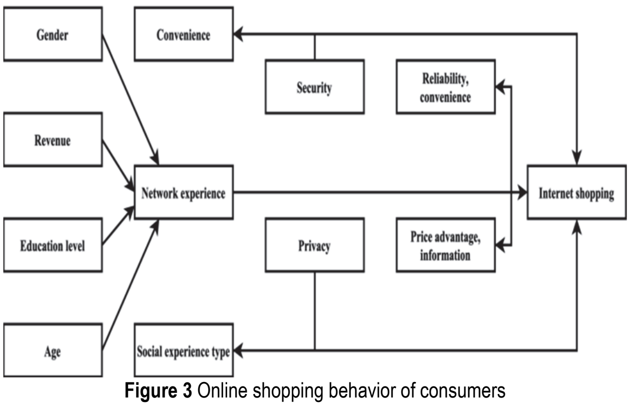

Figure 3 Online shopping behavior of consumers

Clients who care more about their social lives like the e-shop model less. Since financial transactions occur on the internet, it makes sense that personal and security issues affecting online interactions affect how people act when they shop online. The effects of consumer traits, customer demographics, e-merchant features, and issues related to challenges and security in online purchases on what customers do when purchasing goods via the internet will be examined and used to lead future studies.

3.5 TOPSIS Method Intention Analysis

The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is a common way to analyze terminal solutions that can be used for multiple things. The main idea behind sorting is to find the space between the item being evaluated and the best solution and the worst option [28]. If the assessed object is nearest to the best choice and longest from the worst solution, it is the best. Otherwise, it is the worst. The optimal answer for each has an index value that is the best value for that index. The worst answer has an index value equal to the worst of each rating index. The upper and lower-level settlement method is another name for it. It can be investigated by looking at the relationship between what the customer is like and what they want to buy. If there are n evaluating items and m evaluating indices, A_{xy}(x =1, 2, …, m and y = 1, 2, …, n) is the value of the xth item for the yth index. With the TOPSIS method, here are the stages needed for resolving the issue:

Step 1. Create the original matrix.

Based on the facts, the following can be said about the related matrix $\boldsymbol{O}$, using Eq. (11).

$$\boldsymbol{O} = \begin{bmatrix} \begin{bmatrix} o_{11} & \cdots & o_{1n} \\ \vdots & \ddots & \vdots \\ o_{m1} & \cdots & o_{mn} \end{bmatrix} \end{bmatrix} \tag{11}$$

The elements of the matrix are denoted o_{ij}.

Step 2. Preprocessing the matrix.

With the TOPSIS way of evaluating, the change direction should be constant or have the same path. Low-quality indications (cost indications) are often utilized. High-quality (benefit indications) can be changed into low-quality (cost indications) and vice versa. With Eq. (12), the low-quality expressions are changed into high-quality indications, and the original information table is found. Eq. (13) shows how the same facts are handled:

$$\overline{A_{xy}} = \frac{1}{A_{xy}} \tag{12}$$

$$\overline{A_{xy}} = \begin{cases} A_{xy} & \text{High} \\ \dfrac{1}{A_{xy}} & \text{Low} \end{cases} \tag{13}$$

where $\overline{A_{xy}}$ refers to the yth number based on the xth evaluating object's equivalence. The Actual matrix is denoted A_{xy}.

Step 3: Figure out the source data array for the same direction. Eq. (14) shows how to do this:

$$T_{xy}=\begin{cases}\dfrac{A_{xy}}{\sqrt{\left(A_{1y}\right)^2+\left(A_{2y}\right)^2+\ldots+\left(A_{my}\right)^2}} & \text{High}\\[2ex] \dfrac{\overline{A_{xy}}}{\sqrt{\left(A_{1y}\right)^2+\left(A_{2y}\right)^2+\ldots+\left(A_{my}\right)^2}} & \text{Low}\end{cases} \tag{14}$$

The direction array is denoted T_{xy}, and the actual array is denoted A_{xy}. Here's how to get the adjusted matrix from Eq. (15).

$$Q=\left[\begin{bmatrix} q_{11} & \cdots & q_{1n}\\ \vdots & \ddots & \vdots\\ q_{m1} & \cdots & q_{mn}\end{bmatrix}\right] \tag{15}$$

The adjusted matrix element is denoted q_{ij}.

