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Evaluating discounts as a dimension of customer behavior analysis

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ABSTRACT
Today, increased competition between organizations has led them to seek a better understanding of customer behavior through identifying valuable customers. Customers' expectations about the price and quality of products and services play an important role in their selection process. In online businesses, competition and price differences between suppliers is high, so discounts will attract different customers. As a result, discounts and the frequency and amount of purchases can lead to better understanding of customer behavior. Customer segmentation and analysis is essential for identifying groups of customers. Hence, this study uses a model based on RFM called RdFdMd, in which d is the level of discount used to analyze customer purchase behavior and the importance of discounts on customers' purchasing behavior and organizational profitability. The CRISP-DM and *k*-mean algorithm were used for clustering. The results indicate that using the $R_dF_dM_d$ model achieves better customer clustering and valuation, and discounts were identified as an important criterion for customer purchases.

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Clustering; data mining; customer relationship management; discount; RFM model

Introduction

Today, increased competition between markets, financial pressure, and customer bargaining power have raised issues such as increasing customer value, improving customer relationship management (CRM), and forecasting customer behavior. To increase their profitability, organizations try to maximize the value of their customers using customers' valuable information and their differences (Chang and Tsai 2011; Farooqi and Raza 2012; Khajvand et al. 2011).

Customers have expectations about the price and quality of products and services. Price expectations play an important role in consumer choice processes (PK Kannan 2001). Pricing is an important decision for any business, and especially for emerging online retailers (Shim, Choi, and Suh 2012). Dynamic pricing is a pricing strategy where prices change over time. Economic theories argue that the dynamic pricing is inherently good for corporate profitability, because it allows companies to obtain a greater consumer surplus. Dynamic pricing

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is determined through up-selling, amount of discount and product packaging (Shim, Choi, and Suh 2012).

In the online business where competition and price difference between different suppliers is high; the discount will attract different customers. Discounts encourage customers so that, in some cases, they prefer particular products or brands simply because of gifts and discounts on offer (Liang 2010).

Studies indicate that prices and discounts are involved in customer expectations and guide their future behavior. The price varies according to supply and demand conditions. For example, offering lower prices to loyal customers or permanent buyers always meets their expectations. Loyal customers get more discounts, which in turn increases their loyalty (Nikumanesh and Albadvi 2014). The positive impact of discount on customer loyalty is twofold: (1) loyal customers call for rewards for their loyalty and rely on bargaining power, and (2) granting discounts by retailers is necessary for maintaining loyal customers.

Marketing managers can make pleasant and long-term relationships with customers through identifying and predicting changes in customer behavior. Understanding customer behavior changes in dynamic retail markets can help managers to create effective promotion campaigns. Therefore, Companies need to assess the value of customers, segment them based on their values, and develop strategies for each segment in order to acquire and retain profitable customers (Khajvand et al. 2011). Organizations can identify valuable customers and predict their future behaviors through data mining and extraction of hidden information from large databases (Chang and Tsai 2011; Farooqi and Raza 2012). The most frequently used model in customer behavior analysis, is the RFM model, which consists of three behavioral variables: R (Recency), F (Frequency), and M (Monetary) (Hosseini, Maleki, and Gholamian, 2010; Lai, Li, and Lin 2017). RFM is a powerful tool in marketing and is widely used in measuring the value of customers according to their previous purchase history (Khajvand and Tarokh 2011).

After all, the amount of discount that each customer receives, along with the amount of purchase, will lead to a better understanding of customer behavior. However, previous studies on the clustering of customers using the RFM model have only added one variable to the model and have not studied this model as two-dimensional.

The importance of discounting in customer behavior analysis has not been investigated, and no appropriate valuation based on discounts has been provided. This raises an interesting question: Therefore, the question arises of how to reach a comprehensive understanding of customer behavior by adding the variable of discount to the RFM model? This study, therefore, aims to provide a more accurate understanding of customer behavior using a two-dimensional approach to customer buying behavior and discount behavior, as well as by adding variable discounts and categorizing customers based on amount of discount and two-dimensional clustering of RFM and RdFdMd, where d is discount, based on recency of discount (Rd), frequency of discount (Fd), and monetary of discount (Md). The results will help managers to develop better marketing strategies.

