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CUSTOMER SEGMENTATION BY USING RFM MODEL AND CLUSTERING METHODS: A CASE STUDY IN RETAIL INDUSTRY

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Abstract

Companies need to understand the customers' data better in all aspects. Detecting similarities and differences among customers, predicting their behaviors, proposing better options and opportunities to customers became very important for customer-company engagement. Segmenting the customers according to their data became vital in this context. RFM (recency, frequency and monetary) values have been used for many years to identify which customers valuable for the company, which customers need promotional activities, etc. Data-mining tools and techniques widely have been used by organizations and individuals to analysis their stored data. Clustering, which one of the tasks of data mining has been used to group people, objects, etc. In this paper we propose two different clustering models to segment 700032 customers by considering their RFM values. We detected that the current customer segmentation which built by just considering customers' expense is not sufficient. Hence, models that recommended in this research are expected to provide better customer understanding, well-designed strategies, and more efficient decisions.

Keywords: Customer segmentation, RFM model, Clustering, K-means clustering.

Jel Codes: C38, M30

Introduction

As it is well known by marketers, customers have various kinds of needs and wants. Companies have used several segmentation criteria

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and techniques to better identify and understand customer groups and provide preferable products and services to them in order to satisfy these different needs and wants. Also, segmentation is important that the company can create profitable segments and react to the selected segment based on its competitive advantages. However, many marketers have difficulty in identifying the right customer segments to organize marketing campaigns (Mohammadian & Makrani, 2016). This causes unsuccessful loyalty programs and promotions conjunction with waste of marketing resources.

Loyalty programs and cards are greatly using in sports retailing industry. Leenheer & Bijmolt (2008) asserted that some industries are more suitable for customer loyalty programs and sport industry is one of the most frequently loyalty program adopted industry. According to Schwarz & Hunter (2008) sport retailers spend time with loyalty programs using a database created in conjunction with types of loyalty cards or tags. When it is considered that sport retailing industry is increasing 6% per year and reaches $2 billion in 2016 in Turkey (Yılmaz, 2016). customer retention become prominent for marketing managers. As an important tool for better customer retention rate, customer loyalty programs and loyalty cards have received considerable attention from marketing researchers and managers. Loyalty programs help companies to segment customers into different status levels based on their cumulative purchases (Ramaseshan et al., 2016). Although companies segment their customers as premium, platinum, gold, bronze, etc., they usually take purchases into account when they offer loyalty cards to customers. However, the term customer loyalty comprise more than purchase consideration. Customer loyalty involves both attitudinal/affective and behavioral dimensions. Behavioral loyalty refers to repurchase behavior of customers and the frequency of repeat purchase (Kandampully & Suhartando, 2000; Gomez et al., 2006). while attitudinal loyalty has key components such as satisfaction, commitment and trust (Bowen & Chen, 2001; Han & Ryu, 2009).

In spite of the limited studies in sport customer segmentation in the meaning of fans and their attitudes towards sport clubs, we did not reach any research which segment sport consumers based on their sport products purchases. From this point of view the purpose of this article is thus to investigate whether customer segmentation can be achieved better by using RFM analysis integrated with cluster analysis. The specific objectives are a) to determine customer groups in sports retailing industry, b) to compare these segments with the company’s current segmentation, c) to detect how RFM values shape the clusters.

Literature Review

Decision makers use many variables to segment customers. Demographic variables such as age, gender, family, education level and income are the easiest and common variables for segmentation. Socio-cultural, geographic, psychographic and behavioral variables are the other major variables that are used for segmentation. In the past years, many researchers investigate segmentation of sport customers. Early of them focused on football and segmentation based on spectators in a dualistic typology. According to Stewart et al. (2003) the typology covers Type 1 and Type 2 consumers. Type 1'ers are genuine, traditional, expressive, irrational, symbolic and die-hard consumers while Type 2'ers are corporate, modern, submissive, rational, civic and less-loyal. Then, multidimensional typologies came to light. Smith & Stewart (1999) categorized sport consumers into five groups: passionate partisans, champ followers, reclusive partisans, theatergoers and aficionados.

