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Customer Clustering Based on Customer Lifetime Value: A Case Study of an Iranian Bank

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***Abstract*— Customer lifetime value (CLV) as a quantifiable parameter plays an important role in customer clustering. Clustering based on CLV helps organizations to form distinct customer groups, reveal buying patterns, and create long-term relationships with their customers. Our research aims at the synthesis of a CLV model and a clustering algorithm in a new comprehensive framework. First, a model for calculation of CLV is suggested, which is called Group LRFM or GLRFM briefly. In this model, four parameters, Length, Recency, Frequency, and Monetary, are determined according to the products/services used by customers. Then, a novel framework based upon the model is presented in eight steps for customer clustering. In traditional methods, the customers of valuable cluster are treated the same. But in proposed framework, company can design different and proper strategies for each cluster based on the use of products/services. The experimental results in banking industry verify that proposed approach allows an accurate and efficient cluster analysis; it provides appropriate information to create clear sales and marketing policies for three identified segments.**

Keywords- clustering; data mining; customer relationship management (CRM); customer lifetime value (CLV)

I. INTRODUCTION

Since the business environment has changed from a product-oriented to customer-oriented, understanding of customer behavior is becoming a significant topic in today's competitive world[1]. The major challenges in customer-centric organizations are customers' cognition, understanding of their differences, and ranking them[2]. Indeed, organizations can analyze the customer behavior to better understand the market, and thus explore new business opportunities. Using a systematic analysis method becomes very important for effective CRM to understand customers and communicate with them. Most companies have realized that their customer database is one of the most considerable assets, and thereby they use the database to develop marketing strategies by analyzing customer behavior characteristics[3]. Firms can do better in identifying and allocating resources to customers by customer database analysis.

Data mining techniques are powerful, well-known tools for customer data analysis within the CRM framework. One of the most significant data mining techniques is clustering which is widely used in customer relationship management. Customer clustering means that customers can be divided into a number of specific groups; customers in one cluster have more similar characteristics and behaviors in comparison with customers in other clusters.

Companies identify customer behavior patterns using clustering techniques to align their marketing strategies with customers' preferences, and thus retain their customers[4].

One of the useful methods for customer clustering is customer lifetime value (CLV) which determines values of each customer by various parameters. The lifetime value of a customer for a firm is defined as the sum of the revenues gained from the customer over the entire lifetime of transactions minus total cost of attracting, selling and servicing customers [5-8]. There are several models for CLV. CLV models are widely used to identify customer loyalty and then determine marketing strategies for different group of customers[9].

In this paper, we review clustering algorithms, CLV models, and the articles published in the scope of CLV-based clustering. Then, we specify that there is a gap between measurement of customer value and what customer bought. This shortage causes imprecise calculation of CLV for customer behavior analysis, and it is unable to provide effective information for promotion of certain products. As a result, we propose a model called Group LRFM (Length, Recency, Frequency, and Monetary) for resolving the gap and calculating customer lifetime value based upon bought products/services in order to acquire better customer behavior analysis. Subsequently, we present a comprehensive framework according to the model to identify customers' clusters which have the same response to a marketing program. According to the suggested framework, we cluster e-banking customers of an Iranian bank. Each cluster is studied about their purchasing behaviors and CLV scores, and differences between clusters are determined. Finally golden, loyal, and low-value customers are three segments identified according to the clusters. It would help in formulating an efficient marketing plan which constitutes the key strategy for the bank to retain good customers and also anticipate their future demands.

The rest of the paper is organized as follows. The following section provides a brief description of clustering algorithms and customer lifetime value models. Section 3 reviews past research papers on the scope of customer clustering with CLV. Section 4 describes our proposed approach. Section 5 demonstrates the experimental evaluation and results. Finally, Section 6 draws conclusion of the paper.

II. Basic Concepts

A. Clustering

Clustering idea was first introduced in late 1935 within the scope of data mining, and today it is applied in varied aspects because of giant evolutions and advances that have emerged in it[10]. Cluster analysis or clustering is the task of assigning a set of objects into groups called clusters so that the objects within a cluster are more similar to each other than to those in other clusters. Whatever intra-cluster homogeneity or inter-cluster difference is greater, clustering is more specific. Clustering techniques group a set of objects only based on the information about the objects and the relations between them.

Although the terminology of a cluster as a group of data objects seems obvious at first, the clusters found by various algorithms significantly differ from each other in their properties. Therefore, there are many clustering methods that use different induction principles. In general, clustering methods can be distinguished as follows. Each of these approaches has different algorithms.

- Hard clustering: each object belongs to a cluster or not.
- Soft clustering: each object can be assigned to multiple clusters according to a membership function.

Clustering algorithms proposed in the literature and various research articles same as [11-17] can be classified as shown in Fig. 1.

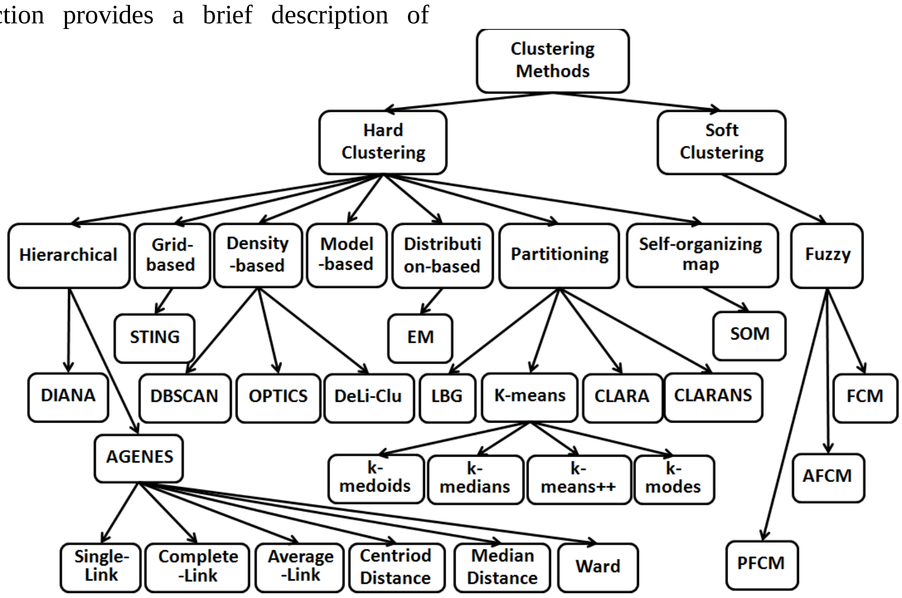

Fig.1. Classification of clustering algorithms

B. Customer Lifetime Value

Customer lifetime value is defined more than 30 years ago by Kotler as "the profit net present value (NPV) that one can obtain in a customer's lifetime"[18, 19]. CLV is an important concept that it encourages companies to switch their focus from quarterly profits to the long-term health of their customer relations. In CRM Literature, this concept has discussed under the names of customer lifetime value (CLV) (or often CLTV), user lifetime value (LTV), lifetime customer value (LCV), or customer value (CV). Customer lifetime value (CLV) differs from customer profitability or CP (the difference between the revenues and the costs associated with the customer relationship during a specified period) in that CP measures the past and CLV looks forward. The total CLVs of all the company's customers is defined as customer equity or CE.

