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Research Article

The Impact of Artificial Intelligence and Digital Economy Consumer Online Shopping Behavior on Market Changes

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The rapid development of online technology has facilitated the gradual growth and development of e-commerce and online marketing, creating a new business model and new opportunities. This has had a major impact on the future development of the market economy and the international competitiveness of companies and countries. At the same time, its appearance has also subverted the traditional retail market, and the convenience, reliability, and security of payment have been quickly recognized by people. Technological innovations represented by artificial intelligence have driven the development of the digital economy for decades. In order to better strengthen the statistics of the online shopping market and promote the development of the real economy, this study discusses the analysis of consumer behavior in online shopping based on the market changes of artificial intelligence and digital economy. Through the questionnaire, it can be found that all age groups have been exposed to online shopping, most of them are young people, and the number of shopping per month is still concentrated between 4 and 11 times. The study also examined the size of China's online retail market and found that there were 820 million Internet shoppers in China by December 2021, which is forecast to be 910 million by 2022. The report also found that the B2C market share will reach nearly 61% in 2021 due to the B2C model featuring higher quality goods and more guaranteed services.

1. Introduction

As computer technology and the Internet develop rapidly, the number of people using computers and the Internet has increased dramatically, and the Internet has become the main tool for people to access various resources and information. The number of Internet users accounts for 48.8% of China's total population. The widespread use of Internet technology marks the entry of human society into "network economy"; e-commerce is one of the main features of today and exposure to e-commerce has created the most direct connection between consumers and buyers. Buyers provide consumers with various information and sales activities directly through online channels. Manufacturers, wholesalers, retailers, and service providers have all seen significant improvements, resulting in a significant increase in the impact of business operations, which greatly increases the efficiency of marketing and transactions. In this situation, almost every business and consumer realize the need to switch from offline sales to online sales.

In the future, the main driving force for the development of China's digital economy will be artificial intelligence, and online transactions will be one of the important components of the digital economy. After more than 10 years of development, China's online shopping market has now entered a stage of prosperity. From the perspective of industry life cycle, the e-commerce industry with e-commerce platform as its main feature is currently in the rising stage of its life cycle. Online shopping is already one of the major developments in the modern digital economy; therefore, it is very important to monitor consumer behavior data for online shopping and predict market changes in a timely manner.

In terms of social development, the number of Internet users in China will continue to expand in the future, creating a very favorable market for the development of online shopping. A knowledge-based online shopping customer behavior analysis and prediction system is proposed to address the above situation. The real-time prediction of online shopping customer behavior is accomplished based on the real-time browsing behavior data and personal data of customers, as well as the existing knowledge in the machine knowledge database.

2. Related Works

In order to study the transaction situation of modern consumers' online shopping, many scholars have conducted research in this area. Park and Lee leverage online home shopping by extending its online services (telephone, ARS, and Internet site) to mobile platforms. Four years of transaction data were obtained by the provider, using a multivariate probability model including sociodemographic variables, communication strategy, ordering time, and product group. Results show that age and gender significantly influence channel choice behavior [1]. The study by Krasonikolakis et al. is related to online retailing and seeks to examine the impact of shopping environment in retail climate on the behavior of consumers in a three-dimensional online shopping environment, focusing on store design as the main influencing factor [2]. The major aim of the project by Díaz et al. is to analyze the differences among online and offline consumer behaviors. The results show that there is a link that exists between the use of technology and its impact on behavior. The link was stronger between values and actions and between behaviors and future intents than the influence of lifestyle on behavior [3]. Xu et al. examined the factors influencing consumer behavior during the World Online Shopping Carnival (OSC) such as Double 11. Using theories of binge and herd behavior, an explanatory model was developed to explain how informational motivation and social influence affect consumers' OSC behavior. Herd behavior is a special kind of irrational behavior, which refers to the behavior of being influenced by others, imitating others' decision-making, or relying too much on public opinion without considering their own information when the information environment is uncertain. Partial least squares (PLS) regression was employed to validate the conceptual mold. Partial least squares is a mathematical optimization technique that finds the best functional fit for a set of data by minimizing the sum of squares of errorsSome absolutely unknowable truth values are found in the simplest way, while minimizing the sum of squared errors. Results show that engagement, interactivity, and acceptability jointly influence consumers' OSC-related behavior [4]. Chiou et al. examine customer-selling partnerships, customer acceptance of online store shopping, and their impact on customer attitudes toward multi-channel shopping behaviors when companies decide to build online stores. The results show that buyer-seller partnerships significantly reduce shoppers' attitudes toward offline shopping but not online shopping. The adoption of online shopping has a significant impact on buyer attitudes [5]. Singh and Katiyar explore an online shopping system that allows shoppers to order goods and services online from individual stores and online shops. The online shopping system displays the customer's selected goods order with the associated due date and delivery window. The customer browses and makes changes to the order, but it has not been widely used [6]. Lee and Wu investigate the virtual experience of consumers in an online shopping environment and use participating online consumers to explore how consumers' desire influences customer satisfaction and unplanned shopping behavior to create valuable shopping relationships. Results show that perceived flow control and attentiveness positively influence consumers' utilitarian value, while attentiveness and cognitive enjoyment positively influence hedonic value [7]. Weeks et al. use behavioral statistics gathered on a popular social networking site (Polyvore.com) from its two neighbourhoods. By studying consumer behavior in curating on social shopping sites, style brand managers can better understand how consumers shape their perceptions of brands collectively [8]. International online shopping (IOO) is a concept. Ramkumar and Ellie Jin experimentally tested a two-stage theoretical model of U.S. consumer behavior in Chinese and UK e-commerce and found that trust positively influences initial e-commerce intention in these two countries [9]. Duarte et al.'s study aimed to determine the components of online shopping expediency that influence the online shopping preferences of consumers, and the findings extend earlier work on online expediency and contribute to the overall understanding of the factors that contribute to online satisfaction and improved behavior [10]. Driediger and Bhatiasevi's research is one of the earliest studies to investigate Thai people's receptive and usability behavior toward online shopping. The results obtained using partially minimal solution structural formula modeling (PLS-SEM) indicate that a statistical link between percentages of perceived usability, perceived usefulness, intention to use, topic norms, subjective norms, and perceived pleasantness was found to be correlated with the acceptance of online shopping among Thais [11]. It is clear that the Internet has fundamentally changed retail practices, both in terms of consumer and business behavior, and the Nisar and Prabhakar's study aimed to analyze customer satisfaction in the e-business market. Findings indicate that in terms of spending abroad, there is an immediate link between online service quality, online satisfaction, and online loyalty. Yet, the results of the analysis indicated that e-commerce still suffers from some problems than conventional retail outlets offline because customers are unable to try and test offerings and might eventually select offerings, which they would not desire [12]. Rogus et al. provided policy recommendations for online shopping for Supplemental Nutrition Assistance Program (SNAP) welfare through a study of SNAP recipients' behaviors, beliefs, and attitudes. Costs were particularly affected by quality control of porous foods and mistrust of the total process. Participants reported interest in advisory services to augment the benefits of online grocery shopping [13]. The above studies have conducted a detailed analysis of online shopping. It is undeniable that these studies have greatly promoted the development of the corresponding fields. We can learn a lot from methodology and data analysis. However, there are relatively few studies on online shopping in the field of artificial intelligence and digital

