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Bayesian Network Process Modeling of Consumer Behavior Decisions on Digital Economy Platforms

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Abstract Consumer behavioral decision-making process on the digital economy platform is complex and fuzzy, and traditional models are difficult to accurately reflect irrational consumer decision-making characteristics. This paper proposes a consumer behavior decision modeling method based on fuzzy logic and prospect theory to address the complexity of the consumer behavior decision-making process on the digital economy platform. Firstly, a consumer three-dimensional portrait system is constructed, and the consumer behavior data is analyzed in multiple dimensions by FCM clustering algorithm; secondly, a consumer multi-attribute behavioral decision-making model is constructed based on prospect theory, and an intuitive triangular fuzzy number is introduced for optimization, to overcome the limitations of the traditional model in dealing with the fuzzy decision-making information; lastly, a B2C e-commerce service whole-process evaluation index system is constructed by using the service blueprint method, and an evaluation index system for B2C e-commerce service whole-process evaluation is built through LDA topic extraction and LSTM sentiment analysis techniques to mine consumer behavior attributes and preferences. The experimental results show that the optimized model has an accuracy of 84.59% in the test of 120 commodity samples, which is 2.63% higher than that of the unoptimized model; the stability of the model prediction improves significantly with the increase of the sample size to 480 items. Tests based on 12 commodities show that the model predicted sorting matches the actual sales sorting well, with only 2 commodities not matching the sorting. This study provides new ideas for the analysis and prediction of consumer behavior on digital economy platforms, and has practical value for service quality evaluation and decision optimization of e-commerce enterprises.

Index Terms digital economy platform, consumer behavior, fuzzy logic, prospect theory, FCM clustering, stereo portrait

I. Introduction

With the rapid development of Internet technology and the continuous improvement of the level of informationization, all kinds of digital technology in the consumer market continue to carry out in-depth integration, the digital economy has become an important driving force to release the consumption potential of residents, expand domestic demand, and then build a new development pattern [1]-[3]. On the demand side, the digital economy platform can provide new products and services to meet the consumption demand of residents and increase their disposable income [4], [5]. On the supply side of enterprises, the digital economy releases consumption potential by injecting new kinetic energy into production and meeting consumption demand [6]. At the same time, technological advances and market development have made enterprises focus on optimizing their marketing strategies by understanding consumers' purchasing behavior [7], [8]. Since the decision-making process of consumers is not completely rational, but can be influenced by various psychological and environmental factors, this provides a new perspective for analyzing the purchasing behavior of users of digital economic platforms [9].

The status of data resources in the modern economic system has become increasingly prominent, and in the operation of digital economic platforms, data is not only the infrastructure to support their daily operation, but also the core element to drive scientific decision-making, optimize service processes and improve market competitiveness [10]-[13]. Currently, many digital economic platforms rely on increasingly popular and intelligent cell phones to accumulate a large amount of user behavior data, such as browsing records, purchase history, evaluation feedback, etc. [14], [15]. These data not only reflect users' consumption preferences and behavioral patterns, but also provide e-commerce platforms with valuable resources to optimize services and enhance user experience [16], [17]. Through real-time collection, proper storage and in-depth analysis of massive consumer behavior data, digital economy platforms are able to gain precise insights into consumers' behavioral patterns and preferences, and then formulate highly targeted marketing strategies to achieve optimal allocation of resources [18]-

[21]. However, how to effectively mine these data and predict consumer behavior has become an important challenge for e-commerce platforms.

In the era of digital economy, e-commerce platforms have become the main channels for consumers to shop, and an in-depth understanding and accurate prediction of consumers' behavioral decision-making process on these platforms are of great significance to the business strategy and service optimization of enterprises. However, consumer behavior in the digital environment presents a high degree of complexity and uncertainty, and consumers often show irrational characteristics in the face of diversified goods and services, which makes the traditional decision-making model based on the assumption of "rational man" face many challenges in explaining and predicting consumer behavior on digital platforms. Consumer decision-making is not only influenced by objective factors such as product price and quality, but also closely related to subjective perception, risk appetite, and situational factors. These factors often exist in a vague and imprecise form on digital platforms, and are difficult to be accurately portrayed by deterministic mathematical models. In addition, although the huge amount of user behavior data generated in the era of big data provides rich materials for consumer behavior research, how to effectively integrate heterogeneous data from multiple sources and extract valuable consumer characteristics is still a difficult problem to be solved. Prospect theory, as an important theory in behavioral economics, provides a theoretical basis for explaining irrational consumer behavior by introducing value function and weight function to portray people's decision-making preferences in risky and uncertain environments. However, the traditional prospect theory has limitations in dealing with fuzzy information and multi-attribute decision-making problems. Therefore, it has become an important research direction to introduce the fuzzy logic method into prospect theory and construct a consumer behavioral decision-making model suitable for the digital platform environment. Meanwhile, the B2C e-commerce service process involves multiple links, and how to construct an evaluation index system that comprehensively covers the consumer experience is also a key prerequisite for realizing accurate behavior prediction. Based on the above issues, this study proposes a fuzzy logic-based modeling method for consumer behavioral decision-making process in digital economy platform. The study first builds a three-dimensional portrait system of consumers, and analyzes consumer behavior data in multiple dimensions through FCM clustering algorithm; then builds a multi-attribute behavioral decision-making model of consumers based on prospect theory and introduces intuitionistic triangular fuzzy numbers for optimization; finally, builds an evaluation index system for the whole process of B2C e-commerce service through the service blueprint method and combines the LDA topic extraction and LSTM sentiment analysis technology to Mining consumer attention attributes and preferences to achieve quantitative modeling of consumer behavioral decision-making process. The effectiveness and stability of the model is verified through experiments, and the prediction performance of the model under different sample sizes and different types of goods is explored, so as to provide new technical paths and methodological support for the study of consumer behavior on digital economy platforms.

II. Construction of three-dimensional portrait of consumers in digital economy platforms

Aiming at the problems of the existing digital economy platform with a large amount of user consumption behavior data and poor analysis ability of consumption behavior data, this chapter constructs a consumer stereoscopic portrait system, which realizes the multi-information analysis of the consumption behavior of users in the digital economy platform, so as to provide data support for the research on modeling of the decision-making process of consumer behavior.

II. A. Design of consumer stereoscopic imaging system based on platform data

Consumer stereoscopic image can reflect the characteristics of various consumer behavior information of digital economy platform users, and can visualize user consumption through the construction of stereoscopic image. Through the extraction of portrait data features, to achieve the analysis of the platform user consumption behavior, and then improve the user portrait analysis capabilities, to improve the control and application of consumer behavior data information is very helpful. The overall architecture design of the digital economy platform data consumer stereoscopic portrait system is shown in Figure 1.