The researchers attempted to estimate the customer lifetime value according to different calculation models. Tabaei and Fathian[20] divided the methods to popular metrics and strategic metrics. Table1 shows various CLV models.

III. RELATED WORKS

CLV concept plays an important role in customer clustering. There are numerous articles which focused on customer clustering with the purpose of more profitability for the organization. Most articles used CLV models as the key inputs for clustering. RFM model is one of the fundamental models for calculating the customer lifetime value, and it can be applied to every business and industry [20]. Due to the success in this model, many efforts are assigned to clustering customers based on their RFM values. Clustering algorithms such as k-means, SOM and FCM are widely used in different articles to implement RFM model.

Hosseini et al. [33] developed a new methodology based on extended RFM model by including one additional parameter as the period of product activity (L). They determined weight of each parameter by eigenvector technique and joined weighted-RFML by k-means algorithm in an automotive company. Chang and Tsay [34] suggested LRFM model for clustering customers to meaningful groups with four dimensions: customer relationship length (L), recent transaction time (R), buying frequency (F), and monetary (M). Li et al. [3] used LRFM model to carry out clustering customers of a textile company by implementing ward and k-means algorithms. Khajvand and Tarokh [35] presented a framework for estimating customer future value based on adapted weighted-RFM analysis for each segment of customer in retail banking industry. They used k-means, two-step, and x-means algorithms for clustering. Wang [36] proposed a hybrid approach to achieve robust segmentation which applied to a noisy data set. He used RPCM and RFCM (Robust Possibilistic/Fuzzy Clustering Method) with two real data sets, including the WINE and the RFM in an automobile retailer.

Since a lot of research papers related to CLV-based clustering are published, Table2 classified most of them regarding to their clustering algorithms and CLV models.

Frequent use of RFM model in diverse industries for analyzing customer consumption behavior and determining customer loyalty and share, is proven that it's a useful and powerful model in CRM and marketing. Although RFM model provides effective measurement to analyze customer behavior, previous papers are computed RFM value regardless of customer's purchased products. This makes the calculation of RFM value illogical for customer analysis. Furthermore, it cannot be provided effective information for promotion of certain products.

Table1. Customer lifetime value models

CLV Models	Popular Metrics	Size Of Wallet (SOW)	▪ Total volume of a customer's spending in a category [21, 22]	▪
		Share of Wallet (SW)	▪ Proportion of category volume accounted for by a brand or focal firm within its base of buyers [22]	▪
	Strategic Metrics	Past Customer Value (PCV)	▪ Predicting future based on previous transactions [23] ▪ Returns the past monetary value into present time [24] ▪ Its formula in [25]	▪
		Life Time Value (LTV)	▪ Predicting the future monetary value of customer and time duration that customers will be active [23] ▪ Converts the future net profit achievement from customers into the present ▪ There are various models for LTV calculation [26] ▪ Its general formula in [27]	▪
		RFM Model	▪ Proposed by [28] and including three parameters used for extracting customer behavior characteristics [29] ▪ RFM stands for: **R**ecency, *How recently did the customer purchase?*, **F**requency, *How often do they purchase?*, and **M**onetary, *How much do they spend?* ▪ Widely applied in many practical areas like banking and insurance industry [30, 31] ▪ Various versions of RFM model are extended such as RFD (Recency, Frequency, Duration) for the web site visitors to consider the duration [32]	▪

Table2. Classifying researches on the field of clustering based on CLV

No.	Clustering Algorithm	CLV model	Industry	Ref.
1	FCM	RFM	Digital content provider	[1]
2	Ward, k-means	LRFM	Textile manufacturing business	[3]
3	k-means	WRFM	Electronic retailing	[20]
4	k-means, two step, x-means	WRFM	Banking industry	[35]
5	RPCM and RFCM	RFM	Automobile retailer and wine dataset taken from UCI web site	[36]
6	k-means, two-step	RFM	Grocery store	[37]
7	k-means	LRFMC	Insurance industry	[38]
8	k-means, SOM	RFM, LTV	E-banking	[39]
9	k-means, SOM	WRFM	Banking industry	[40]
10	Proposed improved clustering algorithm	RFM	Fertilizer manufacturing company	[41]
11	k-means	RFM	Healthcare industry	[42]
12	ART 2	RFM	Retail Company	[43]
13	SOM, k-means	WRFM	Online retailing	[44]
14	k-means	WRFM, W-RFMCI	Health and beauty company	[45]
15	k-means++	RFM	Sports store	[46]
16	k-means	W-RFML	Automotive industry	[33, 47]
17	A constrained clustering method PICC	GRFM	Purchase data by generating program	[48]
18	Fuzzy c-means	WRFM	Electrical goods Producer	[49]
19	SOM	RFM	Healthcare industry (dental clinic)	[50]
20	ANN SOM	WRFM	Department store	[51]
21	k-means	RFM	Food industry	[52]
22	k-means	RFM	Automobile insurance company	[53]
23	LMCM (a soft-clustering approach)	RFM	Online shopping website	[54]
24	k-means	WRFM	Banking industry	[55]
25	K-means	WRFM	Banking industry	[56]
26	FCM	RFM	Retailing company	[57]
27	k-means, SOM	RFM, LTV	Banking industry	[58]
28	k-means	RFM	Purchase log data from SLDS09 challenge	[59]
29	Unascertained clustering	CCV, CPV	Banking Industry	[60]
30	k-means	CCV, CPV	Newspaper office	[61]
31	k-means	Wallet size, Wallet share	62 companies' disclosure of financial obtained from Hexun financial network	[62]
32	FCM	Fuzzy WRFM	Northwind Traders database (Microsoft Access 2000)	[63]
33	k-means	RFM	Banking Industry	[64]
34	Two-step	RFM	Mobile telecommunications service provider	[65]
35	Optimized k-means	WRFM	Insurance industry and wine recognition data from UCI web site	[66]
36	k-means	RFM	Electronic industry	[67]
37	k-means, SOM, fuzzy k-means	CPV	Stock market	[68]

The reasons for why the characteristics of purchased products should be noted in analyzing customers' purchasing behavior with the RFM measurement are as follows:

1) There is a high fluctuation in price and lifetime of products. For example, frequency and cost of buying a notebook are more different than buying a cloth. This indicates that loyalty and share of customer shall be measured as for bought goods. This is in contrast to the RFM model variables which are evaluated together.

