International Journal of Industrial Engineering & Production Research

International Journal of Industrial Engineering & Production Research

September 2014, Volume 25, Number 3
pp. 197-206

pISSN: 2008-4889

http://IJIEPR.iust.ac.ir/

Combining Data Mining and Group Decision Making in Retailer Segmentation Based on LRFMP Variables

A. Parvaneh, M. J. Tarokh* & H. Abbasimehr

***Amin Parvaneh**, Department of Industrial Engineering, K. N. Toosi University of Tech, Tehran, Iran.*
***Mohammad Jafar Tarokh**, Department of Industrial Engineering, K. N. Toosi University of Tech, Tehran, Iran.*
***Hossein Abbasimehr**, Department of Industrial Engineering, K. N. Toosi University of Tech, Tehran, Iran.*

KEYWORDS

Market segmentation;
Customer Lifetime Value (CLV);
LRFMP model;
Analytic Hierarchy Process (AHP);
Clustering;
Cluster analysis

ABSTRACT

Data mining is a powerful tool for firms to extract knowledge from their customers' transaction data. One of the useful applications of data mining is segmentation. Segmentation is an effective tool for managers to make right marketing strategies for right customer segments. In this study we have segmented retailers of a hygienic manufacture. Nowadays all manufactures do understand that for staying in the competitive market, they should set up an effective relationship with their retailers. We have proposed a LRFMP (relationship Length, Recency, Frequency, Monetary, and Potential) model for retailer segmentation. Ten retailer clusters have been obtained by applying K-means algorithm with K-optimum according Davies-Bouldin index on LRFMP variables. We have analyzed obtained clusters by weighted sum of LRFMP values, which the weight of each variable calculated by Analytic Hierarchy Process (AHP) technique. In addition we have analyzed each cluster in order to formulate segment-specific marketing actions for retailers. The results of this research can help marketing managers to gain deep insights about retailers.

1. Introduction

Data mining tools are used to extract the valuable information and knowledge embedded in the vast amount of data [1, 2]. Data mining techniques have been used in many different areas such as market basket analysis [3] customer churn prediction [4], and credit scoring [5]. However, in this paper, we focus on applying data mining to clustering retailers. In fact, we have considered retailers as customers.

There is product homogeneity in many consumer categories and any product has a lot of substitutable products. In this situation the consumers might be susceptible to change their consuming products by retailer recommendation. This issue becomes more important for an industry that features considerable interaction between retail salesperson and consumers during in the buying process.

The essence of Business-to-Business marketing is building long term relationship with customers [6]. Especially in manufacture-retailer context, a long term relationship requires manufactures to set up a high level of loyalty [6]. B2B loyalty researches are considerably few. Davis-Sramek, et.al. [7] had focused on retailer loyalty in the supply chain for consumer durable products. They investigated factors affecting retailer loyalty that includes: service quality, satisfaction and commitment. They examined technical service quality and relational service quality as service quality aspects for retailer order fulfillment. They also

* **Corresponding author: Mohammad Jafar Tarokh**
Email: *mjtarokh@kntu.ac.ir*
Paper first received May 25, 2013, and in accepted form May, 05, 2014.

divided commitment into two types: (1) affective commitment (2) calculative commitment. They found technical and relational service quality impacted satisfaction and consequently it impacted both affective and calculative commitment. Finally, affective commitment directly influenced retailer loyalty.

Market segmentation efforts to put similar customers into homogeneous groups. Market segmentation enables marketing department to perform segment-specific marketing actions. By performing different marketing actions for each segment, the firm ensures improvement in its marketing strategies. Some researches used the RFM (Recency, Frequency, and Monetary) model (e.g. [8-11]) for market segmentation.

Chang and Tsay [12] proposed LRFM model by incorporating customer relation length to RFM model. In this study, we have proposed LRFMP model by adding P (Potential) to LRFM model. P is the maximum value of retailer purchases over a particular period. We used K-Means algorithm for clustering retailers based on RFMLP variables. After clustering customers, 10 clusters were obtained. Analytic Hierarchy Process (AHP) was used to determine the weight of each LRFMP variable, according to decision-makers opinions. Then the integrated rating of clusters was computed as the weighted sum of LRFMP values. Finally, cluster-specific marketing actions were formulated to improve behavior and loyalty of each cluster to the firm.

The reminder of this paper is organized as follows. First background of the work is presented in section 2. In section 3, research methodology is explained and experimental results are analyzed. In section 4, the marketing actions are analyzed and formulated. Conclusion is considered in section 5.

