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Proposing Appropriate Marketing Strategies to Improve CRM Performance: Study of Behavioral Characteristics of Customers Based on Measures of RFM Model with the Aim of Determining Customer Lifetime Value in Iran

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Abstract: Customer relationship management (CRM) is an efficient instrument to attract and retain customers and enhance their satisfaction in competitive industries. On the other hand, one of the most important tools to achieve a profitable CRM is calculation of customer lifetime value driving the organization to focus its most efforts on retention of its more profitable customers. Customer lifetime value is a value expected to be created for organization by a customer in a certain time horizon and it undoubtedly has a direct relationship with the extent of benefit gained by organization from this group of customers. So purpose of this study is to provide an appropriate model to determine customer lifetime value along with optimal allocation of limited recourses in Iran. After determining weights for measures of RFM model using analytic hierarchy process (AHP), processing of values obtained for measures and hierarchical clustering of customers were conducted and finally customer lifetime value was determined in six clusters. According to present study, determining value created by each customer in his\her lifetime, firms are able to prepare the grounds for allocating limited resources, employing appropriate marketing strategies and managing profitability besides customer relationship management. At last, according to results obtained in the study, some recommendations are provided for improving customer relationship management performance.

Key words: Customer life time value (CLV) · Customer relationship management (CRM) · Fuzzy Delphi Analytical Hierarchy Process (FDAHP) · Hierarchical Cluster Analysis (HCA) · RFM model

INTRODUCTION

In today competitive market, along with moving of firms towards customer orientation, customer relationship management has faced with certain complexities. According to previous studies, it is estimated that acquiring new customers costs five times of retaining existing ones [1]. Pareto principle also known as 20-80 rule says that 20 percent of customers account for 80 percent of firm transactions, 80 percent of firm profits and 80 percent of services and problems of the firm [2]. Recently 20-80 rule has been turned into 20-80-30 rule for market i.e. besides previous meaning, it says that a 30 percent group of consisting of customers who buy rarely are a heavy burden on firms and reduce organizational profit to half [3]. Research shows that firms are of more chance to sell their goods or services to their existing customers than new ones. Thus chance of repeated selling to an active customer is about 60-70 percent and this number for a new customer is 5-20 percent [4]. Given the above explanations, many managers are of the idea that firm should not incur costs in order to acquire every customer with every profitability level but it should spend its limited resources to attract and retain key customers optimally [5]. On the other hand focus of today firms is not only on selling their goods, but also on creation and retention profitable customers. But the main question is that how profitable and key customers can be identified.

Firms can prepare the grounds for allocating limited resources in an optimal way, employing proper marketing strategies and finally managing profitability along with

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customer relationship management by determining the value created for firm by each customer during its lifetime period (customer life time value). This concept describes the value created by every customer during his\her lifetime period for the organization and the main purpose for its calculation is to create a weighted perception of customers based on present and potential values they have for firm and this value is determined using different models. RFM model is a widely used method for determining customer lifetime value. In present research RFM model combined with Fuzzy Delphi Hierarchical process and Hierarchical cluster analysis is exploited. The proposed model prepares the ground for identifying key and profitable customers, choosing appropriate marketing strategies and optimal resource allocation given characteristics of various customers towards improving customer relationship management.

Theoretical Bases and Background of Research

Customer Relationship Management: Although appearance of customer relationship management (CRM) always identified as a significant business approach is dated back to 1990 s, but there is not a single accepted definition for it [6]. Kamar and Reinartz [7] define CRM as a strategic process of choosing high-profitable customers and intracting with them with purpose of optimizing current and future values of customers for the firm. Ngai *et al.* [8] state that new definitions emphasize on importance of CRM as a strategic and systematic process for maximization of customer value for organization. Mishar and Mishar [9] divided CRM framework in to 3 general parts. Operational CRM which emphasizes on automatization of business processes. Analytic CRM which addresses analysis of behavioral characteristics of customers in order to support CRM strategies and provide a significant aid in allocating resources to profitable customer group effectively. Interactional CRM focuses on communication and cooperation with customers which ensures communication between customers and firms through telephone, email, web, etc.