The RFM has been widely applied model for customer value analysis. It has been used by many scholars to accomplish customer segmentation (Spring et al., 1999; Jonker et al., 2006; Cheng & Chen, 2009; Khajvand & Tarokh, 2011). Since RFM analyzes the behavior of the customers, it can be possible to encounter behavior-based models in the literature (Yeh et al., 2008; Wei et al., 2012).

Over the past twenty years, several researchers have considered RFM models in developing prediction and classification models. For example, Etzion et al. (2004) classified customers in terms of their profitability and created a customer lifetime value. Cui et al. (2006) proposed a model, used RFM variables to estimate customer's response. Cheng & Chen (2009) exposed a data-mining model to predict customer loyalty. Additional literature includes RFM models integrated with clustering algorithms, actually related to the model which will use in this paper. These researches are detailed in Table 1.

Table 1: Literature overview on researches includes RFM models and clustering techniques

Studies	**Context, research design and analysis**	**Purposes and key findings**
Chen et al. (2009)	• Context: Taiwan • Retailing sector • RFM analysis + Apriori algorithm	• Aim to develop an algorithm for generating all RFM patterns from customers' purchasing data. • To generate valuable information on customer purchasing behaviour for managerial decision-making. • This model demonstrated the benefits of using

		RFM for analyzing customers' purchasing data in retail sector.
Khajvand & Tarokh (2011)	• Context: Iran • Retail banking sector • RFM analysis + K means algorithm + Two step algorithm	• This framework collected the required information in a six-season periods, then the collected data were divided based on the seasonal divisions. • Customers' background in different periods was examined and their behaviors in the future were estimated. • The RFM parameters were extracted for each customer and calculate clusters based on K-means and customer loyalty were calculated.
Khajvand et al. (2011)	• Health and beauty company • RFM analysis + K means clustering	• To propose a model that clustered customers into segments according to RFM. • Clustering customers into different groups helped decision-makers to identify market segments more clearly and developed more effective marketing and sale strategies for customer retention.
Chen et al. (2012)	• Context: Taiwan • A dataset included 183,947 samples that were characterized by 44 attributes. • RFM analysis + K means clustering	• Aim to propose a two-stage clustering-classification model. • This model initially integrated the RFM attribute and *K*-means algorithm for clustering the patients and optimizing health care services. • A potential determinant for gender differences was found. The age attribute was not significant to the hospital departments.
Kumar et. al. (2012)	• Context: India • Banking sector • RFM analysis + K means clustering	• To establish the relation between marketing campaign and customer segmentation along with the enhancement using the RFM approach. • This study focused on clustering e-banking customer to analyze customer characteristics and behaviors with appropriated criteria: access time, transaction access and RFM Analysis, LTV, demographic variables. • Analyses included two phases. Firstly, K-Means clustering was included, where the customers were clustered according to their RFM. Then, with demographic data, each cluster was again partitioned into new clusters.
Cho et al. (2013)	• Context: India • Mobile convergence service environment. • RFM analysis + K means clustering	• To propose a new clustering method using item preference based on RFM for recommendation system in u-commerce in order to develop the accuracy of recommendation with high purchasing. • The results showed that the performance of the proposing system with new clustering method was improved better than the existing system.

