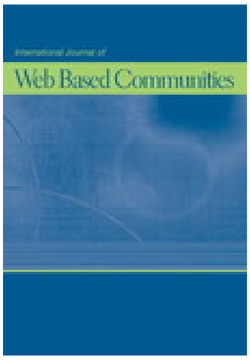

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Cluster analysis of perceptual demands of users' internet consumption behaviours based on improved RFM model

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Cluster analysis of perceptual demands of users' internet consumption behaviours based on improved RFM model

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Abstract: In order to overcome the problems of traditional clustering analysis methods, such as low accuracy, long consuming time and less demand types, a clustering analysis method based on improved RFM model is proposed in this paper. The intelligent internet of things platform is used to collect the data of users' online consumption behaviour, and the frequent patterns of the data collection results are mined according to the big data fusion method. The improved RFM model is used to obtain three parameters: users' latest consumption, user consumption frequency and consumption amount, so as to realise the clustering analysis of users' perceptual demand of online consumption behaviour. The experimental results show that with high clustering analysis accuracy and ability of consuming clustering analysis time by always less than 9.0 s, this proposed method can effectively cluster more types of user needs, suggesting that the clustering analysis effect of this method is relatively ideal.

Keywords: improved RFM model; online consumption behaviour; perceptual demand clustering; smart IoT platform; frequent patterns.

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1 Introduction

Under the background of the continuous development of economic development and social productivity, the consumption concept of consumers has changed greatly because of the influence of various factors (Yi and Hao, 2020). The simple material demand has evolved to psychological demand. Under the impact of new commodity and sales mode, the traditional commodity marketing mode can no longer meet the actual needs of consumers (Wu et al., 2020). Compared with the material demand, the emotional demand of users is a deeper form of demand, which can reflect the psychological demand of consumers for goods. The application of user demand analysis to the personalised design of goods helps to improve the perceptual characteristics of goods, provide consumers with more reasonable commodity recommendation mode, and improve the degree of personalisation of goods (Lv et al., 2019). At this stage, when enterprises design products, they pay too much attention to the R&D and design of the products themselves, while ignoring the analysis of the actual needs of consumers, resulting in the production of products that cannot meet the personalised production needs (Jing et al., 2018). Therefore, scholars in related fields have made some progress in this field.

The paper proposes a multi-dimensional perceptual analysis method of user demand, analyses the demand level of consumer behaviour, classifies the demand levels by induction, and uses multi-dimensional analysis to obtain the type of user demand. The multi-dimensional perceptual method is used to determine the type of demand analysis and realise the user demand analysis. This method can help better understand user requirements, with better rationality, but the accuracy of demand clustering analysis is not high. In the paper (Hu et al., 2020), a simple Bayesian based analysis method of user network consumption behaviour is proposed. The user behaviour data is processed by fuzzy c-means clustering, and the user behaviour consumption behaviour is divided by naive Bayesian classifier. According to the results of the classification, the user network consumption behaviour analysis is obtained. This method can effectively analyse the consumer behaviour of the user network, but the real-time performance of demand clustering analysis is not strong. Zhou et al. (2019) proposes an analysis method of user network consumption behaviour based on self-organisation centre k-means algorithm. According to the principle of self-organisation centre k-means algorithm, the user consumption behaviour index is established, and the user consumption behaviour is analysed. The experimental results show that this method has the characteristics of accurate identification of consumer behaviour, but it is still lack of comprehensive clustering analysis.

Due to the shortcomings of traditional methods in the accuracy, real-time and comprehensiveness of clustering analysis, the RFM model is improved to realise the clustering analysis of users' perceptual needs. The following is the specific design idea of this paper:

First of all, the intelligent internet of things data gateway in the intelligent internet of things platform is used to collect the data of users' online consumption behaviour, including consumption quantity, consumption amount, product quantity, product consumption type, product consumption time, etc.

Secondly, the RFM model is improved to extract the perceptual demand characteristics of users' online consumption behaviour, and the data types of users' online consumption behaviour are divided.