Step 4. Identifying the ideal and idealized vectors.

In other words, given a limited number of best-case and worst-case options for the array Q, the best answer, denoted by the symbol Q^+, is the one that has the highest value for each column of Q, as demonstrated in Eq. (16).

$$Q^+=\left\{\max Q_{x1}, \max Q_{x2}, \ldots, \max Q_{xn}\right\} \text{ for } 1<x<m \tag{16}$$

The minimal value in every row of Q makes up the worst-case situation Q^-, as demonstrated in Eq. (17).

$$Q^+=\left\{\min Q_{x1}, \min Q_{x2}, \ldots, \min Q_{xn}\right\} \text{ for } 1<x<m \tag{17}$$

The options of array Q are denoted Q_{x1}. In this paper, adjusting this parameter Q_{x1} can better obtain the optimal index weight, and then get the distance of the best solution.

Step 5. Weight computation.

Eq. (18) and Eq. (19) compute the distances of all the index weights of the analysis of items and the best solution D_x^+ and the worst solution D_x^-, correspondingly:

$$D_x^+=\sqrt{\sum\nolimits_{y=0}^{n-1}\left(\max Q_{xy}-Q_{xy}\right)^2} \tag{18}$$

$$D_x^-=\sqrt{\sum\nolimits_{y=0}^{n-1}\left(\min Q_{xy}-Q_{xy}\right)^2} \tag{19}$$

The options are expressed Q_{xy}, and the minimum and maximum functions are defined min() and max(). The distance equation is shown in Eq. (20) and Eq. (21) if each indication has a weight W_{xy}:

$$D_x^+=\sqrt{\sum\nolimits_{y=0}^{n-1}W_{xy}\left(\max Q_{xy}-Q_{xy}\right)^2} \tag{20}$$

$$D_x^-=\sqrt{\sum\nolimits_{y=0}^{n-1}W_{xy}\left(\min Q_{xy}-Q_{xy}\right)^2} \tag{21}$$

The options are denoted Q_{xy}, and the minimum and maximum functions are shown min() and max(). W_{xy} is the jth indicator's weight factor.

Step 6: Determine how closely the assessed items are to the ideal solution (C_x). Eq. (22) displays the computation procedure:

$$C_x=\frac{D_x^+}{D_x^+ + D_x^-};\ 0<C_x<1 \tag{22}$$

The positive and negative distances are denoted D_x^+ and D_x^-.

Step 7. To find the best answer, sort each evaluation object based on C_x size.

The fundamental concept behind a Markov model is to infer tendencies for future product movement based on historical activity patterns. The following are the steps:

(1) Calculating each sort of online product's sales rate based on previous data and dispersing that rate according to the shift matrix.

(2) As a starting point for determining the breakdown of various transaction types.

(3) Develop a Markov model to forecast each product's supply in the future.

Identifying the table of product sales rates is essential to utilizing the Markov model to estimate when products will be available online. The purchase intention analysis flow of consumers is plotted in Fig. 4. The precision of the predicted findings is impacted since it is difficult to identify the sales rate of items owing to the effect of several variables, and it is often an approximation.

