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Article

Teaching Practice of Consumer Clicking Behavior Recognition Algorithm on E-Commerce Platform in E-Commerce Education of Higher Vocational Colleges and Universities

Yi Yang and Qiang Li *

School of Economics and Management, Shanghai Technical Institute of Electronics & Information, Shanghai 201411, China; Liqiangmpp1@sina.com

Abstract: With the goal of accurately mining consumer clicking behavior data on e-commerce platforms, this paper proposes a clustering algorithm based on FCM fuzzy operations, which is applied to e-commerce education in higher vocational colleges and universities. The collected e-commerce platform consumer data are normalized, and the FCM fuzzy clustering analysis algorithm is applied to the acquired two data structures, namely, dissimilarity matrix and data matrix, and after obtaining the clustering map, the data points within the space of the data structure are used as sample inputs to search for the constituent properties of the sample points and the space of the data structure, and to obtain the e-commerce platform consumer data mining results. The clustering results of the algorithm categorize the e-commerce platform consumers into three categories: selective type, comparison type and decisive type, which improves the resource allocation efficiency of the enterprise and further enhances the enterprise profit. The effect of teaching practice shows that the students in the experimental group improved their average grade by 4.3 points compared with the control group through the application of the teaching mode based on the clicking behavior recognition algorithm of consumers on the e-commerce platform. It shows that this algorithm provides a more scientific and perfect teaching mode for students of higher vocational e-commerce majors and enhances the effectiveness of teaching.

Keywords: FCM fuzzy cluster analysis algorithm; data mining; consumer clicking behavior recognition; e-commerce education in higher vocational colleges and universities

1. Introduction

As the digital economy emerges as a new driving force for socio-economic development, online retail—led by e-commerce—has created new consumer demand and provided a significant number of job opportunities for society [1]. By December 2024, the number of online shopping users in China had exceeded 900 million, with online retail sales surpassing 15 trillion yuan in the same year, marking a new trend in the e-commerce industry [2]. As a typical example of the deep integration of the digital economy and the real economy, e-commerce is increasingly becoming a key enabler for industrial digital transformation. According to the “2024 China E-commerce Talent Report,” 35% of enterprises urgently need talent in e-commerce platform operations, and 27% of enterprises urgently need composite-skilled talent. Talent with composite skills such as digital operations and new media marketing has become a scarce resource [3-5]. However, the practical teaching system of e-commerce majors in traditional higher vocational colleges suffers from issues such as lagging technological updates, mismatches between practical teaching and job practices, and insufficient industry-education collaboration, making it difficult to adapt to the rapidly evolving needs of the e-commerce industry [6-8]. Against this backdrop, this study



focuses on the characteristics of talent demand in the digital economy era, analyzes the issues in the practical teaching of e-commerce majors in higher vocational colleges, and explores new reform approaches to meet the new demands for talent in the digital economy era.

Online e-commerce platform advertisements directly or indirectly influence their target audience by disseminating information about products and services [9]. Advertisements stimulate consumers' cognitive and emotional systems, which respond positively, inducing consumers to click on the advertisements. Consumers' clicking behavior is their first reaction to advertisements, and this clicking intention to some extent reflects the effectiveness of the advertisement [10-12]. Jerath et al. examined consumers' clicking behavior on organic links and sponsored links and found that the overall click-through rate was low and primarily concentrated on organic links. However, less popular keywords resulted in higher click-through rates and a higher proportion of clicks on sponsored links, indicating higher consumer engagement and a closer proximity to purchase decisions [13]. Cheng and Anderson explored consumers' online search processes, and categorized consumers into three distinct groups based on their click behavior, providing insights for marketers to improve their search advertising campaigns and strategies [14]. Lu and Du investigated differences in consumer click behavior across different devices in paid search advertising, examining user behavior and sensitivity to changes in ad placement [15]. Daryaie and Khadivi proposed a recognition model, aimed at predicting consumer click behavior in search engine ads by leveraging similarity and relevance, thereby addressing the challenge of limited historical data for new objects [16]. Scholz utilized the functionality of Markov chains for reading, writing, clustering, and analyzing clickstream data to assist e-commerce platform retailers and researchers in understanding consumer click behavior and identifying usability issues [17].

This paper takes the consumer clicking behavior of e-commerce platform as the entry point, and discusses the application of the algorithm in the teaching practice of e-commerce education in higher vocational colleges. The research designed an improved FCM fuzzy operation clustering e-commerce platform consumer clicking behavior recognition algorithm, using a random initialization method to initialize the clustering center of the FCM fuzzy operation clustering algorithm. Based on the obtained clustering center, the affiliation function value is updated, and then the updated affiliation function is cyclically updated to the clustering center, and the above operation is repeated until the affiliation matrix is stable. The algorithm is applied to the empirical case of consumer clicking behavior on the e-commerce platform, and then design the senior e-commerce platform consumer clicking behavior recognition algorithm for senior e-commerce teaching experiments, to verify the feasibility of combining the algorithm of this paper and teaching.