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Hu &Yeh (2014)	• Retailing sector • RFM analysis + K means clustering	• Aim to define the RFM pattern and develop a novel algorithm to discover complete sets of RFM patterns to approximate sets of customers. • They evaluated the values of patterns from a customer's point of view. Instead of evaluating values of patterns from a customer point of view, this study directly measures pattern ratings by considering RFM features. • The results showed that the proposed approach was efficient and discovered the greater part of RFM-customer-patterns.
Zalaghi & Varzi (2014)	• Context: Iran • RFM analysis + K means clustering + Genetic algorithm	• A method used to obtain the behavioral traits of customers using the RFM approach. • For their suggested approach, the customers' records clustered and then the RFM model items were specified through selecting the effective properties on the customers' loyalty rate. • Customer scores regarding to their loyalty for each cluster was calculated.
Cousseme nt et al. (2014)	• Marketing • Two empirical direct marketing data sets provided by the Direct Marketing Educational Foundation • RFM analysis + Decision tree + Logistic regression	• Aim to investigate the influence of problems with data accuracy using RFM analysis for customer segmentation for two real-life direct marketing data sets. • Results showed the impact of the level of data accuracy on the performance of three segmentation algorithms.
You et al. (2015)	• A real data from a Chinese company • RFM analysis + K means clustering + Decision tree	• To propose a model to accurately predict monthly supply quantity, using the RFM approach to select attributes to cluster customers into different groups. • This framework helped managers to identify the latent characteristics of different customer categories. • The model was also helpful to predict marketing strategies, which can greatly reduce inventory for every customer category.
Abirami & Pattabira man (2016)	• Context: India • Retailing sector • RFM analysis + K means clustering + Association rules	• They suggested a approach of customer classification. • RFM model to analyze and estimate customer behavior using clustering algorithms and data mining techniques.
Ansari & Riasi (2016)	• Context: Iran • Data from 250 bank customers. • RFM analysis + Two step clustering	• Aim to identify the main clusters of bank customers in order to help classifying customers and create more efficient customer strategies. • According to the results, five different clusters of the customers were identified, namely, favorite

		customers, creditworthy customers, non-creditworthy customers, passers, and friends. • The findings showed that disparate clusters of bank customers are based on their loan amount, default risk, account balance, degree of loyalty and profitability for the bank.
Dursun & Caber (2016)	• Context: Turkey • A sample of 369 from the population 5939 • Hotel customers • RFM analysis + K means clustering	• Aim to segment hotel customers • Eight clusters were obtained according to their RFM score • Loyal customers, loyal summer season customers, collective buying customers, winter season customers, lost customers, high potential customers, new customers and winter season high potential customers were identified. • Customers' card types were compared with new segmentation.
Sarvari et al. (2016)	• Context: Turkey • A data from a global pizza restaurant chain. • RFM analysis + K means clustering + Association rules	• Aim to determine the best approach to customer segmentation. • Different types of scenarios were designed, performed and evaluated under test condition. • They showed that having an appropriate segmentation approach is vital if there are to be strong association. Also, the weights of RFM attributes affected rule association performance positively.

Leenheer & Bijmolt (2008) defines loyalty program as "an integrated system of marketing actions, which aim to make member customers more loyal. A customer must become a member and identify himself as such with his loyalty card at every purchase occasion, to take advantage of the loyalty program". The major reasons of companies loyalty programs usage are increasing customer loyalty (Meyer-Waarden, 2008; Demoulin & Zidda, 2009), collecting customer and shopping habit data (Liu, 2007; Sands & Ferarro, 2010), retaining customers and selling them more (Liu et al., 2011) rewarding frequent shoppers (Jere and Posthumus, 2014) and promoting customized offers. Segmenting customers and implementing more successful loyalty programs has become more easy and useful in recent years thanks to advances data mining techniques. Authors like Gomez et al. (2006). Kandampully & Suhartando (2000) and Bulut (2015) also refer customers' repurchase behavior and the frequency of repurchases as a component of customer loyalty.

The existing marketing literature is also full up with studies that revealed the relationship between loyalty program membership and brand loyalty (Sharp and Sharps, 1997; Bolton et al., 2000; Maity & Gupta,

2016) and shows remarkable results. Customers who are a member of loyalty program show higher behavioral and attitudinal loyalty, visit retailer more than non-members and purchase more (Ha & Stoel, 2014; Melnyk & Bijmolt, 2015; Liu, 2007). Kim et al. (2009) found that higher level of loyalty is related to higher status in the company's loyalty program. Benavent et al. (2000) also revealed that customers spend more when they have loyalty cards. Similarly, Ramaseshan et al. (2016) determined that demotion on ownership of loyalty program has stronger negative effects on customers' attitudes and behavioral intentions.