The digital economy platform data consumer stereo image system mainly includes platform user data layer, platform user data fusion layer, data label extraction layer, data label analysis layer and label image application layer. The method proposed in the research is to convert the macro behavior of digital economy platform user consumption into micro data for analysis by constructing a three-dimensional portrait, and to constitute an information label library of platform user characteristics with multi-dimensional, multi-business, multi-indicator, and multi-featured data information, which can realize the acquisition of different consumption behavior information in the platform user data layer, the fusion of different data information in the platform user data fusion layer, and the fusion of different data information in the data label In the data label extraction layer, different dimensions and types of platform user data information are extracted, and the analysis of user consumption behavior data on different platforms is realized by constructing a consumption behavior analysis model, and the analysis results are output through the label image application layer to show the consumption situation of the users, so as to carry out a full-aspect control of user consumption behavior.

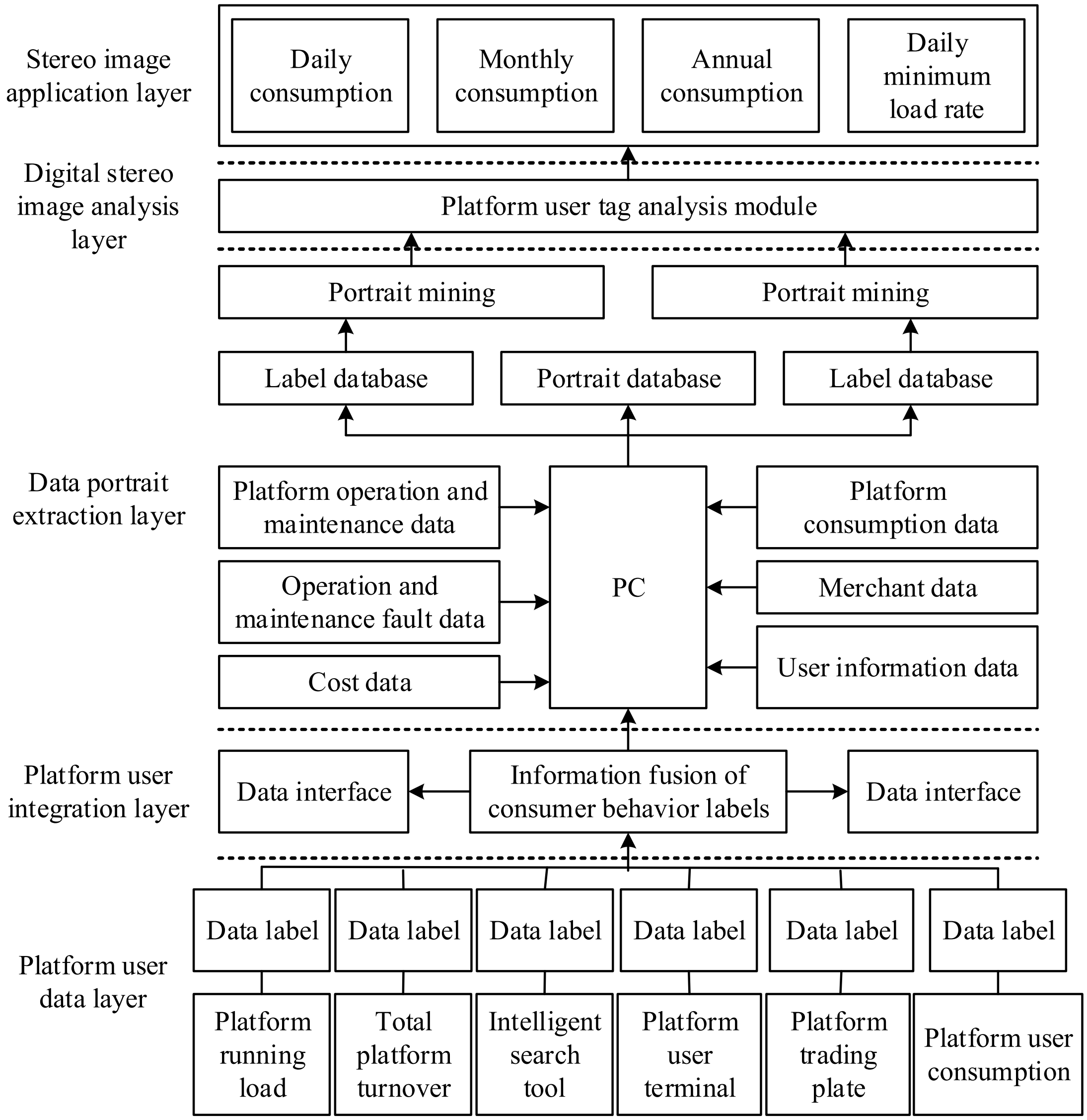


Figure 1: Overall architecture design of the consumer stereoscopic portrait system

II. B.Methods of constructing stereoscopic portraits

The method proposed in this paper realizes the identification of different user consumption behaviors through label construction, and then realizes the extraction, marking, analysis and application of different consumption behavior data labels through clustering algorithms to extract the characteristics of consumption behaviors possessed by different user groups, so as to realize the differentiated services for different consumption groups.

Based on the description of user consumption behavior attributes, tags are used for definition, and then the tags are processed with numerical information. Due to the wide variety of tags, when computing, analyzing and data mining the tags, this paper adopts the FCM clustering algorithm [22] to achieve the classification of different data information. The FCM clustering algorithm process is schematically shown in Figure 2.