2. Research on Teaching Practice of Consumer Clicking Behavior Recognition Algorithm

2.1. Research Data Sources

2.1.1. User Behavior Dataset

The public dataset used in the paper is sourced from the Ali Tianchi big data platform on Taobao website. The dataset contains a large amount of information about the purchasing behavior of users in the e-commerce industry. Through timely and scientific analysis of user behavior, we can have a comprehensive grasp of user needs and situations.

The information contained in the dataset is the ID of the user, the ID of the commodity, the ID of the commodity category, the type of behavior, and the time. Among them, the data of user ID, product ID, product category ID, and behavior type are all integer types.

The behavior types here include the type of click, click volume, purchase volume, add purchase volume, and collection volume. The data of click type, click quantity, purchase quantity, add purchase quantity and collection quantity are all integer types. From this we can clearly see the behavioral characteristics of each user.

User behavior data can clearly see the way a user's purchasing behavior. Behavioral data includes user ID, number of purchases, shopping cart additions, user favorites, user views, and number of products clicked by the user.

The number of users in the dataset is 44000, the number of products is 4165000, the number of product categories is 9500, and the number of all behaviors is 100050000.

This project actually extracted 1 million pieces of data for analysis for functionality reasons. The project includes the following parts:

- (1) Data processing: data import/data cleaning/time variable processing.
- (2) Platform traffic analysis: basic indicators of e-commerce platform (UV/PV) analyzed by day/time.
- (3) User behavior analysis: user behavior change trends of various types, repurchase behavior

analysis.

(4) Conversion funnel analysis[18]: behavior/user funnel analysis.

(5) Teaching effect analysis: test the effectiveness of the consumer behavior identification algorithm of e-commerce platform in the e-commerce education of higher vocational colleges and universities.

2.1.2. Other Sources of Data Sets

Regarding the data related to users' online purchasing behavior, we can also obtain it through questionnaires, web crawling, and contests for public data. Here we take the public dataset, the user purchase behavior dataset of Jingdong platform, as an example. The user behavior data contains information about users' shopping behavior from 2020-02-01 to 2021-02-01, and the data has been desensitized. The information contained in the dataset is the ID of the user, the ID of the product, the ID of the product category, the type of behavior, the time, and the storage order number. The user ID, product ID, product category ID, and behavior type are all integer types.

2.2. Fuzzy Operational Clustering Algorithm in E-commerce Customer Data Mining

2.2.1. Clustered Data Processing in Data Mining

Clustering algorithm applied to e-commerce customer data mining contains two parts:

1) based on the characteristics of the implementation of e-commerce customer data selection, e-commerce customer data input, the presence of clear features structure data, based on the output samples to achieve the structure and nature of the analysis. Typically, the feature output data is a matrix, the rows and columns of the output data matrix represent the samples and indicators, and the indicators in the matrix are variables, and the selected indicator features directly affect the clustering results.

2) Implementation of the clustering algorithm, through the clustering algorithm to obtain the clustering map. The data points within the matrix space matrix samples are entered, and the clustering algorithm is utilized to obtain the compositional properties of the sample points and space.

The flowchart of clustering algorithm in e-commerce customer data mining is shown in Figure 1.

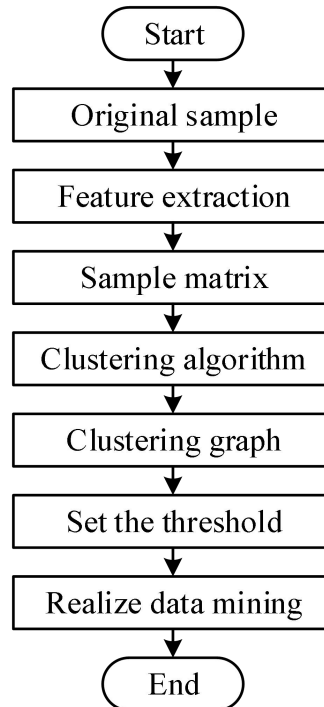


Figure 1. Clustering algorithm in data mining.

Data preparation is an important step in data mining, data preparation includes the specification and processing of selected data, pre-processing data to be mined is an important prerequisite as well as a necessary condition for cluster analysis and data mining. Cluster analysis of data objects can obtain the clustering between different targets. Cluster analysis algorithms are not the same when the type of data to be mined is different. When pre-processing e-commerce customer data, two data structures can be obtained, respectively, the dissimilarity matrix and the data matrix.

1) Phase dissimilarity matrix. Each structure within the dissimilarity matrix represents an object, there are a number of different objects in the dissimilarity matrix although n of the difference between the two produced by the matrix relationship through the $n \times n$, which is presented in the form of:

$$f(p,q) = \begin{bmatrix} 0 & & & & & \\ f(2,1) & 0 & & & & \\ f(3,1) & f(3,2) & 0 & & & \\ f(4,1) & f(4,2) & f(4,3) & 0 & & \\ \vdots & \vdots & \vdots & \vdots & \ddots & \\ f(n,1) & f(n,2) & f(n,3) & f(n,4) & \cdots & 0 \end{bmatrix} \quad (1)$$

where $f(p,q)$ represents the difference between target p and target q . Normally $f(p,q)$ is a non-negative number, the data are closer to 0 when p,q is infinitely close, and p,q the two data are farther apart at larger values.