2. Literature Review

2-1. CRM

Despite of being an important approach to business, there is no general accepted definition of CRM. For example Ling and Yen [13] defined CRM as "a set of process and enabling systems supporting a business strategy to build long term, profitable relationship with specific customers". Kincaid [14] defined CRM as "the strategic use of information, process, technology, and people to manage the customer's relationship with your company (marketing, sales, services, and supports) across the whole customer cycle". These definitions view CRM as a process of customer acquisition and retention with the help of business intelligence to maximize customer value to organization. Ngai et al. [15] considered four dimensions for CRM cycle: identification, attraction, retention, and development. These dimensions are critical factors to achieve customer insight.

Applying CRM to a business leads to improvement of customer loyalty. Benefits of increasing customer loyalty are as follows: (1) effectively no acquisition cost; (2) less need to offer incentive; (3) less price sensitivity; (4) recommendation of the company to others by loyal customers; and (5) individual revenue growth as trust increasing [16].

2-2. Customer Value Analysis

Customer Lifetime Value (CLV) is defined as the obtained profit net present value in a customer's lifetime [17]. RFM is a common used technique that can be used effectively for customer value analysis and market segmentation.

Liu & Shih [8] and Cheng & Chen [11] used the RFM model to quantify customer lifetime value. The RFM model was proposed by Hughes [18]. RFM model has three dimensions: (1) Recency: is the time interval between the last purchase and a present time reference, the shorter time interval, the bigger R; (2) Frequency: is the number of customer's purchases in a particular period, the higher frequency, the bigger demand and the higher loyalty; (3) Monetary value: the total amount of money consumed by the customer over a particular period, the higher monetary, the bigger contribution to business. RFM model is a simple and direct metric for measuring customer value. Chang and Tsay [12] proposed the LRFM model, mainly adding the customer relation length to RFM model.

In spite of being effective method for customer segmentation, RFM model brings some challenges for researchers.

The problem with RFM model is determining the weights of the three variables. There are two studies that have contrast idea about this issue. Hughes [18] indicated that the importance of each variable is identical. However, Stone [19] considered that the weights of the three variables are not equal and depend on the characteristics of the industry. In addition, there are some researches that have used the weighted RFM and LRFM models (e.g. [8,20]). In this study, we have determined the weights (relative importance degrees) of each LRFMP variables through conducting a survey.

2-3. Market Segmentation

The aim of market segmentation is putting the right products or services to a targeted customer group and hence improvement of marketing strategies efficiency. One of the important challenging issues for successful market segmentation is choosing the right data mining techniques. There are many clustering techniques that were used in literature. Table 1, summarizes some researches from the market segmentation context. The clustering algorithms used in these researches are identified.

2-3. Clustering

Clustering is the process of grouping a set of objects into classes of similar objects [1]. The goal of clustering is that the objects within a cluster have the most similarity to each other and the objects in different clusters have the most dissimilarity to each other ([1,2]). Clustering techniques are subsets of unsupervised learning techniques.

Han and Kamber [1] organized clustering techniques into the following categories: partitioning methods, hierarchical methods, density-based methods, grid-based methods, model-based methods, methods for high dimensional data, and constraint-based methods. In this study we have used K-means, from partitioning methods, for grouping customers into different segments according to their LRFMP values.

Tab. 1. Market segmentation research review

Author	Clustering algorithm	Application area	Variables
Shin and Sohn [21]	K-means, SOM, fuzzy k-means	Stock corporation	Total trade amount, trade amount in representative assisted mode
Liu & Shih [8]	K-means	Hardware retailing company	RFM
Lee and Park [22]	SOM	Motor company	Customer satisfaction and social-demographic data
Ho Ha [9]	SOM	Retail industry	RFM
Hung and Tsai [23]	Hierarchical self-organizing segmentation model (HSOS)	Multimedia on demand	Demographic, psychographics, and buying attitude
Chan [10]	Genetic algorithm	Nissan automobile retailer	RFM
Cheng & Chen [11]	K-means	Electronic industry	RFM
Li, et al. [24]	Ward's method	Textile manufacturing business	LRFM
Seyed Hosseini, et al. [20]	k-means	Automobile industry	LRFM
Lopez, et al. [25]	Hopfield-k-means	Electric utility	Usage data

K-means algorithm was suggested by MacQueen [26] and has been used widely due to its ability for quick processing of large amount of data. The operation of K-means is illustrated as follows: (1) selecting K initial centroids; (2) assigning each object to its closest centroid; (3) updating the centriod of each cluster to the mean of its constituent instances; and (5) repeating steps 2 and 3 until centroids don't change.

2-4. AHP

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making method developed by Thomas L. Saaty [27]. The AHP has been proposed for integrated and fuzzy problems based on human brain assessment.

