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Research Paper

PRFM Model Developed for the Separation of Enterprise Customers Based on the Distribution Companies of Various Goods and Services

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Abstract

In this study, a new model of combining variables affecting the classification of customers is introduced which is based on a distribution system of goods and services. Given the problems that the RFM model has in various distribution systems, a new model for resolving these problems is presented. The core of this model is the older RFM. The new model that has been proposed as PRFM, consists of four dimensions: Profit margins (P), time period from customer's last purchase (R), Frequency of transactions (F) and the Monetary Value (M). Adding variable (P) makes a huge change in customer clustering and classification systems and makes it more optimized for future planning. For review and approval, the model was implemented in one of the largest and most diversified distribution companies in Iran. Using Ward's clustering, the optimal number of clusters was prepared and entered by hierarchical clustering and based on Euclidian distance customers are clustered and separated. One of the most important results of this study is introducing a new model and resolving the problems of the old RFM model in determining customer's value.

Keywords *RFM Model, PRFM Model, Clustering, WARD'S Method, Customer's Value*

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Introduction

In today's competitive markets and companies focusing on customer orientation, customer relationship management also has a tendency towards a certain complexity (Kafashpour, Tavakoli, & Alizadeh, 2012). According to previous studies, it is estimated that the cost of attracting new customers is five times greater than the costs of retaining an existing one (Kotler, 1994). On the other hand, many managers believe that the company should not pay the costs to acquire any customer at any level of profitability, instead should optimized their usage of limited resources to gain and maintain key customers (Blattberg, 2001). Considering high costs of advertising spent for a new customer to get to know a distribution company, losing any customers is the loss of money and time spent on attracting them and it shows the importance of current customers. In today's markets, focusing on customer is the most important part of the marketing. Therefore, finding and keeping customers is very important and valuable. In fact, mere focus on sales in any forms may results in serious problems and insufficient purchase from customers. So Along with the sales, attracting and retaining customers should be considered as well. But the most important question is which model is suitable for classification of customers? What method should be used for clustering customers to get better results? What are the characteristics of each customer? Who is a good customer? Which product is more important in attracting good customers? In this study, an attempt has been made to identify problems of RFM model in distribution companies with diverse goods and services and the new PRFM model is presented which resolves the mentioned problems to some extent. This research uses newer and more effective methods than traditional methods used in previous studies for clustering.Moreover, more practical analysis has been offered for clustering that can be a good guide for the development of distribution industry in Iran. Based on a study, Helt illustrated that in RFM, customers of each group of products should be ranked individually. So, he provided a new model based on RFM known as RFM/P (Heldt, Silveira, & Luce, 2019). Abbasimeh and Shabani believed customer behavior is represented as a time series. Therefore, customer behavior forecasting implemented based on RFM is changed into a time series forecasting problem (Abbasimehr & Shabani, 2020). Huang concluded that traditional RFM is not suitable for the industry with distinct attributes of social groups. So, he introduced a new model of RFM known as RFMC with adding parameter C of social relations(Huang, Zhang, & He, 2020). Sohrabi and Khanlari (2007) calculated customer lifetime value in a private bank based on RFM model. In their study, multi-mean clustering method was used to classify customers. At the end, valuable and profitable customers of the bank were divided into 8 clusters based on customer lifetime value using RFM and their characteristics were analyzed (Sohrabi & Khanlari, 2007). Hosseini began Data Mining the database in an Engineering design and spare parts supply company using extended RFM model. In that study, the indicator's weights of extended RFM model were determined by Paired comparisons. Also based on the optimal number of clusters determined by Davis index, multi- mean algorithm was used for clustering data (Hosseini, Maleki, & Gholamian, 2010). Jing and Hu 2008 investigated RFM model capability in the classification of customers in the automotive after-sales service companies. In their study 5821 clients were selected. And the weight of each component was determined by AHP[2] model. Then customers were divided into 8 clusters based on multi-mean clustering method. Finally, after analyzing customers characteristics, their lifetime value was determined in each cluster (Jing, 2008). Wu used RFM and multi-mean clustering method to analyze customer value in an industrial equipment manufacturing company After data