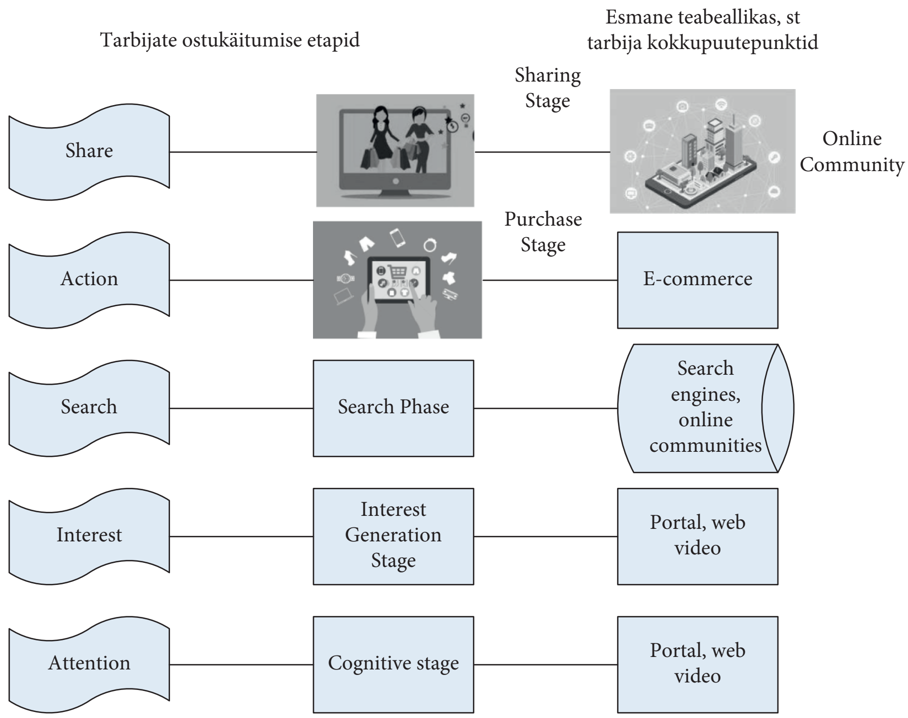

Figure 1: Consumers have online touchpoints at different stages of purchase.

economy, and it is necessary to fully apply these algorithms to the research in this field.

3. Methods and Models

3.1. Artificial Intelligence and Digital Economy. Online shopping is the purchase of goods through the Internet, which is a typical shopping behavior in the Internet environment. Traditional consumer behavior surveys use the following indicators to measure purchase behavior: product brand purchased, quantity purchased, and cost spent, mainly measured by current purchase behavior [14].

It can be said that in the 21st century, Internet technology has the greatest impact on economic and social development. Its rapid development has brought unprecedented vitality and opportunities to the global economy, especially the use and development of the Internet and business technologies, and it has also facilitated network marketing using Internet technologies [15]. Because e-commerce has the main advantages of low cost and high efficiency, the emergence and rapid development of e-commerce have brought a new consumption method for netizens—online consumption. This has also brought about major changes in their consumption behavior, norms, and status and promoted the dominance and purchasing freedom of Internet consumers, while also rationalizing their purchasing decisions [16]. In recent years, both the number of Internet users and the number of online shopping have been increasing year by year.

Today, customers have become the core of the company's development and competitiveness and the source of company value. With a large population, China has a huge potential for growth in the quantity and scale of the consumer electronics market. Although Internet technology and network application technology have developed rapidly in recent years, they still lag behind the developed countries such as Europe, USA, and Japan [17].

Consumers are the product of the times. Different historical and cultural environments, especially different media environments, have created different user groups. Online audience buying behavior usually goes through several stages: product awareness stage, product interest stage, product information collection and comparison stage, product purchase stage, and product purchase and use stage to share experiences with others. In the product awareness and product interest stage, the main exposure is the integrated portal and web video. In the product information search stage, the main contact is with search engines and online communities; in the purchase stage, the main contact is with e-commerce websites; after using the product, the main contact is with the online community. As shown in Figure 1, external information is required to support brand or product information in both the preconsumption and postconsumption stages. Each website provides different brand or product information, some directly promote the brand, and some directly sell. While the brand or product message delivered at each stage will vary, each stage requires accurate publicity and the right message strength to achieve the perfect media mix.

The basic course of buying goods electronically from the consumer's point of view can usually take place in terms of three levels: preparations leading up to the purchase, purchase, and postpurchase communication. The preparatory tasks before purchase include gathering information, finding

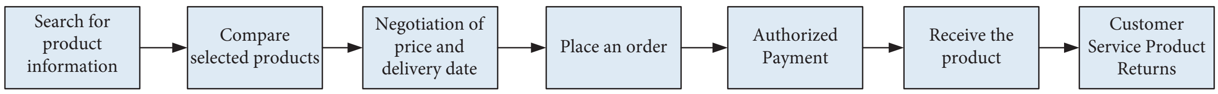

Figure 2: Basic flow chart of online shopping.