2) Association between customer and bought product points about what customer would like to purchase in the future, well. Considering bought products can predict the customer's purchasing regularity. So, if the RFM value of a customer is calculated with regard to different product sets, not only customer needs can be met in a superior way but also a better personalized purchasing management system can be developed to further improve customer relationships.

3) The importance of sales management and customer management is equal in the success and failure of an organization. A sales manager may want to know "Which products are often bought together?" while a customer relationship manager may want to know "Who are potential buyers of a certain product?". They both may be interested to know that "What are the consumption interval, frequency, and money amount of a customer over a particular product?" Thus, measuring RFM with respect to purchased products can be very useful to create an effective inventory management system.

Given the above explanation, it is necessary to measure the customer behavior with attention to the bought products for more accurate analysis. Chang and Tsai [69] suggested a new framework called GRFM (for group RFM) analysis with considering the characteristics of the purchased items. They applied a constrained clustering method PICC (for Purchased Items-Constrained Clustering) for purchase data which are randomly generated by a generating program. So, in this paper, we present a new methodology using the idea that the CLV value must be calculated according to the customers' used products/services to accurately reflect the customers' actual consumption behavior and improve analysis.

IV. Research Method

A. New model for determining CLV

In this paper, the parameters affecting the customer lifetime value are determined according to the customer's used products/services. These parameters are four LRFM variables (Length, Recency, Frequency, and Monetary) instead of three RFM parameters. In LRFM model, the variable L as the length of the customer relationship added to RFM model which is shown the time interval between the first and the last transaction of customer.

When we consider bought products together, values of variables F and M are equal to the sum of their values in each group of purchased products/services, and R value is its lowest value in each of these groups. However, the L parameter may be varied in any case depending on the customer transaction time for each of the products/services and thus we cannot judge about its value. In addition, the customer loyalty depends on the relationship between consumers and business [70], and obviously the key of customer loyalty is built from a long customer relationship management [34]. According to [71], RFM model cannot assess "which customer has a long-term relationship" and "which customer has a short-term relationship". Therefore, considering the parameter L next to the variables R, F and M will be fruitful in calculating customer value, and the relationship between customer and business can be numerically determined.

Hence, this paper presents a new model which is called Group LRFM. In this model, the values of the four variables L, R, F and M of customers are gathered over any products/services that the customers have already used. In order to this purpose, first we need grouping firm's products/services hierarchically. Second, we consider customer transactions separately with respect to each group, and then we calculate LRFM value for each group of purchased products or used services. By this model, a customer who has employed a variety of items or services can have different LRFM values. So, we can create accurate sales and marketing policies to fulfill market needs better.

B. Methodology

In this section, the proposed research framework for clustering customers based on customer lifetime value is described step by step. This framework is based on the combination of the GLRFM model to analyze customer value and a clustering algorithm. The steps of suggested framework are derived from CRISP-DM (Cross Industry Standard Process for Data Mining) methodology[72]. It is a flexible and useful methodology which uses six phases to provide a structured approach for planning a data mining project. These phases include business understanding, data understanding, data preparation, modeling, evaluation, deployment. Fig. 2 illustrates the proposed framework.

Step 1. Business understanding

At first, selecting an enterprise for empirical case study and understanding of the business must be done to elucidate the proposed methodology. A meeting with expert personnel can be conducted to collect the related information about the business goals, scope, problems and products/services of company.

Step 2. Data extraction and understanding

This step involves selection, collection and description of initial data. Generally, company database includes a wide variety of data. In this step, the required primary data sets for this research must be collected from the company database. In order to reduce data size and enhance data processing efficiency, only fields that we need, are selected from data sets. These fields include data relating to products/services (product/service ID, type of product/service and the price per unit) and data related to customer transactions (customer ID, transaction date, transaction amount, type of purchased product/service and the first time of customer transaction).

Step 3. Data preparation and preprocessing

There are many data fields recorded into the company database. As not all of the data are related to the chosen purposes of the research, the company database needs to be preprocessed to make knowledge discovery correctly. Data preprocessing step is the most important and often time-consuming part of any data mining project. It is required to ensure data field consistency in the proposed model of customer value analysis. The goal of this step is to prepare the data to be ready to analyze through studying the transaction data and make clustering process to be done easily and effectively. So, this step includes data cleansing and reduction, eliminating outlier, inconsistent and incomplete values of records and generally all necessary actions for data preparation.