[2] Analytic Hierarchy Process

preparation, customer were divided into 6 clusters using multi-mean clustering method based on RFM indicators then customer characteristics were analyzed in form of clusters and customer lifetime value analysis and recommendations for the use of proper promotion programs with various customer segments were suggested (Wu, Chang, & Lo, 2009). Lee used a two-stage clustering method to analyze the customer characteristics of a textile factory Cluster analysis base in the mentioned study was extended RFM model. After data preparation, the optimal number of clusters was determined by using Ward 2 and the customers were divided into 5 clusters based on multi-mean method and the characteristics of each cluster were analyzed based on scoring RFM (Lee, 1981). Kafashpour in his study based on the RFM model, calculated customer lifetime value of 260 customers of Touse-e-Shargh Trading Company. In the study, to determine the number of clusters "Ward" method was used and for clustering customers multi-mean method was used. Ultimately, the company's customers were divided into 8 clusters based on lifetime value using RFM model and their characteristics were analyzed.

Literature Review

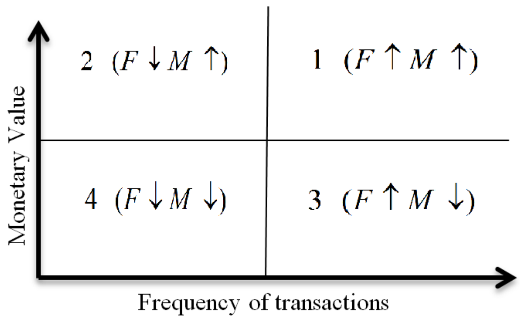
Although the emergence of customer relationship management, which is an important approach in business, goes back to 1990s, there is no widely accepted definition (Ngai, 2005). Kumar and Rynartz (2006) have defined customer relationship management as the strategic process of selecting and interacting with profitable customers with the aim of optimizing the value of current and future customers for company (Kumar & Reinartz, 2006). Ngai et al., (2009) argue that new definitions emphasize on the importance of customer relationship management as a strategic and comprehensive process for maximizing the value of customer (Ngai, Xiu, & Chau, 2009). Mishar &

Mishar (2009) state that customer relationship management analysis that investigates the behavioral characteristics of customer usually uses data mining tools to run different analysis. This is done to support customer relationship management strategies (Mishra & Mishra, 2009). The root of term "data mining" refers to coal mining and gold mining. Turban, et al (2007) define Data mining as a process in which different tools are used to extract and recognize useful information from database in order to access knowledge (Turban, Aronson, Liang, & Sharda, 2007). Data mining help companies to extract patterns and trends of customers and improve customer relationship management (Cheng & Chen, 2009). Nga et al. (2009) summarized several papers on data mining models in customer relationship management and divided these models into seven main groups. These models include: dependence, classification, clustering, and regression predicting, detecting sequence and indexing. Also, they suggest that to better support the decisions made in customer relationship management systems, it is often necessary for organizations to use a combination of these models and techniques (Ngai, 2005). Customer lifetime value analysis and clustering are among the techniques mentioned in data mining models that have been proposed in recent years and are considered by many researchers as the basis for classification of customers. Customer lifetime value has been investigated with terms such as customer value, lifetime value, customer rights and customer profitability in numerous studies(Hwang, Jung, & Suh, 2004). In general, customer lifetime value is the value created by customer over the course of his life for organization. This concept, in addition to the current value of the customers, considers the potential and future value for company and the main purpose of calculating that is to create a weight perception of customers in order to allocate resources for them (Razmi & Ghanbari, 2009). There are various definitions of customer lifetime value, which indicate different views and methods for this subject. The most common methods proposed to determine customer lifetime value are the net present value method, the share of wallet method, Markov chain method, the passed value of customer method, return on investment and RFM method. Among methods mentioned above, RFM is one of the most common methods, Battle (2004) investigates the value of the customer based on three criteria, Therefore, it proposes a multi-dimensional approach, while many methods are single-dimensional and usually use only one dimension in determining the customer lifetime value (Buttle, 2004). Furthermore, RFM not only considers financial approaches in analyzing customer characteristics but also it focuses on non-financial issues (Razmi & Ghanbari, 2009). while many other methods just focus on financial aspects of this issue. RFM was first introduced in 1994 by Hughes. For RFM analysis he used customer's past behavior, which is easy to follow and is available to be used (Hughes, 2000). This model uses three dimensions of customer transaction data to analyze their behavior. Parameters/indicators are defined as follows (Cheng & Chen, 2009).

- The freshness of exchange: This indicator refers to time interval between the last purchase made by customer and the end of that period. The lower the period of this interval the higher the value of this indicator.
- The frequency of exchange: This indicator shows the number of transactions that a customer has made in a specific period of time. A high number of transactions indicates a high value of this indicator in the model.
- The monetary value of exchange: This indicator shows the amount of money that a customer spends in a specific time period. A high volume of money spent indicates a high value of this indicator in the model.