2) Data Matrix. One of the data within the acquired data matrix can embody a data structure that consists of a matrix of n data. When the target object is an e-commerce customer, the attributes contained in the matrix are: gender, age, weight, height, occupation and other information. The data matrix is obtained by utilizing the correspondence relationship, and the form of the obtained data matrix is as follows:

$$R = \begin{bmatrix} a_1 & a_2 & a_3 & \cdots & a_p \\ b_1 & b_2 & b_3 & \cdots & b_p \\ c_1 & c_2 & c_3 & \cdots & c_p \end{bmatrix} \quad (2)$$

The dissimilarity matrix as well as the data matrix in clustering algorithms are often referred to as unimodal and bimodal matrices.

2.2.2. FCM Fuzzy Cluster Analysis Algorithm

Denote the set of samples to be clustered with $X = \{x_1, x_2, \dots, x_n\}$ containing the number of n samples, and there exist a number of d feature indicators within each sample x_k , and let the number of feature categories contained within the sample set be $c(2 \leq c \leq n)$. The degree of affiliation of the j th class in sample k is denoted by $\mu_{jk} \in [0, 1]$, based on the fact that each cluster conforms to the sum of the degrees of affiliation of the respective samples as 1, which can be obtained:

$$\sum_{j=1}^c \mu_{jk} = 1 \quad (3)$$

where $k = 1, 2, \dots, n$.

The fuzzy division matrix U is given by the following equation:

$$U = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{c1} & \mu_{c2} & \cdots & \mu_{cn} \end{bmatrix} \quad (4)$$

Where: the j th row and k th column of matrix U represent the affiliation function of the j th clustered subset and the affiliation value of sample x_k for c subsets, respectively, and it can be known that $\mu_{jk}(1 \leq j \leq c, 1 \leq k \leq n)$ is the affiliation of the sample x_k for the j class.

Fuzzy operational clustering algorithms [19] are essentially algorithms in which the uncertainty of the affiliation of a sample to different clusters is represented by an affiliation function. The affiliation function can be divided from a definite value to an interval, and the obtained interval is utilized to mine more details that can objectively represent the real world.

FCM fuzzy cluster analysis algorithm based on the objective function is used to realize the data mining of e-commerce customers, and the algorithm can use the constraint optimization problem to reflect the clustering problem, and the optimization objective function is used to obtain the fuzzy division matrix and the final clustering center. It is necessary to establish scientific and reasonable clustering criteria, so that the fuzzy clustering problem based on the objective function can obtain reasonable clustering results from a large number of clusters.

The FCM fuzzy cluster analysis algorithm [20] is a combination of hard C-mean clustering algorithm and fuzzy set theory. The FCM fuzzy cluster analysis algorithm has the following intraclass weighted error sum of squares objective function:

$$J_f = \sum_{j=1}^c \sum_{k=1}^{n_j} \mu_{jk}^b \|x_k^{(j)} - m_j\|^2 \quad (5)$$

Where: m_j and μ_{jk} denote the clustering center and the affiliation function, respectively; b denotes the fuzzy weighting index, usually b is greater than 1, the use of weighting index to achieve the fuzzy degree of clustering results in the control of the degree of crossover between different clusters in the value of the value of the larger the greater.

Let J_f minimize as the clustering criterion for optimizing the clustering results, the relevant formula for the constrained optimization problem can be obtained as follows:

$$\begin{cases} \min \sum_{j=1}^c \sum_{k=1}^{n_j} \mu_{jk}^b \|x_k^{(j)} - m_j\|^2 \\ s.t. \quad \sum_{j=1}^c \mu_{jk} = 1 \end{cases} \quad (6)$$

Using the Lagrange multiplier solver, obtain the equation as follows:

$$L = \sum_{j=1}^c \sum_{k=1}^{n_j} \mu_{jk}^b \|x_k - m_j\|^2 - \sum_{k=1}^n \lambda_k \left[\sum_{j=1}^c \mu_{jk} - 1 \right] \quad (7)$$

where λ_k denotes the Lagrange multiplier.

Solving for the partial derivatives of L with respect to m_j, μ_{jk}, λ_k and making them equal to 0 yields:

$$\mu_{jk} = \frac{\|x_k - m_j\|^{1-b}}{\sum_{j=1}^c \|x_k - m_j\|^{1-b}} \quad (8)$$

$$m_j = \frac{\sum_{k=1}^n \mu_{jk}^b x_k}{\sum_{k=1}^n \mu_{jk}^b} \quad (9)$$

From the above analysis, the FCM fuzzy operation clustering algorithm applied in e-commerce customer data mining is realized as follows:

1) Set the number of clustering categories c for the characteristics of e-commerce customer data, set the weighting index b , the initial number of iterative operations is $I = 1$, and set the clustering algorithm iteration stopping threshold ε ;

2) Initialize the clustering center of FCM fuzzy operation clustering algorithm using random initialization method;

3) Repeat the iteration of the FCM fuzzy operation clustering algorithm until the affiliation matrix stabilizes to a fixed range.

Update the value of the affiliation function according to the obtained clustering center; update each clustering center according to the obtained affiliation function. Repeat the above process until the

convergence of the clustering algorithm, the end of the operation, the final fuzzy classification matrix and the clustering centers of the different categories obtained is the e-commerce customer data mining results.