Table 1: Comparison of online shopping with other shopping methods.

	Diversity of products	Interactivity	Not controlled by business hours	Trial availability	After-sales service
Internet shopping	1	2	1	2	2
TV shopping	3	4	2	3	3
Mailing	4	3	3	4	4
Malls	2	1	4	1	1

the right product line for the needs, and selecting the product after comparison; the buying stage includes the circulation of information and related products and the negotiation of price and delivery method between buyers and sellers, selecting payment method and term. After-sales communication, including after-sales service provision, complaint handling, and product return, is shown in Figure 2.

Online shopping is the development and supplement of traditional shopping. In this sense, the traditional and network factors that affect consumers' shopping behavior have a common scope and are similar. When consumers choose traditional purchasing methods, the choice of retailers or stores usually takes into account factors such as their geographical location, store traffic location, sales network circulation, and store word-of-mouth and product advertisements. The choice of shoppers for online shopping is mainly reflected in the choice of commercial websites. Key factors to consider are the size of the site, the adequacy of the product information provided, and the availability of similar sites. In inclusion, as consumers selected conventional purchasing methods, they were primarily concerned with the quality of customer service and after-sales service at the time of purchase, the convenience of the shopping environment, and the exploration of the product during the purchase process. Consumers are increasingly concerned about online shopping, the security and privacy of information during the purchasing journey, and the usability and ease of the electronic shopping interface. In addition, from an individual point of view, purchasing experience and past purchasing experience influence the purchasing behavior of traditional consumers, while online experience and computer experience have a greater impact on online shop consumers. Table 1 presents a comparison of online purchases with other purchase methods (ranked in numerical order).

As can be seen from Table 1, a simple comparison between online shopping and other shopping methods shows that online shopping has the advantages of time saving, convenience, speed, interaction with consumers, and unlimited shopping time. However, there are shortcomings in the selection of products and samples.

Communication between businesses and consumers reduces the time lag between information and feedback, enabling businesses to provide consumers with adequate and effective information, thereby reducing the risk of asymmetric decision-making. When consumers actively collect and analyze information, they can make psychologically balanced purchasing decisions, reduce their sense of risk, and increase their confidence in products.

A system was developed for analyzing and predicting customers' online buying behavior. The architecture of the system is shown in Figure 3. According to the architecture scheme, the system is divided into three subsystems, namely, customer knowledge acquisition subsystem, knowledge service subsystem, and real-time customer behavior prediction subsystem. The main function of the customer knowledge acquisition subsystem is to acquire knowledge to predict customer behavior and transfer the acquired knowledge to the knowledge service subsystem. The main function of the knowledge service subsystem is to organize and store the knowledge obtained by the customer acquisition subsystem and provide cognitive support for the customer behavior prediction subsystem in real time. The real-time customer behavior prediction subsystem mainly analyzes the products browsed by customers in the current visit behavior and completes the real-time customer behavior prediction according to the knowledge in the knowledge base.

From a technical point of view, payment security and privacy are key issues and critical issues in Internet marketing. Business security is currently among the top factors affecting the development of e-commerce, and it is very critical to all aspects of online shopping. Ensuring that trade secrets are not disclosed or stolen, database confidentiality, fraud prevention, safe operation of online transaction systems and buyer identification, credit, electronic signature verification, antifraud, and the safety of merchants when collecting money provides a theoretical basis for shaping the good attitude and behavior of consumers toward online shopping. In addition, the model will be extended and combined with other theories to better predict and explain consumer buying behavior to study consumer buying behavior. Based on perceived risk theory, perceived trust theory, and innovation diffusion theory (IDT), a widely extended online consumer purchase intention model has been developed, as shown in Figure 4.

Conjoint analysis is a multivariate statistical analysis method. It uses quantitative analysis features to study consumers' purchasing preferences, in particular, to assess

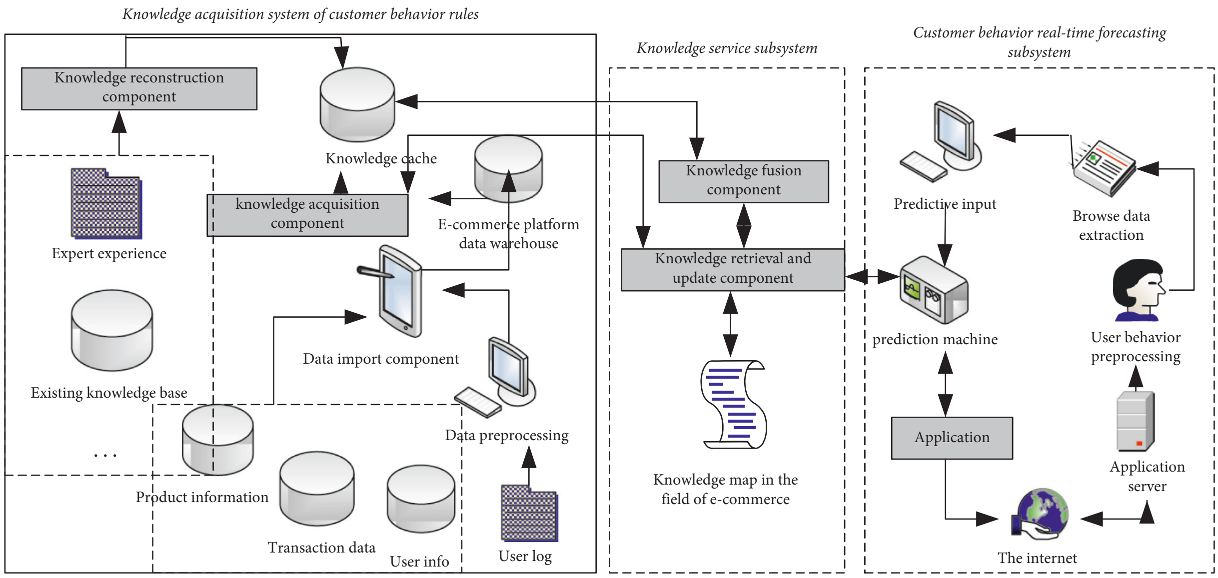

Figure 3: System architecture diagram.