In RFM, the lifetime value of each customer is equal to the total value of the RFM indicators. It is assumed in this model that the customers who have a high value in all parameters of the model are the best customers, as long as their future behavior is consistent to their past ones (Kim & Ahn, 2008). Hughes states that these three criteria are equally important, therefore, their weights are the same (Hughes, 2000). On the other hand, Stone believes that due to different characteristics of each industry, three factors have different importance and, in his study, he determined weight of indicators subjectively (Stone, 1995). Later, Liu and Xie (2005) used AHP to better determine the weights of RFM criteria that were used in the evaluation of customer lifetime value. Figure 1 shows customer value matrix proposed by Marcus (1998) in which the number of purchase and sale of the customers are presented.

Figure 1
Customer Value Matrix Marcus (1998)



The importance of clustering and its interdisciplinary nature can be inferred from having many articles on this subject. A number of books in the field of clustering were also published by GINA (1988), Duran (1974), Ourit (1993), Andrea Berg (1977), Bajsy (1997), SPOT (1980) and Hartygan (1975). Also, a study was presented by Davis in 1980 on new techniques of clustering. The comparison between different methods of clustering for building minimum tree and minimum path was presented by Lee in 1981 (Duran & Odell, 2013), (Hartigan, 1975). This method is among the hierarchical clustering methods. In this clustering method to reduce losses due to remote data, a new criterion for calculating the differences between clusters is used (In Ward's method the sum of squares of the differences with the mean vector of a cluster is used as an indicator to measure a cluster). Multi-means clustering is one of the common and simple mean clustering methods that uses the Square error function (MacQueen, 1967). The method starts with an initialization of the clusters number and by assigning a new sample to the clusters continues to the point that no samples is moved from a pattern to another pattern or the Square error function value is not significantly change after a few stages. In fact, Multi-means clustering takes input parameter (K) and divides series devoted members by that, in a way that the intra-cluster similarity is large and the inter-cluster similarity is small (Johnson & Wichern, 2002). Multi-means method is faster than hierarchical clustering algorithm and is used for a wide range of data. This method of clustering is usually the fastest way for large datasets (Bin, Peiji, & Dan, 2008). One of the problems of multi-means is the number of clusters. The main issue in this algorithm is its sensitivity to initial cluster, and it may fall into trap at the minimum of the objective function. "Dunn" index/indicator was introduced in 1974 by J.Duun which is a standard for evaluating clustering algorithms (Dunn, 1974). Duun index defines the minimum distance between the clusters to the maximum distance.The index equals to equation (1):

$$D = \frac{d_{\min}}{d_{\max}}$$

(1)

d_{min}= minimum distance between the clusters

d_{max}= maximum distance between the clusters

Where d_{min} is the smallest distance between two objects of different clusters and d_{max} is the largest distance between two objects of the same cluster. Duun index is limited to range of [0, 1] and its maximum amount is optimized for clustering.

In RFM model, Customers whose purchase, the number of transactions and the time period to their recent purchase is equal have equal value and this condition is for the case that we are selling one single product or if we have diversity all products have equal margin. While the major distributer companies usually have high commodity diversity and distribute large numbers of manufacturer's products, Profit for each item varies with each product and it is completely different. For customers who have the equal number of Orders, number of transactions and time interval to their recent purchase, but margin index is different inefficiency of RFM model is obvious. In these cases, the profit margin would be the main determinant variable, which being added to previous model it develops it and shapes PRFM model. The value of each index in RFM model is determined by multiplying the standardized index to its weight. The value of these indicators is respectively Ms, Ps, Fs, Rs and W is the weight of each indicator which are defined as equation (2):

$$Ms_i' = W_{Ms} \times Ms_i \qquad Ps_i' = W_{Ps} \times Ps_i \qquad Fs_i' = W_{Fs} \times Fs_i \qquad Rs_i' = W_{Rs} \times Rs_i \qquad (2)$$

Ms= Value of monetary indicator
Ps= Value of profit margin indicator
Fs= Value of frequency indicator
Rs= Value of recently indicator
W= weight of each indicator

Customer lifetime value of each cluster is calculated by the average sum of RFM model indicators in that cluster based on equation (3):

$$CLV = Ms_i' + Ps_i' + Fs_i' + Rs_i'$$

(3)