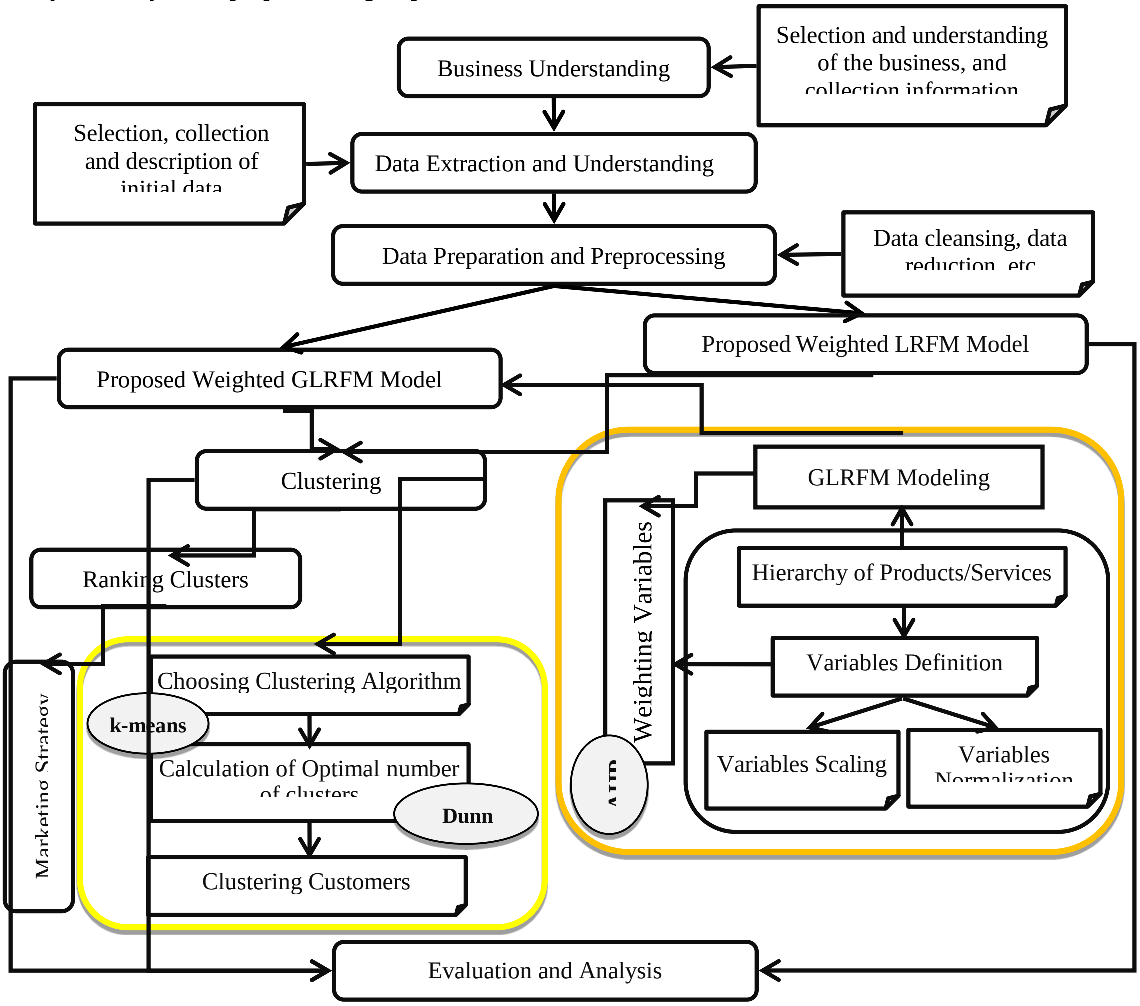

Fig.2. Proposed framework

Step 4.1. GLRFM modeling

GLRFM modeling consists of five phases:

Phase 1. Hierarchy of products/services

To calculate the parameters of the proposed model, we first need grouping products/services hierarchically. Usually, products can be categorized in such a way that the lower sets of products with similar characteristics are assigned to a higher category. In fact, a hierarchy of products is defined as a sequence of mappings from low-level sets of products to a higher-level and more general product category. So, data can be generalized by replacing its low-level characteristics, such as a product name, by their higher-level characteristics, such as a category in the category hierarchy [15].

Phase 2. Grouping customers based on used products/services

As previously mentioned, data preprocessing step is required for ensuring that the data fields are consistent with the customer value model. In the proposed research model, customers are grouped according to the purchased products or used services. Therefore, after dividing products/services hierarchically, data must be preprocessed again. As a result, a separate phase will be considered in the GLRFM modeling step.

Phase 3. Variables definition

In this phase, the variables required for GLRFM model are extracted. These variables are the parameters affecting the customer value, which are needed to implement the proposed model and then used as inputs of the clustering algorithm at the next step. For this purpose, the R, F, M and L variables are defined for each group of products/services and they are calculated for entire customers with respect to their transactions. LRFM model divided data into four fields as shown in Table 3.

Table3. Definition of LRFM parameters

Parameters	Definition
Recency (R)	Time interval between last transaction of customer and end of the analysis period
Frequency (F)	Total number of customer transactions during the analysis
Monetary (M)	Total amount of money spent over analysis period
Length (L)	Time interval between the first and the last customer transactions (duration of customer relationship)

Phase 4. Variables scaling

After extraction of GLRFM model variables, the scaling of R-F-M-L parameters is defined in this step. So, we can evaluate each customer GLRFM value. There are several methods for scaling and scoring variables. Generally, one of the best methods that can be used for scaling variables is quintile method. It can be done in two ways: (a) customer quintile method scoring variables based on the number of customers; (b) behavior quintile method based on the range of numerical values of parameters.

In quintile scoring method, first the customers' data are sorted by each variable individually, and afterwards they are divided into 5 exact sections according to (a) the number of customers, or (b) the values of variables. Then, the top 20% values are given a score of 5; the next 20% values are given a value of 4, and so forth. After scoring, the values of L, R, F and M are from 1 to 5. Sorting the values of F–M–L variables are done by descending order but the values of parameter R are sorted by ascending order. Because of the definition of research variables, lower value of parameter R yields greater customer value. The F, M, and L variables are vice versa.

Methodology of this research for scaling variables is based on this approach, but we will try to keep a balance between the number of customers and value of parameters. The reason we do this is that these methods are illogical in some cases due to the values of the data. So, in this research, grouping is done based on the number of customers but customers with equal values will be not in a same group.

Phase 5. Variables normalization

It is necessary to use normalized values in calculating CLV to ensure that larger amounts do not conduct the analysis. So, a normalization process is introduced in this phase which is called min-max approach [15]. This method performs a linear transformation on the original data and maps a value, v, of A to NV in the range of [$newmin_A$, $newmax_A$] by computing in equation (1):

$$NV = \frac{V - min_A}{max_A - min_A}(newmax_A - newmin_A) + newmin_A \qquad (1)$$

In this formula, min_A and max_A are the minimum and maximum values of variable A, respectively. After normalization, variables' values are mapped in 0 to 1 interval, because the desired interval is equal to [0, 1].

Step 4.2. Weighting variables

In this study, it is not considered equal weights for variables of the model. Hence, the relative importance (weight) of each variable of GLRFM model is determined by using AHP method and a survey of experts. It is clear that importance of variables is different in any business and industry. Hence, the decision makers of the industry are asked to be determined the importance of each variable with questionnaire and pairwise comparison matrix.

The AHP method converts the evaluations of relative importance of variables to numerical values (weights or priorities), which are used to calculate a score for each variable [73]. AHP is a reliable method for calculating the weight of each criterion since it is based on decision makers' points of view rather than decision matrices. AHP also allows performing sensitivity analysis over criteria and sub-criteria. A unique feature of AHP is the possibility of calculating compatibility/incompatibility of decisions made by the decision makers. Taking into account these advantages, many outstanding works have been published based on AHP. They include applications of AHP in different fields, such as ranking alternatives as in our case, optimization, selecting a best alternative, resource allocation, planning, resolving conflicts, etc., as well as numerical extensions of AHP. Our objective is to employ AHP for weighting of parameters. Furthermore, variables' dependence is an assumption of implementing AHP. Though the variables of the paper are correlated, the distinguishable method is AHP, which amplifies differences between the variables.