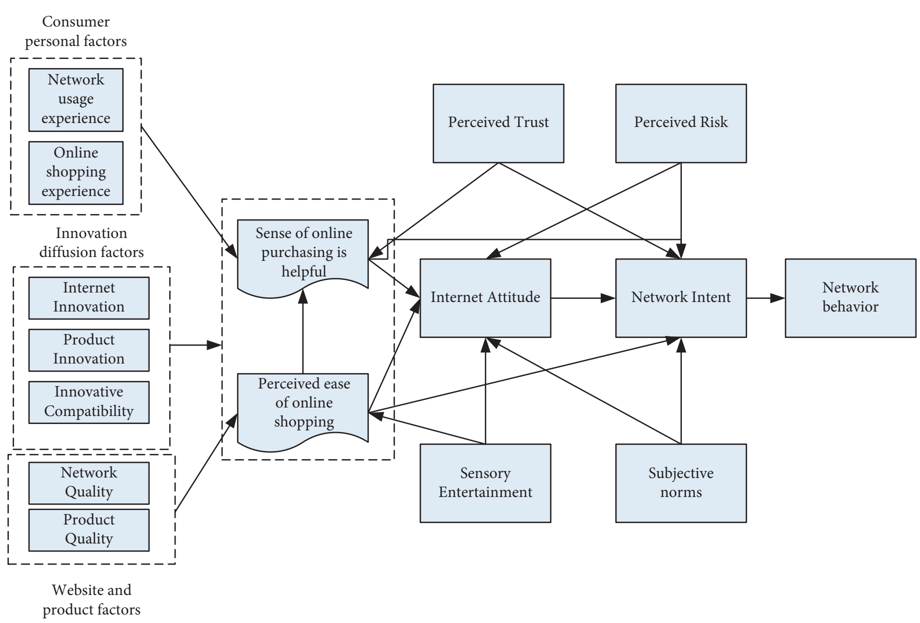

Figure 4: Extended model of consumer online shopping intention.

the overall level of preference, the relative importance of different product features in consumer preferences, and the level of utility that each level of feature can provide to consumers. The conjoint analysis calculates preference scores, weights, and desirability scores by asking consumers to rate some product profiles. Although not originally designed for marketing research, it has become one of the most popular tools in consumer research due to its unique advantages.

When using the conjoint analysis method, the terms that are often used are as follows:

(1) *Attributes*. Attributes are indicators or main characteristics of a product or service that may affect consumer behavior decisions. For example, online commodity prices and online purchase evaluations in this article are attributes of group-buying products.

(2) *Level of Attribute*. There are different values of product attributes, and the level of the attribute price can be below 100 yuan, 100–200 yuan, etc.

(3) *Full Profiles*. Full profiles are all combinations of product or service levels.

(4) *Utility Functions*. Utility functions describe the utility value given by consumers to each profile, in which layman's terms mean the effect on consumer behavior preference.

(5) *Relative Importance of Weights*. When consumers make purchasing decisions, the relative importance of weights describes the importance of the attributes of products or services on consumers' purchasing decisions.

(6) *Internal Validity*. The degree of correlation between the user assessment tool and the prediction tool indicates the reliability of the survey results.

(7) *Maximum Validity Simulation*. The most common market segment simulation model, the highest utility simulation, assumes that consumers will definitely buy the highest value product or service and make a choice when making a purchase decision.

Users appreciate feature-level usage through a variety of features and different levels of selection in product images. The product is expected to have some key characteristics, the actual results are simulated and combined, the user evaluates or evaluates the substantive product combination according to their own preferences, and finally, the multivariate statistical analysis method is used to compare these attributes. There is a distinction between each attribute and each attribute level. Feature-level functions are used to describe the importance of each feature in each product profile, and horizontal utility predictions are used as independent variables:

$$S = w + \sum_{i=1}^{p} \sum_{j=1}^{q} v_{ij} x_{ij}, \tag{1}$$

where S represents the full-profile preference score, w represents the utility value of the consumer choice profile, v_{ij} represents the j-th estimated high-level usefulness of the i-th parameter, and x_{ij} represents the j-th estimated level utility of different attribute levels:

$$x_{ij} = \begin{cases} 1, & \text{The } j\text{th level of the } i - \text{th attribute} \\ 0, & \text{Other} \end{cases}. \tag{2}$$

The relative importance of an attribute is usually considered to be the bigger the variance of the horizontal utility value of the attribute, indicating that users prefer it, the more important the attribute is. Conversely, an attribute has little impact on consumers' purchasing decisions. Usually, the difference between the price of the highest-level attribute and the price of the lowest-level attribute is the difference below the attribute, and the formulas are shown in formulas (3) and (4):

$$R_i = \left\{ \mathrm{Max}\left(v_{ij}\right) - \mathrm{Min}\left(v_{ij}\right) \right\}, j = 1, 2, \ldots, m. \tag{3}$$

$$w_i = \frac{R_i}{\sum_{i=1}^{m} R_i}, \quad i = 1, 2, \ldots, m, \tag{4}$$

where i stands for the quantity of attributes, j stands for the quantity of levels, R_i stands for the importance of product attributes, and w_i stands for the relative importance of attributes among those of total properties. $\mathrm{Max}\,(v_{ij})$ stands for the value of an attribute's utility at the greatest level and $\mathrm{Min}\,(v_{ij})$ stands for the valuation of an attribute's utility at the smallest level.