The AHP uses paired comparison judgments from a fundamental scale of absolute numbers, approached from decision-makers, for prioritize alternatives to a problem in an architectural structure [28, 29] . Decision-makers must assign a number from 1 to 9 to any comparison (Table 2). This method also measures the degree of inconsistency of judgments. If the inconsistency degree exceeds from 0.1, judgments must be revised.

3. Research Methodology

CLV is a common metric used for planning marketing strategies by managers. Recently, LRFM model is used for quantifying CLV [20, 24]. But this model is not effective for developing some marketing strategies such as cross-selling. In this research we have added customer potential value (P) to LRFM model. By doing so we have derived LRFMP model (Length, Recency, Frequency, Monetary, and Potential value). Potential value is the maximum value of the all purchases of a customer in a particular period. It can represent a measure of additional sales opportunity. Furthermore, it can be used to recommend additional products to a retailer. In other words, it is a measure of conducting cross-selling effort. In this paper we define the potential value of customers as expected purchases that can be obtained from a certain customer. Our argument is that the firm may not be able to formulate differentiated cross-selling action for each retailer if the potential of each customer is not recognized. In addition, using LRFMP values for clustering resulted in better separation of retailers from the perspective of managers.

Tab. 2. Numbers for representing paired comparison judgments

Comparison importance	Description
1	Equal
2	Intermediate between equal and moderately dominant
3	Moderately dominant
4	Intermediate between moderately and strongly dominant
5	Strongly dominant
6	Intermediate between strongly and very strongly dominant
7	Very Strongly dominant
8	Intermediate between very strongly and extremely dominant
9	Extremely dominant

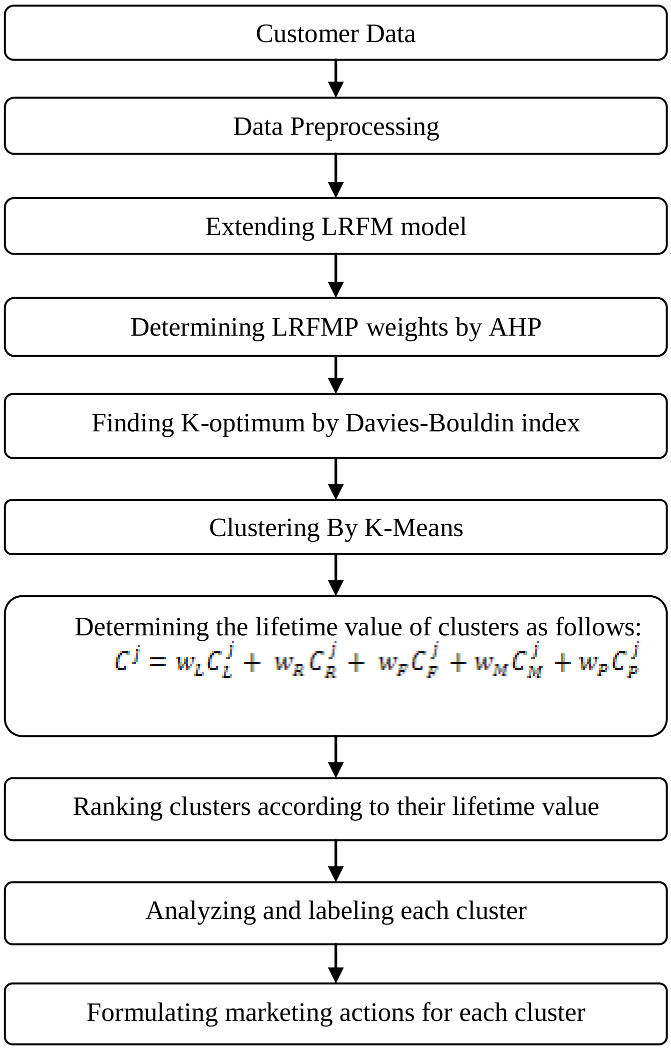

Fig. 1. Research framework

3-1. Customer Data

A case study used for evaluate the proposed model was a hygienic manufacture. This manufacture is one of the biggest and oldest producers of hygienic and cosmetic products in Iran. This corporation distributes its products to his customers that range from small retailers to chain and big retailers in any place of Iran.

Customers' data was received from two datasets; an 18-months customers` transactions dataset with about 1000000 records, and a customers' profiles dataset with about 72000 records. R, F, M and P values for any customer was extracted from customers' transactions dataset and L value was received from customers` profiles dataset.

According to experts' discretion, the P values were set to 1 to 6. In this research L values was computed 6 monthly, because of short period of customers' submission in firm`s MIS system.