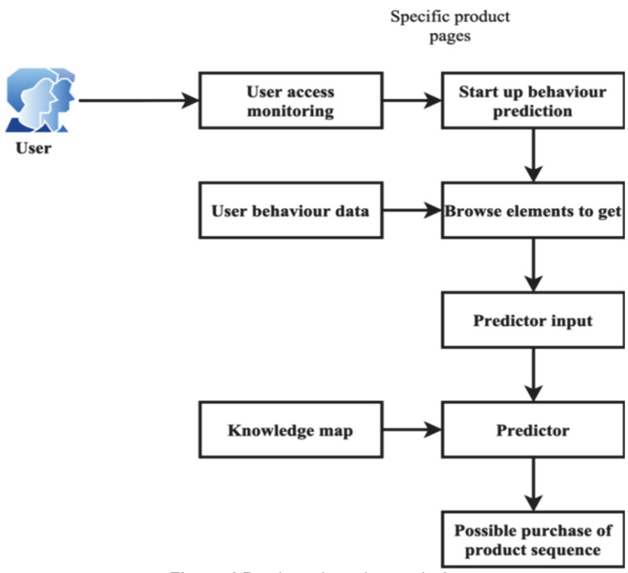

Figure 4 Purchase intention analysis

One of the critical elements of the prediction structure, the forecasting subsystem enables real-time forecasting of the actions of the present user. The system keeps track of consumers' browsing activity, and when a user navigates to a particular product on the website, the customer forecasting procedure is launched. The system gathers the customer's data and current surfing information. These two components serve as the prediction machine's input. It uses this information and knowledge from the knowledge graph to determine the most probable product sequencing the user will buy. TOPSIS method has no special requirements for consumer sample data, simple calculation and wide range of use. In addition, this method can make full use of traditional consumption data information and combine it with relevant consumption information in the current network era.

This section discusses the benefits of using ML-CBIAM to study customer behavior and determine the most effective parts of digital marketing in China for affecting online sales. This method builds a model to predict whether a customer will make a purchase based on their online shopping habits and demographic information. It uses a cost modeling technique to estimate the prices of different digital marketing methods and how they affect a customer's likelihood to buy. This section discusses how the TOPSIS method can be used to evaluate digital marketing efforts more thoroughly and accurately. This method provides a complete set of tools for studying how customers act and improving digital marketing strategies.

4 SIMULATION ANALYSIS AND FINDINGS

4.1 Experimental Analysis

This section deals with the simulation analysis using the Alibaba Cloud Tianchi dataset and Google Analytics. Alibaba Cloud Tianchi has several statistics linked to online shopping and digital marketing [21]. The files contain information on customer activity, user interaction, and social media. Different datasets are of different sizes, but most are significant and have millions of records. Most people who add to the datasets do so anonymously and reflect a wide range of Chinese customers. The information can be used to model how digital marketing efforts affect people's buying plans and give marketers valuable insights. The file has information about user IDs (Identity document signal), item IDs, groups, actions (like click, add-to-cart, and buy), and timestamps.

Google tracking is a web tracking service that tracks and reports how many people visit a website. Google Analytics uses to model the effect of a digital marketing effort on a consumer's desire to buy [22]:

- Set up a Google Analytics account: Make a Google Analytics account and link it to the website.
- Set a goal: Set a goal for the digital marketing effort, such as a purchase or a form entry. This will let it keep track of how well the plan works.
- Make a campaign. Use a tool like Google Ads or Facebook Ads to make a digital marketing strategy. Use focused terms and ad text to get the right people to visit the site.
- Check how well a campaign is doing: The Google Analytics panel can track how well the digital marketing strategy is doing. Look at click-through, bounce, and sale rates to determine the campaign's performance.
- Optimize the plan: Use the information from Google Analytics to improve the digital marketing strategy. Change the campaign's targeting, ad copy, and landing pages to improve it.
- Repeat the process. Repeat step 3 through step 5 to perfect the digital marketing strategy and improve the return rate.

By keeping an eye on website traffic and conversion rates, it can use Google Analytics to model the effect of digital marketing efforts on Chinese consumers' buying plans. Optimizing the actions based on what it learns from Google Analytics can make them work better and increase sales or leads. Depending on the study question and analysis, the Alibaba Cloud Tianchi dataset can look at different modeling measures. But here are some measurements to adopt.

Click-through rate (*CTR*): The number of times an ad or website is seen split by the number of times it is clicked on. *CTR* is expressed in Eq. (23).

$$CTR = \left(\text{Clicks}/\text{Impressions}\right)\cdot 100\% \tag{23}$$

Conversion rate (*CR*): The conversion rate refers to the proportion of individuals who engage in a specific desired behavior, such as purchasing a product or completing a form, among those who access a website or online platform. *CR* is expressed in Eq. (24).

$$CR = \left(\text{Conversions}/\text{Visitors}\right)\cdot 100\% \tag{24}$$

Average order value (*AOV*): Each order's average value is calculated using Eq. (25).