For the purposes of this research, the literature is reviewed first. The research methodology, measurement tools, and statistical analysis are then explained. Finally, the conclusions and recommendations of the study are discussed.

Literature review

In today's competitive business world, the customer is a very important asset for investment. Analyzing and understanding customer behavior and characteristics are the basis for the development of competitive CRM strategy in order to gain and retain potential customers and increase customer value (Ngai, Xiu, and Chau 2009). In online business, competition and price differences between suppliers are high, meaning that discounts attract different customers. Discounts generally mean alleviation of some of the cost of goods at the request of the buyer or with the seller's agreement. Discounts can be classified into different categories. The most important types of discount in commercial organizations are trade discounts, discounts as a result of product defects, and cash discounts of buying or selling. Discounts encourage customers so that, in some cases, they prefer particular products or brands simply because of gifts and discounts on offer (Liang 2010).

Customer segmentation and analysis of different customer groups is necessary to identify valuable groups of customers. Customer segmentation is generally undertaken based on behavior, demographic, and lifestyle variables. Different techniques and models have been used for customer segmentation and customer behavior analysis; the most common are data mining techniques such as classification, clustering, and association rule mining. The most frequently used model in customer segmentation is the RFM model (Rygielski, Wang, and Yen 2002). This behavioral model uses three criteria, namely recency, frequency, and monetary value, to predict the customers' future purchasing behaviors based on their buying history. The advantage of RFM is the extraction of customers' characteristics using lower criteria (three dimensions) as clusters' features, so that the complexity of the customer value model is reduced (Cheng and Chen 2009). Despite the model simplicity, it has some notable shortcomings, such as assigning different weights to attributes based on the specifications of various products and industries. Therefore, several authors have attempted to increase the model accuracy by adding new variables (Yeh, Yang, and Ting 2009). For example, Yeh, Yang, and Ting (2009) developed an RFMTC model by adding two parameters (time since first purchase and churn probability) to the original RFM model. More recently, the studies of (Amine, Bouikhalene, and Lbibb 2015; Ansari and Riasi 2016; Nikumanesh and Albadvi 2014; Wei et al. 2012) developed a revised RFM model by adding customer lifetime value as a new variable. Moreover, Soeini and Fathalizade (2012) expanded the RFM model by incorporating time since first purchase (or length of customer relationship) and cost of a customer as the additional variables. Moreover, Chang and Tsai (2011) proposed a new framework named Group RFM or the GRFM to generalize RFM model to the groups of products and services. Their results indicate that the final customer value is heavily dependent on the monetary value of the purchases made. Chiang (2011) also augmented the RFM model by adding two variables, discount along with shipping and logistics fees, and indicated that while discount enhances customer value, for organizations, it is decreased by shipping and logistics fees. Hosseini, Maleki, and Gholamian (2010) expanded the RFM model by adding product lifecycle/ product duration, and indicated that customer clustering and valuation can be improved by its application. The most pertinent studies based on the RFM model and its revised versions, along with their results, are summarized in Table 1.

According to the findings yielded by the literature review, the importance of discount in customer behavior analysis has not been considered and suitable customer valuation based on discounted is not provided. Since the discounts attract different customers and are an

Table 1. RFM model evolution.