3. Empirical Research on Consumer Clicking Behavior on E-Commerce Platforms

3.1. Results of Data Analysis

The results of consumer clicking behavior statistics are shown in Figure 2. In the 24-hour clicking behavior statistics of consumers, it can be seen that consumers are highly active between 18:00 and 22:30, that is, consumers are most active in the log-in browsing of the website after work or school, and it reaches the highest in the night before going to bed, which is in line with people's daily work and rest patterns. Secondly, the daytime peak is from 9:00 to 15:00, consumers are more active near the time of lunch break, and the clicking behavior is more stable from 11:00 to 16:00, which shows that the time point of consumers' online browsing is also related to the behaviors generated by consumers.

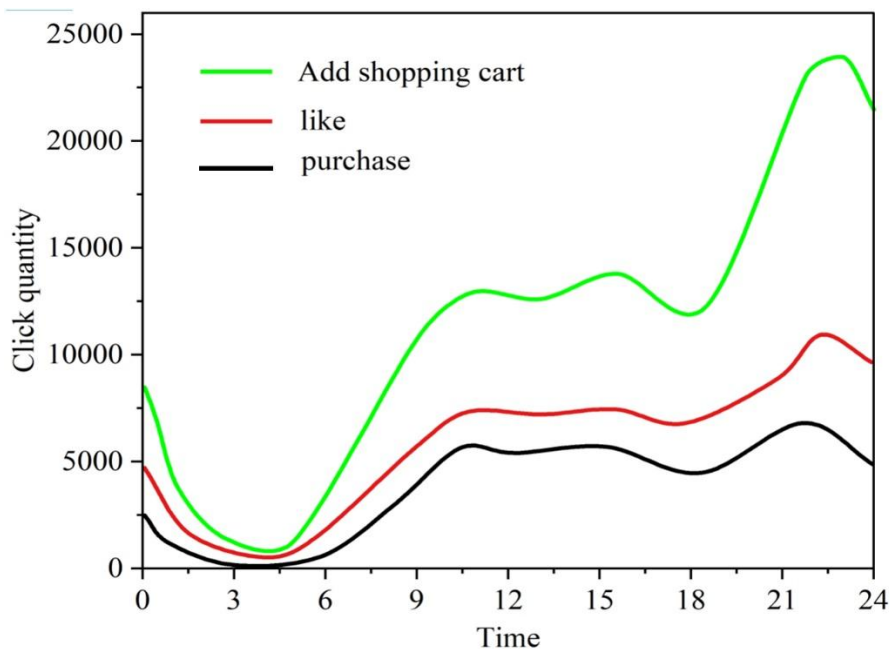


Figure 2. The purchase of the previous point of action statistics.

Analyzed from a qualitative perspective, the statistical results of consumers' pre-purchase clicking behavior are shown in Table 1. Consumers will generate certain click, like or add to cart behaviors before generating shopping behaviors on the online shopping platform. The analysis of the behavioral data of consumers who generate purchase behavior from the dimension of commodities reveals that, before generating purchase behavior, the majority of consumers generate about 0~6 clicks to browse to understand the details of the product and other information. After consumers click to browse consumers will produce 0 to 4 times like behavior, the vast majority of which is 0 times, most people did not add the shopping cart behavior. This is a certain deviation from the daily understanding of consumer clicking behavior, in fact, the vast majority of consumers do not like and add to cart behavior before purchasing, but browse the product information to purchase. This shows that browsing behavior largely predicts consumers' next action goals. In summary, when consumers are active on e-commerce platforms, they tend to purchase goods after generating a short sequence of actions.

Table 1. The purchase of the previous point of action statistics.

Number of clicks	Click on the number of actors	Frequency of behavior	People like actors
0	6000	0	35500
1	17995	1	8000

2	9845	2	300
3	4845	3	150
4	2564	4	50
5	1545	5	0
6	856	6	0
7	300	7	0
8	50	8	0

3.2. Cluster Analysis of Users' Online Shopping Behavior

According to the results of data cleaning, nine representative indicators are selected for factor analysis, including users' gender, age, membership level, users' clicking behavior, browsing behavior, adding cart behavior, deleting cart behavior, collecting and following behavior, and placing orders and purchasing behavior.

Firstly, whether the original variables are correlated or not is investigated, and the commonly used methods are Bartlett's Sphericity Test and KMO test. the closer the KMO value is to 0, the weaker the correlation between the variables, and the closer the KMO value is to 1, the stronger the correlation between the variables, i.e., the more suitable the original variables are to do the factor analysis. The original data were then factor analyzed using SPSS tools. The P-value of most of the factor analysis is less than 0.05, indicating that the correlation between most of the variables is significant.

The KMO test statistic is generally applied to the indicators comparing the simple correlation coefficient and partial correlation coefficient between variables, and is mainly used for factor analysis of multivariate statistics. The value of KMO is 0.75, which indicates that the correlation between the nine selected indicators is significant, and can be used for cluster analysis.