3-2. Data Preprocessing

Data preprocessing is an important step in data mining process because it improves the accuracy and efficiency of the subsequent modeling [1]. In this research data preprocessing techniques such as data cleaning, data transformation, data integration and data reduction were used to improving the quality of data for clustering. Finally, a dataset with 63599 customers and five dimensions (LRFMP) were achieved that the customers had at least one purchase during one last year.

3-3. Determining LRFMP Weights by AHP

In this paper AHP method utilized for calculating LRFMP weights according to decision-makers opinions. This work was done in 3 steps according to AHP definition. At first step, four decision-makers from three different management layers of sale department are selected for making paired comparisons. They include: one top level manager, two middle level managers, and one operational manager. At second step, the inconsistency index was computed and checked for each decision-maker judgments. At last, the LRFMP weights were determined by Eigenvalue computations as 0.232, 0.08, 0.297, 0.333, and 0.057 respectively (Fig. 2).

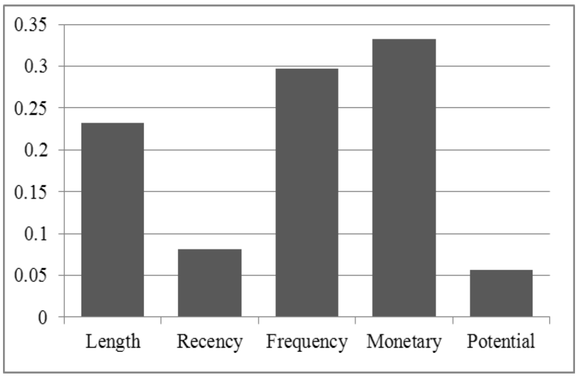

Fig. 2. LRFMP weights achieved from AHP

3.4. Finding K-optimum Davies-Bouldin Index

K-means require the user to determine the number of clusters. There are some kinds of useful indexes to determining k as the number of clusters. In this study we have used Davies –Bouldin index to find the optimal number of clusters. The aim of Davies-Bouldin index is identifying sets of clusters that have small intracluster distances and large inter-cluster distances [30].

The Davies –Bouldin index, DB, is defined as:

$$DB = \frac{1}{k}\sum_{i=1}^{k}\max_{i \neq j}\left\{\frac{a_i + a_j}{d(c_i, c_j)}\right\} \quad (1)$$

Where k is the number of clusters, a_i is the intracluster distance of cluster i and $d(c_i, c_j)$ represents the intercluster distance between clusters i and j. The number of clusters that minimize DB is taken as the optimal number of clusters. In this study optimal number of clusters, based on Davies-Bouldin index, is 10 clusters (Fig. 3).

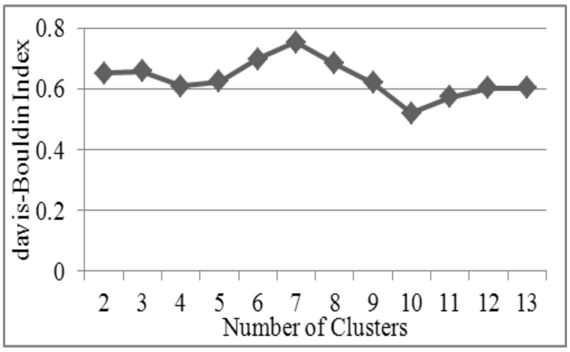

Fig. 3. Cluster validation

3-5. Clustering by K-Means

In this stage customers are segmented into similar clusters according to their LRFMP values. For this purpose values for L, R, F, M, and P were firstly normalized and then clustered into 10 clusters by K-means algorithm. Table3 shows the LRFMP values for each cluster.

3-6. CLV Ranking

The CLV ranking of segments based on LRFMP values and related weights can help managers in knowing more important segments. They can make plans for retaining customers according to this ranking.

For determining LRFMP rating for segments, at first, values of L, R, F, M, and P for centroids were normalized. Then LRFMP rating for each segment were computed as follows:

$$C^j = w_L C_L^j + w_R C_R^j + w_F C_F^j + w_M C_M^j + w_P C_P^j \quad (2)$$

Where C^j is the LRFMP rating for cluster j, C_L^j, C_R^j, C_F^j, C_M^j, C_P^j are the normalized L, R, F, M, and P for cluster j and w_L, w_R, w_F, w_M, w_P are the related weights for L, R, F, M, and P achieved from AHP.