We used the following model for clustering customers:

We define two vectors/arrows with n variables as follows:

$$X = (x_1, x_2, ..., x_n) \qquad Y = (y_1, y_2, ..., y_n)$$

(4)

Euclidian distance between them is expressed as follows:

$$d(\overline{XY}) = \sqrt[2]{\sum_{i=1}^{n} (X_i - Y_i)^2}$$
$$= \sqrt[2]{(x_1 - y_1)^2 + (x_2 - y_2)^2 + ... + (x_n - y_n)^2}$$

(5)

The obtained value is a criterion for Ward clustering. The less the value is, two vectors/arrows are preferred to form a cluster. In this method, all samples that their characteristics have been collected are gathered in a matrix (6), in which d_y is the Euclidian distance between sample in column j and row i.

$$\begin{array}{c c} & \begin{array}{ccc} 1 & \cdots & n \end{array} \\ \begin{array}{c} 1 \\ \vdots \\ n \end{array} & \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nn} \end{bmatrix} \end{array}$$

(6)

At each stage, two vectors/arrows with minimum distance (other than the main column vectors/arrows) are combined. A new vector is obtained. In next stage the new matrix is formed from the combination of two vectors whose row and column have been reduced by one. These steps continue until the optimal number of clusters is reached. The remaining vectors are the combined vectors and each vector is a cluster consist of its forming vectors. The optimal number of clusters also is obtained from difference between minimum distance in two stages. A small example of RFM model efficiency and inefficiency in the distribution of diverse products can be found in Tables (1) and (2).

Table 1

An Example that RFM Indicators are Right for

Companies with limited services or products (companies distributing special products) e.g. banks, insurance companies, single product factories (cement, steel, flour, sugar, petroleum products (gasoline), crops (apples and orange, etc.), etc.)						
RFM	R	F	M	Gross Profit	Total Monetary Value in each purchase	Profit Margin
Customer \`A\`	3	15	1000000$	10%	100000$ 200000$ 700000$	10%
Customer \`B\`	3	15	1000000$	10%	700000$ 200000$ 100000$	10%

Table 2

An Example that RFM Indicators are not Right for

Companies with a variety of services and products (food and pharmaceutical distribution companies imported medicines distribution companies, companies distributing different products from different factories, etc.)							
RFM	R	F	M	Gross Profit		Total Monetary Value in each purchase	Profit Margin
	3	15		goods or services 1	5%	100000$	14.7%

Customer `A`			1000000 $	goods or services 2	10%	200000$	
				goods or services 3	20%	700000$	
Customer `B`	3	15	1000000 $	goods or services 1	5%	700000$	5.7%
				goods or services 2	10%	200000$	
				goods or services 3	20%	100000$	

As seen in Table (1), for the companies that the benefit for all the products was the same, customer profit variable is not useful because this variable cannot be used to classify customers, so the RFM model parameters are suitable and adequate. But for the companies in Table (2) that the profit of each product is different, each customer in accordance to the purchase of each product can have different profitability for the company. In that case customers who purchase a good with higher profitability are a more profitable customer than customers buying the same amount of a good with lower profitability. PRFM model is the developed form of RFM model and it consists of following characteristics: margins (P), recent Exchange (R), repeat purchases (F) and the monetary value of the exchange (M). Now due to the parameters having values over or below the average, there will be 16 states. Table (3) distinguishes the characteristics of each group with the symbols of PRFM column.

Table 3

Possible Clustering in PRFM

The Amount of Sales	Frequency of Transactions and Profit Margins	Customer Recent Purchase	P&R&F&M
The main	Loyal & High profitability	1	↑↓↑↑
		2	↑↑↑↑
	Loyal	3	↓↓↑↑
		4	↓↑↑↑

The Amount of Sales	Frequency of Transactions and Profit Margins	Customer Recent Purchase	P&R&F&M
Subsidiary	High Potential & High profitability	5	↑↓↓↑
		6	↑↑↓↑
	High Potential	7	↓↓↓↑
		8	↓↑↓↑
	Seasonal & ineffective	9	↑↓↓↓
		10	↑↑↓↓
		11	↓↓↓↓
		12	↓↑↓↓
	Consumer Resources	13	↑↓↑↓
		14	↑↑↑↓
		15	↓↓↑↓
		16	↓↑↑↓