Step 5. Clustering

This step includes using the variables defined in previous step as inputs of the clustering algorithm. So, three phases must be done: choosing clustering algorithm, calculation of the optimal number of clusters, and clustering customers.

Phase 1. Choosing clustering algorithm

Expected form of clusters must be considered in the choice of the clustering algorithm. Due to the purpose of the study based on clustering customers with focus on CLV, the value of each customer must be measured according to the cluster. Therefore, one representative point is needed in each obtained cluster to represent all data within it. The model-based clustering methods like k-means algorithm can be useful for this purpose.

K-means algorithm is one of the most popular algorithms that have been applied practically. The positive points of this algorithm are easy to implement, acceptable speed, simplicity of adjustment (applicable for any data types), and widely common. The negative point of k-means algorithm is the user's obligation to determine the number of clusters that is resolved in the next phase of this study by calculating the optimal number of clusters. Another disadvantage of the algorithm is reaching a local optimum. Effect of this problem can be reduced by raising the number of iterations. Hence, in this study, k-means clustering algorithm is used for clustering customers based on factors affecting customer lifetime value.

Phase 2. Calculation of the optimal number of clusters

K-means algorithm requires that user determines the number of clusters. Improper selection of k as the number of clusters may lead to inaccurate results. There are several methods that used in various articles for determining the optimal number of clusters, such as Dunn index, Davies-Bouldin index, Silhouette index, and Sum of Squared Error (SSE). According to the characteristics of different methods, Dunn index is selected to find the optimal number of clusters in this study due to the ease of calculating the index. For any partition C = {C_1, C_2, …, C_k}, where C_i represents the i^{th} cluster of such partition, the Dunn index, D, is defined as in equation (2):

$$D(C) = \frac{min_{\,i,j=1,\dots,k\ (i\neq j)}\ \delta(C_i,C_j)}{max_{i=1,\dots k}\ \Delta(C_i)} \qquad (2)$$

Where $\delta(C_i, C_j)$ defines the inter-cluster distance between clusters C_i and C_j, and $\Delta(C_i)$ represents the intra-cluster distance of cluster C_i or the size of the cluster C_i. Inter-cluster and intra-cluster distance are calculated in equation (3) and (4), respectively:

$$\Delta(C_i) = max_{x\in C_i}\{d(x,\bar{C}_i)\} \qquad (3)$$

$$\delta(C_i,C_j) = d(\bar{C}_i,\bar{C}_j) \qquad (4)$$

Where $\bar{C}_i$ and $\bar{C}_j$ are the centroid of cluster C_i and C_j. Large value of D corresponds to good clusters. Therefore, the number of clusters that maximizes D is taken as the optimal number of clusters. This index is used in [2, 35].

Phase 3. Clustering customers

This step aims to clustering customers using k-means algorithm according to the optimal number of clusters obtained in the previous phase.

Step 6. Ranking clusters based on their CLV values

At this step, CLV values of each cluster based on WLRFM model are obtained using equation (5), and then clusters are ranked based on their CLV values. For calculating CLV value of cluster, it is used normalized values of parameters multiplied by weights of parameters.

$$CLV_{C_i} = (NR_{C_i}\times W_R) + (NF_{C_i}\times W_F) + (NM_{C_i}\times W_M) + (NL_{C_i}\times W_L) \qquad (5)$$

Where NR_{C_i} and W_R are respectively normalized value of R for cluster C_i and weight of parameter R. Other variables are used in the same way. Cluster with the highest value obtained from this equation has loyal customers, and its CLV rate is 1.

Step 7. Analysis and evaluating of GLRFM model

The customers also clustered based on the traditional LRFM model, and the result compares with the result of GLRFM model to analysis and evaluate the utility of proposed model.

Step 8. Specifying marketing strategy

The last step of research is definition of proper strategies per cluster. This must be performed by analyzing and studying the customer behaviors of each cluster adequately. These strategies must be in direction of increasing profits of company or other goals.

V. Experimental results

In this section, the empirical implementation of the proposed framework is discussed in detail. The case study of this research is Mellat bank, one of the largest commercial banks in the Islamic Republic of Iran; ranking among the top 1000 banks around the world. Different services of Mellat bank can be divided into four areas: local services, foreign exchange services, electronic services, and special plans. Among the wide range of bank services, this research focused on the bank's electronic services due to widespread use of information technology and facilitated access to e-banking services.

Mellat bank has followed propagation of electronic banking as one of its strategic objectives in the field of information and communication technology. Advances in customer acceptance of e-banking services proved that customer satisfaction and loyalty can be achieved by offering new services in this scope. Therefore, by presenting specific marketing strategies for customers of this area, more customers' demands can be met. The scope of e-banking services includes a variety of activities. Given the nature of the model presented in section 4, it seems that e-banking area can be chosen for this study better than the other areas. Hence, e-banking customers' data is used for clustering in this research.

First, the required data of 700 customers are taken from the Mellat bank randomly. Customers' transactions contain 370,915 records during the 3-month period, from 8 January 2013 until 8 April 2013. For each customer, information of customer ID, transaction ID, date and time of transaction, type of transaction (service use), branch name and code, liquidator name and ID, and amount of customer transactions (amount of debt, credit and balance) were extracted.

Data include all transactions of customers' accounts. The transactions' records are involved the bank services, and also other customer services to the customer via bank. We must just consider bank services for analyzing, and other services to customer like different types of deposit should not be audited. Hence, the records related to the various types of deposit (cash deposits, transfers, and subsidies) were eliminated. Transaction records, when the customer is a creditor, also excluded. For example, in purchasing by POS or card to card transferring with ATM, the transaction of a payee, which is related to depositing money into card holder's account, is not considered. Another reason is that we will not encounter to any problem in the variables definition step for calculating the parameter M. The transactions conducted in branches are also not considered because the selected scope for review and analysis is e-banking services. Records related to transactions such as cash withdrawals/transfers for cheque/document and deducting fees were removed. Moreover, the records relating to the transactions canceled by the customer are deleted at this step. Generally, this stage involves removing records with no amount, canceled purchase transaction, cash deposit, deposit of fund transfer, subsidy deposit, Internet transferring deposit, ATM fund transferring deposit, withdrawal for fee deduction, and cash withdrawals/transfer for cheque/ document.