Tab. 3. Clustering results

Cluster	Number of Customers	Length	Recency	Frequency	Monetary	Potential
1	29273	7.574	34.065	13.871	12409809.22	1
2	560	7.429	33.645	25.639	462029414.4	5.212
3	3507	1.603	265.211	3.525	4649959.767	1.078
4	7837	1.418	47.65	4.985	6252123.775	1.066
5	6493	7.611	30.676	17.041	58733267.85	2.347
6	1209	7.669	25.139	25.443	209801879.9	3.911
7	5595	5.941	245.488	5.245	5677092.515	1.075
8	1174	2.717	51.823	12.23	103976068.8	3.531
9	556	5.986	219.574	7.876	63019682.42	3.435
10	7395	3.855	39.894	12.953	15403570.12	1.112

Tab. 4. CLV ranking by weighted sum of normalized LRFMP values

Cluster	Length	Recency	Frequency	Monetary	Potential	LRFMP rating
2	0.961606143	0.964568963	1	1	1	0.988222711
6	1	1	0.991136836	0.448537682	0.691120608	0.796124563
5	0.990721485	0.976936086	0.611196527	0.118246037	0.31980057	0.548109139
1	0.984802432	0.962819487	0.467848422	0.01696589	0	0.451063165
8	0.207806751	0.888850012	0.393642037	0.217163469	0.600902184	0.343686562
9	0.730763078	0.190097138	0.196753188	0.127617719	0.578110161	0.318819579
10	0.389857623	0.938539272	0.426336258	0.023511354	0.026590693	0.302435468
7	0.72356423	0.08215452	0.077778783	0.002245691	0.017806268	0.199384488
4	0	0.906232297	0.066021525	0.003502921	0.015669516	0.095072844
3	0.029595265	0	0	0	0.018518519	0.007921657

3-7. Analyzing and Labeling Each Cluster

After clustering by K-means algorithm, we achieved 10 clusters. Tables 3,4 summarized clusters information in detail. The examination of results shows that the values of P (potential) are separable in a certain point. This point is the median point of all P values. This median point is equal to 1.7. The p=1.7 point separate the higher half of P values from the lower half. Therefore, some clusters take low potential label while others take high potential label.

According to opinion of firm's marketing managers, new customers are those who have launched their relationship with firm in the last 1.5 years (three 6-months periods).

On the basis of this assumption, we have took into consider customers with L (length of relationship) lower than 3 as new customer, on the other hand we took into consider customers with L higher than 3 as long life (established) customers. This is shown in Fig. 4.

After analyzing each segment, in this section we labeled each cluster according to its status (Table 5).

4. Marketing Actions

Once a firm performed segmentation on its customers, it should devise differentiated marketing actions for each cluster. In this section we have identified three marketing actions that the firm should perform on clusters.

These actions are includes: Cross-selling, Strong anti-attrition, and loyalty program. We also found out that for increasing its purchases, the firm should take some procedures to inform consumers about its products. Advertising is an effective strategy for firm to persuade consumers to purchase the firm's products. The details of work are presented below.