Due to the different data outline of each indicator, and the clustering algorithm requires that the differences between the data should not be too large, so in order to make the data comparable, first of all, eliminate the bias between the data through standardization, and then use the SPSS software to cluster the above indicators, and the K value of the clustering center is selected as 3, and the clustering model divides the data through the number of iterations by adjusting the clustering center, until it converges. Table 2 shows part of the iteration process, the data after 70 iterations, reached the convergence state and get the final clustering center of each category.

Table 2. Partial iterative process.

Epoch	1	2	3
58	14.849	14.613	0.145
59	5.117	3.977	0.099
60	3.274	2.059	0.097
61	1.297	1.322	0.095
62	1.627	0.842	0.087
63	0.992	0.506	0.074
64	0.906	0.323	0.047
65	0.683	0.225	0.032
66	0.499	0.164	0.027
67	0.359	0.108	0.021
68	0.431	0.076	0.017
69	0.497	0.061	0.015
70	0.497	0.061	0.001
71	0.497	0.061	0.001

72	0.497	0.061	0.001
73	0.497	0.061	0.001

The algorithm obtains the number of user groups in the 3 categories and the final clustering centers after 70 iterations. The final clustering centers and the number of cases in each cluster are shown in Tables 3 and 4, respectively, with 5,280 users in the first category, 17,600 users in the second category, and 21,120 users in the third category. The percentage of users in these three clusters is 12%, 40% and 48% respectively. Overall the distribution of these three groups is quite even, indicating that the clustering effect is better.

Table 3. Final cluster center.

Variable	Clustering		
	1	2	3
Zscore(x1)	0.08334	0.05819	-0.07702
Zscore(x2)	-0.13597	-0.97491	0.94104
Zscore(x3)	0.40750	0.39306	-0.47729
Zscore(z1)	1.83443	-0.21494	-0.3098
Zscore(z2)	1.62531	-0.20179	-0.26395
Zscore(z3)	1.61270	-0.19250	-0.26905
Zscore(z4)	0.81136	-0.10537	-0.1275
Zscore(z5)	0.90149	-0.10118	-0.15631
Zscore(z6)	1.81952	-0.19903	-0.32030

Table 4. The number of cases in each cluster.

Clustering	Number	
	1	5280
2	17600	
3	21120	

And based on this clustering result, one-way analysis of variance (ANOVO) was conducted, and the results of the analysis are shown in Table 5. The significance of each indicator is less than 0.05, indicating that this variable is better classified and the classification results are highly credible. It is also possible to discriminate the importance of each type of indicator to the clustering based on the size of the F-value, and it can be seen that gender has the greatest impact on the clustering results; age has the least impact on the clustering results.

Table 5. Analysis of single factor variance.

	Clustering		Error		F	Sig.
	Mean square	Freedom	Mean square	Freedom		
Zscore(x1)	72.568	2	0.995	43995	72.924	0.000
Zscore(x2)	11684.452	2	0.202	43995	59533.175	0.000
Zscore(x3)	2750.438	2	0.812	43995	3392.006	0.000
Zscore(z1)	7073.400	2	0.520	43995	13775.581	0.000
Zscore(z2)	5542.531	2	0.627	43995	8957.107	0.000
Zscore(z3)	5463.142	2	0.619	43995	8751.594	0.000

Zscore(z4)	1379.756	2	0.907	43995	1524.334	0.000
Zscore(z5)	1710.894	2	0.884	43995	1938.962	0.000
Zscore(z6)	6977.296	2	0.521	43995	13415.695	0.000

Although we have roughly classified the users into 3 categories, the specific characteristics of each category still need to be further studied and analyzed. The obtained cluster analysis results are shown in Table 6.

The first user group is mostly female users, with high membership level, high user activity, strong desire to buy, browsing, clicking, adding purchase collection are much higher than the other two categories of users, the age of about 20-35 years old, is a young user group, accounting for about 12%, belonging to the senior users.

The second category of user groups are mostly male users, membership level is higher, although not as active as the first category of users, but still have space for consumption, belong to the intermediate users, accounting for about 40%.

The third category of user groups most of the gender confidentiality, membership level is also lower, the degree of activity is not high, belongs to the ordinary users, accounting for about 48%. From the analysis results can be seen more in line with the consumer behavior in life. General consumer groups are about 20-35 years old young users in online shopping more, and female users in online shopping more frequently than men.

Table 6. Cluster analysis results.

Clustering	x1	x2	x3	z1	z2	z3	z4	z5	z6
1	3.03	0.88	4.61	876.57	32.00	15.74	2.77	5.49	1413.11
2	2.96	0.12	4.58	210.33	7.46	3.10	1.52	1.15	341.30
3	2.76	1.92	3.80	179.45	6.54	2.47	1.50	0.91	276.91
Total	2.93	0.99	4.27	280.21	10.12	4.45	1.60	1.62	447.02

3.3. User Profile Modeling

An accurate user portrait model needs to label and vectorize the user's behavioral data, and the online shopping user's portrait model includes the user's personal attributes and behavioral attributes, which is established by three levels: data source, data analysis and processing, and data indicator system.

In order to be able to more intuitively show the relationship between the various types of user behavioral characteristics, tableau tool is used here to draw the funnel plot of various types of user behavioral characteristics, the first category, the second category and the third category of users' behavioral funnel plot are shown in Fig. 3-Fig. 5, in order to analyze the conversion rate between the various paths. Funnel plot is an effective data analysis tool.