After data preprocessing, some customers are completely excluded from the analysis process. Because, they didn't use any services, and all their transactions were related to the services of other customers. Obviously, such customers cannot be analyzed. They did not receive any services from the bank. So, we cannot determine marketing strategies for them to improve their relations with the bank. After data cleansing and integration, the total number of customers becomes 642 customers.

Each customer transaction should be grouped according to the type of used services because of the proposed model of research. As mentioned before, this paper focuses on the area of electronic banking among the variety of bank services. A wide range of services generally offered to the customers in the field of e-banking. These services are classified into six main domains: ATM, Internet banking, point of sale (POS), virtual terminals, mobile banking, and telephone bank. So, regarding to this hierarchy of e-banking services, bank customers are grouped based on the used services.

After grouping customers and surveying their transactions, it was observed that the number of customers is respectively declined in domains of virtual terminals, mobile banking, and telephone bank. So, both mobile banks and telephone bank groups due to the low number of transactions and time-consuming analysis were excluded from the field of study. Finally, in ATM services, Internet banking, retail terminals and virtual terminals groups were 536, 389, 582 and 132 customers, respectively. Then, four variables, R, F, M and L, were calculated with respect to the transactions of bank customers in each of the above services. In this case study, these parameters were defined as follows:

- L parameter, duration of customer relationship, is based on the subtraction of first date from last date of customer transaction during analysis period.
- R parameter is based on the last customer transaction that is calculated by deduction of end date of analysis period from last date of customer transaction. The smaller R value means that customer transaction date is closer to the present.
- F parameter is the total number of customer transactions during the analysis period.
- M parameter is the sum of all money owed by a customer for the use of bank services. Therefore, the amount in the field of debit rather the field of credit is considered.

Afterwards, scaling of these variables is done with RFM analysis method in the SPSS Clementine software. Table4 to Table7 show the results.

Table4. LRFM variables scaling in the first service group (ATM)

Score	Analysis	L	M	F	R
1	Very Low (VL)	[0, 9)	(20000, 4500000]	[1, 2)	(0, 1]
2	Low (L)	[9, 40)	(4500000, 29512000]	[2, 6)	(1, 4]
3	Medium (M)	[40, 75)	(29512000, 85030000]	[6, 13)	(4, 10]
4	High (H)	[75, 87)	(85030000, 329625000]	[13, 37)	(10, 33]
5	Very High (VH)	[87, 90]	[329625000, 990000000000]	[37, 994]	(33, 89]

Table5. LRFM variables scaling in the second service group (Internet banking)

Score	Analysis	L	M	F	R
1	Very Low (VL)	0	[578955, 10000250)	1	(51, 90]
2	Low (L)	(0, 34)	[10000250, 60000500)	(1, 4)	(10, 51]
3	Medium (M)	[34, 80)	[60000500, 294501000)	[4, 18)	(3, 10]
4	High (H)	[80, 89)	[294501000, 14609671500)	[18, 176)	(0, 3]
5	Very High (VH)	[89, 90]	[14609671500, 990550000000]	[176, 993]	0

Table6. LRFM variables scaling in the third service group (POS)

Score	Analysis	L	M	F	R
1	Very Low (VL)	[0, 34)	[40000, 13400500)	[1, 5)	(9, 79]
2	Low (L)	[34, 82)	[13400500, 146788750)	[5, 32)	(3, 9]
3	Medium (M)	[82, 88)	[146788750, 881018918)	[32, 77)	(1, 3]
4	High (H)	[88, 90)	[881018918, 4822653630)	[77, 141)	(0, 1]
5	Very High (VH)	90	[4822653630, 949997980000)	[141, 2049]	0

Table7. LRFM variables scaling in the fourth service group (virtual terminals)

Score	Analysis	L	M	F	R
1	Very Low (VL)	0	[20000, 40000)	1	(48, 87]
2	Low (L)	(0, 3)	[40000, 50000)	(1, 2)	(40, 48]
3	Medium (M)	(3, 36]	[50000, 500000)	[2, 4)	(16, 40]
4	High (H)	(36, 57]	[500000, 670020000)	[4, 16)	(11, 16]
5	Very High (VH)	(57, 85]	[670020000, 6900507500]	[16, 55]	[0, 11]

In this study, SPSS Clementine 12.0 software is used to implement k-means algorithm. SPSS Clementine has been recognized as commercial software in the field of data mining, and some of the popular clustering algorithms are implemented in it. This software provides an intuitive environment of data, methods, and data mining tools by a network of nodes and streams for simple modeling and performance analysis of various data mining techniques. Iterations of k-means algorithm was set from k = 2 to k = 12 to reduce the problem of achieving to local optimum. We used Dunn index [74] to find the optimal number of clusters. The parameters needed to calculate Dunn index are available due to the capability of SPSS Clementine, and calculation of this index is as easily as possible. We must do adjustments in software before running the k-means algorithm to specify the values required for calculating Dunn index. Fig. 3 shows the optimal number of clusters for all service groups according to the results of Dunn index.

Table8 to Table11 show specifications of obtained clusters for each service group. LRFM score uses scaled variables and it is obtained by equation (6), where $R\ Score_{Ci}$, $F\ Score_{Ci}$, $M\ Score_{Ci}$, and $L\ Score_{Ci}$ are respectively the scores of R, F, M, and L parameters in cluster C_i.

$$LRFM\ Score_{C_i} = R\ Score_{C_i} + F\ Score_{C_i} + M\ Score_{C_i} + L\ Score_{C_i} \qquad (6)$$

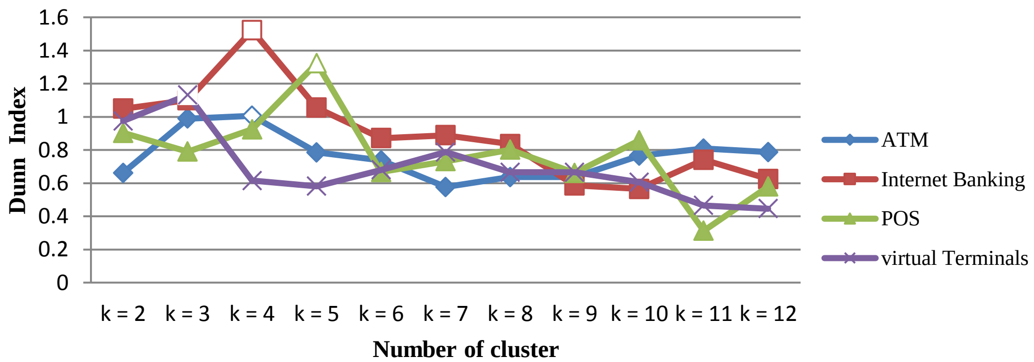

Fig.3. The results of Dunn index

Table8. Clustering result based on LRFM variables in the first service group (ATM)