Reseach Methodology

This research aims to develop a model to classify and rank customers in the distribution companies with diverse goods and services that their core is formed based on RFM model. Accordingly, given the importance of customer profitability for the company which is one of the most important indicators for ranking customers in these companies, by adding this indicator PRFM model which is the developed model of RFM is presented. To evaluate the model, 7054 customers of one of the branches of one of the largest distribution companies of pharmaceutical, sanitary and food products with high level of product diversity were examined. To collect data for PRFM model parameters, secondary data in the company was used. To determine the weight of PRFM indicators, based on AHP pair comparison questionnaire was used. The questionnaire was based on 9 point scale (Wind & Saaty, 1980) and was completed by experts in the company which was explored. Then relative weight of indicators was determined by “Choice” software. Also, for clustering customers in SPSS 21 and analyzing their characteristics and the optimal number of clusters, Ward hierarchical clustering method was used. Using Ward method increased the quality of clustering. This can be acknowledged through comparing ward method with multi-means method. This process includes the following steps.

Step1: Defining PRFM Model Variables

1. Exchange novelty: the period between customer last purchase and the end of specified time.
2. The number of exchanges: number of purchasing at a specified time period (equal to number of sales invoices).
3. The monetary value of exchange: The Order of the customer based on the monetary value at a specified time period determined by management's report (MAP) of company.
4. Margins: this index is calculated using the weighted average based on equation (7).

$$m = \sum_{i=1}^{n} x_i \qquad p = \sum_{i=1}^{n} \frac{x_i}{m} \times p_i$$

(7)

In this regard, P is the profit margin, X is the sale value of i product of customer, n is the number of products purchased, m is the total monetary value of goods purchased by customers and Pi is the profit margin of each product for the customer.

Step2: Weighting Variables

The AHP is used to determine the relative weights of the RFM variables. To weight data “Saaty” hierarchical method was used to create the questionnaire and company's experts answered it. After entering data to expert choice software, the weight output was received

Step3: Standardization of Variables

For the standardization of the variables we use formulas (8). So, the variables are standardized in the range of [0, 1]. M is the standard sale, P is each customer profit ratio, F is the number of purchases and R is the date of last purchase.

$$Ms_i = \frac{m_{MAX} - m_i}{m_{MAX} - m_{MIN}}, Ps_i = \frac{p_i - p_{MIN}}{p_{MAX} - p_{MIN}}, Fs_i = \frac{f_i - f_{MIN}}{f_{MAX} - f_{MIN}}, Rs_i = \frac{r_i - r_{MIN}}{r_{MAX} - r_{MIN}}$$

(8)

Ms= Value of monetary indicator, m_{MAX}= maximum value, m_{min}= minimum value

Ps= Value of profit margin indicator, p_{MAX}= maximum value, p_{min}= minimum value

Fs= Value of frequency indicator, f_{MAX}= maximum value, f_{min}= minimum value

Rs= Value of recently indicator, r_{MAX}= maximum value, r_{min}= minimum value

Step 4: Determination of Indicators Value for Each Customer

The value of each index in RFM model is determined by multiplying the standardized index in its weight based on equation (9). The value of these indices are respectively Ms, Ps, Fs, Rs and W is the weight of each indicator.

$$Ms_i' = W_{Ms} \times Ms_i \qquad Ps_i' = W_{Ps} \times Ps_i \qquad Fs_i' = W_{Fs} \times Fs_i \qquad Rs_i' = W_{Rs} \times Rs_i$$

(9)

Ms= Value of monetary indicator

Ps= Value of profit margin indicator

Fs= Value of frequency indicator

Rs= Value of recently indicator

W= weight of each indicator

Step 5: Calculate Customer Lifetime Value of Each Cluster

Customer lifetime value of each cluster is computed by average sum of RFM indicators value in that cluster based on equation (10).

$$CLV = Ms_i' + Ps_i' + Fs_i' + Rs_i' \quad (10)$$

Ms= Value of monetary indicator
Ps= Value of profit margin indicator
Fs= Value of frequency indicator
Rs= Value of recently indicator

Customers are categorized in the form of clusters based on customer life time value pyramid which shows the rank of customers in clusters.