Companies have more useful data to better segment their customers by using these techniques depending upon their competencies in data analysis and interpretation. RFM technique, one of the leading parts of these techniques, has been used over 50 years in order to segment customers. RFM which is based on **R**ecency, **F**requency and **M**onetary value of purchases is simple-in-use and powerful for producing knowledge from customer data (McCartey & Hastak, 2007).

Methodology

The proposed research methodology includes three major steps. The first phase was related to pre-analysis efforts which refer data cleaning and transformation. Second, data were analyzed by using RFM analysis, two-step cluster analysis and K-means clustering. Finally, the results were presented. The full step methodology process is presented in Fig. 1.

The secondary data set obtained from the customer loyalty cards accounts from the database of a sports retailing company as suggested from Hu & Yeh (2014). In this study, we used data that have been collected by a retail store chain which is one of the biggest of Turkey in sports retailing. Like any other sports retailing companies, the company offers products such as footwear, shirts, sweats, accessories and sports equipment. Managers had decided to create customer loyalty card system for the year 2010 on the purpose of segmenting customers and creating a customer loyalty program. The loyalty card program consisted of three card levels; bronze, gold, and premium. Customers who are members of the loyalty program have been upgraded from the points they earn depending upon their spending in a one calendar year. Customers who have bronze card are the members who spent less than 2000 Turkish Lira (TL) (≈ $520) in a year. Gold card members are the customers who spent between 2000-4000 TL (≈$520-$1040). The customers who spent more than 4000 TL (≈$1040) are deserved to have premium card.

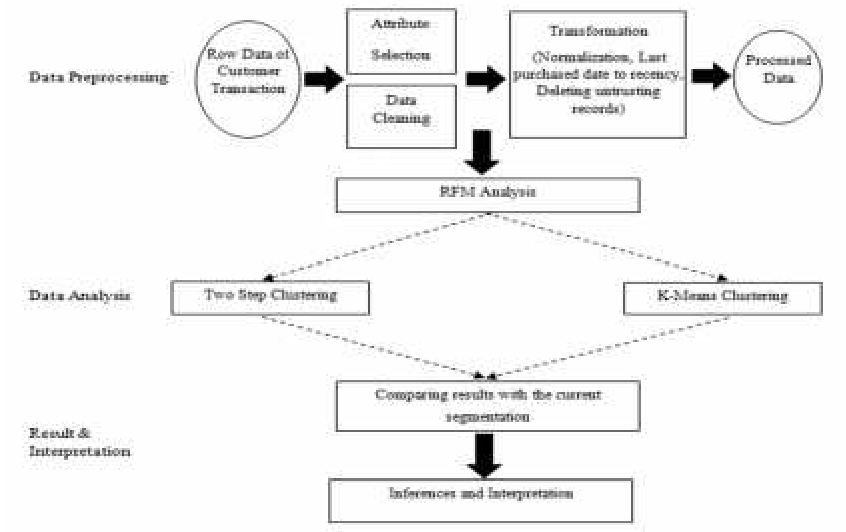

Figure 1: Research methodology flow chart

The dataset includes the customer variables which belong to the period from January 1, 2016 to December 31, 2016. The dataset consist of 715328 register which are belong to both customers and e-customers. Data cleaning process have been executed and some missing values, wrong values have been excluded from data set. 700032 registers which belongs to customers that made any purchased in 2016 both in store and online have been extracted and used for the analysis. We use whole prepared population in the analysis. Thus, we did not use any sampling method. According to company's current segmentation; out of 700033 customers, 694647 have bronze card, 4469 have gold card and 916 have premium card.

RFM analysis has been conducted to define R, F and M values of the customers and these indicators have been used to define proposed cluster for the company. Table 2 represents the R, F, M indicators. (R). the capital letter of *recency*, refers to the time of the most recent purchase. (F) which represents *frequency* indicates the total number of purchases and (M) which represents the *monetary* indicates the total expenses of customer.

