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Research Article

A SOM-Based Customer Stratification Model

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This paper used the SOM in combination of the optimized RFM for customer stratification, to develop targeted marketing strategies for enterprises. In this paper, customers were grouped into four categories, including core customers, opportunistic customers, service drain customers, and marginal customers, using the customer consumption data of a retail enterprise by SOM, a clustering algorithm based on neural networks, in combination with the optimized RFM from the perspective of machine learning. The value of customers in different categories was determined based on their typical features for a visualized analysis, to develop targeted marketing strategies for enterprises.

1. Introduction

Economic globalization and the global supply chain system provide consumers with abundant choices, contributing to a consumer-dominated market since long ago. Zheng et al. believed that customers' demand for products has evolved from the most basic version of needing a product itself to higher requirements for the quality and price of various products and services [1]. However, enterprises cannot meet the needs of all customers at the same time due to the scarcity of resources and the high service costs, which makes customer stratification management even more necessary [2, 3]. When marketing everything to everyone was proved ineffective in terms of profits, companies began to divide customers into different groups [4]. It is worth mentioning that, although both of the customer stratification and traditional market segmentation are aimed at improving profits by classifying customers, market segmentation mainly through the analysis of overall characteristics of consumers or specific consumption situation for segmentation criteria to select the target customers increases revenue to increase profits [5], while customer stratification is based on the match of customer value and the services provided by the enterprises to reduce costs to improve profits. Homburg et al. proved that customer stratification is so profitable as it distinguishes the value of customers that it should become the active strategic choice of marketers [6]. Accurate marketing strategy is the key to the healthy and sustainable development of enterprises, and profits can be maximized by establishing customer stratification models.

In the era of big data, artificial intelligence (AI) and machine learning are applied to customer stratification models. The marketing strategies of enterprises are improved to increase profits based on the customer value evaluating results. In particular, COVID-19 has had a severe impact on offline retailing, making online retailing increasingly important [7]. The traditional marketing approach of face-to-face interaction with customers has been limited, and it must be transformed to leverage information contained in data to support the marketing decisions of enterprises. Therefore, enterprises urgently need data mining tools enabled by machine learning to support marketing decisions and need guidance from related theoretical research on customer stratification [8].

In this paper, customers were grouped into four categories using SOM in combination with the optimized RFM from the perspective of machine learning. The value of customers in different categories was determined based on their typical features for a visualized analysis, so as to develop targeted marketing strategies for enterprises [9, 10].

2. Research Status at Home and Abroad

Studies on customer stratification at home and abroad can be classified into two types. The first type of studies put forward the theoretical basis for customer stratification without discriminating between different industries. The second type conducted customer stratification according to industry-specific characteristics and proposed different evaluation models and clustering methods.

2.1. Studies on Customer Stratification Theories. The concept of customer stratification dates back to 1989. Bellis-Jones believes that many corporates suffer loss of profits because they fail to match the profits brought by customers with their service costs. Fowler et al. believed that developing accurate marketing strategies through an effective customer stratification model can help enterprises reduce service costs and increase profits [11]. Especially, technological advances have driven the shift in marketing strategy from product-centric to customer-centric, and the increasing availability of customer transaction data enables marketing managers to better understand the customer base of a firm [12]. A large number of theories and research methods at home and abroad show that analyzing customer consumption records through RFM and machine learning can help enterprises develop targeted marketing strategies based on customer value. Hughes proposed the RFM and used indicators such as regency (consumption proximity), frequency (consumption frequency), and monetary (consumption amount) for customer stratification [13]. Sampson proposed that a service could be treated as a modifiable process, rather than a result, as most previous studies did [14]. And Robinson and Chen believe that service will cause cost [15]. Lawrence and Pa established the core framework of customer stratification, adding the indicator of service costs to the customer stratification model and grouping customers into core customers, opportunistic customers, service drain customers, and marginal customers [16]. Dursun and Caber adopted different management strategies for different customers according to the different evaluations of RFM to achieve the purpose of customer relationship management [17]. The purpose of customer relationship management (CRM) is for enterprises to be customer-centric, to constantly understand customer needs, to provide products and services to customers, to promote customer transactions, and to achieve customer value [18–21]. And RFM model can explore quantitative characteristics and enrich the criteria of potential relationships in CRM [4]. Therefore, Ramón Alberto et al. [22] believe that customer purchase behavior can be obtained from transaction data through RFM model, to actively trigger appropriate direct marketing movement. To sum up, the above studies focused on how to evaluate the level of customer profit contribution, but rarely consider how to maximize customer value. On this basis, this paper innovatively proposes that enterprises should provide accurate services for customers of different categories to improve their value contribution to enterprises.