Cluster	Number of members	percentage of members	R	F	M	L	RFML Analysis	RFML Score
C1	242	45.15%	6.269	34.471	308056751.431	78.031	3444	15
C2	42	7.84%	65.261	2.0	14186913.043	6.739	1221	6
C3	198	36.94%	21.469	4.134	23221467.039	18.458	2222	8
C4	54	10.07%	0.886	827.0	686061095346.286	88.429	5555	20

Table9. Clustering result based on LRFM variables in the second service group (Internet banking)

Cluster	Number of members	percentage of members	R	F	M	L	RFML Analysis	RFML Score
C1	72	18.51%	0.623	704.094	633239628072.472	88.774	4554	18
C2	89	22.88%	72.914	1.271	26377970.757	1.271	1222	7
C3	95	24.42%	18.75	3.171	88540734.487	20.737	2232	9
C4	133	34.19%	4.447	61.956	5109909145.43	81.158	3444	15

Table10. Clustering result based on LRFM variables in the third service group (POS)

Cluster	Number of members	percentage of members	R	F	M	L	RFML Analysis	RFML Score
C1	57	9.79%	0.474	642.132	683570510380.895	88.053	4554	18
C2	79	13.57%	48.55	1.917	21860418.833	1.983	1121	5
C3	330	56.7%	2.032	96.897	3066307872.068	86.023	3443	14
C4	12	2.06%	0.917	1365.75	47831082698.0	89.667	4554	18
C5	104	17.87%	8.741	6.953	208716314.812	28.094	2231	8

Table11. Clustering result based on LRFM variables in the fourth service group (virtual terminals)

Cluster	Number of members	percentage of members	R	F	M	L	RFML Analysis	RFML Score
C1	63	47.73%	43.364	1.5	4982568.182	2.318	2242	10
C2	28	21.21%	11.0	20.778	5964592956.889	54.232	5554	19
C3	41	31.06%	13.545	14.591	234756916.818	59.817	4445	17

In third service group (POS), it can be seen that clusters C1 and C4 with a total of 69 members nearly have 12 percent of customers and the RFML scores are equal to 18. Cluster C2 with 13% of the customers has the lowest score. Fig. 4 shows pie chart of clusters regarding to their scores to better analysis of clustering results within each service group.

Clustering algorithm doesn't need normalized values because they do not affect the result of clustering. However, it is necessary to use normalized values for calculating customer lifetime value to ensure that larger amounts do not affect the analysis. Thus, normalization is done for the clusters' centers. Calculation of CLV score also requires the weights of parameters. The decision makers of the industry were asked to make pairwise comparison by questionnaire and paired comparisons matrix for determining the importance of each variable. Table12 shows the comparison matrix, which is used to compare the importance of LRFM variables. The result of this matrix is recorded in another matrix as shown in Table13.

Table12. A comparison matrix for pairwise comparisons between LRFM variables

	Comparative Importance									
	9: 1	7: 1	5: 1	3: 1	1: 1	3: 1	5: 1	7: 1	9: 1	
R	9	7	5	3	1	3	5	7	9	F
R	9	7	5	3	1	3	5	7	9	M
R	9	7	5	3	1	3	5	7	9	L
F	9	7	5	3	1	3	5	7	9	M
F	9	7	5	3	1	3	5	7	9	L
L	9	7	5	3	1	3	5	7	9	M

Table13. The result matrix of paired comparisons

	R	F	M	L
R	1			
F		1		
M			1	
L				1

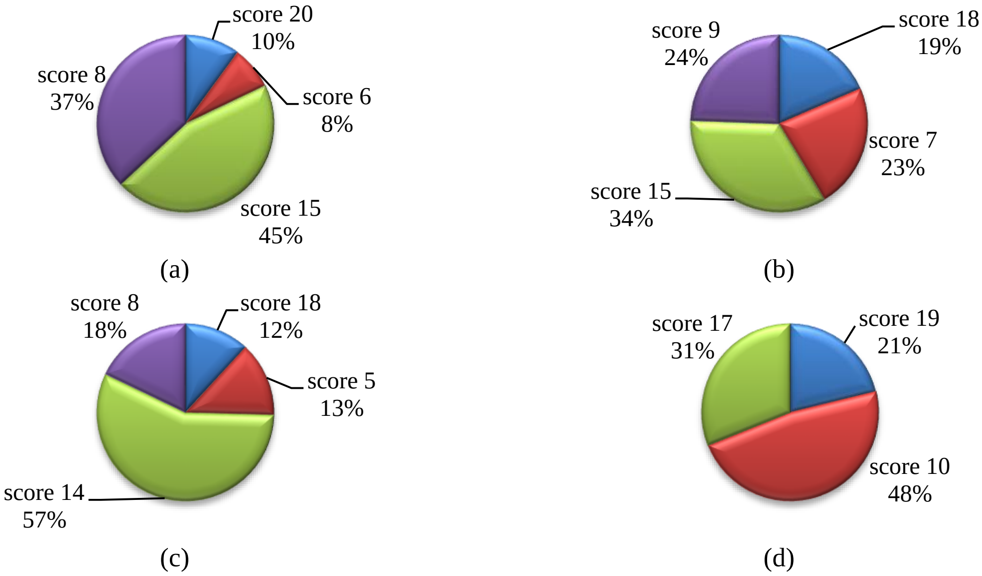

Fig.4. Pie chart of clusters in (a) first service group (ATM); (b) second service group (Internet banking); (c) third service group (POS); (d) fourth service group (virtual terminals)

Today with the development of AHP method, several software programs are written based on the theory of AHP which facilitate the process of solving comparison matrix and calculation of the weights. In this study, Expert Choice software (version11) is used to determine the effective parameters in customer value. Table14 shows the computed weights for the relevant parameters.

The remarkable thing is that some researchers multiplied parameters' weights by the numerical values of the parameters while it does not affect the clustering result. These weights are essential only for calculating the formula of CLV. Hence, CLV score of each cluster is calculated by equation (5). Table15 to Table18 show CLV rates of each cluster.