Table 2: RFM statistics

	R	F	M
N	**700032**	**700032**	**700032**
Mean	**119,46**	**1,9**	**336,67**
Std. Deviation	**71,635**	**2,336**	**498,8**
Minimum	**1**	**1**	**1**

Maximum	**261**	**489**	**130103**

Results

Demographics of the customers

Demographics of the customer consisted of 62.04% of males and 37.96% of females. The age of customers ranged from 16 to 74 and a great majority of consumers (85.5%) are under age 30. The average expense of the customers is 336 TL (≈$87) and they shop approximately 2 times (1.93 times) in a year. Credit card is the most preferred payment tool with the 59.9%, followed by cash (25.13%) and gift card (14.65%) respectively. Most of the customers (86.8%) preferred shopping in traditional stores rather than online shopping.

RFM results

There are 3 different level have been defined for every indicators before carrying out RFM analysis and for every indicator a value have been evaluated (1, 2 or 3). R, F and M values and number of customers are shown in Table 3.

Table 3: Cross tabulation of RFM indicators

				Monetary Values		
				1	2	3
Recency Values	1	Frequency Value	1	-	-	-
			2	**56146**	**56130**	**56170**
			3	**22015**	**21936**	**21933**
	2	Frequency Values	1	-	-	-
			2	**53050**	**52629**	**52245**
			3	**25173**	**25023**	**25068**
	3	Frequency Values	1	**39156**	**39246**	**39120**
			2	**16208**	**16206**	**16134**
			3	**22147**	**22145**	**22152**

Figure 2 illustrates RFM heat map which is creating categories according to R and F scores and also represents average monetary value for these categories.

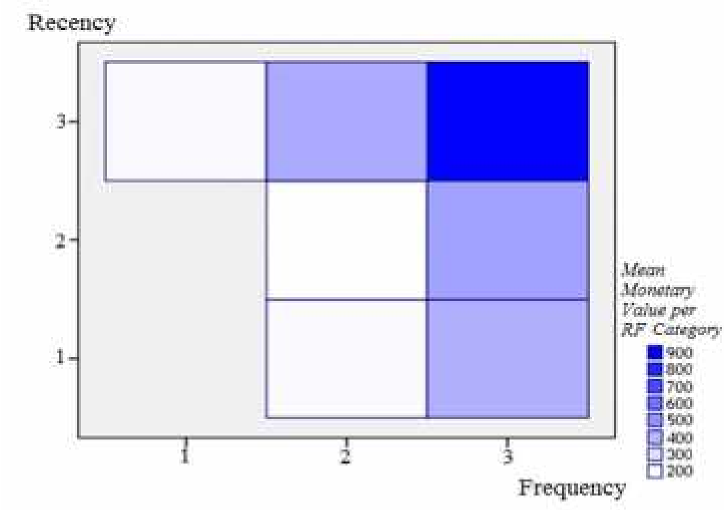

Figure 2: RFM Heat Map

According to the heat map (Fig. 2) there are some sub-groups which differ according to their R, F and M values. There are some customers who have high R and F values and their expense also high (top left box/defined darkest). And also some other groups that have F score which is equal to 3, but R scores are relatively low which are 1 and 2, but their expense more than the average. According to this figure, we could easily observe the trace of some different clusters in reference to customers shopping behavior.

Furthermore, a final RFM score have been obtained for every customer – e.g. '323' means that customer's recency value is 3, frequency value is 2 and monetary value is 3 (higher is better). Comparison between RFM scores and current card types is shown in Table 4.