Resource	Added variable	Industry	Results
Hosseini, Maleki, and Gholamian (2010)	• Product Life Cycle/Product Duration	Outfits and Accessories for Automobiles	• The proposed model was acceptable and had high level of confidence
Khajvand et al. (2011)	• Customer Lifetime Value • Number of items	Cosmetics Industry	• customer segmentation in four clusters • the parameter of number of item didn't have effect on clustering
Kandeil, Saad, and Youssef (2014)	• Customer Lifetime Value	Steel Company	• customers were segmented into two groups • The hybrid model had lower mean error than the fuzzy model of C-mean
Amine, Bouikhalene, and Lbibb (2015)		E-commerce Website	• The payment method is one of the key indicators of a new index which allows to assess the level of customers' confidence in the company's Website
Wei et al. (2012)		Children's Dental Clinic	• Extraction of 12 clusters using SOM algorithm
Nikumanesh and Albadvi (2014)		Banking	• Extraction of 4 clusters using *k*-mean algorithm • normal customers who were 80% of the total customers had lowest profitability
Chiang (2011)	• Discount • shipping and logistics fees	Online Market	• clustered data in three groups • Extraction of five rules using Apriori Algorithm
Khajvand and Tarokh (2011)	• Customer Lifetime Value • Customer future Value	Retail Banking	• Extraction of four clusters using *k*-mean algorithm • Provide marketing strategies
Chang and Tsai (2011)	• Groups of Products and Services	Educational Organization	• PICC clustering result contains additional information within each cluster • the time of clustering and re-clustering reduced
Soeini and Fathalizade (2012)	• Customer Lifetime Value • Imposed Costs	Insurance	• Extraction of seven cluster • Comparison of the two models using association rules • Efficiency of new model compared to RFM model

(*Continued*)

Table 1. (*Continued*).

Resource	Added variable	Industry	Results
Liu and Shih (2005)	• Customer Lifetime Value • Purchase preferences	Hardware Retailer	• The experimental results showed that the algorithm is better than WRFM and CF-based approach separately • Extraction of eight clusters using *k*-means algorithm • the recommendations were extracted from each group to improve the quality of advice

important strategy for attracting and maintaining customers and organizational profitability, the aim of the present study is to examine both the discount and the purchasing behavior of different customer groups by conducting two-dimensional clustering of RFM and RdFdMd models.

Methodology

This study aims to provide a more accurate understanding of customer behavior using a two-dimensional approach to customer buying behavior and discount behavior, as well as by adding variable discounts and categorizing customers based on amount of discount. Different algorithms and techniques are being used to classify, valuate, and model customer buying behaviors which are classified in two groups of clustering and association rule mining. Accordingly, clustering techniques and *K*-Mean algorithms are used in this study. This algorithm is a non-hierarchical clustering method, and is a common method for partitioning a set of data in a group (Liu and Shih 2005). It is especially suitable when the number of observations or data file is very large. The *K*-Means algorithm has been widely used for market segmentation due to its simplicity of understanding, interpretation, and implementation. In this study customers are segmented based on their behavioral characteristics; therefore, the *K*-Means algorithm which is a kind of behavioral segmentation method based on the RFM model is used for customer segmentation (Liang 2010).

In addition, the CRISP-DM methodology 'Cross-Industry Standard Process for Data Mining' which is one of the flexible and widely used analytical methods for data mining projects (Larose 2006) is used in this study. CRISP is a process model that is used in six steps to organize the results. Moreover, *K*-Mean algorithm and Davies–Bouldin measure of clustering quality are used to measure and to determine the number of clusters. This is done on 130091 normalized records related to customer purchase model (RFM) and 64036 normalized records related to the discount model (RdFdMd) using SpssModeler.18 software. Then, the ANOVA test is run on obtained clusters to determine the average weight of clusters using the Spss.24 software. The RapidMiner Studio software is also used for modeling.

Data analysis

This study was conducted based on the CRISP-DM methodology, which consists of six phases pertaining to business understanding, data understanding, preparation, modeling, evaluation, and deployment, respectively (Moro, Laureano, and Cortez 2011):

Phase 1. Business understanding

In the first phase, an overview of the type of business being studied is conducted, and the overall targeting is done based on the current strategies and business nature (Moro, Laureano, and Cortez 2011). The objective of this study is to propose a model that evaluates the importance of discounts in understanding customer behavior. Therefore, by conducting two-dimensional clustering of RFM and RdFdMd and applying the model to the data provided by an online retailer company, this work can add value to the sector characterized by high competition. Moreover, the model can be used to provide a detailed analysis of customer behavior, to determine the similarity of customers based on their equity value, and to allow companies to identify high-value customers.