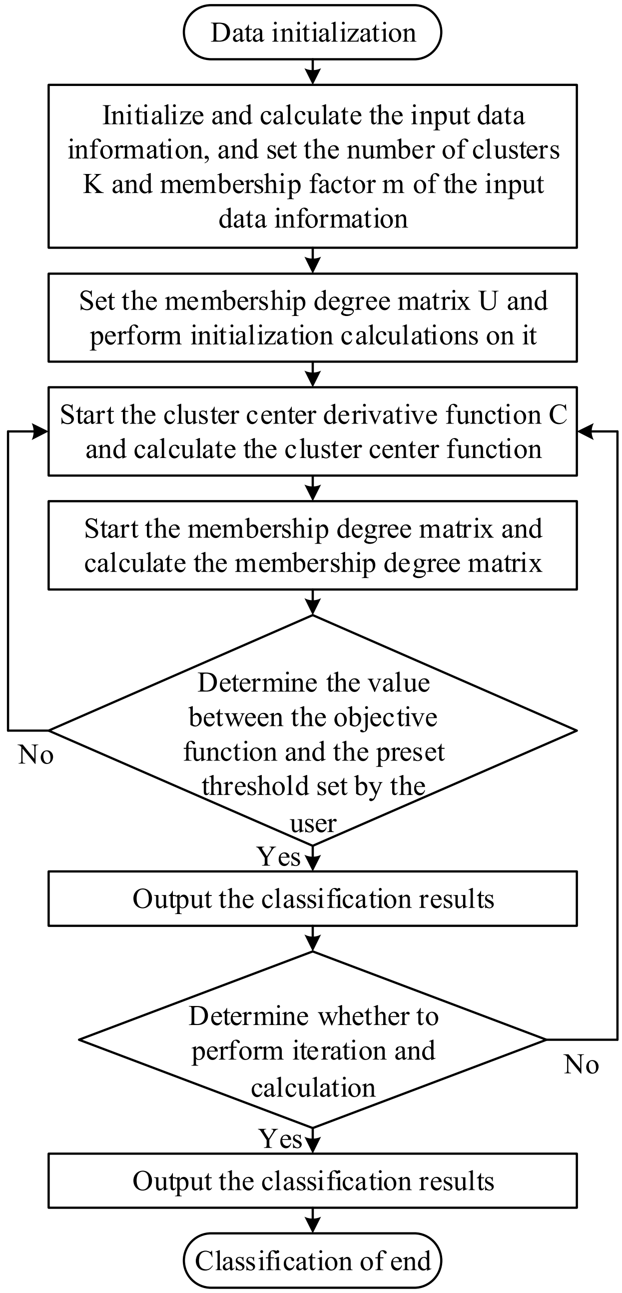


Figure 2: Schematic diagram of the FCM clustering algorithm process

Assuming that the platform user consumption behavior data information is N and the dimension of the data information is D, the platform user consumption behavior data information sample can be noted as:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1D} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iD} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{ND} \end{bmatrix} \tag{1}$$

Then the original platform user consumption behavior data information can be divided into different subclasses, which are represented by the platform user consumption behavior data set $C = \{c_1, \cdots, c_i, \cdots, c_K\}$. The probability that sample j of the original platform user consumption behavior data information belongs to the i th clustering subset is denoted as u_{ij}, then the FCM can set the following objective function:

$$\min J = \sum_{i=1}^{K}\sum_{j=1}^{N} u_{ij}^{m} \| x_j . - c_i \|^2 \tag{2}$$

In Equation (2), J denotes the objective function of FCM classification of platform user consumption behavior data information, x_j denotes the input stereo image raw data information of platform user consumption behavior data information, c_i denotes the clustering center set by the user, u_i^m denotes the affiliation of platform user consumption behavior data information classification degree function, m denotes the weighting coefficient of the objective function of the platform user consumption behavior data information, which can be expressed as the degree of influence of the user's image label in the target classification. In order to improve the computational efficiency, the Lagrange multiplier method is invoked in the specific algorithm, then the objective function of the platform user consumption behavior data information classification can be output as:

$$J^{'} = \sum_{i=1}^{K}\sum_{j=1}^{N} u_{ij}^{m} \| x_j - c_i \|^2 + \sum_{i=1}^{K} \lambda_i \left(\sum_{i=1}^{N} u_{ij} - 1 \right) \tag{3}$$

In order to achieve the minimum of the platform user consumption behavior three-dimensional portrait classification information calculation, then through the partial derivative of the objective function for the next calculation. The clustering center function c_k and the affiliation function u_{kj}^m of the platform user consumption behavior data information are derived from the data information, then the following function information can be output:

$$\begin{cases} \dfrac{\partial J^{'}}{\partial u_{ij}} = m \| x_j - c_i \|^2 \, u_{ij}^{m-1} + \lambda_j = 0 \\ \dfrac{\partial J^{'}}{\partial c_i} = \sum_{j=1}^{N} \left[-2u_{ij}^{m} (x_j - c_i) \right] = 0 \end{cases} \tag{4}$$

In order to improve the classification accuracy of the platform user consumption behavior data information, it is necessary to repeat the data derivation of the affiliation coefficient and the clustering center function, then the output of the iterative formula can be expressed as follows:

$$c_i = \frac{\sum_{j=1}^{N} (x_j u_{ij}^m)}{\sum_{j=1}^{N} u_{ij}^m} \tag{5}$$

$$u_{ij} = 1 / \sum_{k=1}^{K} \left(\frac{\| x_j - c_i \|}{\| x_j - c_k \|} \right)^{\frac{2}{n-1}} \tag{6}$$

After repeated iterative calculations, the final output target data information.

When further calculations are required, the initial step is returned, the clustering center is restarted, and the derivation calculations of the affiliation function and the clustering center function are performed again until the FCM function meets the convergence conditions, i.e., the output objective function reaches the maximum number of iterations or the objective function is smaller than the preset value, and the data calculations are stopped, and the final data classification is realized.

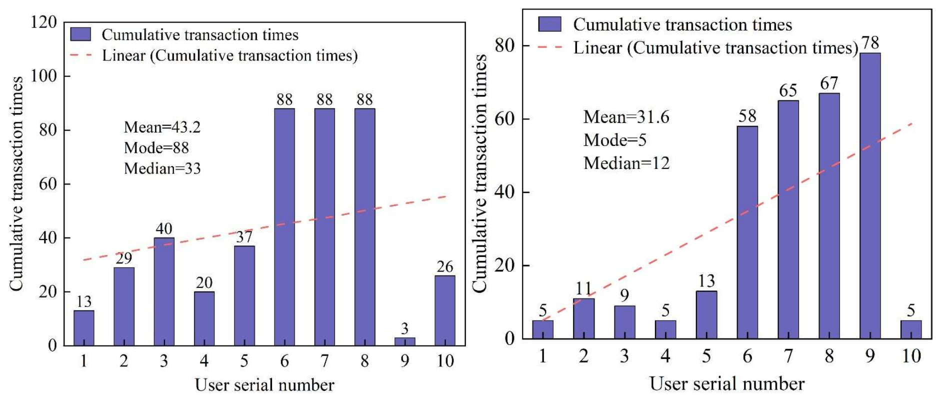
II. C.Empirical study of three-dimensional portrait construction based on user consumption behavior

In this section, based on the key fields selected from the UnionPay card swiping records, the improved big data mining algorithms are used to analyze the data respectively, so as to mine multiple consumption labels about the users of the digital economy platform, and to achieve the purpose of perfecting and enriching the three-dimensional portrait of consumers.