From the funnel plot, we can see that the conversion rate of browsing-payment of the three types of users is relatively low, which is lower than 0.6%, in which the browsing-payment conversion rate of the first type of users is the lowest, which can be seen that this type of users are more cautious about shopping, and generally do not directly buy the favorite products; secondly, through the browsing-addition rate of the user can be seen that the first type of users like to add the goods to the cart and then buy them, which can be deduced that the Secondly, through the browsing-adding rate of users, we can see that the first type of users like to add the product to the shopping cart and then buy it, which can be inferred that the user likes to compare the price with different merchants or wait for the discount period before purchasing, thus we can label this type of user as a selective user profile.

By observing the highest browsing-collection attention rate of the second type of users, it can be seen that the second type of users tend to collect the products first, so as to facilitate their selection of goods between different merchants, so we can give the second type of users can be labeled as a comparative type of his user profile.

By observing the highest browsing-buying rate of the third type of users, it can be seen that this type of users browsing to their favorite products will usually buy them directly without waiting for the discount period or comparison, so we can give the third type of users as his user profile a decisive purchase type of labeling.

At the same time can also be seen in the stage of browsing to add the shopping cart user turnover rate is the highest, are higher than 50%, which can be inferred that the user is not interested in the platform

recommended products, indicating that the platform's marketing strategy needs to be improved, and here can be some discount activities such as the issuance of coupons or compensation for shipping costs and so on to improve the user's shopping experience.

The AB model divides users into three types of groups, which is conducive to enterprises to target different types of groups to carry out precise marketing: for the first type of carefully selected type, let them keep consumption, and appropriately launched full reduction activities or consumption coupons to stimulate their consumption. For the second type of comparison type, according to their purchase frequency to recommend the most suitable goods for them to reduce their worries, so as to achieve the purpose of promoting consumption. For the third type of decisive purchase type, on the one hand, often recommend the goods that this type of user is concerned about, on the other hand, the introduction of cross-store discount activities to promote their consumption.

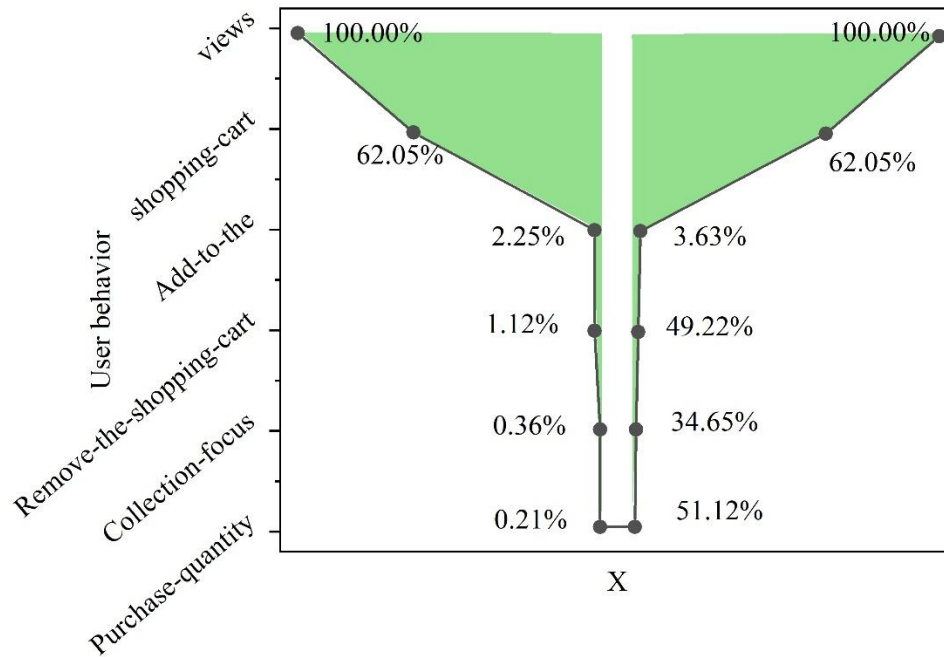


Figure 3. The first type of user behavior funnel.