Findings

Firstly, for clustering customers, using the raw data in the secondary data, the exchange novelty on the day basis, the number of exchanges based on the frequency of purchase (invoice number), the monetary value based on the sales transaction, and percent profit based on the average percentage of the profits for the company's customers are obtained. We standardized the obtained indicators between 0 and 1 and for data weighting indicators table was made using "Saaty" hierarchical method then it was given to planning, sales, marketing experts and managers of the company. The completed tables were entered to expert choice software and the weighted results are shown in table (4). For the weight to take effect on indicators, each PRFM index is multiplied by its weight based on the "Saw" method. The mean and standard deviation after standardizing and weighting indicators are shown in table (5). To determine the number of clusters required, Dendrogram and compression table were used.

Table 4

Weights Extracted of Expert Choice Software

Index	Symbol	Weight
Monetary Value	M	65%
Profit margins	P	20%
transactions Frequency of	F	12%
transaction novelty	R	3%

Table 5

Means and Standard Deviation of Indicators

Weighted Index	Monetary Value	Profit Margins	Frequency of Transactions	Time Period from the Last Purchase	Customer Value
mean	0.0227	0.01859	0.02	0.025	0.087
Standard deviation	0.00029	0.00006	0.00016	0.0000084	0.00047
Count	7054	7054	7054	7054	7054

The results show that the optimal number of clusters is 6. The clustering results using Ward method is shown in table (6). According to the results obtained, each cluster can be defined as table (7). To obtain customer value hierarchy within clusters, the average of customer value in each cluster is measured and is shown in figure 3. In reviewing multi-mean method with 6 clusters, 2 single-member cluster and 2 clusters with members less than 50 were formed. The main volume was put in 2 clusters, which did not show a proper classification. Also, the results of "Dunn" test confirmed the superiority of Ward method. Results value Duun measurement is shown in Table (8). The variances within the clusters were much lower in Ward method indicating its superiority. Results value measurement is shown in Table (9).