Customer Life Time Value: Customer life time value (CLV) has been addressed with such titles as customer value, life time value, customer equity and customer profitability in various studies [10]. Generally it can be said that customer life time values (CLV) is a value being created for organization by customer during it's life time. This concept points to potential and future as well as present value of customer for firm and the main purpose for calculation of it, is to create a weighted perception of customers in order to allocate resources to them optimally [11]. Presence of various definitions for customer life time value, implies different perspectives and methods being used for measuring of it the most common methods proposed for determining customer life time value consists of net present value method share of willet method, Markof chain method, past customer value method, return on investment method and RFM (Recency, Frequency, Monetary) method.

Among above-mentioned methods, RFM model is one of the common and widely used methods [12] which considers3 measures in determining customer value; thus it presents a multi- dimensional view in this respect while many other methods take a one-dimensional view and usually use one single measure for determining customer life-time value. On the other hand in RFM model, not only financial attitudes are relevant, but also the main focus of model is on non-financial issues in analyzing customer characteristics [11], while many other methods mostly emphasize on financial side.

RFM Model: RFM model was firstly introduced by Hughes [13]. He used past behavior of customer which is readily available and tracable for RFM analysis. This model uses 3 dimensions related to customers transaction data in order to analyse their behavior. Model measures are defined as below [14].

Recency: This measure points to the interval between last purchase of this measure the higher its value would be in the model.

Frequency: This measure refers to the number of transactions conducted by one customer in a certain period the greater the number of transactions, the higher the value of this measure would be in the model.

Monetary: This measure points to the money spent by one customer in a certain period for transaction. The greater this amount, the higher the value of this measure would be in model.

In RFM model, life-time of each customer is obtained by aggregating values from RFM measures. Thus in this model, it is assumed that customers having high values for each of model measures are the best customers, of course until their future behavior is similar to previous one and in this case it is believed that they are more profitable for firm than others [15].

There are various opinions an importance of RFM model measures [16]. Hughes [13] states that these 3 measures are of the same importance, thus their values are clear and same. On the other hand, Stone [17] is of the idea that 3 measures will have different values because of different characteristics of each industry. He determined weights of RFM measures based on subjective judgment in his research. Later, Liu and Shih [18] exploited from analytical hierarchy process in order to make better decisions on determining relative weights of RFM measures in evaluation of customer life-time value. Since in present research fuzzy Delphi analytical hierarchy process (FDAHP) is used for weighting these measures, thus this method is explained in the following.

Fuzzy Delphi Analytical Hierarchy Process (FDAHP): Delphi method is a product of studies done by Rand' company in 1950s in order to create a method for obtaining consensus among group experts. This method replaced traditional research approaches using statistical methods. Indeed, Delphi method is a method for structuring a group relationship process in a way that allow group members to be challenged by problem. In order to implement this structured relationship, feedback on individual roles, group judgment evaluation, opportunity for modifying viewpoins and some level of anonymity is required [19]. Thus aim of this method is to use questionnaires and expert surveys repeatedly given the feedback for them [20].

Traditional Delphi method, always has suffered low- convergence of expert opinions, high cost of administration and probable elimination of opinions of some individuals. Later, concept of integration of traditional Delphi method with fuzzy theory was proposed to improve traditional Delphi method [19]. Indeed, fuzzy Delphi method was proposed by Kafman and Guptain [21]. This method is generalization of traditional Delphi method in management science. In Delphi method expert opinions are stated in definite numerical form while using definite numbers for long-term predictions diverts the prediction result from reality. On the other hand, experts draw on their mental capabilities and competencies for prediction and this shows that uncertainty governing these conditions is of possibility but not of probability type. Possibility type of uncertainty is compatible to fuzzy sets. Thus it is better to use fuzzy sets (fuzzy numbers) for decision making in real world. In fuzzy Delphi method, the required information is obtained from experts in natural language format and are analyzed in a fuzzy way [20]. Characteristics of traditional and fuzzy Delphi methods are compared in Table 1.