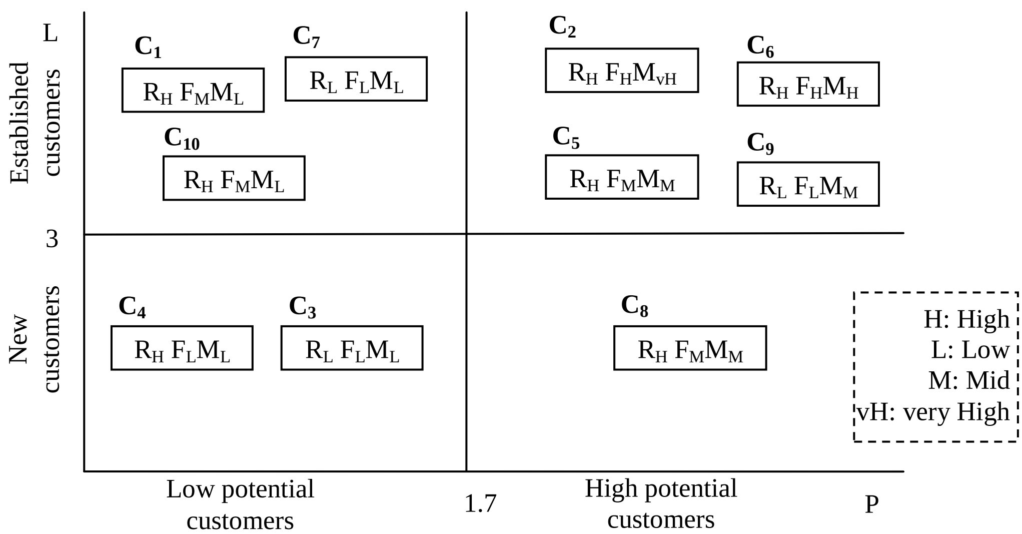

Fig. 4. Cluster CLV segmentation

Tab. 5. Cluster Labeling

Cluster	Cluster Label	Description
C_2	Superstar Segment	Highest value, highest frequency, highest recency, highest potential, and highest life time.
C_6	Golden segment	The second highest value, highest frequency, highest recency, highest potential, and it also has high lifetime.
C_5	Average value segment	Despite of having High potential, this segment does not show good performance in term of Frequency and Monetary.
C_9	Dormant average value segment	Although, this segment has high potential, the low frequency leads to middle monetary value. The low recency of it may be a sign of churn.
C_8	New average value segment	This is a new segment that has the highest rank among the other new customer segments. It has high potential, but due to low frequency, the monetary value of it is middle.
C_1	Small retailers segment	This segment has low potential, and middle frequency with low monetary value. It has long duration life. By considering that the number its members is very high (nearly it is equal 46 percent of total retailers), significant attention should be paid for this segment.
C_{10}	Young Small Retailers segment	This segment shows similar performance to C_1 with the exception of that its lifetime is smaller than C_1.
C_7	Dormant segment	This segment has low recency, low frequency, and low monetary value. Although they have a long time relationship with the firm, they exhibited very bad performance. In addition the recency of this segment is very low; this may be a sign of attrition or long hiatus
C_4	New Low value customer	This segment has high recency; this means that they maintain their relationship with the firm. But they have low frequency and low monetary value.
C_3	New Dormant segment	This segment has low recency, low frequency, and low monetary. This customer maybe churned the firm or in long hiatus

Tab. 6. Marketing actions for retailers

Potential	Clusters	Cross-Selling priority	Strong anti-attrition	Loyalty program investment
High	C_2	1		Very High
	C_6	2		High
	C_8	3		Mid
	C_9	4	*	Mid
	C_5	5		Mid
Low	C_{10}	1		Mid
	C_1	2		Mid
	C_7	3	*	Low
	C_4	4		Low
	C_3	5	*	Low

4-1. Cross Selling

The phenomenon cross-selling by retailers enables consumers to cross-buy their products. By doing so, retailers can increase their revenue contribution from existing customers [31]. One of the key benefits of cross-selling is improving customer retention since Cross-buying by consumers increase their switching costs. The other benefits of cross-selling are increasing profitable lifetime duration of customers [32]. Similar to other marketing initiatives, it is not logical to target all existing customers for cross-selling since marketing resources is limited. The firm should first identify the right customers for cross-selling. In addition, the firm should identify the drivers of cross-buying. Kumar, et al. [31] identified some of important drivers of cross-buying, includes: average inters purchase time, ratio of products returns, and focused buying. They also considered trust as an enabler of cross-buying.

When looking to clusters' information, we notice that some retailer segments have low monetary value. Cross- selling is an effective strategy for manager to increase customers' life time value along with their lifetime duration and to improve customer retention. This shows that cross-selling program should be applied for all customer segments. However, it is not possible for firm to target all of customer segments for cross-selling due to limited marketing resource of the firm. By considering this issue, the firm must prioritize the customer segments for cross-selling.

We have recognized the priority of each segment for cross-selling as follows: (1) we have constructed two sets, the first set contains the high potential customer segments and the second one includes the low potential customer segments; (2) For both sets, we have computed the value of Cross-selling index (CSI) as follows:

$$CSI_i = (P_i - M_i/F_i) \tag{3}$$

Where P_i, M_i and F_i are maximum value, monetary value and frequency for segment i during the time window. As the value of CSI is more, the priority of that segment for cross-selling becomes high.

We have sorted the segments of each set according to their cross-selling index. By doing so, for high potential segments, clusters C_2, C_6, C_8, C_9, C_5 become the most prior to least prior segments respectively for cross-selling actions. Also for low potential retailer segments, clusters C_{10}, C_1, C_7, C_4, C_3 become worth for cross-selling respectively. The priority of each cluster for cross-selling is shown in Table 6.

4-2. Loyalty Program Investment

Customer loyalty has been generally known as valuable assets in competitive markets for all firms especially for those that active in a non-contractual setting [33]. The business setting for this firm is a non-contractual/continuous according to Fader & Hardi [34], since retailers face low switching cost in this setting; investment in loyalty program is especially important. However, resource investment in building loyalty should be performed according to profitability and value of customers [33]. Kumar & Shah [33] proposed to use CLV as a decision support tool to set maximum dollar value limit for marketing investment on a loyal customer. In this study we have used LRFMP rating as a metric for allocating marketing budget for loyalty program. In this way as the LRFMP rating is high; the level of loyalty program investment becomes high. The levels of investment for each retailer segment are showed in Table 6.