2.2. Studies on Customer Stratification Application. The purpose of customer stratification is to clearly identify customers with different value and inform the marketing decisions of enterprises. The commonly used methods include single-dimensional classification, multiple factor clustering, and RFM [23, 24]. Therefore, combining theories with actual enterprise data to provide useful theoretical support and guidance for enterprises is the focus of studies on customer stratification application. In application studies, the RFM is currently the most recognized customer stratification model. Hughes first proposed the RFM and the three indicators of R (recency), F (frequency), and M (monetary) in 1994 [13]. Chen et al. used computer simulation of 2, 000 pieces of data according to the RFM to achieve customer stratification, which is the earliest study on RFM in China [25]. Table 1 summarizes the customer stratification studies on RFM over the past decade and its application to different industries.

The studies shown in Table 1 have their own specific use environments and practical application advantages in the evaluation and improvement of RFM-based models and the selection of customer stratification methods with their industry-specific characteristics and data types.

(1) Development of evaluation models

Studies on model development can be divided into two categories: the first sticks to the three indicators of R, F, and M of the traditional RFM, while the second deletes, replaces, or increases indicators based on the three indicators of R, F, and M of the traditional RFM according to industry-specific contexts to develop a new customer evaluation model. References [26, 27, 30, 34, 36] adopted the three indicators of the traditional RFM. References [29, 31, 37, 39, 40] added new indicators according to industry-specific characteristics. References [33, 35] deleted and added indicators based on the three indicators of the traditional RFM to develop a new customer evaluation model. Although the RFM has been widely used, most of the studies focused on the number of indicators rather than the question of whether the feature extraction of the RFM is reasonable [41, 42]. In particular, a large number of studies tend to adopt the feature extraction method of the traditional RFM without reflecting on the potential mathematical regularity and meaning, which might no longer be appropriate for the era of big data.

(2) Customer stratification methods

The most widely used customer stratification method currently is the K-means clustering algorithm (hereinafter referred to as K-means). Studies related to customer stratification and machine learning can be grouped into three categories: traditional K-means, optimized K-means, and other algorithms.

References [29–31, 33] used the traditional K-means for customer stratification according to the characteristics of different industries, but the clustering results were inaccurate because of the impact of K (initial value) and a long clustering time [19]. As a result, references [24, 26, 28, 35] improved the traditional K-means by combining it with other algorithms. In addition, Chan subdivided customer value through GA; Yan and Liu used optimized SOM for

Table 1: Customer stratification studies on RFM at home and abroad.

Author	Method	Industry	Model optimization
Chan et al. [26]	SOM, K-means, PSO	Auto retailing industry	RFM
Chan [27]	GA	Auto retailing industry	RFM, CLV
Güçdemir and Selim[28]	K-means, fuzzy AHP	Equipment manufacturing industry	RFM, five variables
Huang and Liu[29]	K-means	China's railway industry	RFMICT
Momtaz et al. [30]	K-means	Fast food industry	RFM
Li et al. [31]	Hierarchical clustering, K-means	Insurance company industry	LRFM
Pu et al. [32]	Density information entropy, K-means	4 artificial datasets in UCI	TFA
Ren et al. [33]	K-means	Autoindustry	LRFAT
Sarvari et al. [34]	K-means, SOM, Aprior	Pizza catering industry	RFM, demographic
Weng and Xie[35]	Adaboost, K-means	Highway industry	RFMS
Xu [36]	AHP	Communications industry	RFM
Yan and Liu[37]	Optimized SOM	Insurance companies	RFMC
Zheng [38]	SAS	Retail industry of refined oil products	Five indicators
Zhou et al. [39]	DBN prediction	E-commerce industry	RLFGM(MM)D

an optimized customer stratification model, which prove that using SOM is available [27, 37].

SOM is characterized by mapping multidimensional input to low-dimensional network, with no parameters, high accuracy, and good visual effects [23]. As an unsupervised learning method, it requires neither the labeling of testing sets nor the initial value as required by the K-means. Therefore, it is easier to use and more practical in big data processing while reducing the influence and error of human factors. Kiang used the cluster analysis results of three typical cases in machine learning to compare the SOM neural network combined with neighboring constraint clustering with k-means method and other methods, which showed that the clustering effect of the extended SOM neural network was superior to other methods [41]. In addition, the purpose of this study is to provide effective guidance and tools for the practice of enterprises. In this way, compared with other methods, neural network has more convenient operation, stronger practicability, and stronger data processing ability in practical application.