Fuzzy Delphi analytical hierarchy process (AHP) is indeed a hybrid of Delphi method and analytical hierarchy process in fuzzy environment. Basis of weighting parameters in analytical hierarchy process is paired. Comparison of them in paired comparison matrix format. In present study method proposed by Hosseini and *et al.* [22] was used for conducting fuzzy Delphi hierarchy method. Process of this method includes following steps:

Expert Survey: First experts are asked to score parameters influencing decision given their importance in a qualitative or a quantitative way if possible (survey scales consisting of: very important = 9, important = 7, moderately important = 5, slightly important = 3, not important = 1).

Calculation of Fuzzy Numbers: In order to calculate fuzzy numbers ($\tilde{a}_{ij}$), opinions resulted from survey are directly considered. Based on logic of triangle fuzzy numbers, maximum and minimum values of expert opinions are registered as boundary points and geometrical mean is recorded as membership degree of triangle fuzzy numbers. In this case a fuzzy number is defined as followers:

$$\tilde{a}_{ij} = (a_{ij}, \delta_{ij}, \gamma_{ij});\ a_{ij} = \text{Min}(\beta_{ijk}),\ \delta_{ij} = \left(\prod_{k=1}^{n}\beta_{ijk}\right)^{\frac{1}{n}}, \gamma_{ij} = \text{Max}(\beta_{ijk}),\ k = 1,2,...,n$$

Table 1: Comparison of Fuzzy and Traditional Delphi Methods [19]

Evaluation Criteria	Traditional Delphi Method	Fuzzy Delphi Method
Number of required steps	After several examination step, experts reach a consensus on subject	In one examination step, all opinions are covered
Necessity of flexibility	Experts modify their opinions in order to reach average of others opinions. Otherwise they may be eliminated	Opinions of all experts are respected and different membership degrees are considered as probable for consensus
Cost and time	It takes high cost and a lot of time and vagueness of process cannot be eliminated	It take little time and costs and vagueness of process will be eliminated

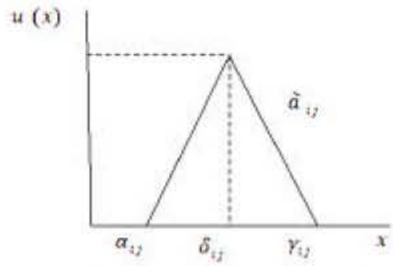

Fig. 1: Triangle Membership Function in Fuzzy Delphi Method [23]

In above relations, β_{ijk} shows relative importance of parameter t over parameter j from view point of Kth person, γ_{ij} and α_{ij} are respectively upper and lower limits of opinions and δ_{ij} is also geometrical mean of these opinions. It is obvious that fuzzy number components are defined in a way that $\alpha_{ij} \le \delta_{ij} \le \gamma_{ij}$ (Figure 1); Also these components varies in range of (1.9, 9).

Formation of Fuzzy Paired Comparison Matrix: In this step, based on fuzzy numbers obtained in previous step, fuzzy paired comparison matrix for parameters, is formed as follow:

$$\tilde{A}=[\tilde{a}_{ij}]_{n\times n}, \tilde{a}_{ij} \times \tilde{a}_{ij} \approx 1 \ \forall, j = 1,2,...,n$$

$$\tilde{A}=\begin{bmatrix} (1,1,1) & \cdots & (\alpha_{1j},\delta_{1j},\gamma_{1j}) & \cdots & (\alpha_{1n},\delta_{1n},\gamma_{1n}) \\ \vdots & & \vdots & & \vdots \\ \left(\frac{1}{\gamma_{1j}},\frac{1}{\delta_{1j}},\frac{1}{\alpha_{1j}}\right) & \cdots & (1,1,1) & \cdots & (\alpha_{2n},\delta_{2n},\gamma_{2n}) \\ \vdots & & \vdots & & \vdots \\ \left(\frac{1}{\gamma_{1n}},\frac{1}{\delta_{1n}},\frac{1}{\alpha_{1n}}\right) & \cdots & \left(\frac{1}{\gamma_{2j}},\frac{1}{\delta_{2j}},\frac{1}{\alpha_{2j}}\right) & \cdots & (1,1,1) \end{bmatrix}$$