Then, the big data fusion method is used to mine the frequent patterns of different types of demand data to obtain the perceptual demand characteristics of users' online consumption behaviour. With the improved RMF model, the clustering analysis results of perceptual demand of users' online consumption behaviour are obtained.

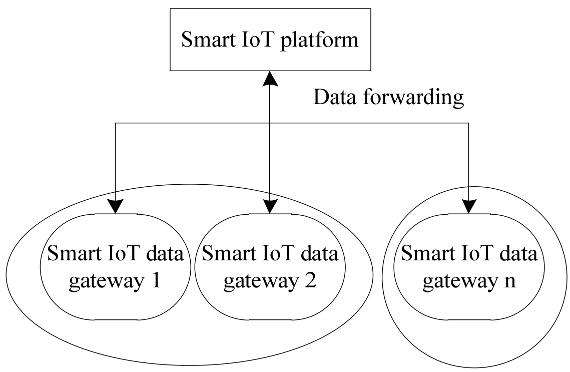
Finally, the accuracy of clustering analysis, real-time clustering analysis and comprehensiveness of demand clustering analysis are taken as experimental indicators, and the clustering analysis effect of Cao et al. (2019), Hu et al. (2020), Zhou et al. (2019) and this method is compared, and the conclusions are drawn.

2 Classification of users' perceptual demand for online consumption behaviour

In the process of user network consumption behaviour perceptual demand clustering, the clustering process is divided into three links, namely demand classification, demand feature extraction, and demand cluster analysis (Si, 2021). The user network is realised through three levels of interconnection. Consumption behaviour analysis provides a reference for corporate sales.

The smart IoT platform is used to collect user network consumption behaviour data. This platform can provide a data foundation for network marketing, having a relatively broad market application prospect (See-To and Ngai, 2019). The overall architecture of the platform is shown in Figure 1.

Figure 1 Smart IoT platform architecture



According to Figure 1, different types of user network consumption behaviour data are collected through each smart IoT data gateway in the smart IoT platform, and then the collected data are aggregated into a data collection through data transmission (Subahi et al., 2019). Tthe set can be expressed by equation (1):

$$K = (k_1, k_2, \ldots, k_n) \tag{1}$$

where k is the data type and n is the number of types, $n = 1, 2, \ldots, N$.

According to the results of data collection, the different data types are classified in order to analyse the perceptual needs of users' online consumption behaviour in a targeted manner. In the process of data type classification, the decision tree method is mainly used. The traditional classification method does not take into account the characteristics of the continuity of data characteristics and the existence of certain missing values in the dataset, so it is easy to cause over-fitting problems (Ben-Hassen et al., 2020). The decision tree method uses information gain as a measurement standard (Li et al., 2019) to divide decision tree nodes, which can effectively solve the over-fitting problem. The following describes the process of user network consumption behaviour perceptual demand data classification based on decision tree:

First, decision tree nodes are selected through information entropy, and the information entropy calculation equation is:

$$E_\eta = \int_{-\infty}^{\infty} f(\tau_{ei}, \tau_{i,rms}) \tag{2}$$

where τ_{ei} represents the boundary data in the dataset; $\tau_{i,rms}$ represents the optimal feature subset; f represents the node partition attribute; η represents the internal node in the decision tree.

In the process of perceptual demand data classification, if there are S different categories, then the probability coefficient of the s-th category is r_s, and its Gini coefficient $F(k)$can be calculated by equation (3):

$$F(k) = A_n \cdot E_\eta \left[\cos\left(2 f_a / f_s\right)\right] \tag{3}$$

where A_n represents the normal distribution of the Gini coefficient; f_a represents the data dimension; f_s represents the evaluation function for data category selection.

If the classification of perceptual demand data is regarded as a binary classification problem, then the Gini coefficient can be converted into:

$$A_\alpha = \sum_{m=1}^{M} \sin\left[\theta(m) \times F(k)\right] \tag{4}$$

where $\theta(m)$ represents the training set; m represents the number of sample data; M represents the threshold of the Gini coefficient, and the calculation equation is:

$$M = \frac{f_t \times c_{t-1}}{C} \tag{5}$$

In equation (5), c_{t-1} is the missing value of perceptual demand data of user consumption, and f_t is the information gain of user consumption behaviour.