II. C. 1) User activity, types of merchants followed and merchants

User activity is a concept that depicts whether a user is active or not, and can reflect whether a user of a digital economy platform shops and spends frequently over a certain period of time. Active users, on the other hand, is a concept that refers to the group of users who regularly spend money on their cards and who generate revenue for the bank or the organization, as opposed to churned users. In the process of depicting the activity of a user, it is necessary to determine whether he or she is active or not with the help of one or more attribute fields and their standard thresholds, and when the value of the attribute is greater than or equal to the threshold, the user is labeled as active. When the value of the relevant attribute of the user is less than the threshold value, the user is labeled as inactive.

In the card swipe record, the cumulative number of successful transactions for each customer in a certain time period is utilized as a parameter to measure the activity level, the so-called successful transaction means that the value of the Transaction Amount field is satisfied to be greater than zero. Note that the key to threshold selection is the ability to divide a column of data into two categories: active and inactive. Since there is only one attribute of the data, there is no need for a complex algorithm to divide it; simple mathematical statistics will do the trick. In general, calculating the average is the most common method, and there are positional averages and numerical averages, with medians and plurals for the former and arithmetic averages for the latter. When the median is used as a threshold, there will be the same value with different results. The multitude refers to the value that occurs the most times in a set of data, and if it is used as the threshold value, it cannot avoid extreme cases and there is a large error, and the comparison of the averages is shown in Fig. 3, where (a) and (b) denote the data group 1 and data group 2, respectively. Considering various factors, the arithmetic mean is finally used as the threshold value to measure the activity level.



(a) Data Group 1 (b) Data Group 2

Figure 3: Comparison of averages

First, the cumulative number of successful transactions for each user in any time period is calculated using information such as the transaction amount, the transaction date, and the master account number in the card swipe record. Then, the average value is derived from the dataset of cumulative number of transactions of all users and is used as a threshold to measure the user's activity, and when the cumulative number of transactions of a user is greater than or equal to the average value, it is labeled as an active tag. Conversely, it is labeled as inactive. Similarly, if merchant type or merchant number is used as the object of study, the merchant type or merchant that the user has paid attention to during a certain period of time can be mined. Among them, merchant type (MCC), also known as merchant category code, is mainly composed of four Arabic numerals, and the merchant type code is shown in Table 1. The merchant category code is set by the acquirer for the special merchants, and is used to indicate the UnionPay card transaction environment, the main business scope and industry affiliation of the merchant where it is located.

Table 1: Merchant type codes

Merchant type code	Merchant type name	Merchant type code	Merchant type name
7593	Veterinary services	5651	Hardware store
5813	Wine producer	5411	Department store
1920	Construction engineering	5960	Art dealers and galleries
5947	All kinds of publishing and printing services	5993	Stamp and commemorative coin store
4582	Railway passenger transport	6300	Insurance company
8244	Ambulance service	7298	Laundry

In mining the types of merchants that users are concerned about, it is first necessary to count which types of stores each master account has transacted at during a certain period of time and the cumulative number of transactions. Then, the average value of the cumulative number of transactions of each master account in different merchant types is used as a threshold to determine whether the user pays attention to that type of merchant. In mining the merchants that a user is concerned about, if the average value of the cumulative number of transactions that each master account has made at different merchants is used as a threshold, it can be determined whether the merchant is concerned about or loved by that user.

II. C. 2) User consumption levels

From the perspective of user contribution, taking into account the user's transaction amount, fee amount and other expenditures, a large number of users are classified into three different levels: low users, medium users and high users, thus enabling banks, enterprises and other organizations to adopt different preferential measures, tailored to the needs of each individual, and avoiding the waste of resources. Among them, high users represent users with higher total consumption in that time period, reflecting their high consumption level. Medium users represent users with average total consumption in that time period, reflecting their average consumption level. Low users represent users with low consumption in the time period, reflecting their low level of consumption.

Firstly, using the main account number, transaction amount, total fee amount and transaction date in the card swipe record, the total transaction amount, total fee amount and cumulative number of transactions of each user in a period of time are counted. Secondly, due to the existence of transaction amount, total handling fee amount and other information in the card swiping records, in order to avoid clustering errors due to different unit magnitudes, it is necessary to normalize the above metrics by using MapReduce-based normalization method. In this case, the data normalization requires the execution of two MapReduce processes: the first one is responsible for calculating the maximum and minimum values of the indicators, and the second one normalizes the data based on the maximum value. Finally, the number of clustering clusters is set to three categories: low, medium and high users, and the normalized data are clustered using MapReduce-based K-means [23] and FCM algorithms, respectively.

The cluster centers of the two clustering algorithms are shown in Table 2. It can be seen that the cluster centers and clustering results of the two algorithms are approximately the same, but the average number of iterations of FCM is smaller than that of K-means algorithm, so the MapReduce-based FCM algorithm is finally used for the division of the user class, and the FCM clustering results of part of the data are shown in Figure 4.

Table 2: Cluster centers of the two clustering algorithms

Parameters	FCM			K-means		
Number of iterations	4			18		
Clustering center	0.1924	0.8851	0.6374	0.0783	0.9905	0.0158
	0.0653	0.6578	0.0112	0.1947	0.8753	0.6376
	0.0942	1.0000	0.0156	0.0468	0.6715	0.0072

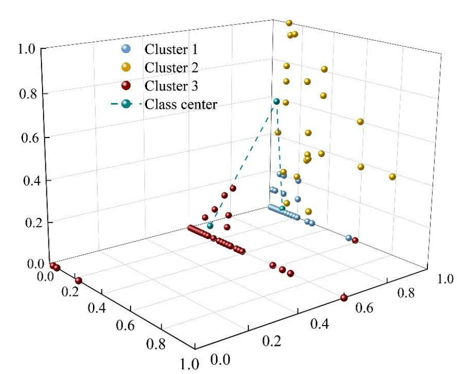


Figure 4: The classification of user's grades

Among them, the user stereo portrait of several consumers is shown in Fig. 5, where the activity level and user level indicate the transaction frequency of the user and its consumption level over a period of time, respectively, and the merchant number and merchant type indicate the type of stores and merchants that the customer has been concerned about over a period of time.