Calculation of Fuzzy Weight of Parameters: Relative fuzzy weights of parameters are calculated using following relations:

$$\tilde{Z}_i = [\tilde{\alpha}_{ij} \otimes ... \otimes \tilde{\alpha}_{in}]^{1/n} \quad , \quad \tilde{W}_i = \tilde{Z}_i \oslash (\tilde{Z}_i \oplus ... \oplus \tilde{Z}_n)$$

In these relations: $\otimes$: stands for multiplication of fuzzy numbers, $\oslash$: stands for division of fuzzy numbers and $\oplus$: stands for addition of fuzzy numbers. If $\tilde{M}$ and $\tilde{N}$ are two fuzzy numbers, then we have:

$$\tilde{M} = (a_1, b_1, c_1), \tilde{N} = (a_2, b_2, c_2) \Rightarrow \tilde{M} \oplus \tilde{N} = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$$

$$\tilde{M} \oplus \tilde{N} = (a_1, a_2, b_1, b_2, c_1, c_2) \quad , \quad \tilde{M} \oplus \tilde{N} = (a_1/c_2, b_1/b_2, c_1/c_2)$$

$\tilde{W}_i$ is also a linear rector which shows fuzzy weight of ith parameter.

Defuzzying Parameters Weights: In this step, for defuzzying parameters weight, according to following relation, geometrical mean of fuzzy number components of parameters weights are obtained and in this way, parameter weights are defined as definite numbers:

$$W_i = \left(\prod_{j=1}^{n} \tilde{W}_{ij}\right)^{1/n}$$

Hierarchical Cluster Analysis (HCA): Clustering is to devide a heterogenous group in to several homogenous subgroups which seeks to maximize inter-group differences and minimize intra-group differences [24]. Hierarchical clustering method is also the most widely used HCA being used for low volume of data (typically less than 250 respondents or variables). In performance mechanism of this method, first ranges of subgroups are defined using a criterion and then the proper method for forming clusters and linking them together is chosen. Finally, appropriate cluster number for available data is determined and clustering is conducted. Hierarchical clustering starts whit separating each case in an individual cluster. In each step of analysis separating cases is done until two most similar clusters are integrated and finally all cases are integrated in one complete classification three criterion for clustering is distance. The cases being close together, are integrated in one cluster and cases being more far from another are put in different clusters. It should be noted that the most common measure for distance in clustering is Euclidean distance [25]. Euclidean distance between two dimensional observations (items) is obtained as follows:

$$d(x,y) = v \ \textstyle\sum_{j=1}^{n} \ (x_j\text{-}y_j)^2 \ x_j, y_j : j = 1, 2, \ldots, n$$

$$x : [x_1, x_2, \ldots, x_n], \ y : [y_1, y_2, \ldots, y_n]$$

In employing Euclidean distance, when two or more variables are used, the variable which is of more importance becomes dominant. Thus it is necessary to standardize all variables in order to prevent this problem [24].

Research Background: Sohrabi and Khanlari [26] calculated customers life-time value of a private bank based on RFM model. In that research, k-means clustering approach was used for segmenting customers and finally valuable and profitable customers of this bank was separated into 8 clusters and their characteristics were analyzed. Seyed Hosseini *et al.* [27] explored data in database of an engineering design and auto part supply firm. In that research weights related to components of developed RFM model were determined. Using paired comparisons and again model components were considered as non-weighted and clustering weighted and non-weighted data was done using k-means algorithm. Hu and Jing [28] studied the Capability of RFM model in segmenting customers of automobile after-sales services firms. In that research with a sample consisting of 5821customers the weight related to each model component was determined using AHP and then customers were separated in to 8 cluster based on k-means clustering method. finally after analyzing customer characteristics, their life time value was determined in each cluster. Wu *et al*. [29] addressed analysis of customer value of a industrial equipment manufacturing firm using RFM model and k-means clustered in to 6 groups using k-means clustering method based on RFM measures and customer characteristics were analyzed in cluster format using customer life time value valuation and also recommendations were provided for employing promotion plans appropriate to various parts of customers. Li *et al*. [30] analyzed customer characteristics of a wearing factory using a 2-step clustering method basis for cluster analysis in this research was developed RFM model and customers were separated in to 5 clusters via k-means method and analysis of characteristics of each cluster was performed based on RFM scoring model.