Figure 2

Dendrogram Using Ward Linkage

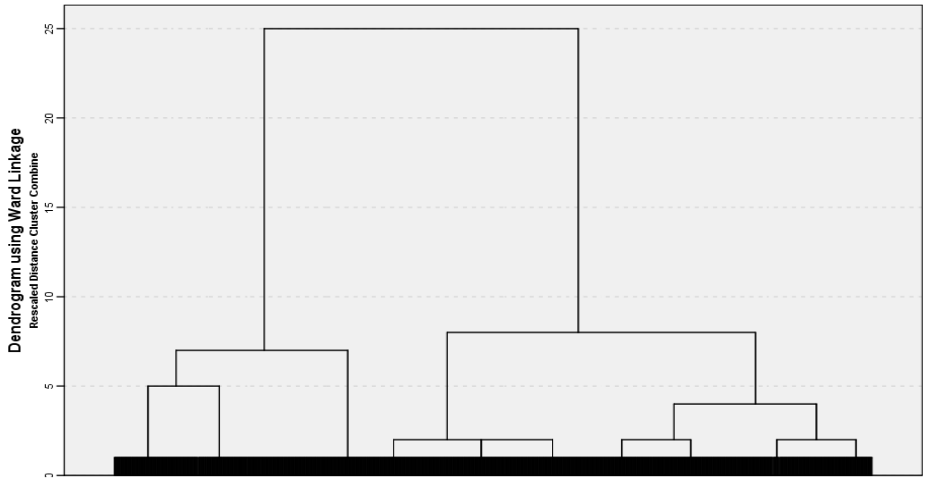


Figure 3

Clusters Based on Mean Value in Ward's Method

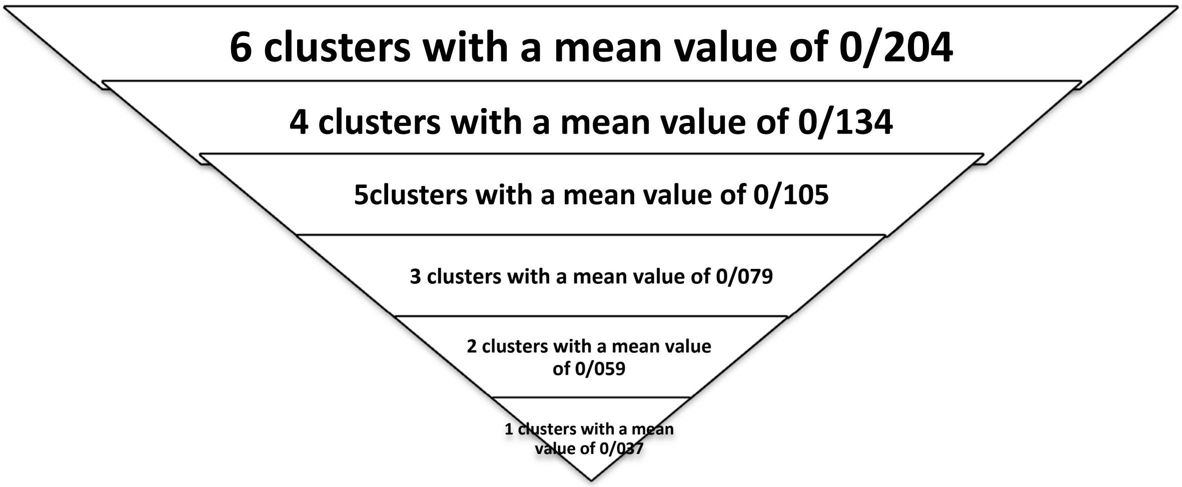


Table 6
Results of Clustering

Numbers in Clusters	Cluster Value	Recently	Frequency of Transactions	Profit Margins	Monetary Value	Index	Cluster
947	0.04	0.67	0.046	0.091	0.0059	mean	1
	0	0.0062	0.0013	0.0004	0.00017	Standard error	
1370	0.06	0.046	0.052	0.091	0.0098	mean	2
	0	0.002	0.0009	0.0003	0.00014	Standard error	
1561	0.08	0.07	0.147	0.091	0.023	mean	3
	0	0.003	0.0011	0.0003	0.00017	Standard error	
957	0.13	0.027	0.3	0.1006	0.073	mean	4
	0	0.0018	0.0026	0.0014	0.00045	Standard error	
2009	0.1	0.042	0.24	0.093	0.042	mean	5
	0	0.0015	0.001	0.0032	0.00021	Standard error	
210	0.2	0.026	0.37	0.09	0.17	mean	6
	0.01	0.004	0.0096	0.006	0.007	Standard error	
7054	0.09	0.13	0.17	0.09	0.035	mean	Total
	0	0.0028	0.0014	0.0003	0.00045	Standard error	

Table 7
Information of Clusters

The Amount of Sales	Frequency of Transactions & Profit Margins	Recently did the Customer	Cluster	P &R&F&M	Members of Each Cluster
The main	Loyal & High profitability	1	4	↑↓↑↑	957
	Loyal	3	6	↓↓↑↑	210
		4	5	↓↑↑↑	2009
Subsidiary	Ineffective & Seasonal Consumer Resources	11	2	↓↓↓↓	1370
		12	1	↓↑↓↓	947
		15	3	↓↓↑↓	1561

Table 8

Results of Dunn Index

Clustering	Ward	Multi-Mean Method
Value Dunn index	0.106652	0.0008363

Table 9

Comparation Between Ward Method and K-mean Method

Time Period from Last Purchase	Frequency of Transactions	Profit Margins	Monetary Value	Index
1.071	0.407	0.00075	1481619	Mean (Varian 6 clusters) The Ward Method
1.745	1.169	0.00015	4576455	Mean (Varian 6 clusters) The K-mean Method

Conclusion

In the present study, a model of customer ranking adopted based on priorities in distribution companies was introduced. Since the importance of some factors related to customer ranking which are not covered in prior studies, in this paper considering profit margin, the model of customer ranking known as PRFM based on RFM have been introduced. Based on this form of customer ranking, high ranked customers, playing prominent role in raising profit, will be appeared and along this fact, distribution companies should pay more attention on the goods and services attracting high ranked customer in order to present these services to low-ranked ones. In fact, it can be predicted that providing same goods and services may give rise to empower lower customers based on our desired factors. In other words, the company shall review customer changes in clusters and put more emphasize on losing and attracting main or subsidiary customers. This fluctuation can be a sign for company successful or unsuccessful. Losing customers from superior cluster is a big loss. Also, a customer leaving lower clusters to higher cluster can have huge benefits for the company. Moreover, it should focus more on Seasonal ineffective customers because they are high in number and have high potential for creating sales. the weaknesses of services offered to these types of customers should be determined.

References

Abbasimehr, H., & Shabani, M. (2020). A new framework for predicting customer behavior in terms of RFM by considering the temporal aspect based on time series techniques. *JOURNAL OF AMBIENT INTELLIGENCE AND HUMANIZED COMPUTING*.

Bin, D., Peiji, S., & Dan, Z. (2008). *Data mining for needy students identify based on improved RFM model: A case study of university.* Paper presented at the 2008 International Conference on Information Management, Innovation Management and Industrial Engineering.