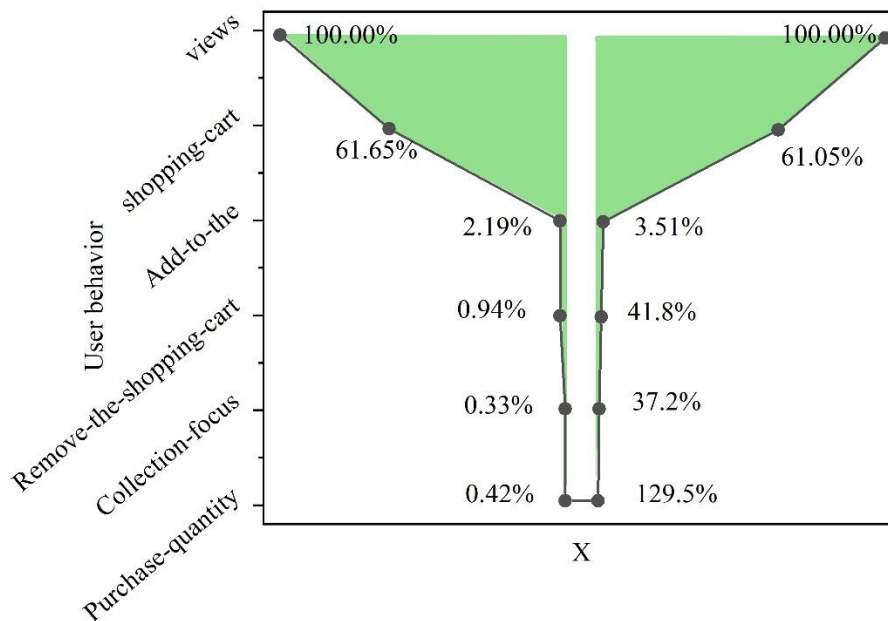


Figure 4. The second type of user behavior funnel diagram.

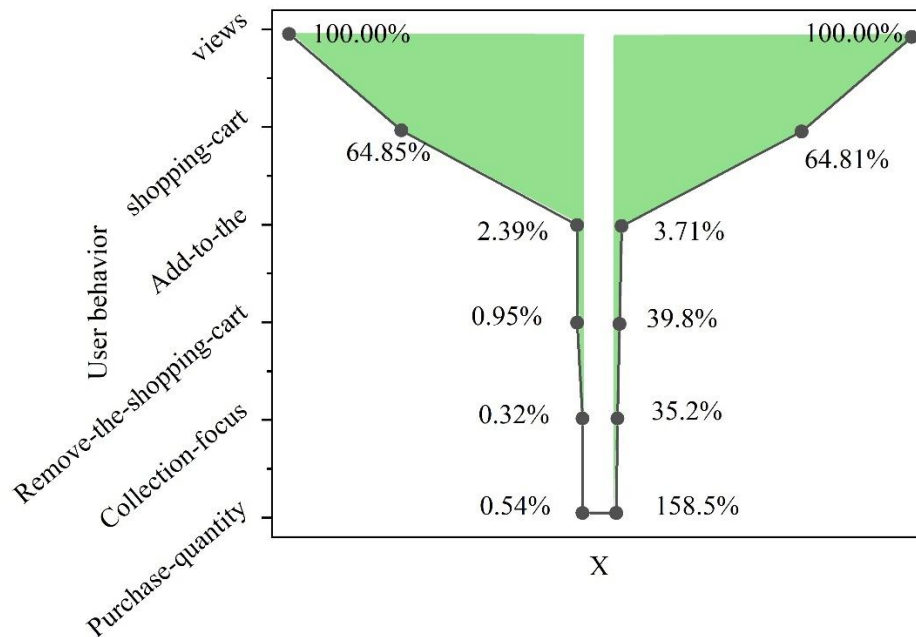


Figure 5. A third type of user behavior funnel.

4. Effect of Teaching Practice of E-Commerce Education in Higher Education Institutions

4.1. Experimental Study Design

4.1.1. Purpose of the Experiment

Develop and design the teaching resources of consumer clicking behavior recognition algorithm of higher vocational e-commerce platform, and apply them in higher vocational e-commerce teaching, test the teaching effect, explore its influence on the learning effect of students and teachers' teaching behavior of higher vocational e-commerce teaching, so as to find the basic law of teaching resources in higher vocational e-commerce teaching, improve the effectiveness of the application of the consumer clicking behavior recognition algorithm of the e-commerce platform in higher vocational e-commerce teaching and serve the reform of vocational education e-commerce teaching reform services.

4.1.2. Subjects

The second book of e-commerce education (basic module), a new national planning textbook for curriculum reform of national higher vocational education, is used as the learning content, and the e-commerce class 1 is an experimental class, which is taught by using the algorithm of consumer clicking behavior recognition on the e-commerce platform, and the e-commerce class 2 is a control class, which is taught by the conventional teaching method. Both classes were taught by the same teacher, and the learning bases of the two classes were basically the same, and the class hours, teaching materials, test contents and test methods were exactly the same.

4.1.3. Tools for Research

(1) Pre-test and post-test

In this study, pre-tests and post-tests were conducted for the experimental and control classes before and after the teaching experiment using the simulation paper of the 2020 Academic Level Qualifying Test for Students in Higher Vocational Schools in Province A. The Academic Level Qualifying Test for Students in Higher Vocational Schools in Province A is mandatory for higher vocational students, and will be fully introduced to higher vocational schools across the province in June 2020, and the questions are divided into four areas, with 10 points for each and a total score of 40 points. After the pre- and post-tests of the experiment, the data obtained were analyzed using SPSS software to compare the changes in students' performance in e-commerce education before and after the experiment.

(2) Teaching experiment

In the experimental class using the e-commerce platform consumer clicking behavior recognition

algorithm for e-commerce teaching, the control class uses the conventional e-commerce teaching method, to observe and compare the e-commerce teaching effect of the two methods.

4.2. Analysis of Pre-Laboratory Test Results

Before the experiment was carried out, this study was done on the students of cross-border e-commerce classes 1 and 2 about the pre-course written test, which was scored out of 40 points. And the students' scores were graded, where 0-23 is failing, 24-29 is passing, 30-34 is good, and 35-40 is excellent.