In present research, using a fuzzy Delphi hierarchy process (FDAHP) and Hierarchical clustering (HCA) in RFM model, determining life time value of customers and analyzing their characteristics are done in separated clusters format.

Research Methodology: In present research, organizational customer of a trading firm named T.S. (210 customers) which is a distributor of glass objects were studied. In order to determine weights of RFM measures, first opinion of 4 senior managers were captured using a questionnaire with a 5-point Likert scale (very important = 9, important = 7, moderately important = 5, slightly important = 3, not important = 1). Finally, relative weights of measures were determined using fuzzy Delphi hierarchy analysis process. In order to collect data related to RFM measures firm, internal secondary data (customer database) for 2010 was used and for hierarchical clustering of customers, software SPSS16 was employed. In should be noted that the reason for using hierarchical clustering method for customer clustering is that this method is more compatible with number of analysis unit members. Finally, customers life time value were calculated in determined cluster format. Based on different processes of implementing RFM model in various studies, finally a model was proposed for present research which has a specific scientific logic. As can be seen in Figure 2, the proposed model had 4 main steps including weighting RFM measures, processing measures, clustering and determining CLV and cluster analysis which in each step, specific operations are performed. In the following each of these 4 steps are explained:

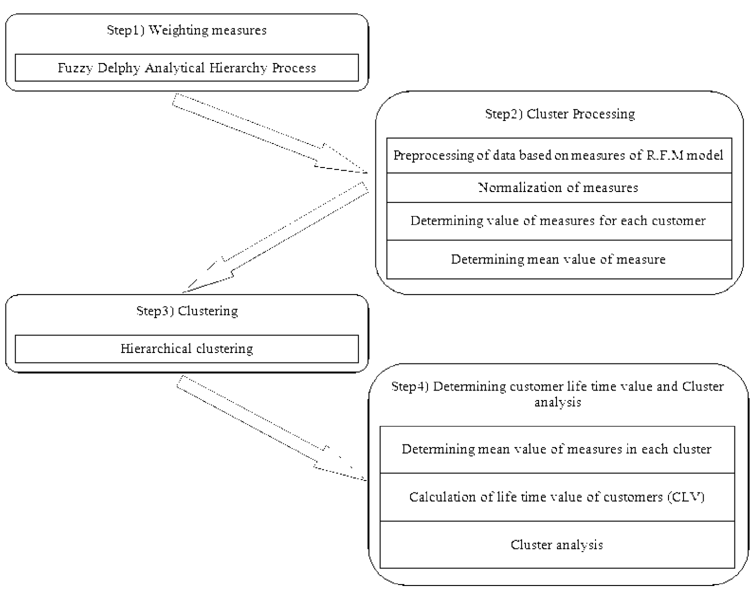

Fig. 2: Proposed Model of Research

Step 1) Weighting Measures: In this step, RFM measures (Recency, Frequency, Monetary) are weighted based on procedure explained in FDAHP.

Step 2) Processing Measures

Pre-Processing of Data based on RFM Model Measures: This section consists of all phases are conducted before main data processing in order to prepare data for later processing.

Normalization of Measures: Because of differences in measure units, it is necessary to normalize them based on same unit (standardization). These measures are normalized (standardized) between 0 and 1 using the following formulate.

$$R' = \frac{R_{max} - R}{R_{max} - R_{min}},\ F' = \frac{F - F_{min}}{F_{max} - F_{min}},\ M' = \frac{M - M_{min}}{M_{max} - M_{min}}$$

In above relations; R_{max}, F_{max} and F_{max} stand for the maximum values of measures, R_{min}, F_{min} and M_{min} stand for minimum values of measures and R, F, M stand for actual values of measures. R', F' and M' stand for normalized values of measures.