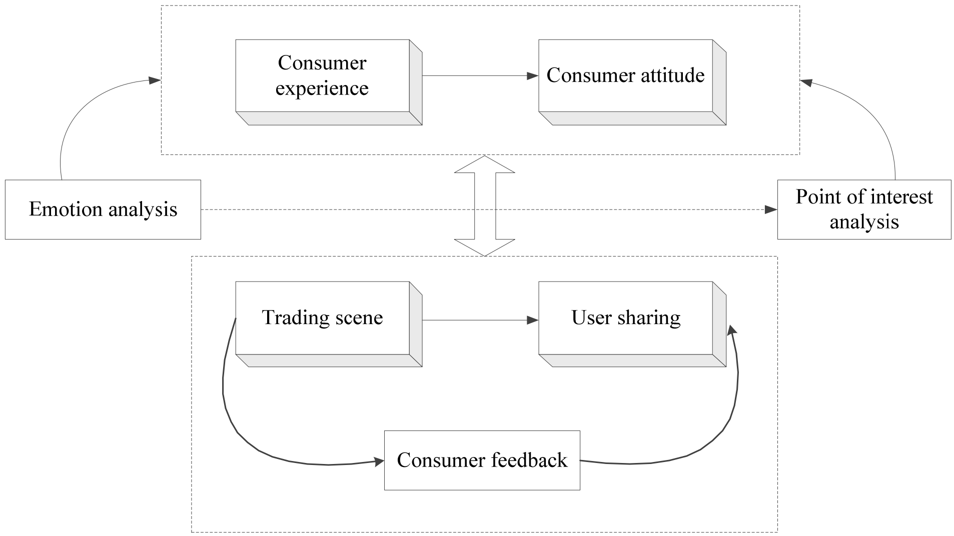
The Gini coefficient corresponding to each feature in the decision tree node is analysed to divide the data types, and the perceptual demand of the user's consumption behaviour can be classified. The above coefficients are substituted into the improved RFM model to cluster the consumption behaviour perceptual demand.

3 Clustering analysis of users' perceptual demand of online consumption behaviour based on improved RFM model

3.1 Feature extraction of perceptual demand of users' online consumption behaviour

Through big data technology, users' online consumption behaviour can be analysed, summarised and classified, and the results generally do not have users' personal characteristics (Chen et al., 2020). This paper extracts the characteristics of users' online consumption behaviour based on the data classification results, so as to obtain the consumption characteristics with users' personal characteristics, It is used to reflect the real feelings of users and their attitude towards products (Fook and Mcneill, 2020). Based on the classification results, the model of user perceptual demand feature extraction is established by emotional analysis. The overall structure of the model is shown in Figure 2.

Figure 2 Schematic diagram of user perceptual demand feature extraction model



According to Figure 2, in the process of extracting the user's perceptual demand characteristics, the user consumption attitude and user consumption feeling are the basis (Augsburger et al., 2020). The user transaction scenario and user feedback information are obtained through emotional analysis and interest point analysis, and the feature analysis results are obtained by analysing the user's perceptual demand characteristics according to the user feedback information. In feature analysis, a large number of user emotional needs information will be generated. It is helpful to effectively mine these information, which is conducive to improve the feature extraction effect (Maciaszczyk and Kocot, 2021).

In the process of mining, the big data fusion method is used to mine the frequent patterns of different types of demand data, and the feature extraction is realised according to the mining results. The frequent pattern set of demand data can be expressed as:

$$N' = \left(n_{1,i}, n_{2,i}, \ldots, n_{ij}\right) \tag{6}$$

where n_{ij} is the frequent pattern set item of consumer behaviour demand data, and i is the weighting coefficient of frequent patterns; j represents static data in demand data.