Table 4: Comparison between RFM scores and current segmentation

		Current Card Type			Total
		Bronze	Gold	Premium	
RFM score	121	**56146**	**0**	**0**	**56146**
	122	**56130**	**0**	**0**	**56130**
	123	**56123**	**44**	**3**	**56170**
	131	**22015**	**0**	**0**	**22015**
	132	**21936**	**0**	**0**	**21936**
	133	**21663**	**242**	**28**	**21933**
	221	**53050**	**0**	**0**	**53050**

222	**52629**	**0**	**0**	**52629**
223	**52228**	**17**	**0**	**52245**
231	**25173**	**0**	**0**	**25173**
232	**25023**	**0**	**0**	**25023**
233	**24528**	**487**	**53**	**25068**
311	**39156**	**0**	**0**	**39156**
312	**39246**	**0**	**0**	**39246**
313	**39092**	**25**	**3**	**39120**
321	**16208**	**0**	**0**	**16208**
322	**16206**	**0**	**0**	**16206**
323	**16083**	**45**	**6**	**16134**
331	**22147**	**0**	**0**	**22147**
332	**22145**	**0**	**0**	**22145**
333	**17720**	**3609**	**823**	**22152**
Total	**694647**	**4469**	**916**	**700032**

As we mentioned before, the company clustered the customers just according to their expense (in other words monetary). We could easily see it in Table 4, customers who have gold and premium card have high M scores.

Proposed model 1: Two step cluster results

During the analysis, number of clusters was not fixed to evaluate the clusters. That means the number of clusters determined automatically. We have chosen log-likelihood method to measure the distance and Shwarz's Bayesian Criterion (BIC) as clustering criteria. There are three clusters evaluated by the results of two step cluster analysis. We named clusters as Bronze*, Gold* and Premium* to ease comparison with the current segments and we have used * sign to not confuse with the current segments. First cluster named as Bronze* consisted of 279717 customers, 40% of all population. Customers of this cluster had scores below the overall mean for all indicators. Thus, we signed this cluster as R^-, F^-, and M^-. Second cluster called as Gold* (R^+, F^-, M^-) which consisted377379 customers, 40% of all population. Mean of the recency scores of customers of this cluster had better than overall mean. But their shopping frequency and total expenses are below the mean. And customers of the third cluster which named Premium* (R^+, F^+, M^+) had better scores for all indicators. This cluster includes 42936 customers, 6,1% of all population. The results are summarized in Table 5.

Table 5: Model 1 Results

Indicator	Overall Mean	Bronze* (40,0 %) $R^- F^- M^-$	Gold* (53,9%) $R^+ F^- M^-$	Premium* (6,1%) $R^+ F^+ M^+$
R	**119,46**	**193,23**	**72,31**	**53,25**
F	**1,9**	**1,49**	**1,57**	**7,49**
M	**336,67**	**261,18**	**282,07**	**1308,18**
Cluster Size (N)		**279717**	**377379**	**42936**

Comparison between current customer segmentation and model 1 is shown in Table 6.

Table 6: Comparison between model 1 and current segmentation

	Card Type			
	Bronze	Gold	Premium	Total
Bronze*	**279717**	**0**	**0**	**279717**
Gold*	**377379**	**0**	**0**	**377379**
Premium*	**37551**	**4469**	**916**	**42936**
Total	**694647**	**4469**	**916**	**700032**

The company defined 694647 customers that should have bronze card by considering just their expense. But according the results of proposed model 1, 54,3% of this customers (377379 customers) should be defined as gold member and 5,4% of this customers (37551 customers) should be defined as premium member. 4469 customers defined as gold member according to current profiling. But pursuant to proposed model 1, all of these customers should have premium card. 916 customers defined as premium member according to current profiling. They also should have premium card according to proposed model 1. But in proposed model 1 there are 42936 customers right to have premium card. If the company distributes card types according to proposed model 1, 60% of the customers should change their card type. In other words there are 40% similarity between current profiling and proposed profiling.