The results of the pre-test are shown in Table 7, with 70% and more students failing in both the control class and the experimental class, indicating that before the experiment, the students' knowledge of e-commerce education was generally poor. In order to observe whether there is a difference in the knowledge mastery of the two classes at the initial stage, a difference t-test was carried out on the written scores. Due to the small sample size, before the t-test, it is necessary to determine whether the two samples conform to a positive too distribution. The Sig value of the K-S test results of the written test scores of the two classes is 0.202 and 0.187, respectively, and the significance of the two classes is greater than 0.05, i.e., they are all in line with the normal distribution, and can be subjected to a T-test. The results of the T-test are shown in Table 8, and the significance value of the students' scores of the written questions of the two classes is 0.895, which is much greater than 0.05, which shows that, before conducting the teaching experiments, the experimental class and the control class have no difference in the There is no significant difference in the written test scores of ECE.

Table 7 Statistical analysis of written test results

Grade	Frequency	
	Laboratory class	Cross-reference class
Inferior lattice	28	29
Passing	10	9
Good	1	1
Excellence	1	1

Table 8 Two-class written test score T test results

		F	Significance	t	Sig.2
Written score	Assumed equal variance	0.052	0.826	-0.138	0.895
	Unassuming equal variance			-0.138	0.895

4.3. Analysis of Post-Experimental Test Results

At the end of the teaching experiment, this study also conducted a written test on the content of e-commerce teaching for 80 students using the same test paper, and analyzed the questions of the test paper according to Bloom's cognitive goal classification theory by examining the dimensions of the classification, and the results of the analysis are shown in Table 9, which shows that the written test scores of the 80 students in the experimental class and the control class in this study were scored and counted in accordance with the levels of the individual examining goals. Afterwards, the scores of the latter four dimensional questions were summed up as the total depth score. And the K-S normal distribution test and independent samples t-test were conducted on the depth score and the total score of e-commerce education. The results of the K-S normal distribution test and the independent samples t-test are shown in Table 10 and Table 11, respectively, that the total score of the test content as well as the total score of the deep dimensions in the two classes are normally distributed. And the significance values of the t-tests of the total scores of the written test and the in-depth scores of the two classes are less than 0.05,

so there is a significant difference between the two classes. Initially, it is verified that the teaching model proposed in this study has a certain effect on improving students' performance and helps to achieve deep learning in e-commerce education.

The total scores of the test contents of the two groups were analyzed descriptively, and the results of the data of the test contents scores of the two groups are shown in Table 12, where the mean of the experimental group is 4.3 points higher than that of the control group, and the standard deviation is lower than that of the control group. Therefore, the teaching model proposed in this study is effective in improving students' performance.

Table 9. Written test paper title test.

Target level	Issue number
Memory	A1
Understand	A3,A7
Applied	A2,A5,A9
Analysis	A4,A10,A12,A8,A15
Evaluation	A6,A11,A13
Created	A14

Table 10. K-s test results.

Class	Statistical project	Sig
Cross-reference class	Word depth score	0.202
	Word has to be divided	0.187
Laboratory class	Word depth score	0.202
	Word has to be divided	0.202

Table 11. T test results.

Statistical project		Sig.2
Word depth score	Assumed equal variance	0.050
	Unassuming equal variance	0.047
Word has to be divided	Assumed equal variance	0.043
	Unassuming equal variance	0.043

Table 12. Comparison of the score data of the two groups of test content.

Group	Mean value	Standard deviation	Minimum value	Maximum value	Median
Control group	25.7	6.784	10	33	24
Experimental group	30.0	6.298	15	39	30
Statistics	27.6	6.792	11	39	26

5. Conclusion

This study applies the FCM fuzzy cluster analysis algorithm to the identification of consumer clicking behavior on e-commerce platforms, and applies the identification algorithm of consumer clicking behavior on e-commerce platforms to the teaching practice in e-commerce education in higher vocational colleges and universities, exploring the feasibility of combining the algorithm and educational practice.

Applying the model of this paper to predict the short-term clicking behavior of consumers on the e-commerce platform, it is found that consumers will buy goods after generating shorter operations, and the results of the data analysis help e-commerce platform merchants react to the consumers' purchasing behavior in advance, and do a good job in stocking up and recommending goods.

E-commerce platform consumers can be clustered into three categories, the first category of users for the pick-and-choose type, this type of user likes to compare prices in different merchants before making a purchase. The second category has the highest browsing-collecting attention rate, and is the comparison-type customer. The third type of user browsing - the highest rate of purchase, browsing to like the goods will be directly purchased, the purchase behavior is more decisive. The above analysis results help enterprises to target the promotion of their own products, to enhance corporate profits.

The experimental group of students who applied the teaching mode constructed based on the consumer clicking behavior recognition algorithm on the e-commerce platform had a higher average score of 4.3 points compared with the control group, indicating that the teaching mode constructed in this paper can help to promote the e-commerce education of students in higher vocational colleges and universities, and help to improve the knowledge level of e-commerce education of students in higher vocational colleges and universities.

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