On this basis, the dynamic feature segmentation method is used to obtain the standard error z_t of demand feature extraction：

$$z_t = N'(k_t - b_t) \tag{7}$$

where k_t represents the constraint feature vector; b_t represents the average error.

The feature extraction model of frequent patterns of different types of demand data is established. P_{h+1} represents the characteristics of user transaction feedback information, and the output of feature extraction results is obtained θ_t:

$$\theta_t = k\mu_t P_{h+1}(e) \tag{8}$$

where μ_t represents an eigenvalue pair, and its calculation equation is:

$$\mu_t = f_{i,j}\left(x_i - y_i\right) \tag{9}$$

From this, the extraction results of perceptual demand characteristics of users' online consumption behaviours are obtained, which provides a basis for demand clustering analysis.

3.2 Cluster analysis of users' perceptual demand for online consumption behaviour

On the basis of Section 3.1, cluster analysis of users' perceptual demand for online consumption behaviour is carried out. RFM model has the advantage of a wide range of applications. It has been widely used in all walks of life, which helps the industry to analyse the consumer demand of consumer groups. The traditional RFM model is effective when it only analyses a small number of user needs. However, when the amount of data to be processed increases or the data changes greatly in a short period of time, the clustering analysis effect is not good, it is necessary to improve the traditional RFM model.

In the improved RFM model, *R* represents the user's last consumption, *F* represents the user's consumption frequency, and *M* represents the total amount of the user's consumption at one time. Based on the above three parameters, the perceptual needs of the user's consumption behaviour are analysed. Firstly, get the user's last consumption behaviour expression as:

$$C(X,Y) = \frac{P(X \cap Y)}{\min(P(X), P(Y))} \tag{10}$$

where *X* means interest and hobby driven; *Y* is the user's consumption intention, *P* is the symbol of probability operation:

$$X = \begin{bmatrix} 1 & x_{11} & x_{1l} \\ 1 & x_{21} & x_{2l} \\ 1 & x_{n1} & x_{nl} \end{bmatrix} \tag{11}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{(n \times m)} \tag{12}$$

Secondly, to obtain user consumption frequency $F(x, y)$, the calculation equation is:

$$F(x,y) = \sum\nolimits_{a=1}^{n} \sum\nolimits_{b=1}^{n} \frac{1}{(2a+1)(2b+1)} \tag{13}$$

where *b* represents the frequency of the user's consumption attribute value.

Finally, the total amount of the user's consumption is obtained at one time and the calculation equation is:

$$C_{total} = \frac{2P(X \cap Y)}{P(X) + P(Y)} \tag{14}$$

In equation (14), $C(X)$ is the individual consumption amount driven by the user's interests, $C(Y)$ is the individual consumption amount driven by the user's consumption behaviour intention, and $C(X \cap Y)$ is the actual consumption amount driven by two-way factors.Through the above three elements, the cluster analysis results of perceptual demand of users' online consumption behaviours are obtained. These three parameters are the best indicators for analysing user's consumption behaviours.

In summary, through the three links of demand classification, demand feature extraction and demand cluster analysis, the user's consumption behaviour demand analysis is realised, and the user's latest consumption, consumption frequency and consumption amount are obtained, which provides a certain amount of information for demand analysis. The foundation helps to improve the comprehensiveness and accuracy of the analysis results.

4 Simulation experiment analysis

In order to verify whether the perceptual demand cluster analysis method of user network consumption behaviour based on the improved RFM model has practical value in the field of user behaviour analysis, the simulation experiment design is carried out.

4.1 Experimental plan design

Before the start of the experiment, in order to clarify the experimental process and improve the efficiency of the experiment, the specific experimental plan was designed.

4.1.1 Experimental hardware environment

The experiment is carried out in a simulation platform, and the simulation diagram of the experiment is shown in Figure 3.