$$AOV = \text{Average Order Value}/\text{Number of Orders}\cdot\left(RMB\right) \tag{25}$$

Customer lifetime value (*CLV*): The value that a consumer is expected to bring to an enterprise over their time as a consumer. The *CLV* is computed using Eq. (26).

$$\begin{gathered} CLV = \left(\text{Average Order Value}\cdot\text{Purchase Frequency}\cdot\right. \\ \left.\cdot\text{Customer Lifespan}\left(RMB\right)\right) \end{gathered} \tag{26}$$

Return on investment (*ROI*): The amount of money a campaign brings in compared to how much it costs to run. The *ROI* is analyzed using Eq. (27).

$$ROI = \left(\left(\text{Revenue} - \text{Cost}\right)/\text{Cost}\right)\cdot 100\% \tag{27}$$

These measures can determine how well digital marketing efforts are working, find where they can be improved, and tweak marketing strategies to make them work better.

4.2 Results and Discussion

Fuzzy, SVM, PCA, LDA and ML-CBIAM are common learning methods. The ML-CBIAM method proposed in this paper consistently outperforms other methods in terms of conversion rate, average order value, customer lifecycle value, and return on investment. ML-CBIAM is superior to the existing methods Fuzzy, SVM, PCA and LDA in five indexes: click-through rate, conversion rate, average order value, customer life cycle value and return on investment.

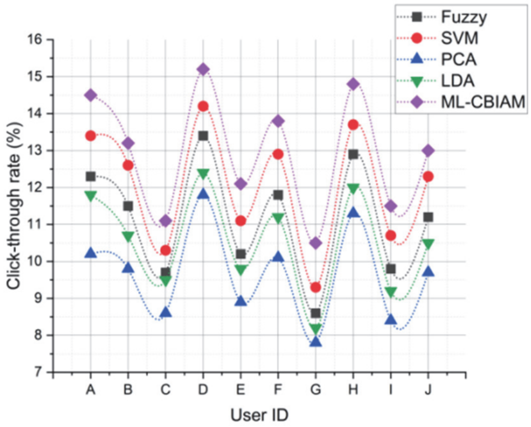

Figure 5 CTR analysis of the proposed ML-CBIAM

Fig. 5 shows the Click-through rate (%) for Fuzzy [26], Support Vector Machine (SVM) [23], Principal Component Analysis (PCA) [24], Linear Discriminant Analysis (LDA) [25], the suggested ML-CBIAM, and four other known methods. The click-through rate (%) is better with the proposed method than the current methods. For user A, for example, the ML-CBIAM gives a Click-through rate of 14.5%, while the highest Click-through rate of the existing methods is 13.4% for SVM. For user J, the click-through rate for the suggested plan is 13%, while the best click-through rate for a current method is 12.3% for Fuzzy. The ML-CBIAM idea is built on techniques based on machine learning that can measure a customer's desire to buy, and it can be used to create an effective digital marketing campaign plan in China. It uses user behavior and personal information to guess what people will buy. So, the suggested way can help businesses in China improve their click-through rate, leading to a higher sale rate and return on investment.

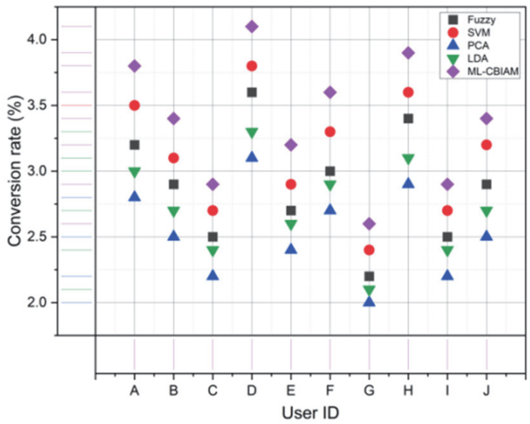

Figure 6 Conversion rate analysis of the ML-CBIAM

The effect of Digital Marketing Campaign Strategies on Consumer Buying Intention in China, as measured by the Conversion Rate (%) is plotted in Fig. 6. The suggested ML-CBIAM method did better than the current methods (Fuzzy, SVM, PCA, and LDA) in all user IDs, getting the best conversion rates. On average, the ML-CBIAM was 18.4% better than the already used methods. The data show that ML-CBIAM could be a good way for digital marketing efforts in China to get more people to sign up for them. When the outcomes of each method are compared, it is essential to remember that the SVM and LDA methods did better than the Fuzzy and PCA techniques, but the suggested ML-CBIAM method did even better.