Phases 2 and 3. Data understanding and preparing

The second phase involves collecting, describing, and evaluating the data quality. In this study, data related to an online retailer's six-month sales records, including customer id which is unique to each client, product id, purchase date, monetary, rates, and types of discounts including market pricing (Depending on the type and price of the product and the market conditions, if the product yields high profits, the online retailer system will automatically discounts the customer, and it does not discounts otherwise), total discounts (the price that a product sold in the market, this retailer sells the products at the lower price than the market, and most of the retail products include this discount), and codex (A code that includes the conditions that a customer will discount based on the type of the products, the volume of the purchase, and the time of the purchase) were used.

A record is stored in the database based on the purchasing transaction. The data of 130097 records were stored in databases, of which 64,038 records were related to the customers who had received discounts. The customer purchase transaction data were used to calculate the values of R, F, and M and the purchase transaction data related to the customers who received discounts were used for the calculations of Rd, Fd, and Md. Since the customer purchase recency and discount recency are considered based on the days, the last date of purchase and the last discounted purchase were converted to the number of days that had passed since the period under review, and the characteristic values of both RFM and Rd, Fd, and Md were obtained for each customer. Afterward, aggregation functions were used to aggregate data about each customer in the SQL database and the data were prepared for modeling (third phase). Data preparation includes the process of excluding outliers and data normalization. RapidMiner Studio software was used to identify outliers, and the Max function was used to count the R and R_d of purchase, the Count function for counting the F and Fd of purchase, and the Sum function for the M and Md. In this case, the quintile method was used to calculate the customer characteristic scores. In this method the customers' data are sorted based on each attribute and then customers are categorizing into five groups. To calculate the value of R and Rd customers are arranged ascending based on the days elapsed since their last purchase. For calculating the F, Fd, M, and Md customers are arranged in descending order. Since the customers with lower R and Rd, and higher F, Fd, M, and Md are more valuable, the score of 5 is given to the first 20% of customers; the score of 4 is given to second 20% of customers and so continues.

Phase 4. Modeling

In this phase, according to the purpose specified in the first phase, the model is developed using the CRISP-DM methodology and the *K*-mean algorithm. To determine the optimal number of clusters within the range of 2–30, this study uses the Davies–Bouldin measure, which combines the two criteria of solidarity and density (Davies and Bouldin 1979). Then, the mean value of behavioral variables in each cluster is evaluated to ensure customers are grouped in significant clusters, before proceeding to the next test. According to Khajvand and Tarokh (2011) the lower values of the Davies-Bouldin index indicate the best clusters.

The results indicate that the best value for the Davies–Bouldin criteria in the RFM model is four clusters with the value of 0.895, and in the $R_dF_dM_d$ model, five clusters are optimal with the value of 0.908. After determining the optimal number of clusters, the *K*-Mean algorithm was used for clustering customers in the RFM and $R_dF_dM_d$ models separately. Then, the data from the RFM model were separated into four clusters, and the data from the RdFdMd model were separated into five clusters using the RapidMiner Studio software. The value obtained for each cluster is shown in Table 2.

Table 2. Davies–Bouldin index of RFM and RdFdMd.

Cluster	RFM Model	RdFdMd Model
2	1.199	1.246
3	1.043	1.008
4	**0.895**	0.965
5	0.912	**0.908**
6	1.081	0.992
7	1.135	1.004
8	1.046	1.065
9	*N*	1.058
10	*N*	1.044
11	1.088	1.088
12	1.013	*N*
13–30	*N*	*N*

After determining the optimal number of clusters, the *K*-Mean algorithm was used for clustering customers in the RFM and $R_dF_dM_d$ models separately. After that, the Mean value of behavioral variables in each cluster is evaluated. This helps to ensure that before proceeding to the next test, customers are grouped in significant clusters.Then, the total value of each cluster is divided by the number of members of that cluster, in order to determine the mean value of each cluster (Khajvand and Tarokh 2011). Then, the data from the RFM model were separated into four clusters, and the data from the RdFdMd model were separated into five clusters using the RapidMiner Studio software. The value obtained for each cluster is shown in Table 3.

Table 3. Clusters' Index's mean.