The summation type model is the least sophisticated model for calculating the whole spectrum of joint contour utilities. Generally speaking, a combined profile utility is to add up the utility values of each attribute. Here is the most commonly used model—the linear vector model:

$$U_c(x) = w + \sum_{i=1}^{p} \sum_{j=1}^{q} w_i v_{ijc} x_{ijc} c = 1, 2, 3, \ldots, m, \tag{5}$$

where i represents the number of attributes, j represents the total number of profiles, and w represents the utility value when consumers do not choose profiles, which is a constant. $U_c(x)$ represents the total utility value of the c-th profile, w_i represents the religious value of the i-th parameter, and v_{ijc} represents the utility value of the j-th level of the i-th profile of the c-th profile:

$$x_{ijc} = \begin{cases} 1, & \text{The } j\text{th level of the } i - \text{th attribute of the c} - \text{th contour} \\ 0, & \text{Other} \end{cases} \tag{6}$$

There are three main modeling methods for segmented market share: BTL module, logit module, and maximum utility model, of which the most widely used is the maximum utility model. The greatest possible model of utility presumes the idea that shoppers will always buy what they think is the best value for money. If U is the maximum utility value of the product's overall benefit function, then the probability that the consumer chooses the product is 1; otherwise, it is 0. We calculate the average probability value of all consumers choosing the product and use T to simulate the market share of the product portfolio:

$$T = \frac{\sum_{i=1}^{N} 1/n\mathrm{pi}}{N}, \tag{7}$$

where n is the number of people who are estimated to have the maximum utility for all products. N is the total number of people who participated in the survey:

$$p_i = \begin{cases} 1, & \text{When} U_c = \max\{U_c(x)\} \\ 0, & \text{When} U_c \neq \max\{U_c(x)\} \end{cases}. \tag{8}$$

The results of joint analysis, including attribute significance analysis and attribute utility value analysis, are interpreted and analyzed. The results of the analysis can be interpreted from the perspective of a single user, the preferences of each user can be examined, the usefulness and importance of attributes at different levels can be measured, and whether each user is significantly different in the product can be measured. Group effects can also be analyzed, and the results of group analysis can also be divided into groups, allowing important or useful groups of users, identifying market segments, and estimating market shares for different target markets, to analyze product profit margins, allow market segmentation, and identify the largest, profitable product bundles, as well as assess the achievable market share for all product bundles.

The TOPSIS method is a widely used method for analyzing multipurpose terminal solutions. The basic principle is to sort by detecting the distance between the evaluation object and the optimal solution and the worst solution. If the evaluation object is closest to the optimal solution and farthest from the worst solution, it is the best; otherwise, it is not optimal. Among them, each index value of the optimal solution reaches the optimal value of each evaluation index. Each index value of the worst solution reaches the worst value of each evaluation index. It is also known as the upper and lower level resolution method. It can be explored by studying the correlation between customer attributes and the products the customer wants to buy. Suppose there are q evaluation items and p evaluation indices, X_{ij} $(i = 1, 2, \ldots, q;\ j = 1, 2, \ldots, p)$ represents the value of the i-th item to the j-th index.

The steps to solve the problem using the TOPSIS algorithm are as follows:

Step 1. Building the original matrix.

According to the original data, the corresponding matrix A can be established:

$$A = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ X_{q1} & X_{q2} & \cdots & X_{pq} \end{bmatrix}. \tag{9}$$

Step 2. Preprocessing the matrix data.

With the TOPSIS method for evaluation, the direction of change should be consistent, that is, the same trend. High-quality indicators (benefit indicators) can be converted to low-quality indicators (cost indicators), and vice versa; the latter is often used. The low-quality indicators are converted to high-quality indicators using formula (10), and the original data table is also determined. The same data are processed as shown in formula (11):

$$X'_{ij} = \frac{1}{X_{ij}}, \tag{10}$$

$$X'_{ij} = \begin{cases} X_{ij} \text{ High} - \text{performance indicators} \\ \dfrac{1}{X_{ij}} \text{ Low} - \text{performance indicators} \end{cases}, \tag{11}$$

where X'_{ij} stands for the j-th index upon reciprocity of the i-th evaluation object.

Step 3. Calculating the original data matrix of the same trend, and the calculation method is shown in the following formula:

$$T_{ij} = \begin{cases} \dfrac{X_{ij}}{\sqrt{\sum_{i=1}^{q} \left(X_{ij}\right)^2}} \text{ (Original high superiority index)} \\ \dfrac{X'_{ij}}{\sqrt{\sum_{i=1}^{q} \left(X_{ij}\right)^2}} \text{ (Former low or neutral indicator)} \end{cases}. \tag{12}$$

From this, the normalized matrix is obtained as follows:

$$T = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1p} \\ T_{21} & T_{22} & \cdots & T_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ T_{q1} & T_{q2} & \cdots & T_{pq} \end{bmatrix}. \tag{13}$$

Step 4. Finding the best and worst-case vectors. That is, based on a finite number of best and worst-case solutions of matrix T, the best solution T^+ consists of the maximum value of each column of T, as shown in the following formula:

$$T^+ = \left(\max T_{i1}, \max T_{i2}, \ldots, \max T_{ip}\right) 1 \leq i \leq n. \tag{14}$$

The worst-case scenario Z– consists of the minimum value in each column of Z, as shown in the following formula:

$$T^- = \left(\min T_{i1}, \min T_{i2}, \ldots, \min T_{ip}\right) 1 \leq i \leq n. \tag{15}$$

Step 5. Calculating the distances of all the index values of the evaluation objects and the optimal plan R_i^+ and the worst plan R_i^-, respectively:

$$\begin{aligned} R_i^+ &= \sqrt{\sum_{j=1}^{p} \left(\max T_{ij} - T_{ij}\right)^2}, \\ R_i^- &= \sqrt{\sum_{j=1}^{p} \left(\min T_{ij} - T_{ij}\right)^2}. \end{aligned} \tag{16}$$

If each indicator has a weight W_{ij}, then the distance formula is as follows:

$$\begin{aligned} R_i^+ &= \sqrt{\sum_{j=1}^{p} W_{ij}\left(\max T_{ij} - T_{ij}\right)^2}, \\ R_i^- &= \sqrt{\sum_{j=1}^{p} W_{ij}\left(\min T_{ij} - T_{ij}\right)^2}, \end{aligned} \tag{17}$$

where W_{ij} is the weight coefficient of the j-th indicator.