4-3. Strong Anti-Attrition

Customer retention is an important strategy to keep existing customers. Acquisition of new customer costs more than keeping existing customers [4]. It is even suggested that it costs 12 times more to attract new customer than retaining new one [35]. As can be seen from Table 5, some retailer segments have low recency. This means that the time interval between last purchase and present time reference is high for them. Having low recency, may be sign of retailer defection. There are three segments that have low value of recency; these are including: Cluster 9, Cluster 7, and cluster 3 (Table 5).In order to retain these retailers, the firm should implement strong anti-attrition actions. As fig. 2 shows, the importance of R (recency), from managers' perspective is low. This means that managers do understand that keeping existing customers is profitable than acquiring new customers; for this reason they assigned low weight for R; this lead to low recency segments still become valuable for firm.

4-4. Advertising

Since retailers are intermediaries between manufacture and consumers, the increase in their buying frequency depends on buying frequency of consumers. In other words, as the buying frequency and volume of the consumers' purchases increases, consequently the buying frequency of a retailer increases. Therefore, in order to increase the buying frequency of retailers, the firm should execute effective advertising program on consumers.

Another way for increasing buying frequency of retailers is improving relationship with them. As the firm improve its relationship with retailers, their loyalty to firm increase. The increase in loyalty cause that retailer place the firm product in the appropriate shelves. Furthermore, since consumers of products still require assistance in selection of products, a loyal retailer may present the firm's product for them. This issue may lead to consumer purchase of the firm's products.

5. Conclusion

Today intensive competition and product homogeneity in many consumer categories enables retailers to switch from one manufacture to another for providing their needs. Manufactures do understand that for staying in the competitive market, they should improve their relationships with retailers. Market segmentation is an approach for performing segment-specific marketing actions.

Recently, LRFM variables have been used for market segmentation. But this model is not effective for developing some marketing strategies such as cross-selling. For addressing this problem, in this study, we have extended LRFM model by adding an extra parameter P (Potential) to it.

After clustering customers by K-Means algorithm, we have obtained ten clusters. After analyzing each segment, we found that there are two segments that are top spenders. In addition, there are five segments that are average value segments. The other three segments have low value. According to segments information, we identified three marketing actions to be implemented on retailers segments these including: cross-selling, strong anti-attrition, and loyalty program. We also recognized that the firm should improve advertising program on consumers. Improved advertising program does inform consumers about the firm's products and hence increases consumer purchases. The increase in consumers purchases lead to increase in retailers' purchases, since the retailers are intermediaries between the manufacture and consumers.

This research is concerned with one manufacture in hygienic industry. It is worthy future studies applying this model to other cases in different industries.

References

[1] Han, J., Kamber, M., *"Data Mining Concepts and Techniques"*, Morgan Kaufmann, 2006.

[2] Tan, P. N., Steinbach, M., Kumar, V., *"Introduction to Data Mining",* Pearson Education, 2005.

[3] Berry, M., Linoff, G., *"Data Mining Techniques: For Marketing, Sales and Customer Relationship Management"* John Wiley & Sons, New York, 2004.

[4] Coussement, K., Van den Poel, D*., " Churn prediction in Subscription Services: An Application of Support Vector Machines While Comparing Two Parameter-Selection Techniques",* Expert Systems with Applications, Vol. 34, 2008, pp.313–327.

[5] Luo, S., Cheng, B., Hsieh, C., *"Prediction Model Building with Clustering-Launched Classification and Support Vector Machines in Credit Scoring"*, Expert Systems with Applications, Vol. 36, 2009, pp. 7562–7566.

[6] Cater, T., Cater, B., *"Product and Relationship Quality Influence on Customer Commitment and Loyalty in B2B Manufacturing Relationships"*, Industrial Marketing Management, (2010), Vol. 39, 2010, pp.1321 –1333.

[7] Davis-Sramek, B., Droge, C., Mentzer, J. T., Myers, M. B., *"Creating Commitment and Loyalty Behavior Among Retailers: What are the Roles of Service Quality and Satisfaction?",* J. of the Acad. Mark. Sci., Vol. 37, 2009, pp. 440–454.

[8] Liu, D. R., Shih, Y.Y., *"Integrating AHP and Data Mining for Product Recommendation Based on Customer Lifetime Value"*, Information & Management, Vol. 42, 2005, pp. 387–400.

[9] Ho Ha, S., *"Applying Knowledge Engineering Techniques to Customer Analysis in the Service Industry",* Advanced Engineering Informatics, Vol. 21, 2007, pp. 293–301.

[10] Chan, C. C. H., *"Intelligent Value-Based Customer Segmentation Method for Campaign Management: A Case Study of Automobile Retailer"*, Expert Systems with Applications, Vol. 34, 2008, pp. 2754–2762.

[11] Cheng, C.H., Chen, Y.S., *"Classifying the Segmentation of Customer Value Via RFM Model and RS theory",* Expert Systems with Applications, Vol. 36, 2009, pp. 4176–4184.