	RFM			RdFdMd		
Cluster	R	F	M	Rd	Fd	Md
1	**4.141**	**3.926**	**4.613**	1.835	1.453	4.529
2	1.793	1.132	1.829	1.461	1.158	2.044
3	4.292	1.340	2.608	4.062	1.345	3.752
4	2.199	1.467	4.456	3.913	1.216	1.544
5	–	–	–	**4.072**	**4.115**	**4.611**

As indicated, in the RFM model, the customers in the first cluster had lower recency and higher frequency and monetary compared to the other clusters. The customers in this cluster were high-value customers that had more favorable average values of the indexes in the data cluster. The second cluster included low-value customers that had lower recency, frequency, and monetary compared to the other clusters. The third cluster included customers with higher recency and was ranked third in terms of frequency and monetary. The fourth cluster included customers that were ranked third in terms of recency and second in terms of frequency and monetary. In the $R_dF_dM_d$ model, the first cluster had lower recency and was ranked second in terms of frequency and monetary. The second cluster had lower recency

Table 4. ANOVA Test Results for RFM and RdFdMd.

Model	Variable	Source of change	SOS	df	Mean square	*F*	Sig
RFM	R	Intra group	173845.759	3	57948.586		
		Inter group	86341.061	130088	0.664	57948.586	0.000
		Total	260186.820	130091			
	F	Intra group	112233.093	3	37411.031		
		Inter group	47615.807	130088	0.366	102208.206	0.000
		Total	159848.900	130091			
	M	Intra group	171274.323	3	57091.441		
		Inter group	88520.373	130088	0.680	83900.589	0.000
		Total	259794.696	130091			
RdFdMd	Rd	Intra group	92440.513	4	23110.128		
		Inter group	34928.630	64032	0.545	42366.040	0.000
		Total	127369.143	64036			
	Fd	Intra group	52852.776	4	13213.194		
		Inter group	20985.397	64032	0.328	40316.953	0.000
		Total	73838.172	64036			
	Md	Intra group	94260.398	4	23565.100		
		Inter group	29317.853	64032	0.458	51467.631	0.000
		Total	123578.251	64036			

and frequency, and was ranked fourth in terms of monetary. The third cluster included customers that were ranked second in terms of recency, and third in terms of frequency and monetary. The customers in the fourth cluster had lowered monetary and in terms of recency and frequency were ranked third and fourth, respectively. The customers in this group also received the lowest discount. Finally, the fifth cluster included customers with the highest recency, frequency, monetary, and those who had recently received the highest discounts.

Phase 5. Evaluation

After clustering and analyzing the data, the quality of clusters was assessed using the Davies–Bouldin criteria, which was 0.895 for the RFM model and 0.908 for the $R_dF_dM_d$ model. In addition, the differentiation of clusters created by the *K*-mean algorithm and their resolution were evaluated using an ANOVA test (Table 4). The significance levels (sig) of all variables R ($F = 57948.58$, sig = 0.000), F ($F = 102208.20$, sig = 0.000), M ($F = 83900.58$, sig = 0.000), R_d ($F = 42366.04$, sig = 0.000), F_d ($F = 40316.95$, sig = 0.000), and M_d ($F = 51467.63$, sig = 0.000) are lower than 0.05. Therefore, the homogeneity of populations' mean is rejected, showing that the clusters have different means in both models, and the clustering was done correctly.

- Valuation and Determination of the RFMV Model Parameters Weight Using A Shannon's Entropy And Hierarchical Analysis:

The weight of each parameter should be determined in order to rate and cluster customers. In this study, Shannon's entropy was used to calculate the weights of R, F, and M of purchased data, discount data, and the customer's lifetime value (Ranjbar Kermany and Hossein Alizadeh 2012):

Step 1: Normalize the evaluation index as Equation (1):

$$P_{ij} = \frac{X_{ij}}{\sum_{j=1}^{m} X_{ij}} \tag{1}$$

Step 2: Calculate the entropy measurement of every index using the Equation (2), in which $K = (\mathrm{Ln}\,(m))^{-1}$:

$$Ej = -k\sum_{j=1}^{n} p_{ij}\,\mathrm{Ln}\,(p_{ij}) \tag{2}$$

Step 3: Define the divergence through Equation (3):

$$D_j = 1 - e \tag{3}$$

In this equation, D_j is the uncertainty and the degree of deviation of data and provides insight into the usefulness of the relevant criteria for making an informed decision. Whatever measured values of one criterion are close to each other, the competing alternatives are not much different in terms of those criteria and the role of that criterion in decision-making should be reduced.