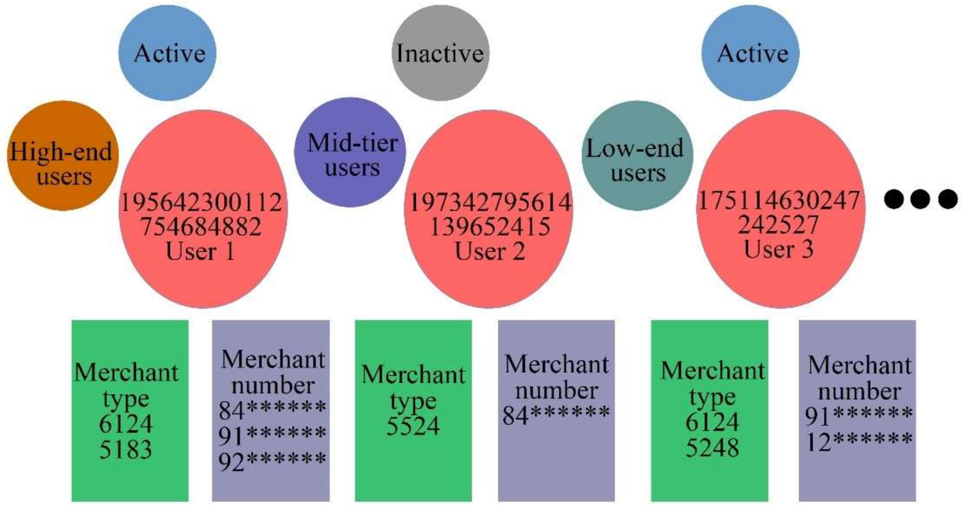


Figure 5: The user's portrait

III. Fuzzy logic-based modeling of consumer multi-attribute behavioral decision-making

Based on the analysis of user consumption behavior on digital economy platform, this chapter constructs a multi-attribute behavioral decision-making model of consumers on digital economy platform for B2C e-commerce environment, based on the prospect theory of behavioral research with the assumption of "irrational man", and grasps the preference of consumer groups by mining the word-of-mouth data of merchants, which provides a basis for quantitative research on consumer behavioral decision-making. It also mines the word-of-mouth data of merchants to grasp the preference of consumer groups, so as to provide a basis for quantitative research on consumer behavioral decisions.

III. A. Constructing a Consumer Behavior Decision Model Based on Prospect Theory

In prospect theory, which assumes "irrational people", "prospect" is the most basic unit of study. In the B2C service process, different platform companies are called "prospects", and consumers make decisions from these prospects. Each "prospect" may have different results, such as the overall service quality of B2C enterprises has different results such as "satisfactory", "average", "unsatisfactory", etc., and there are also different results when subdivided into specific service links, such as "expensive", "moderate" and "cheap" commodity prices.

For each outcome, it can be composed of an outcome value and a probability value, e.g., the probability of buying an expensive item on a B2C platform is 10%. However, prospect theory is not concerned with the final state of gain or loss, but the gain or loss relative to a reference point, i.e., "expensive" is not an absolute amount of price, but a comparative value relative to a reference point. Therefore, for each enterprise, its outlook on an indicator can be expressed as a combination of the outcome and probability values of each outcome under that indicator: $(x_1, p_1; x_2, p_2; ...; x_n, p_n)$, the outlook for a B2C e-commerce enterprise is calculated as follows:

$$V_{i,j}(x_{i,j1}, p_{i,j1}; x_{i,j2}, p_{i,j2}; \cdots; x_{i,jn}, p_{i,jn}) = \sum_{k=1}^{\pi} w(p_{i,jk}) v(x_{i,jk}) \tag{7}$$

$V_{i,j}$ denotes the prospect value of the i th firm on the j attribute, W is the weight and V is the value. The value function is shown in equation (8):

$$v(\Delta\chi_i) = \begin{cases} \Delta\chi_i^{\alpha}, & \Delta\chi_i \geq 0 \\ -\lambda(-\Delta\chi_i)^{\beta}, & \Delta\chi_i \leq 0 \end{cases} \tag{8}$$

where $\Delta\chi_i$ is the deviation of the result relative to the reference point, and the parameters α and β denote the degree of concavity of the power function of the value of the region of gain and loss, respectively. $\alpha, \beta < 1$ denotes decreasing sensitivity. To ensure that "loss aversion" is satisfied, a λ coefficient is introduced to indicate that the region of loss is steeper than the region of gain, and $\lambda > 1$ to indicate loss aversion.

The weighting function reflects the change in overall utility due to the p_i of each individual event in the outlook, and is not a measure of probability, but a function of evaluation probability. To wit:

$$\omega(p)=\frac{p^{\gamma}}{\left[p^{\gamma}+(1-p)^{\gamma}\right]^{1/\gamma}} \tag{9}$$

where γ denotes the fitting parameter.

In the in-depth study and application regarding prospect theory, it is found that there are violations of the principle of randomness predominance, or the processing is more cumbersome when there are prospects with multiple outcomes. Therefore, the cumulative generalized function is introduced in the subsequent research, thus the cumulative prospect theory is proposed. That is, instead of transforming each probability event individually, the overall transformation of the entire cumulative distribution function is realized. And the weighting functions in the two cases of gain and loss are distinguished:

$$\omega^{+}(p)=\frac{p^{\gamma}}{\left[p^{\gamma}+(1-p)^{\gamma}\right]/\gamma} \tag{10}$$

$$\omega^{-}(p)=\frac{p^{\delta}}{\left[p^{\delta}+(1-p)^{\delta}\right]^{1/\delta}} \tag{11}$$

III. B. Introducing Intuitionistic Fuzzy Numbers to Improve Consumer Behavior Decision-Making Models

In each link of the B2C service process, consumers make decisions based on a variety of information, and the decision-making information it contains is fuzzy and cannot be expressed in the form of real numbers. Therefore, it is necessary to introduce intuitionistic fuzzy numbers to expand the value function, weight function and prospect function after determining the behavioral model, so as to make the model more in line with the real requirements.

Intuitionistic fuzzy numbers can be divided into intuitionistic triangular fuzzy numbers and intuitionistic trapezoidal fuzzy numbers, and in this paper, intuitionistic triangular fuzzy numbers [24] are introduced for refining the model. The improvement of the original value function expression (8) is shown in equation (12):

$$v(\Delta\chi_i)=\begin{cases}(d(\tilde{x},\tilde{x}_0))^{\alpha}, & d(\tilde{x},\tilde{x}_0)\geq 0\\ -\lambda(d(\tilde{x},\tilde{x}_0))^{\beta}, & d(\tilde{x},\tilde{x}_0)\leq 0\end{cases} \tag{12}$$

For the improved value function, the substitution is the distance d between the two fuzzy numbers.