[12] Chang, H. H., Tsay, S. F., *"Integrating of SOM and K-Mean in Data Mining Clustering: An Empirical Study of CRM and Profitability Evaluation",* Journal of Information Management, Vol. 11, 2004, pp.161-203.

[13] Ling, R., Yen, D.C., *"Customer Relationship Management: An Analysis Framework and Implementation Strategies"*, Journal of Computer Information Systems, Vol. 41, 2001, pp. 82- 97.

[14] Kincaid, J.W., *"Customer Relationship Management: Getting it right*", Prentice Hall PTR, 2003.

[15] Ngai, E. W. T., Xiu, L., Chau, D. C. K., *" Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification"*, Expert Systems with Applications, Vol. 36, 2009, pp. 2592–2602.

[16] Chaffey, D., Ellis-Chadwick, F., Mayer, R., Johnston, K., " *Internet Marketing Strategy, Implementation and Practice",* FT Prentice Hall, 2006.

[17] Kotler, P., *"Marketing Management",* Prentice Hall International, Inc, New York, 2000.

[18] Hughes, A.M., *"Strategic Database Marketing"*, Probus Publishing, Chicago, 1994.

[19] Stone, B., *"Successful Direct Marketing Methods",* NTC Business Books, Lincolnwood, 1995.

[20] Seyed Hosseini, S. M., Maleki, A., Gholamian, M.R., *"Cluster Analysis using data Mining Approach to Develop CRM Methodology to Assess the Customer Loyalty"*, Expert Systems with Applications, Vol. 37, 2010, pp. 5259–5264.

[21] Shin, H.W., Sohn, S.W., *"Segmentation of Stock Trading Customers According to Potential Value"*, Expert Systems with Applications, Vol. 27, 2004, pp. 27–33.

[22] Lee, J.H., Park, S.C., *"Intelligent Profitable Customers Segmentation System Based on Business Intelligence Tools"*, Expert Systems with Applications, Vol. 29, 2005, pp. 145–152.

[23] Hung, C., Tsai, C.F., *"Market Segmentation Based on Hierarchical Self-Organizing Map for Markets of Multimedia on Demand",* Expert Systems with Applications, Vol. 34, 2008, pp.780–787.

[24] Li, D.C., Dai, W.L., Tseng, W.T, *"A Two-Stage Clustering Method to Analyze Customer Characteristics to Build Discriminative Customer Management: A Case of Textile Manufacturing Business"*, Expert Systems with Applications, Vol. 38, 2011, pp. 7186-7191.

[25] López, J.J., Aguado, J.A., Martín, F., Mu ˜ noz, F., Rodríguez, A., Ruiz, J.E., *"Hopfield–K -Means Clustering Algorithm: A Proposal for the Segmentation of Electricity Customers"*, Electric Power Systems Research, Vol. 81, 2011, pp. 716 - 724.

[26] MacQueen, J. *"Some Methods for Classification and Analysis of Multivariate Observations"*, In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume I, 1967,University of California Press.

[27] Saaty T.L., *"The Analytic Hierarchy Process"*, McGraw- Hill, New York 1980.

[28] Saaty, T.L. "*Fundamentals of Decision Making and Priority Theory with the AHP"*, RWS Publications, Pittsburgh, 1994.

[29] Saaty, T.L., *"Decision-Making with the AHP: Why is the Principal Eigenvector Necessary?"* European Journal of Operational Research,Vol. 145, 2003, pp. 85–91.

[30] Davies, D. L., Bouldin, D. W., *"A Cluster Separation Measure"*, IEEE Transactions on Pattern Recognition and Machine Intelligence, Vol. 1, 1979, pp. 224-227.

[31] Kumar, V., George, M., Pancras, J., *"Cross-Buying in Retailing: Drivers and Consequences"*, Journal of Retailing, Vol. 84, 2008, pp.15–27.

[32] Reinartz, W. J., Kumar, V., *"The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration"*, Journal of Marketing, Vol. 67, 2003, pp. 77–99.

[33] Kumar, V., Shah, D., *"Building and Sustaining Profitable Customer loyalty for the 21st century"*, Journal of Retailing, Vol. 80, 2004, pp. 317–330.

[34] Fader, P. S., Hardi, B. G. S., *"Probability Models for Customer-Base Analysis",* Journal of Interactive Marketing, Vol. 23, 2009, pp. 61–69.

[35] Coussement, K. F., Benoit, D., Van den Poel, D., *"Improved Marketing Decision Making in a Customer Churn prediction Context using Generalized Additive Models",* Expert Systems with Applications,Vol. 37, 2010, pp. 2132–2143.