Step 4: Obtaining the normalized weights of index as Equation (4):

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{4}$$

The weight of the R, F, and M parameters for purchase data and discount data are calculated using Shannon's entropy and the results are shown in Table 5. According to the weight obtained by Shannon's entropy for RFM and RdFdMd models, the uncertainty and weight of recency and frequency indexes are close to each other and customers are different in terms of both characteristics. Therefore, the role of these two factors in decision-making is reduced, while the monetary index with a huge difference from two other variables provides useful information for decision-makers about customers.

After determining the weight of each parameter, the indexes' value for each customer is calculated based on formula (5):

$$\mathrm{CLV}_{cj} = \mathrm{NR}_{ci} * \mathrm{WR}_{ci} + \mathrm{NF}_{Ci} * \mathrm{WF}_{ci} + \mathrm{NM}_{ci} * \mathrm{WM}_{ci} \tag{5}$$

Where CLV_{cj} is the average customer lifetime value of cluster *ci* (*i*: 1, 2 … number of clusters). WR_{ci}, WF_{ci}, and WM_{ci} are, respectively, the weights of recency, frequency, and monetary of cluster *ci*, and NR_{ci}, NF_{ci} and NM_{ci} are, respectively, normalized recency, frequency, and monetary of cluster *ci*. After calculating the average customer lifetime value, clusters are ranked. In this stage, each of the characteristics R, F, and M are normalized using decimal normalization scaling and then are multiplied in achieved weights and the customer lifetime value is calculated for each customer. At the end, the average customer lifetime value for each cluster is calculated (see Table 6).

As indicated in Table 6, in the RFM model the first cluster includes high-value customers, the second cluster includes low-value customers, the third cluster is in the second rank, and fourth cluster is in the third rank in terms of the mean value of the parameters. Based on the customer life time value, the first cluster that has a maximum value is labeled high, the third cluster that ranks second is labeled medium, the fourth cluster that is in third place is labeled low and the second cluster with the lowest is labeled very low in terms of values. Moreover, in the RdFdMd model the fifth cluster that has the highest discount will create the most value.

Table 5. Shannon entropy weighting.

	R		F		M	
Criteria	RFM	RdFdMd	RFM	RdFdMd	RFM	RdFdMd
E_j	0.974	0.970	0.977	0.974	0.935	0.939
D_j	0.025	0.029	0.022	0.025	0.648	0.060
W_j	0.227	0.257	0.201	0.218	0.570	0.525

Table 6. Customers' average value.

Cluster	RFM	RdFdMd
1	0.042	0.013
2	0.005	0.011
3	0.025	0.028
4	0.011	0.026
5	–	0.054

Phase 6. Deployment

After reviewing the results and valuation, the model is assessed. At this stage, the project should be summarized and the results of the model should be used in business, and the valuable customers should be identified through the proposed model. At first, data are collected and primary processing is done on them. After normalization and detection of the optimal number of clusters, *K*-Mean algorithm is used for clustering data and clusters are examined from the perspective of business. Then, the ANOVA test is used to evaluate the differentiation of clusters. If the results are consistent with the primary targets of business, and seem to satisfy business needs, they will be used in a real environment. A new phase will be defined otherwise, and the process will be repeated. The studied business can analyze the results to develop marketing strategies and improve its own customer relationship management.

- Two-Dimensional Clustering Analysis

The average customer lifetime value of each part of the composition model is calculated according to the weights of R, F, and M in the RFM model and Rd, Fd, and Md in the RdFdMd model and are categorized into seven groups (Figure 1).