Proposed model 2: K-means clustering analysis results

It has been aimed to conduct K-means analysis to build clusters by considering the R, F and M indicators in proposed model 2. As mentioned before, the number of cluster should be defined in k-means

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method. Many values of k (2 to 8) has been tested and optimal solution have been evaluated for k=4. The clusters that obtained by the k-means clustering analysis have been entitled according to their RFM scores. First cluster named as *"Regular"* consisted of 644081customers, 92% of all population. Customers of this cluster had values below the overall mean for all indicators. It seems that, the member of this clusters are likely one time buyers. Their F value is almost 1. Second cluster called as *"Loyal"* which includes 514 customers. RFM values of customers of this cluster had better than overall mean. Customers of the third cluster which named *"Star"* had elegant scores for all indicators. The company has very few customers which have such RFM scores. This cluster includes just 97 customers. The individuals of fourth cluster which is called *"Advanced"* (55340 customers) also have better RFM score comparing with all population. But their RFM values are less than Loyal customers and Advanced customers such that their values are so close to average scores. The results are summarized in Table 7.

Table 7: Model 2 Results

Indicator	Overall Mean	Regular	Loyal	Star	Advanced
R	**119,46**	120,16	88,5	54,1	111,7
F	**1,9**	1,12	2,63	6,03	2,01
M	**336,67**	327,2	719,2	2823,2	439,1
Cluster Size (N)		644081	514	97	55340

Comparison between current customer segmentation and model 1 is shown in Table 8.

Table 8: Comparison between model 2 and current segmentation

	Card Type			Total
	Bronze	Gold	Premium	
Regular	644081	0	0	644081

Loyal	0	0	514	514
Star	0	0	97	97
Advanced	50566	4469	305	55340
Total	694647	4469	916	700032

As could be seen in Table 8, some of the bronze customers are placed in Regular group, while some of them are placed in Gold group. All of the current gold customers placed in Advanced group by model 2. And current premium customers disperse three clusters; Loyal, Star and Advanced. Main reason behind this is proposed model segmenting the customers according to three indicators; R, F and M while current segmentation segmenting the customers just according to their expense.

Conclusion and Discussion

Organizations should better understand their components. Especially, it is essential for businesses, they should have detailed understanding about their customers' characteristics, behaviors, demographics, etc. In this context, many techniques have been developed. Many models and algorithms had been using to classify the customers. With the aid of these models and algorithms, businesses have pure insight about their customers. Businesses could develop appropriate and special strategies about their customers easily by grouping customers according to their data.

In this study two customer segmentation models have been recommended to a company which operates in retail industry in Turkey. The company already has customer segmentation which created according to customers' expense. This approach could be observed some of the studies. Etzion et al. (2004) classifies customers in terms of their expense to identify customer value. On the other hand, very recent studies asserted that grouping the customers just by their expense is not sufficient (i.e. Coussement et al., 2014; Sarvari et al., 2016; Ansari & Riasi, 2016). That's why we suggested customer segmentation which by using Recency, Frequency and Monetary as indicators when clustering the customers. We suggested two different customer segmentation models, one by using two step clustering method and the other one by using k-means clustering method. As far as the first model which created clusters according to two step clustering method, we determined three different clusters. Recommended model satisfies clusters which totally different from the current clusters. There is 60% discrepancy between first model and current model. There are just 916 customers have premium card according to current segmentation which is relatively small considering all population. Proposed model 1 suggests that 42936 customers should have premium card. Customer segmentation which created by considering more parameters could give more reliable point of view. This may provide companies to better focus on strategies. For example company could make more customized promotions, having more loyal customers which should be the first for retention.

Proposed model 2 suggests four different clusters. One of them contains 644081 customers. The company could define these customers as standard customers since their RFM scores close to average scores. Else, the company could chose not to give any card or any membership to these customers, since most of them are one time buyers. However, some of the studies emphasize that owners of loyalty cards spend much money than people without them (Benavent et al., 2000; Liu, 2007). Therefore giving any card type to these kinds of customers or defining them as any type of customer segment could be useful.

Better segmenting the customers is vital for the retail companies. Because grouping the customers that have similar needs, wants and behaviors give opportunities to companies about better understanding the target market. Thus, companies could make some activities, such as; customize marketing, price regulation, promotions, making more customers touch points, etc.

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