Therefore, this paper used the SOM in combination of the optimized RFM for customer stratification. Customers were grouped into four categories, including core customers, opportunistic customers, service drain customers, and marginal customers, according to the core framework of customer stratification proposed by Lawrence and Pa[16].

There are two reasons to select this framework of customer stratification. First, the framework of customer stratification proposed by Lawrence and Pa is one of the most recognized classification methods, which is convenient for enterprises to understand and accept. Second, this framework meets the needs of this paper, which classifies customers based on customer value. At the same time, this paper draws lessons from the thought of the customer stratification framework and innovatively proposes to redefine the customer stratification according to the service efficiency of enterprises for customers, so as to evaluate the customers' value to match the service. To sum up, this study adopts Lawrence and Pa's customer stratification method.

3. Research Design

This paper redefined the core framework of customer stratification by the SOM in combination of the optimized RFM to match the clustering results, so as to improve the accuracy and practicality of the customer stratification model.

3.1. Optimization of the Customer Evaluation Model Based on RFM. R refers to recency: the time since a customer's most recent purchase, which is the most general one of the three indicators of the RFM. One of the most important reasons is that simply comparing the time interval can easily ignore the differences between individual customers and the potential regularity in transaction times. This paper believes that the time intervals of the same consumer between two adjacent purchases have their own mathematical regularity, which may be gradually increased or decreased, or may generally remain unchanged. There could also be a peak in the probability distribution since the last purchase, satisfying the function curve of standard normal distribution.

First, suppose there has been i purchases from one consumer, x_i is the No. i transaction, and t is the time interval between the last purchase and the currency. After a linear regression is conducted with all the time intervals as the independent variables, the next interval, namely, h, can be predicted, at which the peak of normal distribution curve appears. Given that about 99.7% of the values were distributed within 3 standard deviations from the mean, the initial point was set 3 standard deviations to the left of the distant point. A simple mathematical transformation was then performed to obtain the score of R, namely, $f(w)$.

$$w = \left(3\frac{\sigma}{h} * t\right) - 3\sigma, \tag{1}$$

$$f(w) = \frac{1}{\sigma\sqrt{2\pi}} * e^{-\left(w^2/2\sigma^2\right)}. \tag{2}$$

(1) Because of standard normal distribution, $\mu = 0, \sigma = 1$

(2) When

$$\Delta x_{i+1} = h, f(w) = f(0), \tag{3}$$

where the score of R of customers with only one purchase was assigned 0.

F refers to frequency: the purchase frequency of customers, i.e., the number of purchases of a customer over a period of time. The possibility of the next purchase of different customers can be evaluated based on their different numbers of purchase by Z-score standardization for application in this paper. f_i was the frequency of purchase for No. i customer, and s was the standard deviation of frequency of purchase for all customers.

The score of F was calculated with

$$F = \frac{f_i - \bar{f}}{s}. \tag{4}$$

M refers to monetary: the total consumption expenditure. Simply calculating the total amount by adding all the consumption expenditure means that the model embraces all transactions and considers all transactions beneficial to enterprises. However, it is not the case. According to the whale curve proposed by Turney [40], the top 20% of customers provide nearly 500% of the profits, while the next 60% can only maintain the total enterprise profits, and the bottom 20% would only cause the loss of enterprise profits (Figure 1).

The 80th percentile amount was set as the baseline value (N') by ranking the amount sizes according to the whale curve. The baseline value was then compared with all transaction amounts. If a purchase has a transaction amount above the baseline value, it was considered beneficial to the enterprise. Otherwise, a purchase was considered to hinder other potentially large purchases.

The score of a single transaction was calculated with Formula (5) using the maximum minimum difference method, while N_i means the amount of No. i purchase of all transaction. The scores of all transactions of the same customer were then calculated with Formula (6) to obtain the score of M.

The formulas used are as follows:

$$N_i = \frac{N_i - N'}{N_i - N_{\min}}, \tag{5}$$

$$M_x = E(N_x), \tag{6}$$

where i is the No. i purchase of all customers; x is the No. x customer of all customers.