Blattberg, R. (2001). Customer Equity: Building and Managing Relationships as Valuable Assets.

Buttle, F. (2004). Client Relationship Management: concepts and tools. In: Oxford: Elsevier Butterworth-Heinemann.

Cheng, C.-H., & Chen, Y.-S. (2009). Classifying the segmentation of customer value via RFM model and RS theory. *Expert systems with applications, 36*(3), 4176-4184.

Dunn, J. C. (1974). Well-separated clusters and optimal fuzzy partitions. *Journal of cybernetics, 4*(1), 95-104.

Duran, B. S., & Odell, P. L. (2013). *Cluster analysis: a survey* (Vol. 100): Springer Science & Business Media.

Hartigan, J. A. (1975). *Clustering algorithms*: John Wiley & Sons, Inc.

Heldt, R., Silveira, C. S., & Luce, F. B. (2019). Predicting customer value per product: From RFM to RFM/P. *Journal of Business Research*.

Hosseini, S. M. S., Maleki, A., & Gholamian, M. R. (2010). Cluster analysis using data mining approach to develop CRM methodology to assess the customer loyalty. *Expert Systems with Applications, 37*(7), 5259-5264.

Huang, Y., Zhang, M., & He, Y. (2020). *Research on improved RFM customer segmentation model based on K-Means algorithm.* Paper presented at the 2020 5th International Conference on Computational Intelligence and Applications (ICCIA).

Hughes, A. M. (2000). *Strategic database marketing: the masterplan for starting and managing a profitable, customer-based marketing program* (Vol. 12): McGraw-Hill New York, NY.

Hwang, H., Jung, T., & Suh, E. (2004). An LTV model and customer segmentation based on customer value: a case study on the wireless telecommunication industry. *Expert systems with applications, 26*(2), 181-188.

Jing, W. H. Z. (2008). Study of Customer Segmentation for Auto Services Companies Based on RFM Model.

Johnson, R. A., & Wichern, D. W. (2002). *Applied multivariate statistical analysis* (Vol. 5): Prentice hall Upper Saddle River, NJ.

Kafashpour, A., Tavakoli, A., & Alizadeh, S. (2012). Customers segmentation base on lifetime value, use RFM data mining. *Iran J Public Manag, 5*(15), 63-84.

Kim, K.-j., & Ahn, H. (2008). A recommender system using GA K-means clustering in an online shopping market. *Expert systems with applications, 34*(2), 1200-1209.

Kotler, P. (1994). *Marketing management, analysis, planning, implementation, and control, Philip Kotler*: London: Prentice-Hall International.

Kumar, V., & Reinartz, W. J. (2006). *Customer relationship management: A databased approach*: Wiley Hoboken, NJ.

Lee, R. C. T. (1981). Clustering Analysis and Its Applications. In J. T. Tou (Ed.), *Advances in Information Systems Science: Volume 8* (pp. 169-292). Boston, MA: Springer US.

MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations.* Paper presented at the Proceedings of the fifth Berkeley symposium on mathematical statistics and probability.

Mishra, A., & Mishra, D. (2009). Customer Relationship Management: implementation process perspective. *Acta Polytechnica Hungarica, 6*(4), 83-99.

Ngai, E. W. (2005). Customer relationship management research (1992- 2002). *Marketing intelligence & planning*.

Ngai, E. W., Xiu, L., & Chau, D. C. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert systems with applications, 36*(2), 2592-2602.

Razmi, J., & Ghanbari, A. (2009). Introducing a novel model to determine CLV. *Journal of Information technology management, 1*(2).

Sohrabi, B., & Khanlari, A. (2007). Customer lifetime value (CLV) measurement based on RFM model.

Stone, B. (1995). Successful direct marketing methods NTC Business Books. *Lincolnwood, IL*.

Turban, E., Aronson, J., Liang, T., & Sharda, R. (2007). Decision support and business intelligence systems, 8^ th Edition Prentice Hall. *Upper Saddle River NJ*.

Wind, Y., & Saaty, T. L. (1980). Marketing applications of the analytic hierarchy process. *Management science, 26*(7), 641-658.

Wu, H.-H., Chang, E.-C., & Lo, C.-F. (2009). Applying RFM model and K-means method in customer value analysis of an outfitter. In *Global Perspective for Competitive Enterprise, Economy and Ecology* (pp. 665-672): Springer.