Step 6. Calculating the closeness K_i of the evaluation objects to the optimal solution. The calculation formula is shown in the following formula:

$$K_i = \frac{T_i^+}{T_i^+ + T_i^-} 0 \le K_i \le 1. \tag{18}$$

Step 7. Sorting each evaluation object according to the size of K_i to obtain the optimal solution.

The basic idea of using a Markov model is to draw conclusions about future movement trends from past commodity movement patterns. The steps are as follows:

(1) Predicting the sales rate of each type of online product based on historical data, and redistributing the sales rate to the shift matrix.

(2) Calculating the distribution of different types of transactions as a starting point.

(3) Building a Markov model to predict the future supply of each commodity.

The key to using the Markov model to predict the availability of goods online is to determine the table of sales rates of goods. In actual forecasting, due to the influence of various factors, it is difficult to accurately determine the sales rate of goods, and it is often a rough estimate, which affects the accuracy of the forecasting results.

The prediction subsystem is one of the core components of the prediction system, which realizes the real-time behavior prediction of the current user. Its specific working principle is as follows: the system monitors the current browsing status of customers, and when the user visits a specific product page, the customer behavior prediction process is started. The system obtains the browsing data of the customer at this time and the personal information data of the customer. Taking these two parts as the input of the prediction machine, the prediction machine obtains the most likely product sequence that the user purchases based on the input and the knowledge in the knowledge graph. Its prediction flow chart is shown in Figure 5.

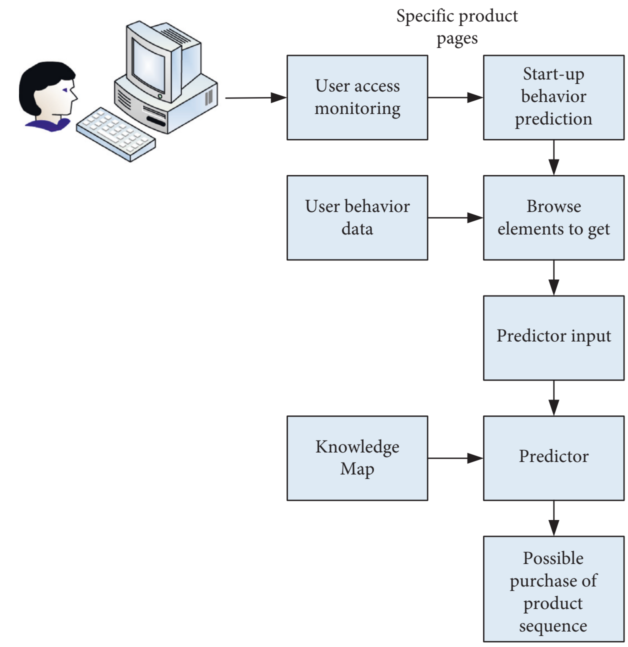

Figure 5: Prediction flow chart.

3.2. Model Design of Consumer Online Shopping Behavior. Online shopping is essentially a social exchange between consumers and retailers in an online environment. The main body of the market is the consumer, and the consumer is the key force that determines the survival and development of the enterprise. The consumer's demand has a fundamental impact on the enterprise's marketing decision and becomes the basic basis for the enterprise to choose the marketing strategy. Therefore, the characteristics of the two main actors involved in online commerce, consumers, and e-merchants, inevitably affect the possibility of e-commerce between them, that is, online shopping. Consumers choose online shopping mainly because it is more convenient and time saving than physical shopping. Socially oriented customers may be less keen on the e-shop format. The Internet is the backdrop for online transactions, so it is clear that the security and privacy issues that affect online transactions also affect consumer behavior when shopping online. The impact of consumer characteristics, consumer demographics, e-merchant characteristics, and security and privacy issues in online transactions on consumer behavior when shopping online will be analyzed and used to guide future research. Figure 6 shows a model of factors influencing online shopping.

In order to understand the current situation of consumers' online shopping, this study investigates the consumption of online shopping in district A. About 100 netizens were randomly selected as research objects for research, and descriptive statistics were used to conduct statistical analysis on the information of 100 investigators. The details of the outcomes are listed in Table 2.

4. Data Analysis and Results

Figure 7 shows the educational background and monthly income of the respondents, and Figure 8 shows the online shopping of the respondents. A month in the statistics below refers to a normal month, excluding shopping festivals, such as Double 11.

Most young people prefer to surf the Internet and understand the online shopping process; their educational backgrounds are concentrated in college and undergraduate degrees, accounting for 92.7%. This group of them is familiar with group buying and uses it frequently. The shopping expenses are mainly concentrated on catering, cosmetics, clothing, daily necessities, and other products. Students do not have a fixed source of income yet. Most students have no monthly income, and others concentrate on 2000–5000 yuan. This part of the group has a certain economic income and is relatively price sensitive. However, the number of shopping is still concentrated between 4 and 11 times, and the number of more than 15 times is relatively small. Table 3 lists the monthly spending on online shopping of respondents of different age groups.

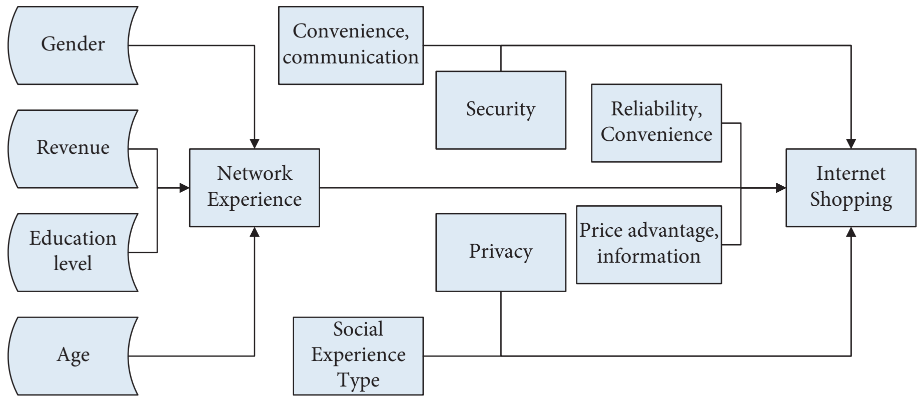

Figure 6: Model of influencing factors of online shopping.