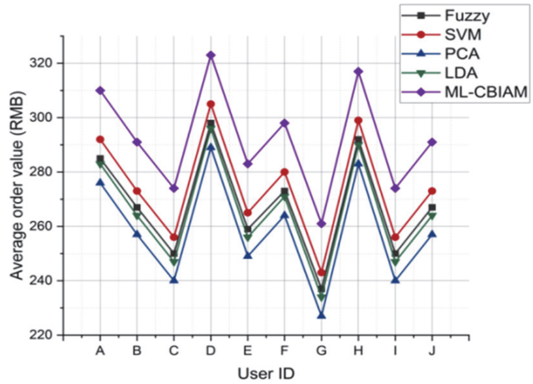

Figure 7 Average order value of consumer analysis

Using Fuzzy, SVM, PCA, LDA, and ML-CBIAM, the table shows how different digital marketing campaign tactics affect the average order value in RMB for users A to J. The average order value of sample consumers is plotted in Fig. 7. The suggested method, ML-CBIAM, shows that user A has the highest average order value, 310 RMB, and user J has the lowest average order value, 291 RMB. Compared to other ways, the proposed system increases the average order value by 7% and 10%. The average results run from 250 RMB to 298 RMB for all courses and people. The idea includes a personalized and focused approach to digital marketing efforts adapted to each buyer's tastes and habits. This leads to more satisfied, loyal, and long-term customers. The results include better business success, more money, and a competitive edge.

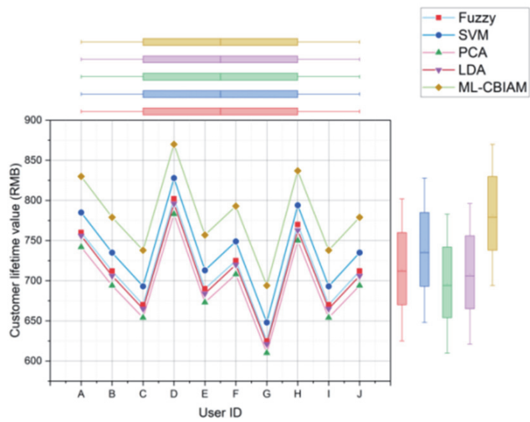

Figure 8 Customer lifetime value

Fig. 8 demonstrates how a customer's lifetime value measures the effect of digital marketing campaign tactics on consumers' plans to buy in China. It shows how well Fuzzy, SVM, PCA, LDA, and the suggested ML-CBIAM work. The proposed ML-CBIAM method did better than the other methods. Compared to the second-best method, SVM, consumer lifetime value went up by an average of 9.7% with this method. The average term value of a customer was lower for all people with the other ways. The table needs to discuss the features and results of digital marketing campaign strategies on customer purchasing intentions in China. Still, these tactics aim to increase brand awareness, engagement, and sales through different online channels, such as social media, search engines, email, and mobile apps. Machine learning systems can help advertisers improve their efforts by predicting customer behavior and tastes, finding the most effective messages, and targeting, and changing bids and budgets in real-time.