For intuitionistic triangular fuzzy numbers: $\tilde{a}_1=\langle(a_{11},a_{12},a_{13}),(b_{11},b_{12},b_{13});\mu_{a1},v_{a1}\rangle$ and $\tilde{a}_2=\langle(a_{21},a_{22},a_{23}),(b_{21},b_{22},b_{23});\mu_{a2},v_{a2}\rangle$. The Hamming distance between them is shown in equation (13):

$$d(\tilde{a}_1,\tilde{a}_2)=\frac{1}{6}\sum_{j=1}^{3}(|\mu a_{1j}-\mu_2 a_{2j}|+|(1-v_1)b_{1j}-(1-v_2)b_{2j}|) \tag{13}$$

Whereas the weight function expression does not change its form after the introduction of intuitionistic triangular fuzzy numbers, Eqs. (6) to (8) still apply. However, it is necessary to point out its arithmetic rules in the case of fuzzy numbers. Let the intuitionistic triangular fuzzy number $\tilde{a}=\langle(a_1,a_2,a_3),(b_1,b_2,b_3);\mu_a,\upsilon_a\rangle$ its intuitionistic triangular fuzzy probability is:

$$\tilde{\omega}(\tilde{p})=\begin{cases}\tilde{\omega}^{+}(\tilde{p}),\tilde{p}\text{ corresponding results for returns}\\ \tilde{\omega}^{-}(\tilde{p}),\tilde{p}\text{ corresponding results for the loss}\end{cases} \tag{14}$$

$$\begin{aligned}\omega^{+}&=\langle(\omega^{+}(a_1),\omega^{+}(a_2),\omega^{+}(a_3)),(\omega^{+}(b_1),\omega^{+}(b_2),\omega^{+}(b_3))\rangle\\ \omega^{-}&=\langle(\omega^{-}(a_1),\omega^{-}(a_2),\omega^{-}(a_3)),(\omega^{-}(b_1),\omega^{-}(b_2),\omega^{-}(b_3))\rangle\end{aligned} \tag{15}$$

After determining the value function and the weighting function that introduce the intuitionistic triangular fuzzy number, the prospect calculus of B2C e-commerce companies can be redefined:

$$\tilde{V}_L(\tilde{f})=(\oplus_{i=1}^{k}\omega_{p(i)}^{+}\tilde{v}(x_{p(i)}))\oplus(\oplus_{i=k+1}^{n}\omega_{p(i)}^{-}\tilde{v}(x_{p(i)})) \tag{16}$$

Denotes the outlook value of the L th business, there are k outcomes for business outlook, and $\oplus$ is the fuzzy number summation. The sum of $\tilde{a}_1$ and $\tilde{a}_2$ is a two-intuitionistic triangular fuzzy number of the form:

$$\tilde{a}_1\oplus\tilde{a}_2=\left(\left[a_{11}+a_{21},\quad a_{12}+a_{22},\quad a_{13}+a_{23}\right]\left[b_{11}+b_{21},\quad b_{12}+b_{22},\quad b_{13}+b_{23}\right]\right) \tag{17}$$

III. C. Multi-attribute structure for modeling service-based processes

Currently, the mainstream B2C e-commerce websites in China include: Tmall, Jingdong, Dangdang, No.1 Store, Vipshop, Suning.com, and so on. In this paper, we study the consumer decision-making behavior under the B2C full-process service scenario, so we choose the three direct-operated enterprises of No.1 Store (yhd.com), Jingdong (jd.com) and Dangdang (dangdang.com) as the alternatives, and do not consider the pure platform-type enterprises, such as Tmall and so on.

This study applies the service blueprint method to analyze the whole process of B2C e-commerce service, and the user behaviors include: choosing shopping channel, visiting website, transaction, payment, waiting for goods, receiving goods and giving feedback on goods information. Based on the user behavior, describing the website behavior in the frontend, the website behavior in the backend and the support process, the service blueprint of the total process of B2C e-commerce service is obtained as shown in Fig. 6, and further describes the process of each sub-service.

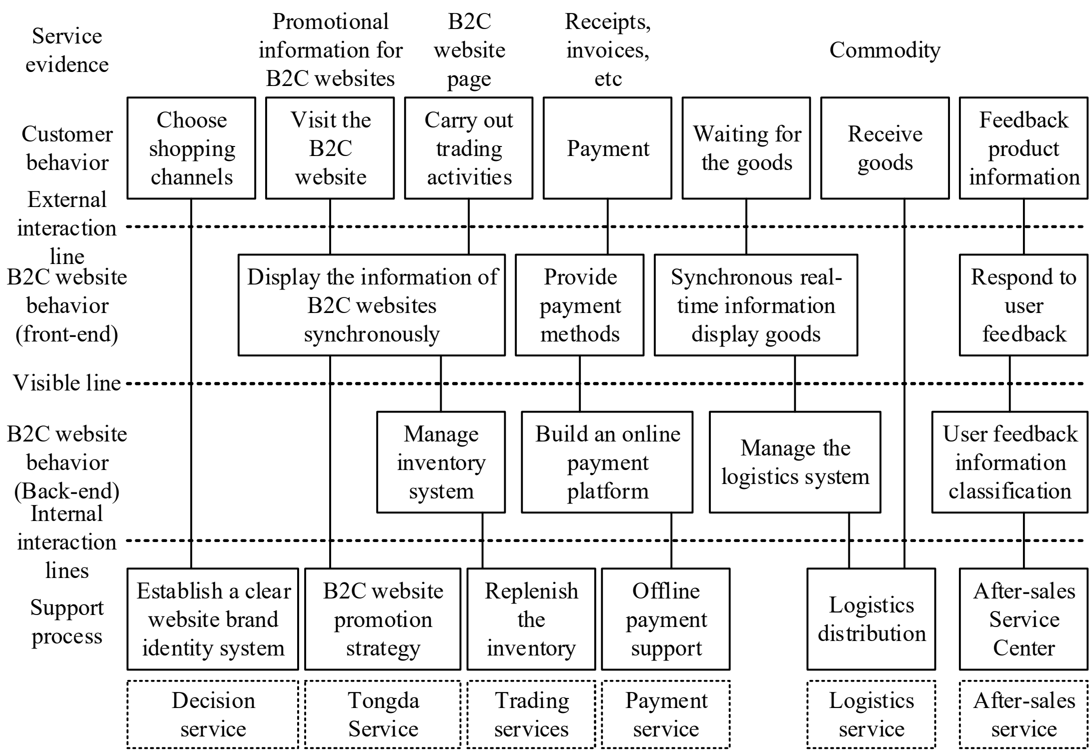


Figure 6: The overall process of B2C e-commerce based on the Service Blueprint method

On the basis of the e-commerce service process constructed by the service blueprint method mentioned above, the evaluation index system of B2C consumer behavior decision-making model based on prospect theory is established, and the overall framework of the evaluation index system is shown in Figure 7.