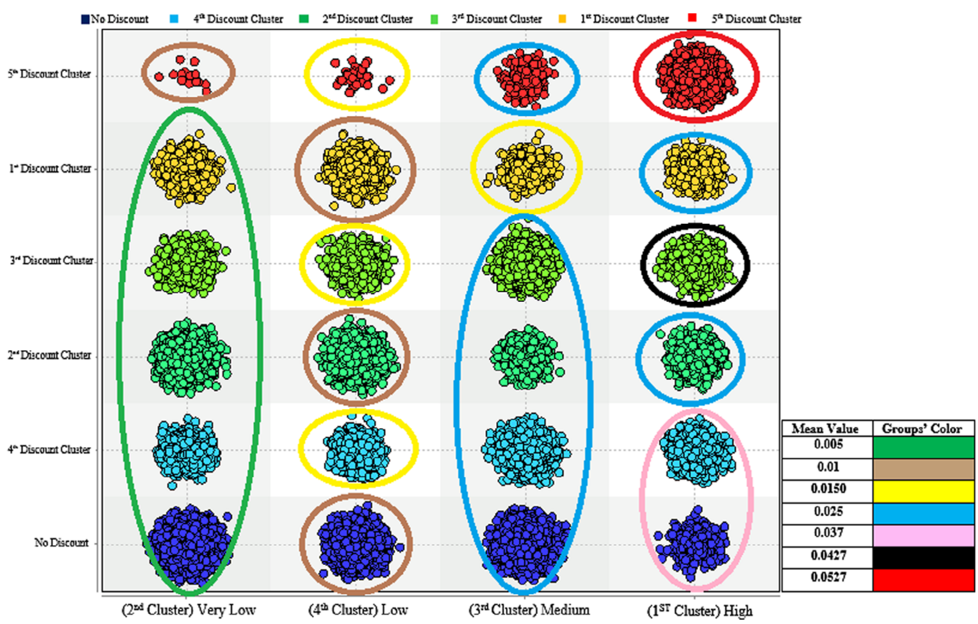

Figure 1. The average customer life value in two-dimensional clustering.

According to Figure 1, the groups shown in green are customers with a mean value of 0.005 who bring us the lowest value despite various discounts. The brown groups include customers whose mean value is almost 0.01. Despite different discounts, the customers of this group have higher recency and they are leaving the organization. Therefore, the organization should try to join them to higher value groups. The yellow color groups have a mean value of 0.0150 and include customers with higher discount recency that currently has a lot of discount. The groups shown in blue have a mean value of 0.0250 and include customers with lower monetary. This group should be presented the advertising with discounts to encourage them to purchase products and consequently provide us more profit. The groups shown in pink include customers with mean rank of 0.0370 that purchase without discount or received lower discount. The groups shown in black include customers with a mean rank of 0.0427 who are second high-value group that received higher discount. The groups shown in red include customers with a mean rank of 0.0524 who have low recency and received high discount. These groups are high-value customers that provide the highest value for business. According to the results, the first and fifth discount clusters are high-value clusters in both the RFM and RdFdMd models and the third discount cluster is also valuable in the RdFdMd model. These groups have recently taken the highest discount. The low-value group is the second group of the RFM model (without discount). This group includes customers who have not had any discount. Comparing the average customer lifetime value and different parameter weight of RFM and RdFdMd suggests that those who have taken the maximum discount offer the highest value. The results indicate that compared with clustering with the RFM model, using the RdFdMd model provides more accurate clustering for companies. Moreover, the discount role in the separation of clusters and valuation of clusters is well known. According to the results, discount is effective on the purchase behavior of customers, leading to customer loyalty, and increases the value and profitability of the business.

Discussion and conclusion

During the past few years, the organizations' interaction with their customers has changed significantly, so that there is no guarantee of a long-term relationship between business and customers. To survive, organizations need to truly understand customers' needs. Organizations can identify the valuable customers, and predict their future behavior through data mining and extraction of hidden information from large databases (Farooqi and Raza 2012; Yadav, Desai, and Yadev 2013). Therefore, understanding customers' behavioral variables and categorizing customers based on these characteristics could provide better insight that will help business owners and industries to adopt appropriate marketing strategies. Marketing managers can also make long-term relationships by identifying and predicting the changes in customer behavior (Chen, Chiu, and Chang 2005). Customer segmentation would target each customer segment with distinct products and marketing services, and would help them to meet the requirements of each section. Therefore, customer segmentation and analysis of different groups of customers are needed for identifying the groups of customers. Since discount is another aspect of consumer behavior, this study used a two-dimensional approach to analyze customers' behavior (Rygielski, Wang, and Yen 2002).