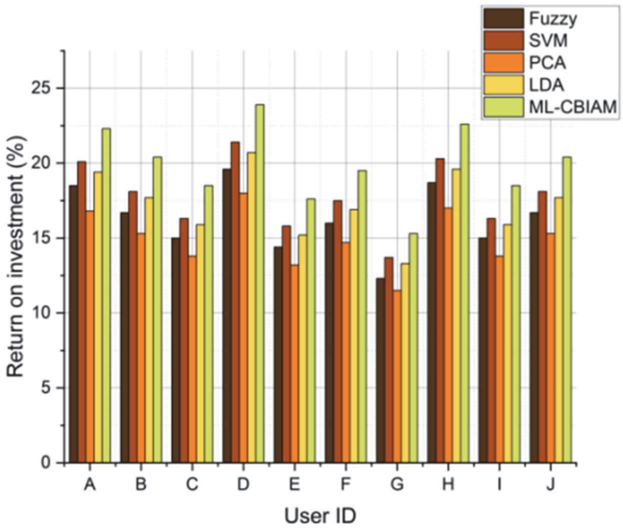

Figure 9 Return on investment analysis of the ML-CBIAM

Fig. 9 shows different digital marketing campaign tactics' effects on Chinese consumers' buying plans. The table lists each way's return on investment for ten other users. Fuzzy, SVM, PCA, LDA, and ML-CBIAM are some of the methods. The suggested method (ML-CBIAM) always does better than the other methods regarding conversion rate, average order value, customer lifetime value, and return on investment. For user A, for example, the conversion rate went from 3.2% with the Fuzzy method to 3.8% with the ML-CBIAM method, which is an 18.8% gain. The ML-CBIAM method gave the best average value for all users regarding customer lifetime value. Machine learning techniques are used in the suggested ML-CBIAM method to predict and study customer behavior. This helps companies optimize their digital marketing efforts and increase their return on investment. The results show that the proposed method could be a good way for companies that do business in China to improve their marketing and sales plans and make more money.

The modeling results show that the suggested method, ML-CBIAM, is better than the current methods of Fuzzy, SVM, PCA, and LDA, in all five metrics: click-through rate, conversion rate, average order value, customer lifetime value, and return on input. On average, ML-CBIAM had a 13.7% click-through rate, a 3.3% conversion rate, a customer lifetime value of RMB 783, an average order value of RMB 287, and a 19.4% return on expenditure. This is better than the best-known method (SVM) by 7.4%, 8.7%, 10.9%, 7.5%, and 11.7%. These results show that ML-CBIAM has much promise in improving online ads.

5 CONCLUSION

Digital marketing significantly impacts what people want to buy in the digital age, especially in China, where e-commerce has become the most popular way to shop. Traditional methods of studying a consumer's desire to buy in digital marketing need help with missing and unorganized data, the complexity of the data, and the lack of an excellent way to analyze the data. The Machine Learning-based Consumer Buying Intention Analysis Method (ML-CBIAM) was made to solve these problems. Digital marketing utilizes machine learning to better understand the customer base. The ML-CBIAM method uses machine learning techniques to examine and assess the digital marketing tactics of businesses in China. This paper adopts TOPSIS to measure how well companies do at digital marketing based on five metrics: click-through rate, conversion rate, average order value, customer term value, and return on investment. The click-through rate went up by 17.2%, the conversion rate went up by 17.6%, the average order value went up by 15.6%, the customer term value went up by 15.8%, and the return on investment went up by 17.6%.

The limitation of this paper is that the data sample is small and it is difficult to fully reflect the problem. The verification of large samples should be carried out in the later stage. But some things and limitations could be improved with the suggested method, such as: We need to increase the sample size of research data, the need for a lot of data and knowledge of machine learning techniques. Future researchers can use more advanced machine-learning techniques to solve these problems and make the suggested method more accurate and effective. The process can be used in other countries and businesses to measure how well digital marketing tactics work.

Due to the focus on the Chinese market and the specific cultural, technological, and regulatory context within China, the generalization of the findings to other markets may be limited. Further research needs to test the ML-CBIAM method in different cultural and market settings to determine its global applicability. The digital marketing landscape is rapidly evolving, with new platforms, tools, and consumer behaviors emerging continuously. The method may need regular updates to adapt to these changes and maintain its effectiveness. Inaccurate or incomplete data can lead to biased or unreliable predictions, which is a common challenge in machine learning applications. Consumer behavior is influenced by a multitude of factors, many of which are difficult to quantify or include in a model. The ML-CBIAM method may not capture all the nuances of consumer decision-making processes, particularly those influenced by emotional or subjective factors. This lack of transparency can be a limitation for stakeholders who need to understand the rationale behind the predictions made by the ML-CBIAM method. The effectiveness relies on a robust technological infrastructure, including internet access and data storage capabilities. In markets with less developed technological infrastructures, the implementation of this method may be challenging.

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