Figure 3 Schematic diagram of simulation experiment platform (see online version for colours)

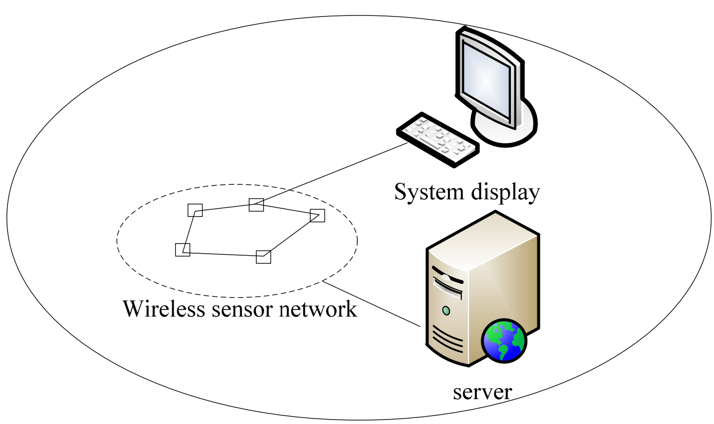


Table 1 Clustering data related to consumption of some users

Serial number	*Full name*	*Age*	*Gender*	*Trade name*	*Price / Yuan*	*Place of origin*	*Other information*	*Commodity category*
1	Liu**	21	female	Estee Lauder lipstick	188	Belgium	3.2g	cosmetics
2	Gao**	27	Male	Lofi mechanical keyboard	1,019	China	Alternate action or ergonomic	electronic correlation
3	Ma*	34	Female	Hegen feeder	278	Singapore	150ml	infant and mom
4	Lu**	41	Male	TISSOT Mechanical watch	2,887	Switzerland	stainless steel	ornament
5	Ling*	32	Male	FILA Dad Shoes	619	Italy	synthetic leather	shoes
6	Wang**	28	Male	Valley Junior Shirt	429	China	polyester fiber	clothing
7	Kang**	22	Female	Nongxin xin ramen noodles	20.9	Korea	120 g*5	fast food
8	Jiang**	38	Female	Honghu tempts spicy shrimp tails	17.99	China	252g	fresh food

4.1.2 Source of experimental data

This paper selects the user consumption records of an online shopping website in the latest month to form a dataset. The total amount of data in the dataset is 1,500mb, including various types of commodity sales data, with a wide range of data types. Some clustering data are shown in Table 1.

According to the above data for experimental verification.

4.1.3 Experimental indicators

1. Accuracy of demand cluster analysis: This indicator can reflect whether the clustering method can accurately cluster user consumption behaviour, and provide a reference for enterprises to make production and sales decisions based on user consumption behaviour. The higher the clustering accuracy, the more reliable the clustering result, which can be calculated by equation (15):

   $$C_i = \frac{u_i - u_j}{U_{ij}} \times 100\% \tag{15}$$

   where u_i represents data generated during clustering; u_j represents invalid data generated during clustering; U_{ij} represents the total amount of user consumption behaviour data.

2. Efficiency of demand clustering analysis: This indicator is used to measure the clustering efficiency of the method. Because user consumption behaviour has real-time variability, it is necessary to perform cluster analysis on user consumption behaviour within a limited time. Analysis will cause the consequences of information lag and affect the production and sales decisions of enterprises.

3. The comprehensiveness of demand cluster analysis: due to the diversity of user types and the differences of consumer behaviour, all aspects must be taken into account when clustering analysis of user consumption demand. Therefore, the comprehensiveness of demand cluster analysis is also a key indicator to measure the practical value of the method. The specific calculation equation of time t_a for demand cluster analysis is as follows:

   $$t_a = t_2 - t_1 + \Delta t \tag{16}$$

   In equation (16), t_1 is the start time of user consumption behaviour clustering, t_2 is the end time of user consumption behaviour clustering, and Δt is the measurement error. The shorter the time of requirement clustering analysis, the higher the efficiency of this method. On the contrary, the higher the efficiency of this method, the lower the time of requirement clustering analysis.