Determining Value of Measures for each Customer: In this step, measures are weighted based on weights obtained from step 1. Value of each RFM model measure is determined by multiplication of normalized value of that measure into its weight. Values of these measures are shown with R', F' and M'. In other words we have:

$$R'' = W_R.\ R',\ F'' = W_F.\ F',\ M'' = W_M.\ M'$$

Determining Mean Value of Measures: Mean value of each measure is determined by diving total value of that measure for all customers in to total number of customers (n) being shown as $\bar{R}'', \bar{F}''$ and $\bar{M}''$. In other words we will have:

$$\bar{R}'' = \frac{\sum \bar{R}''}{n},\quad \bar{F}'' = \frac{\sum F''}{n},\quad \bar{M}'' = \frac{\sum M''}{n}$$

Step 3) Clustering: In order to cluster customers so that they can be separated in to homogenous groups based on values of model measures, hierarchical clustering method was used.

Step 4) Determining Customer Life Time Value (CLV) and Cluster Analysis

Determining Mean Value of Measures in Each Cluster: Mean value of each measure for each cluster is determined by dividing total measure value in that cluster in to total number of customers in it (n). Mean values of measures in each cluster, are shown as $M_{R''}$, $M_{F''}$ and $M_{M''}$. In other words we have:

$$M_{R''} = \frac{\sum R''}{n},\ M_{F''} = \frac{\sum F''}{n},\ M_{M''} = \frac{\sum M''}{n}$$

Calculation of Life Time Value of Customers in each Cluster: CLV of each cluster is calculated by aggregating mean value of RFM measures for that cluster. In other words we have:

$$CLV = M_{R''} + M_{F''} + M_{M''}$$

Cluster Analysis: This analysis is conducted by comparing mean measure values in each cluster with mean measure values for the whole data and also by comparing customer life time values for clusters.

RESULTS AND DISCUSSION

Findings: Given the research proposed process steps, in step 1, including weighting measures, first 4 senior managers of the firm are asked about importance of RFM measures in CLV in a Likert scale survey format and the results of this surveys showed that Monetary, Frequency and Recency measures in descending order of importance for managers were respectively: 34, 22 and 10 (Table 2).

Given the patterns results from surveys, paired comparison matrix corresponding with each measure from various managers' view points were formed separately for each manager. All of these matrices are represented in Table 3.

After conducting surveys and evaluating results of them, all the results were used for forming actual paired comparison matrices for measures. Thus fuzzy paired comparison matrix for 3 measures of RFM is as follows based on surveys (Table 4).

Finally, fuzzy and non-fuzzy weights of measures were calculated and results of these calculations are provided in column 1 in table 5. In two next columns of this table, fuzzy and non-fuzzy weights of measures are shown. Based on table 5, weights associated with RFM measures (Recency, Frequency and Monetary) were respectively determined as 0.121, 0.353 and 0.526.

Table 2: Results of Surveys for Manager

	Experts (Senior Managers)			
RFM Measures	1	2	3	4
Recency (R)	3	3	1	3
Frequency (F)	5	5	7	5
Monetary (M)	9	7	9	9

Table 3: Fuzzy Paired Comparisons Matrix Separated by Manager Opinions

	Experts (Managers)											
	1			2			3			4		
	R	F	M	R	F	M	R	F	M	R	F	M
R	1	0.6	0.333	1	0.6	0.429	1	0.143	0.111	1	0.6	0.333
F	1.667	1	0.556	1.667	1	0.714	7	1	0.778	1.667	1	0.556
M	3	1.8	1	2.333	1.4	1	9	1.286	1	3	1.8	1

Table 4: Final paired comparison matrix for RFM based on surveys of managers

	R	F	M
R	(1, 1, 1)	(0.143, 0.419, 0.6)	(0.111, 0.27, 0.429)
F	(1.667, 2.386, 7)	(1, 1, 1)	(0.556, 0.643, 0.778)
M	(2.333, 3.708, 9)	(1.286, 1.554, 1.8)	(1, 1, 1)

Table 5: Fuzzy and non-fuzzy weights of measures

	$\tilde{Z}_i$	Fuzzy weight of measures ($\tilde{W}_i$)	Non-fuzzy weight of measures (W_i)
R	(0.251, 0.484, 0.636)	(0.051, 0.141, 0.238)	0.121
F	(0.975, 1.154, 1.759)	(0.198, 0.336, 0.659)	0.353
M	(1.442,1.793, 2.53)	(0.293, 0.523, 0.948)	0.526
Total	(2.668, 3.43, 4.925)	-	1