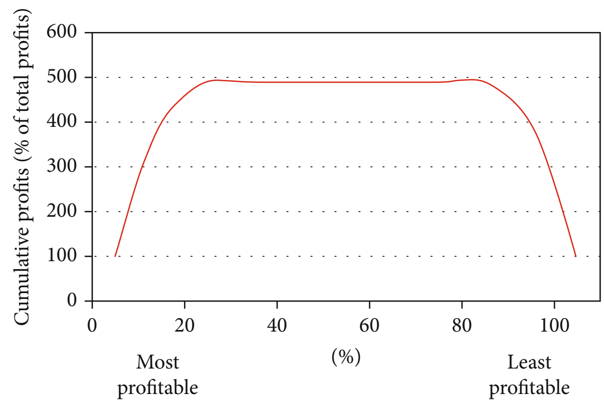

Figure 1: Whale curve.

3.2. SOM. The model of the SOM is illustrated in Figure 2. The clustering results were obtained in the output layer through the input of the input layer. The steps were as follows.

Step 1: after evaluation by the optimized RFM, the R, F, and M were used as the 3D data input layer

Step 2: the machine randomly initialized the parameters and weights for each node. The number of parameters for each node remained the same as that of the dimension of input data

Step 3: the node best matching each input datum was identified. $X = \{x_i\}$, where $i = 1, 2, \cdots, D$, and D was the dimension of input data, as shown in

$$d_j(x) = \sum_{i=1}^{D} \left(x_i - w_{ij}\right)^2. \tag{7}$$

Step 4: the node adjacent to the node $I_{(x)}$ was updated and activated. $S_{i,j}$ was the Euclidean distance between the nodes i and j. The weight between the $I_{(x)}$ and the adjacent node was updated according to the $S_{i,j}$, as shown in

$$W_{j,I(x)} = \exp\left(\frac{S_{j,I(x)}^2}{2\sigma^2}\right). \tag{8}$$

Step 5: the parameters for each node were updated by gradient descent, as shown in

$$\nabla w_{ji} = \eta(t) * W_{j,I(x)}(t) * \left(x_i - w_{ij}\right). \tag{9}$$

Step 6: the process was iterated to reach the final convergence and get the results.

3.3. Core Framework of Customer Stratification. After the clustering of the SOM, customers were grouped into four categories, including core customers, opportunistic customers, service drain customers, and marginal customers, using the R, F, and M according to the core framework of customer stratification. However, to make the results more consistent with the research purpose, the traditional core framework of customer stratification was redefined.

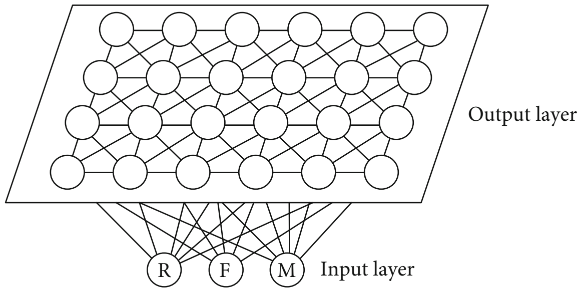

Figure 2: The model of the SOM.

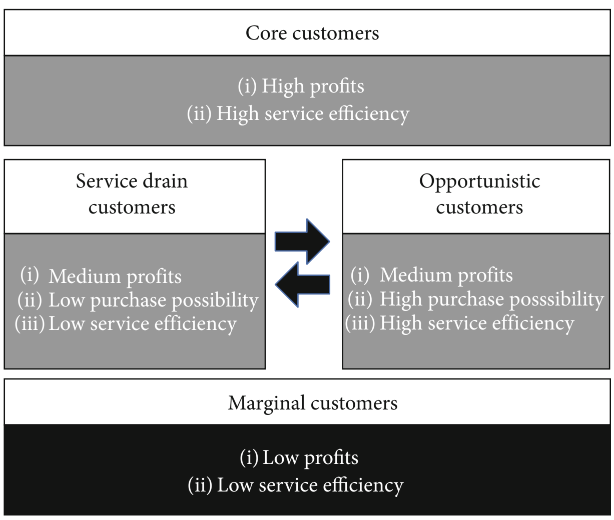

Figure 3: The core framework of customer stratification.

Table 2: Scores of the customer evaluation model.