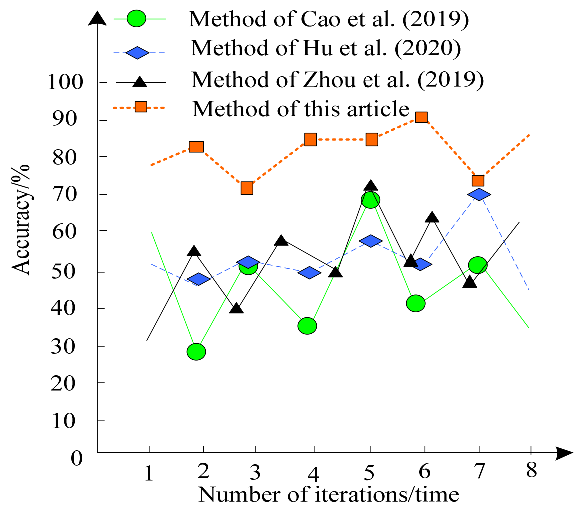
4. Comparative methods: the methods of Cao et al. (2019), Hu et al. (2020) and Zhou et al. (2019) are selected as comparative methods to compare with the methods of this paper.

4.2 Analysis of comparative results

4.2.1 Accuracy of demand cluster analysis

With the accuracy of cluster analysis of perceptual demand of users' online consumption behaviour as the experimental index, the method of Cao et al. (2019), the method of Hu et al. (2020) and the method of Zhou et al. (2019) are compared with the method of this paper. The comparison result is shown in Figure 4.

Figure 4 Comparison of accuracy of demand cluster analysis (see online version for colours)



According to the analysis of Figure 4, when the number of iterations is one, the accuracy of requirement clustering analysis of Cao et al. (2019) method, Hu et al. (2020) method, and Zhou et al. (2019) methodis 60%, 52%, and 31%, respectively, and the accuracy of requirement clustering analysis of this method is 76%; when the number of iterations is 6, the accuracy of requirement clustering analysis of Cao et al. (2019) method, Hu et al. (2020) method, and Zhou et al. (2019) method is 42%, 51%, and 31%, respectively, and the accuracy of requirement clustering analysis of this method is 91%. Through comparison, it can be seen that the accuracy of clustering analysis of perceptual demand of users' online consumption behaviours under the method proposed in this paper is higher than that under traditional methods under different iteration times which shows that the accuracy of this proposed method is higher and the clustering results are more reliable.

4.2.2 Demand clustering efficiency

With the clustering efficiency of perceptual demand of users' online consumption behaviour as the experimental index, this paper compares the methods of Cao et al. (2019), Hu et al. (2020) and Zhou et al. (2019) with the methods of this paper, and the comparison results are shown in Table 2.

According to the data in Table 2, under the condition that the amount of user data is increasing, the clustering analysis time of perceptual demand of users' online consumption behaviour of Cao et al. (2019), Hu et al. (2020), Zhou et al. (2019) and this method is increasing, that is, the efficiency of demand clustering is gradually decreasing. Cao et al. (2019) method from 10.3s to 13.5s, a total increase of 3.2s, Hu et al. (2020) method from 9.9s to 14.3s, a total increase of 4.4s, Zhou et al. (2019) method from 10.6s to 13.8s , A total increase of 3.2s, and the method in this paper from 7.9s to 8.9s, only an increase of 1.0s, the increase is small. And the cluster analysis time of the method in this paper is always lower than that of the traditional method. When the number of iterations is 5–7 times, the cluster analysis time remains unchanged. Through the above analysis, it can be known that the method proposed in this paper requires shorter cluster analysis time, with a higher clustering efficiency, and can perform cluster analysis on user consumption behaviour in a limited time.