Table 6: A part of data related to RFM measures and processing step of them

		Original Values of RFM measures		
Step 2	Customer Code	Recency (R)	Frequency (F)	Monetary (M)
	001	17	51	9507587
	002	114	29	908320
	003	63	42	3898503
A	.	.	.	.
	.	.	.	.
	.	.	.	.
	208	303	1	797
	209	44	17	539284
	210	252	3	15000
B	Normalizing the measures			
C	Determining value of measures for customers			
D	mean value of measures	0.189	0.127	0.119

In second step process, measures were processed. Based on 3-digit codes assigned to each customer, values for measures of Recency (based on day), Frequency (based on number of purchase orders) and Monetary (based on 1000 Rials) were indicated for each customer. After conducting various steps of processing measures based on steps explained in proposed model including pre-processing, normalizing (expressing measures values between 0 and 1) and determining measure values (multiplication of normalized value of each measure into its weight for each customer, finally mean value for each measure was determined. A summary of all described steps is shown in Table 6.

Table 7: Agglomeration Schedule in hierarchical clustering

	Cluster Colligation			Forming Cluster for First Time		
Step	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next Step
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
201	11	14	0.541	198	0	201
202	5	6	0.592	0	0	205
203	8	11	0.650	196	199	202
204	8	62	1.020	201	0	204
205	7	9	1.792	0	0	206
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
209	1	2	16.375	0	208	0

Table 8: Result of Hierarchical Clustering of Customers

Cluster	Number of customers in each Cluster	Number of customers in each Cluster (Percentage)
1	8	4
2	43	20
3	25	12
4	57	27
5	15	7
6	62	30
Total	210	100

Table 9: Mean value of RFM measures and CLV in each cluster

	Mean value of RFM measures			
Cluster	Mean Value of Recency Measure ($M_{R''}$)	Mean Value of Frequency Measures ($M_{F''}$)	Mean Value of Monetary Measures ($M_{M''}$)	Customer Life Time Value $CLV = M_{R''} + M_{F''} + M_{M''}$
1	0.233	0.095	0.635	0.963
2	0.072	0.008	0.006	0.086
3	0.209	0.169	0.492	0.87
4	0.211	0.083	0.086	0.38
5	0.138	0.317	0.226	0.681
6	0.195	0.146	0.063	0.404

Table 10: Cluster Analysis based on RFM model

	Clusters																	
		1			2			3			4			5			6	
	R	F	M	R	F	M	R	F	M	R	F	M	R	F	M	R	F	M
State of mean measure values	↑	↓	↑	↓	↓	↓	↑	↑	↑	↑	↓	↓	↓	↑	↑	↑	↑	↑
Rank in customer life time value		1			6			2			5			3			4	

In third step, regarding value of RFM measures for each customer, customers were clustered based on hierarchical clustering method. Results of this clustering based on output of SPSS software are shown in Tables 7 and 8.

In table 7, agglomeration schedule in consist of 2 main parts: "cluster combination" and "step cluster first appears". First part of table 7 shows how customers are integrated after each step of clustering. This integration is conducted until all customers are joined to a great cluster. Coefficient column shows the distance between 2 clusters being integrated. In general, we have a good clustering if a sudden jumping is observed in distance coefficients. Always the step before jumping is the best one for stopping clustering process [25]. Thus according to table 7, it is noted that the best step for stopping clustering process is step 203. By blocking clustering process in this step, optimal cluster number would equal to 6 (210-204=6). Part 2 of table 7, shows the step in which each cluster first appears. Last column of table shows the step in which a newly formed cluster is integrated in to another newly formed cluster.

Given the optimal cluster number for clustering, each customer was put in one of six cluster. Total results of this clustering are presented in Table 8.

As can be observed in above table, clusters 1 and 6 with respectively 62 (30 percent) and 8 (4 percent) customers have maximum and minimum members among clusters.