Table 2: Basic information of respondents.

Age	Male	Female
Under 20 years old	12	8
20–25 years old	20	28
26–35 years old	8	10
Over 36 years old	6	8

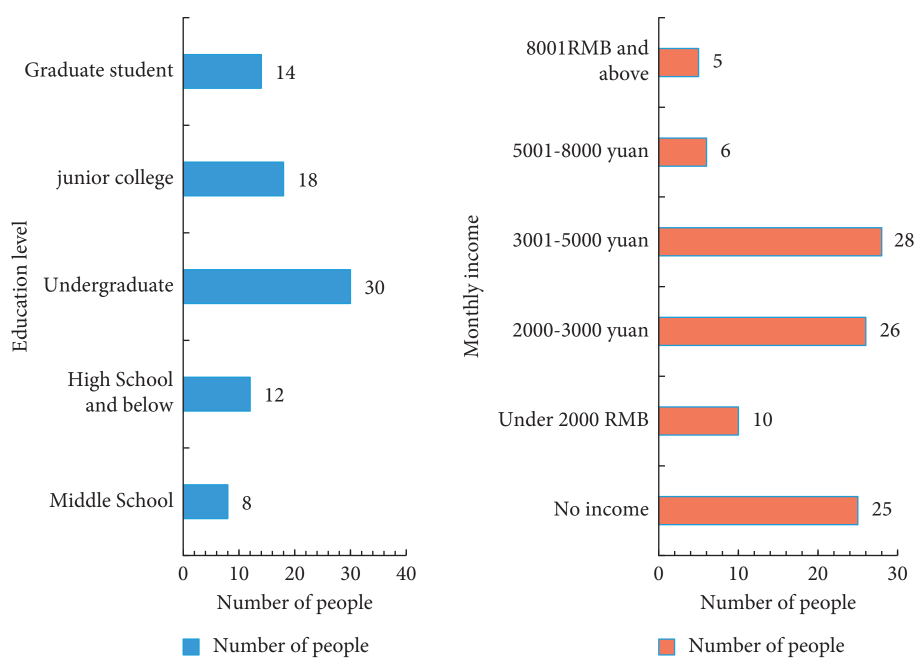

Figure 7: Respondents' educational background and monthly income.

In this study, we take the data of the past three months and the past six months respectively and compare the prediction results in the customer shopping behaviors prediction system with the traditional Markov model-based customer behaviors prediction results. We conducted 5 groups of prediction experiments and comparisons, and the times of each group's prediction of customer online shopping behavior were 3 times, 6 times, 9 times, 12 times, and 15 times, respectively. The corresponding comparison diagram is shown in Figure 9.

The horizontal axis in Figure 9 shows the number of customer behavior predictions for each test group, while the vertical axis shows the average error of each test group prediction. From Figure 9, we can see that the prediction error of the customer shopping behavior prediction system in this study is smaller than the prediction error of the traditional Markov model. Because the system has user access status monitoring, users will predict customers every time they visit a specific product page, which reflects the real-time prediction of users. After adding customer

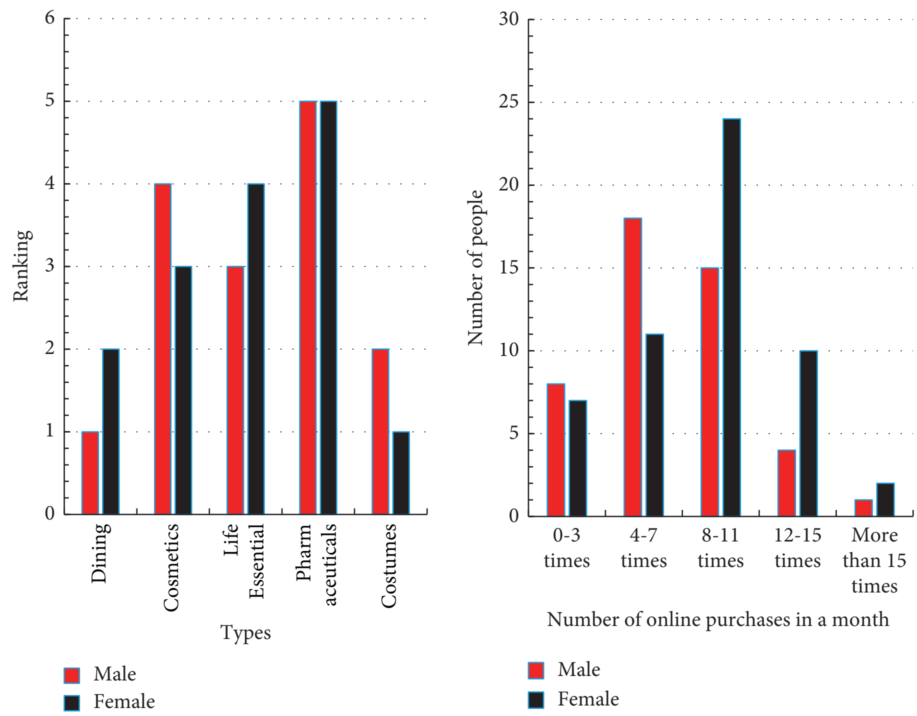

Figure 8: Online shopping of respondents.

Table 3: Amount spent on online shopping in one month by respondents of different age groups.