ID	*R*	*F*	*M*
12347	0.07849752	0.060760722	0.014452207
12348	0.08900186	-0.094768688	0.00608105
12349	0.00553379	-0.172533393	0.022046248
12350	**0**	-0.405827508	0.004503809
12351	**0**	-0.405827508	0.003744018
12352	0.15441788	0.294054837	0.003382034
12353	0.39825267	-0.328062803	0.00152957
12354	**0**	-0.405827508	0.021415794
12355	0.19063161	-0.328062803	0.007668393
12356	0.00910226	-0.017003983	0.021027159
12357	0.00897101	-0.250298098	0.135293308

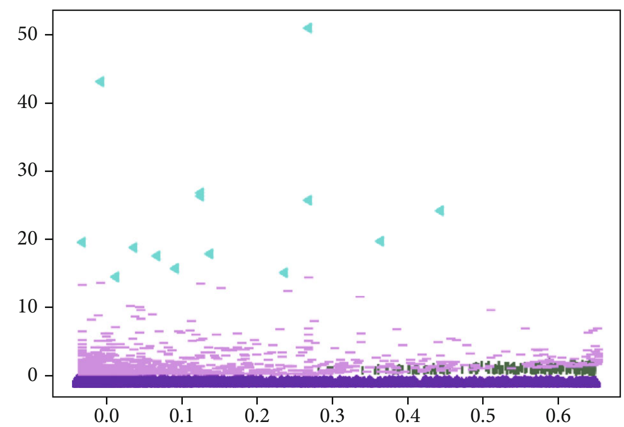

Figure 4: Stratification results of the SOM.

Lawrence and Pa believed that core customers are those bringing high profits and high loyalty, opportunistic customers are those featuring high profits and low loyalty, service drain customers are those bringing low profits and high service costs, and marginal customers are those featuring low profits and low loyalty [16].

This paper innovatively proposed to redefine the core framework of customer stratification according to the service efficiency of enterprises for customers (service efficiency = customer profit/service cost), as shown in Figure 3. Enterprises should serve core customers that represent high profits and high loyalty with more resources to maintain the relationship and provide them with high-quality personalized services as many as possible. As they will bring high profits far greater than the service costs, the service efficiency is very high. Enterprises should timely provide opportunistic customers, who could represent high profits to enterprises currently, with stimulating services to stimulate their consumption so as to maximize the profits they bring with low service costs at a high service efficiency. As service drain customers, although do not bring high profits now, have huge potential value and may be turned into opportunistic customers in the future, enterprises should maintain the relationship, which will cause service costs. Their service efficiency is therefore low. Enterprises should not provide personalized services for marginal customers, who represent low profits and low loyalty, to avoid high service costs, and their service efficiency is very low.

4. Experimental Processes

The experiment was performed using the Intel (R) Core (TM) i7-9750H CPU @ 2.60 GHz, a processor, and the NVDIA GeForce GTX 1650, a graphics card, under Python 3.9 in the Tensor Flow 2.6.0. The experiment used the SOM, with maximum learning rate – Euclidean distance lratemax = 0.9, minimum learning rate – Euclidean distance lratemin = 0.0001; maximum cluster radius–according to dataset rmax = 0.01; minimum cluster radius–according to dataset rmin = 0.005, iterations 100,000.

4.1. Dataset. This paper used the data published by a British online retail business on an official website. The dataset recorded the full transaction details of the business from December 1, 2009, to September 12, 2011, including 1,048,576 entries of data from 5,863 valid customers, with features including transaction invoice, stock code, product description, transaction product quantity, transaction invoice date, product price, customer ID, and country.

4.2. Data Preprocessing

Table 3: Results of the SOM.

Category	Average score of R	Average score of F	Average score of M	Number of customers	Proportion (%)
0	0.107450399	**14.14728157**	**0.023266175**	14	0.24
1	**0.338405726**	0.25454196	0.007399451	185	3.16
2	0.043089992	**-0.277349684**	0.005010768	4519	77.08
3	0.080704757	0.880516171	0.006612268	1145	19.53
Total				5863	100

(1) Data cleaning

First, data features were selected. On the basis of the requirements of RFM model. The five indicators of transaction invoice, transaction product quantity, transaction invoice date, product price, and customer ID were selected. Second, the data cleaning was performed, mainly by deleting noncompleted orders with abnormal transaction numbers, cancelled orders with the number of transaction product quantity less than zero, orders without transaction date displayed, and orders without customer ID displayed. Finally, the indicators were combined. A "single transaction amount" indicator was added, which was obtained by multiplying all product prices under the same transaction number by the quantity and adding the results.

(2) Feature extraction

Feature extraction was performed based on the optimized RFM. The feature R were first grouped according to the customer ID, then the time interval between existing transactions was calculated for linear regression prediction and then fed into the normal distribution function to obtain the score of R. The score of F was obtained by Z-score standardization. After comparing the standard value, the expected value was calculated, and finally, the score of M was obtained, as shown in Table 2.