The evaluation index system of B2C consumer behavioral decision-making model is divided into target layer, index layer, sub-indicator layer and scheme layer.

(1) The goal layer is to establish a B2C consumer behavior decision-making model to explore the decision-making mechanism of consumers in the process of online consumption, and at the same time, this model can be used to evaluate the service quality level of B2C e-commerce enterprises.

(2) The indicator layer is the six sub-processes of B2C e-commerce services: decision-making service, access service, transaction service, payment service, logistics service, and after-sales service, which form the first-level indicators of the evaluation framework.

(3) The sub-indicator layer refers to each sub-indicator under the first-level indicator layer. By collecting consumers' service evaluation IWOM of B2C enterprises, IWOM clustering is performed within each category after categorization according to the six first-level indicators of the indicator layer. The clustering results are evaluated with the aid of QFD (Quality Function Deployment), and each sub-indicator is determined after summarizing the evaluation results.

(4) The program layer includes three enterprises: No.1 Store, Jingdong and Dangdang. This paper captures Sina Weibo and Baidu Word of Mouth, and determines the prospect value of each evaluation object through classification,

clustering, and sentiment analysis. Finally, according to the multi-attribute decision-making method, the comprehensive prospect value of each evaluation object is calculated, and the optimal alternative is determined through comparison.

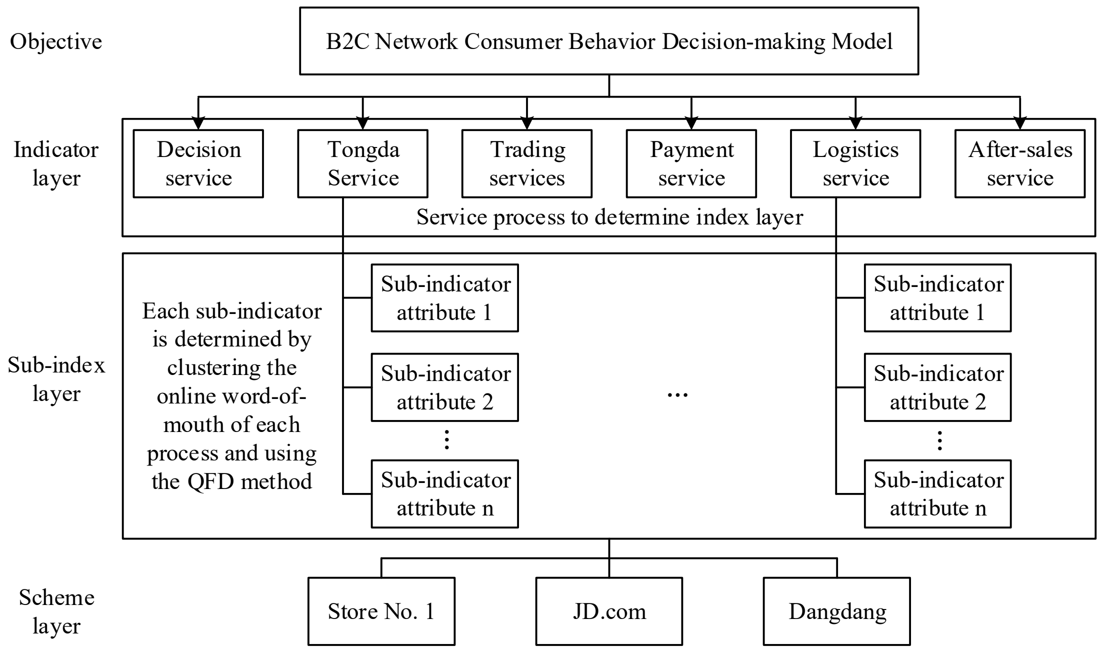


Figure 7: Framework of the evaluation index system

III. D. Example analysis

This section provides an example application of the proposed consumer multi-attribute behavioral decision-making model based on prospect theory and fuzzy logic to verify the accuracy of the model.

III. D. 1) Attribute Mining

In this paper, we have captured the data of 600 after-sale reviews for each of the 12 selected products $A=\left(a_i, i=1,2,\ldots 12\right)$, including the user name, the date of the review, and the content of the review. According to the proposed modeling framework, LDA is utilized to extract and name the potential themes in the online reviews of the selected products, and the key themes of each corpus can be obtained: price-performance ratio, brand loyalty, effectiveness, logistics, and after-sales, and the core key terms under each theme and its corresponding key terms are shown in Table 3, which are the attributes of concern for the users purchasing the products $F=\left(f_j, j=1,2,\ldots 6\right)$.

Table 3: Comment topics and core keywords

Key Words	Key words
Price	Cheap, discounted, cost-effective, great value for money, preferential price, discount, a little expensive, price range, the price in hand, subsidy, coupon
Cost performance	Like, cheap and delicious, repurchase, gift, recommendation, cost performance, good quality and low price, durable
Brand loyalty	Support, fans, consistent use, recognition, trust, store, satisfaction, belief
Quality	Delicious, fast, large in quantity, cost-effective, tasty, clean
Environment	Convenient, parking, clean, quiet, easy to find, located, beautiful, warm
After-sales service	Customer service, after-sales service, guarantee, seller, attitude, refund, exchange, service, positive review

III. D. 2) Determination of attribute weights

According to the user attention attributes extracted from Table 3, the probability distribution of each comment for each attribute is calculated as shown in Table 4, and the attribute probability distributions of all the texts are summarized and the weight of each attribute is derived, and the attribute weight results are shown in Table 5.

Table 4: Attribute probability distribution matrix

Text	Attribute					
	Commodity price f1	Cost performance f2	Brand loyalty f3	Quality f4	Environment f5	After-sales service f6
Text1	0.2461	0.3022	0.1645	0.2213	0.0556	0.0741
Text2	0.3576	0.1643	0.2487	0.1249	0.0441	0.1105
Text3	0.2748	0.0698	0.4102	0.1154	0.1162	0.0664
…	…	…	…	…	…	…
Text7200	0.8135	0.0443	0.0286	0.0829	0.0241	0.0298

Table 5: Prescriptive weight

Attribute	Commodity price f1	Cost performance f2	Brand loyalty f3	Quality f4	Environment f5	After-sales service f6
Weight	0.341	0.112	0.043	0.308	0.119	0.077

III. D. 3) Attribute Sentiment Analysis

Using LSTM [25] to calculate the sentiment distribution of each text, the values of the sentiment distribution are all between 0-1, which means: the higher value indicates that the user is more satisfied with this attribute, and the lower value represents that the attribute of the commodity is not satisfied. According to the grade division, the satisfaction level affiliation of each attribute of each commodity is calculated according to its proportion, taking a_1 as an example, the satisfaction level affiliation of each attribute is shown in Table 6.