Table 2 Comparison of demand clustering efficiency

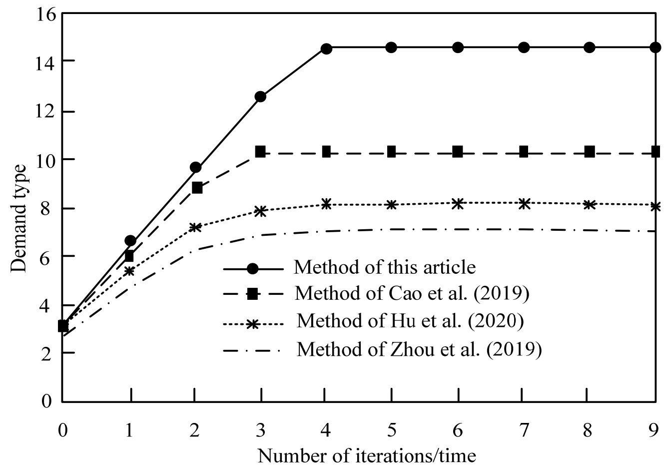
Number of data objects/person	*Demand clustering efficiency/s*			
	Method of this article	*Cao et al. (2019) method*	*Hu et al. (2020) method*	*Zhou et al. (2019) method*
1	7.9	10.3	9.9	10.6
2	8.0	10.4	10.5	10.9
3	8.2	10.5	11.1	11.2
4	8.4	10.9	11.6	11.6
5	8.5	11.4	11.8	11.9
6	8.5	11.6	12.0	12.5
7	8.5	11.9	12.9	12.8
8	8.7	12.5	13.6	13.0
9	8.7	12.8	13.9	13.0
10	8.9	13.5	14.3	13.8

4.2.3 Comprehensiveness of demand cluster analysis

With the comprehensiveness of the perceptual demand cluster analysis of users' online consumption behaviours as the experimental index, the method of Cao et al. (2019), the method of Hu et al. (2020) and the method of Zhou et al. (2019) are compared with the method of this paper. The comparison result is shown in Figure 5.

It can be seen from the analysis of Figure 5 that in the comprehensive comparison results of demand cluster analysis, there are generally two stages of change. In the first stage, the number of iterations is in the range of 0–4. At this time, in the perceptual demand analysis of users' network consumption behaviour, the demand types analysed by the methods of Cao et al. (2019), Hu et al. (2020), Zhou et al. (2019) and this paper show a larger increasing trend; The second stage is that the number of iterations is after 4 times. At this time, the method of Cao et al. (2019), the method of Hu et al. (2020), the method of Zhou et al. (2019) and the method of this article are the needs of analysis in the perceptual demand analysis of user network consumption behaviour, the trend of type changes gradually slowed down. Through comparison, it can be seen that there are more types of needs analysed by the method proposed in this paper, indicating that it has a certain comprehensiveness and can perform cluster analysis for different users and different needs of users.

Figure 5 Comprehensive comparison of demand cluster analysis



5 Conclusions

In order to improve the accuracy, real-time and comprehensive of traditional clustering analysis methods, a clustering analysis method based on improved RFM model is proposed. With the help of the intelligent internet of things platform, data of users' online consumption behaviour are collected, which provides data basis for demand analysis. The traditional RMF model is improved according to the mining results, and the clustering analysis results of users' perceptual needs of online consumption behaviour are obtained. The results are as follows

1. When the iteration times are 60, the accuracy of the method is 91%, which indicates that the accuracy of the method is high and the clustering analysis effect is improved effectively.
2. When the amount of user data increases from 10GB to 100GB, the clustering analysis time of this method is from 7.9s to 8.9s, which only increases by 1.0s. The clustering analysis time is short, which indicates that the analysis efficiency of this method is high.
3. In the range of 10–50 GB, the analysis of perceptual demand types of users' online consumption behaviour shows an obvious increasing trend; After 50 GB times, the number of demand types obtained by this method is obviously more than that by traditional methods, which shows that the method is more comprehensive and can cluster analysis for different users and their different needs.

To sum up, the clustering analysis method in this paper is effective, and can effectively assist enterprises to make sales decisions and equationte sales plans to meet the needs of consumers.

Although this method has achieved some results, because it does not take into account the order cancellation behaviour in user consumption, there are some limitations in the results of demand analysis. Next, we will analyse the whole process of user consumption, so as to further improve the effect of user consumption behaviour analysis.

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