Age	Less than 50 yuan	50–250 yuan	250–500 yuan	500–1000 yuan	Over 1000 RMB
Under 20 years old	10	8	1	1	0
20–25 years old	2	20	15	5	6
26–35 years old	0	5	5	1	7
Over 36 years old	3	5	2	3	1

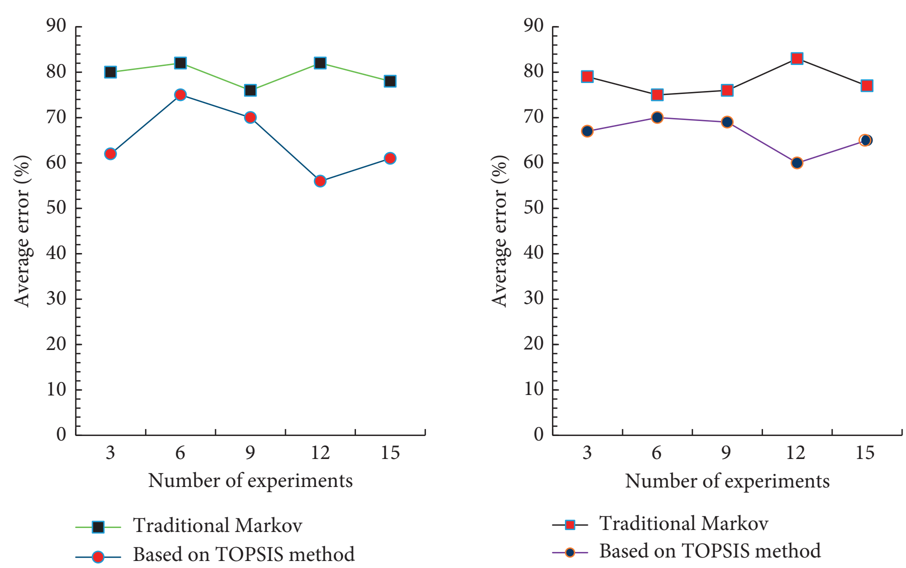

Figure 9: Comparison of forecast mean errors.

attribute information, it can provide customers with more personalized predictions. Figure 9 shows the superiority of the present system in terms of prediction accuracy.

B2C refers to the e-commerce model and the direct-to-consumer retailing of products and services in a commercial setting. The payment method is a combination of cash and

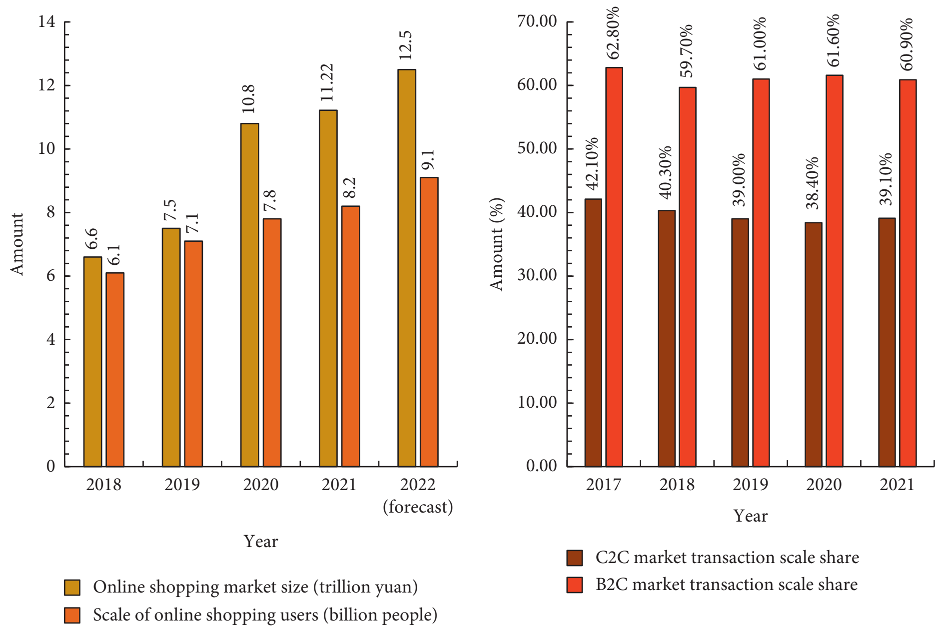

Figure 10: Market size of Internet shopper and comparison of B2C and C2C market shares in China.

electronic payments, and most businesses choose to outsource distribution to save on operating costs. C2C is a user-to-user direct business model, such as Taobao and Paipai. Figure 10 shows the market size of Chinese online shoppers and a comparison of B2C and C2C market shares.

By December 2021, the number of online shoppers in China will reach 820 million, an increase of 5% from the end of 2020. In 2018, the B2C market share of the total online shopping market in China was 40.3%, a slight decrease from 42.10% in 2017, mainly due to the rapid development of C2C social network stores such as Pinduoduo. In 2021, the B2C market share will reach nearly 61%, becoming a new growth driver for online shopping. Compared with C2C, due to the higher quality of goods and safer services, B2C has surpassed C2C in terms of growth rate and market share in recent years, becoming the main growth model of the online shopping market. In the background of modernized consumption, investors are more conscious of the product's reputation for the brand and good taste.

After nearly 20 decades of evolution and sophistication, the e-commerce industry has now reached the perfect stage of growth, which has undoubtedly dealt a major blow to the traditional retail industry. In recent years, it has been the sales of Internet celebrities and star products, and there are more like-minded people. There is also physical traffic brought by the sales of products. As long as the category selection is accurate and there are more adequate preparations, relatively good results can be achieved.

5. Conclusion

As a convenient sales channel, online shopping continues to rise in the total sales of consumer goods, becoming an important sales channel in China and injecting fresh blood into the market consumption economy. From refrigerators and TVs to food and clothing, and even cleaning services, all areas of life are easily accessible through online shopping. The development of the digital economy has become a common choice for major powers and regions in the world to reshape their global competitiveness. The transformation of the digital economy has improved traditional industries and developed emerging industries. The impact of e-shopping on the traditional retail market is reflected in reducing circulation costs and commodity prices, expanding the range of choices, accelerating commodity circulation, improving commodity circulation efficiency, and promoting logistics development. However, the impulse consumption brought by online shopping is prone to unnecessary waste. The quality of online merchants varies, and it is difficult to guarantee business integrity. There are loopholes in network information security, and personal information is easily leaked. It is necessary to improve the relevant laws of e-commerce, strengthen the supervision of the online market, and improve the identification ability of the public online shopping, so as to lead the online shopping market to a stable and healthy development. In the future, with the further advancement of 5G and other technologies, the market environment will continue to be optimized, the platform ecology will continue to improve, and the quality and brand will gradually improve. The large-scale development of e-commerce and social e-commerce is expected to be serious, which will continue to stimulate the consumption potential of China's online retail market.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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