In third step of process, CLV is determined. For this purpose, first mean value of each measure is determined separately for each cluster. By aggregating mean values of every 3 measures of Recently (R), Frequency (F) and Monetary (M), Customers life time value id determined for each cluster. Result of these calculations are shown in Table 9.

According to table 9, it is indicated that cluster 1 and 2 have respectively maximum and minimum mean values of Recency measure. Clusters 2 and 5 have respectively maximum and minimum mean values of Frequency and clusters 1 and 4 have respectively maximum and minimum mean values of monetary measure. Also according to last column of above table, customers of cluster 1 and 2 have respectively maximum and minimum life time value for studied firm.

In final step of process of implementing proposed model, cluster analysis was conducted. For this purpose table 10 was used. In first part of this table, mean values of measures for each cluster are specified based on comparison of mean values of measures in each cluster (Table 9) with mean values of measures for the whole data (Table 6). If mean measure value in each cluster is more than mean value of that measure for the whole data, then this case is indicated by sign □ (desirable state) and if mean value of a measure in one cluster is less than mean value of that measure for the whole data, this case is indicated by sign □ (undesirable state). In second part of table, clusters are ranked based on customer life time value.

According to table 10, customers of cluster 1 have the most customer life time value. In other word, most valuable customers for firm are in this cluster. Undesirable state for Frequency measure in contrast to states of 2 other measures shows that customers of this cluster mostly make infrequent and high volume purchases. Thus they are customers which make voluminous purchases (best customers). Cluster 2 represents customers who are the least value for firm undesirable state of each measure in this cluster already shows this fact (low-value customers). Customers being in cluster 3, are in 2th rank regarding CLV and states of every 3 measures for this cluster is desirable (valuable customers). In cluster 4, there are customers whose Recency measure is desirable in contrast to two other measures and this shows that these customers have Recency purchased goods from firm (new customers). Desirability of Frequency and Monetary measures in contrast to Recency measure for cluster 5 suggests that though customers of this cluster are of high value (3th rank in CLV) but they have not purchased recently (lost or declining customers). In cluster 6, undesirable state of Monetary measure in contrast to 2 other measures shows that customers in this cluster make frequent low-value purchase and also have recently purchased good from the firm. They are in 4th rank regarding CLV (good customers).

CONCLUSIONS

In present research, RFM model was used for determining customer life time value of trading firm T.S.. Combining fuzzy Delphi analytical hierarchy process (FDAHP) with this model is a new method is proposed in present research for the first time and thus is of certain novelty in implementation method. Also in order to cluster and analyze customers characteristics based on RFM measures, hierarchical clustering analysis (HCA) was used, because it was appropriate to volume of analysis unit the proposed process of research prepares a suitable ground for analyzing customer characteristics. Based on finding of research, firm customers are separated into 6 cluster which regarding customer life time value, clusters 1, 3, 5, 6, 4 and 2 were respectively put into 1th to 6^{th} ranks. The studied firm should greatly try to retain its valuable customers in clusters 1 and 3 consider them especially important. Given the fact that customers of cluster 5 are of high value but have not recently purchased, thus the firm should explore the reasons for declining purchase trend for these customers via telephone contacts, email, sms, etc and try to address them. The firm may consider specific volume-based discounts for customers of clusters in order to promote monetary measure level and in turn. CLV for this cluster given the fact that customers of cluster 4 are new ones who have recently purchased good from the firm, thus this firm can take measures in order to attract them and obtain their loyalty. Because of the fact that customers of cluster 2 are of the least life time value and account for a significant number of customers (43), thus a more accurate study should be done to explore the reasons for low values of RFM measures for these customers.

In future studies, other clustering methods including K-means clustering and two-step clustering may be exploited in a way appropriate to volume of analysis unit using more extensive data set from temporal view point will definitely provide stronger results and more extensive scope of applied knowledge on behavioral characteristics of customers for firm. On the other hand, periodical time section from data base of firm, makes it possible to employ RFM model dynamically in order to determine CLV and results of it can play significant role in marketing efforts and improving customer relationship management (CRM) system, because they reflect trend of changes in customer behaviors.

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