Given that RFM is the most frequently used model in customer segmentation and analyzing customer behavior (Rygielski, Wang, and Yen 2002), this study added the new variable of discount to the RFM model and performed two-dimensional clustering using real data from an online retailing company to provide more comprehensive knowledge of customer behavior, which is the innovation of this study.

In this approach, we could demonstrate the purchase behavior and discount behavior of each segment. This study categorized customers based on the amount of discount and has analyzed the behavior of customers doing two-dimensional clustering to answer the main research question of how to reach a comprehensive understanding of customer behavior analysis by adding the variable of discount to the RFM model and doing two-dimensional clustering of the RFM and RdFdMd models and its effect on customers' value. The proposed model combines customer purchasing behavior and discounts, and provides a comprehensive knowledge and understanding of customers. In addition, the model shortcomings, such as inattention to personal characteristics and demographic variables of customers were improved by considering the role of discount.

The results indicated better customer clustering and valuation using the RdFdMd model. On the other hand, the role of discount in the cluster separation and valuation of clusters was well identified. Moreover, according to the results, discount, along with other behavioral variables provides more accurate clustering than the RFM model. It also could provide a more accurate understanding of customer groups. Therefore, organizations can adopt the appropriate strategies in each category, and can increase their Probability of success.

According to the results, discount is effective on the purchase behavior of customers, leading to customer loyalty, and increases the value and profitability of the business. In addition, the weights of different clusters of customer discount data, and the average customers' lifetime value were calculated and compared. The results indicated that, despite the impression that large discount leads the company's expense, in fact, discount encourages, persuades and attracts customers, so that this study indicated that customers with the highest discount monetary and discount frequency that have recently been discounted provide the highest value for the company. In addition, customers with lower discount provide lower value for the company. Therefore, discount is an important criterion for many customers so that they compare the prices of different vendors and retailers to buy more discounted services.

Based on the RdFdMd model, different retailers can do more precise clustering and can specify the most distinctive and meaningful groups to apply up-selling strategies. Therefore, the retailer can retain high-value customers and prevent their churn through the identification of valuable customers and providing more facilities in addition to discounts including free transportation, participating customers in sweepstakes, and offering a reward. The retailer can also ask the reason for the delay in the purchasing process of customers who have not recently purchased and are at risk of churn through constructive interactions. For example, by offering advertising through e-mail or text messages, including a discount, the retailer can encourage low monetary customers to purchase goods and join the high-value group to provide more value and consequently increase customer lifetime value.

Organizations should evaluate the discount behavior of customers in addition to their purchase behavior to attract valuable and loyal customers using strategies such as providing products and services at a discount. Moreover, they should consider discount as a milestone in attracting and retaining more customers.

Moreover, Discount policy should be planned in such a way as to help the company inventory turnover and business turnover speed. Moreover, it should be timely and should not be continued throughout the year as it loses its effectiveness. Therefore, companies should manage discounts that ultimately lead to balances in production and distribution.

The results of this study can be generalized to other retailers and industries, and the proposed model can be used in retail stores with online and digital products that give discounts based on market pricing and conditions. Therefore, it is suggested that future research expand the scope of the study to various industries, and compare the results.

In this study, data related to the sales of six months of an online retailer were used to analyze the purchase behavior of customers. More data will provide better results; therefore, it is suggested that future research do the same study with more data.

Moreover, all the variables that have been added to the RFM model and have improved this model are not considered in this study. Factors such as product diversification, the relationship between the product and discounts are also not considered in this study. Therefore, it is suggested that future studies do the same study with more data and use these variables to improve the RFM model and study the impact of these variables.

Moreover, future research should study the interval between discounts. Dynamic pricing is a pricing strategy where prices change over time. Economic theories argue that the dynamic pricing is inherently good for corporate profitability, because it allows companies to obtain a greater share of consumer surplus.

Previous studies on the clustering customers using RFM model have only added one variable to the model. For more general information, to achieve more practical results, it is suggested that future studies add two or more variables to RFM model so to identify the variable with greater impact on understanding the customer.

Disclosure statement

No potential conflict of interest was reported by the authors.

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