Table 6: Attribute satisfaction level membership degree

Degree of satisfaction	Attribute					
	Commodity price f1	Cost performance f2	Brand loyalty f3	Quality f4	Environment f5	After-sales service f6
Very satisfied	0.6803	0.6054	0.7245	0.7172	0.4826	0.4647
Satisfied	0.1025	0.0167	0.0056	0.2495	0.1654	0.1148
General	0.1819	0.0132	0.0079	0.0092	0.3107	0.0092
Not satisfied	0.0172	0.3548	0.2544	0.0095	0.0261	0.0099
Very dissatisfied	0.0181	0.0099	0.0076	0.0146	0.0152	0.4014

III. D. 4) Data fusion

The attribute satisfaction level affiliation matrix of all commodities is obtained according to the above steps, and then each attribute satisfaction level affiliation is weighted according to Table 5, and the weighted attribute satisfaction level affiliation matrix is obtained. Then the weighted attribute satisfaction level of each commodity is transformed according to the transformation method of decision matrix to get the final decision matrix.

Then the satisfaction level affiliation of each attribute of each commodity is treated as one piece of evidence, and the evidence of different attributes under each commodity is fused to obtain one piece of comprehensive data. After obtaining the combined evidence for each commodity, the total evidence is weighted to obtain the overall satisfaction level p, and the overall satisfaction level for each commodity is as follows: $p^1 = 0.723584$, $p^2 = 0.9795$, $p^3 = 0.70241$, $p^4 = 0.8945$, $p^5 = 0.7479$, $p^6 = 0.9028$, $p^7 = 0.835652$, $p^8 = 0.812547$, $p^9 = 0.698544$, $p^{10} = 0.752943$, $p^{11} = 0.784578$, $p^{12} = 0.774136$.

Comparing the overall satisfaction of each item, the priority ranking of alternative items can be derived: $a_2 > a_6 > a_4 > a_7 > a_8 > a_{11} > a_{12} > a_{10} > a_5 > a_1 > a_3 > a_9$. Comparing the results with the actual sales sequence of the goods, only the ordering of goods a_2 and a_{10} does not match with the actual sales.

III. D. 5) Experimental analysis

In order to verify the effectiveness of the intuitionistic fuzzy number introduced in this paper to optimize the decision-making model of consumer behavior, the optimized model is experimentally compared with the original model. Using a dataset including online review data of 120 alternative commodities, the optimized model is used to analyze and predict them, and the priority ranking of commodities is obtained, which is compared with the ranking of actual sales, resulting in the number of inverse sequences of the predicted sequences and the accuracy rate as shown in Table 7. It can be seen that the number of inverse sequences of the commodity arrangement predicted by using the optimized model is reduced by 98, and the accuracy rate is improved by 2.63%, which indicates that the prediction results of the optimized model are closer to the temporal sales ordering of the commodities.

Table 7: Comparison of the accuracy rates of the prediction results

Predictive model	Reverse order column number	Accuracy rate
Unoptimized model	958	81.96%
Optimized model	860	84.59%

In order to further verify the stability of the optimized model, the number of samples is increased to test the accuracy of the prediction of the two models under different sample numbers. The two models are used to predict 60, 120, 180, 240, 300, 360, 420, 480 sample data respectively, and the prediction results of the two models are compared, and the experimental results are shown in Figure 8. The accuracy of the prediction results of the optimized model is relatively stable under different numbers of samples, and the accuracy of the prediction results increases accordingly with the increase of the number of samples, indicating that the model is suitable for multi-sample prediction.

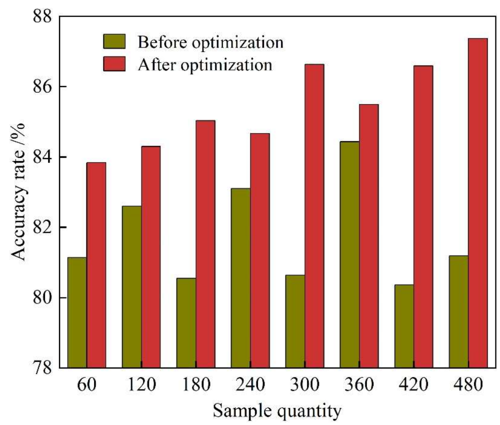


Figure 8: Accuracy comparison

The experimental results show that the introduction of fuzzy logic numbers for optimization of the consumer behavioral decision-making model based on prospect theory, the consideration of the degree of influence of each attribute on the evaluation results of the goods in the fusion of evidence, and the determination of the weight of the attributes by using more objective review data can improve the accuracy of the prediction.

IV. Conclusion

This study obtained the following main conclusions by constructing a fuzzy logic-based consumer behavioral decision-making process model in the digital economy platform:

The consumer stereo portrait construction method based on the FCM clustering algorithm can effectively extract the multidimensional features of the platform users, and compared with the K-means algorithm, the FCM performs better in terms of clustering efficiency, with an average number of iterations of only 4, whereas the K-means requires 18 iterations to achieve similar clustering results. The three-dimensional portrait system successfully constructs multi-dimensional user characteristics including activity, consumption level, and type of merchant to be concerned about, which provides a data foundation for modeling the decision-making process of consumer behavior.

The introduction of the prospect theory model optimized by intuitionistic triangular fuzzy number significantly improves the accuracy of consumer behavior prediction. In a test of 120 merchandise samples, the predicted inverse ordinal number of the optimized model is reduced from 958 to 860, with an accuracy of 84.59%, which is 2.63 percentage points higher than that of the unoptimized model. Multiple sets of experiments show that with the increase of sample size, the optimized model prediction stability continues to improve and is suitable for large-scale data analysis.

The attribute mining method based on LDA topic extraction identifies five key attributes: price-performance ratio, brand loyalty, effectiveness, logistics, and after-sale, and the attribute weighting analysis shows that the commodity price (0.341) and the commodity quality (0.308) are the factors that consumers are most concerned about. Among the 12 test commodities, the priority ranking predicted by the model is highly consistent with the actual sales ranking, and only two commodities have ranking differences.

Taken together, the model proposed in this study provides a new theoretical framework and technical method for analyzing and predicting consumer behavior on digital economy platforms, which is an important reference value for e-commerce enterprises to optimize their service processes and formulate precise marketing strategies.

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