As shown in Table 2, the score of R was between 0 and 0.3989. The higher the score of R, the greater probability for customers to purchase at the moment. Customers with a "0" R score were new customers with only one transaction. The score of F was the length between a customer's transaction frequency and the average of all customers. The higher the score of F, the larger the number of transactions. The higher the score of M, the higher the transaction amount. An M score below 0 indicated that enterprises should terminate the relationship with the customer in time to reduce its loss.

5. Experimental Results

The scores of R, F, and M of the RFM were input into the SOM to obtain the results, as shown in Figure 4.

In Figure 4, the vertical axis was almost effected by F and M, representing the evaluation of customers' current profit contribution to enterprises, and the horizontal axis was mainly effected by R, representing customers' current purchase possibility. It can be clearly observed from the figure that the results can be classified into three groups based on the vertical axis: the high-profit group, the medium-profit group, and the low-profit group. The scatter plots in the upper part of the figure represent the customers bringing high profits. To further analyze the results, the data features for each category were grouped and calculated by category, as shown in Table 3.

6. Result Analysis and Marketing Strategies

According to Table 3, the SOM divided 5,863 valid customers into four categories. Category 0, with only 14 customers, or 0.24% of the total number of customers, was the category with the smallest number of customers. In contrast, category 2, with 4, 519 customers, or 77.08% of the total number of customers, was the category with the largest number of customers. The customers in category 1 and category 3 accounted for 3.16% and 19.53% of the total number of customers, respectively. The customers in category 0, category 1, and category 3 only accounted for 22.92% of the total number of customers, but their scores of R, F, and M were much higher than those in category 2. This showed that the customers in category 0, category 1, and category 3 can bring higher profits despite their smaller number, in line with the "Pareto Principle."

(1) Marketing strategy for core customers

Based on the clustering results, the customers in category 0 can be defined as the core customers. Their scores of F were very high, indicating that they had a high purchase frequency and strong customer loyalty. Their scores of M were also much higher than those of customers in other categories, indicating that they had many transactions with very high transaction amount. Enterprises should always provide them with the best services, although some of them may not have high scores of R, that is, they are less likely to make a purchase now. This showed that it is more important for enterprises to maintain the relationship with core customers, so that they can keep their regular purchase to constantly bring high profits to enterprises.

(2) Marketing strategy for opportunistic customers

The scores of R for customers in category 1 were very high, indicating that they were likely to purchase again at the current moment. In addition, their scores of F and M were not low, indicating that they may bring high short-term profits, in line with the characteristics of opportunistic customers. Enterprises should timely provide them with stimulating services to stimulate their consumption, such as catalogs of newly launched products or limited-time offers, so that they will purchase again to increase the profits of enterprises.

(3) Marketing strategy for service drain customers

Although the scores of R for customers in category 3 were low, their scores of F and M were similar to customers in category 1, indicating that the profit contribution rates of customers in these two categories to enterprises were similar. When the scores of R for customers in category 3 changed over time, the customers in category 3 may be turned into the customers in category 1. Thus, the customers in category 3 were service drain customers with huge potential value. Enterprises should not provide them with stimulating services to stimulate their consumption because enterprises can get little profits from them because of their regular purchases. Instead, enterprises should maintain the relationship so that they will keep the purchase frequency to bring stable profits to enterprises.

(4) Marketing strategy for marginal customers

The customers in category 2 accounted for 77% of the total number of customers. However, their scores of R, F, and M were the lowest, indicating that they cannot bring high profits to enterprises and were therefore marginal customers. Enterprise should not provide them with personalized services to avoid high service costs.

7. Conclusion

Customer stratification helps enterprises better understand customers and provide them with personalized services to ensure accurate marketing and thus increase profits. In this paper, we optimized the traditional RFM and analyzed the customer consumption data. The SOM was adopted to cluster customers and name customer clusters. Finally, corresponding marketing strategies were given to different customer categories, so as to support the accurate marketing of enterprises. However, this paper has its limitations as it analyzed only one dataset. The future research should use the data of enterprises in the same industry or different enterprises in the same region to achieve more universally applicable research results. This study uses a linear regression method to predict customer purchase behavior, also it can be explored whether there is a more appropriate method in the future. In addition, customers' purchasing rules may be affected by holidays and other aspects, so further research can work on this area. Finally, future studies can further subdivide the services provided by enterprises and develop different models for different services.

Data Availability

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

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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