Table14. Weight of LRFM parameters

Parameter	L	M	F	R
Weight	0.063	0.623	0.245	0.154

Each cluster found in implementation of the proposed method for Mellat bank, is further explored to provide a more detailed analysis of customer clusters. We recognized three segments of customers in each service group called golden, loyal and low-value customers. After that, we formulated targeted programs and strategies for each segment with the help of experts at Department of Marketing and Communication, Data Mining Unit, Data Analysis Unit, and Department of Economic and Market Research. Table22 summarizes characteristics and strategies for all customer segments

Table15. CLV scores of clusters in the first service group (ATM)

Cluster	Normalized R	Normalized F	Normalized M	Normalized L	CLV Value	CLV Rate
C1	0.92956	0.03371	0.00031	0.86701	0.20623	**2**
C2	0.26673	0.00101	0.00001	0.07488	0.04605	**4**
C3	0.75878	0.00316	0.00002	0.20509	0.13056	**3**
C4	0.99004	0.83182	0.69299	0.98254	0.84989	**1**

Table16. CLV scores of clusters in the second service group (Internet banking)

Cluster	Normalized R	Normalized F	Normalized M	Normalized L	CLV Value	CLV Rate
C1	0.99308	0.70876	0.63928	0.98638	0.78699	**1**
C2	0.18984	0.00027	0.00003	0.01412	0.03021	**4**
C3	0.79167	0.00219	0.00009	0.23041	0.13703	**3**
C4	0.95059	0.06145	0.00516	0.90176	0.22147	**2**

Table17. CLV scores of clusters in the third service group (POS)

Cluster	Normalized R	Normalized F	Normalized M	Normalized L	CLV Value	CLV Rate
C1	0.99400	0.31305	0.71955	0.97837	0.73969	**1**
C2	0.38544	0.00045	0.00002	0.02203	0.060868	**5**
C3	0.97428	0.04682	0.00323	0.95581	0.223738	**3**
C4	0.98839	0.66638	0.05035	0.99630	0.40961	**2**
C5	0.88935	0.00291	0.00022	0.31216	0.157476	**4**

Table18. CLV scores of clusters in the fourth service group (virtual terminals)

Cluster	Normalized R	Normalized F	Normalized M	Normalized L	CLV Value	CLV Rate
C1	0.50156	0.00926	0.00072	0.02727	0.081676	**3**
C2	0.87356	0.36626	0.86437	0.63791	0.802953	**1**
C3	0.84431	0.25169	0.03402	0.70374	0.257218	**2**

Customers are also clustered based on the traditional LRFM model with the purpose of analysis and evaluation of GLRFM model. It means that previous steps are done for clustering customers without discrimination of used services.

Fig. 5 shows the optimal number of clusters. Table19 to Table21 respectively show scaling of parameters, the results of using k-means algorithm, and CLV score of each cluster and the clusters' rankings.

Table20 shows that clusters C3 and C5 with a total of 163 members have near 26 percent of customers with RFML score equal to 17, and cluster C2 with 4% of customers have the lowest score. Fig. 6 shows pie chart of clusters regarding to their scores. The next section compares outputs of two implemented methods in detail to analyze and evaluate the utility of proposed framework.

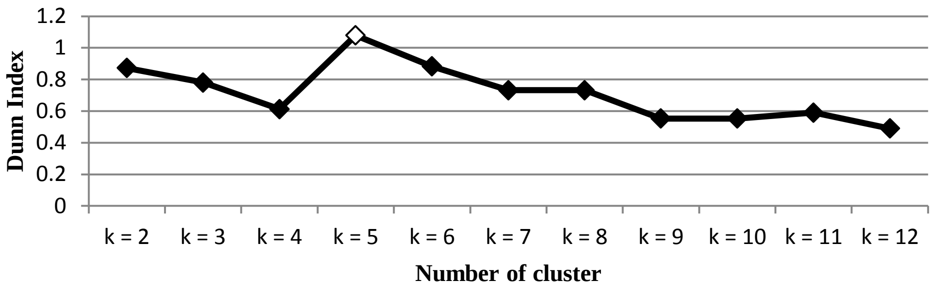

Fig.5. The optimal number of clusters in traditional LRFM method

Table19. Scaling of LRFM parameters in traditional method

Score	Analysis	L	M	F	R
1	Very Low (VL)	[0, 79)	[140000, 100000000)	[1, 23)	(30, 70]
2	Low (L)	[79, 88)	[100000000, 707610750)	[23, 78)	(4, 30]
3	Medium (M)	[88, 89)	[707610750, 3657941780)	[78, 150)	(1, 4]
4	High (H)	[89, 90)	[3657941780, 457025000000)	[150, 498)	(0, 1]
5	Very High (VH)	90	[457025000000, 990550000000]	[498, 2069]	0

Table20. Clustering result based on LRFM parameters in traditional method

Cluster	Number of members	percentage of members	R	F	M	L	RFML Analysis	RFML Score
C1	354	55.14%	1.919	115.367	5021361193.913	86.654	3342	12
C2	28	4.36%	53.0	5.667	136977014.445	2.667	1121	5
C3	17	2.65%	0.647	1193.471	42721764601.529	89.765	4544	17
C4	97	15.11%	8.487	6.474	150121418.269	26.641	2121	6
C5	146	22.74%	0.646	746.661	663316551361.299	88.472	4553	17

Table21. CLV scores of clusters in traditional method

Cluster	Normalized R	Normalized F	Normalized M	Normalized L	CLV Value	CLV Rate
C1	0.97259	0.05530	0.00507	0.96282	0.227144	3
C2	0.24286	0.00226	0.00014	0.02963	0.039908	5
C3	0.99076	0.57663	0.04313	0.99739	0.383557	2
C4	0.87876	0.00265	0.00015	0.29601	0.15472	4
C5	0.99077	0.36057	0.66964	0.98302	0.720034	1

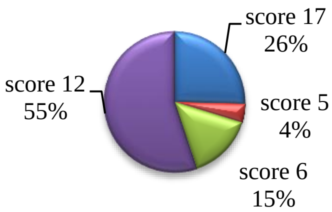

Fig.6. Pie chart of clusters in traditional method

Table22. Characteristics and strategies of customer segments in each service group

Service Group	Name of Segment	Cluster No.	% of Each Group	Parameters	Para-meters' Value	Strategies
ATM	Golden	C4	10.07	R F M L	VH VH VH VH	▪ It is necessary for Mellat bank to recognize that these customers are their most beneficial customers in use of ATM services and they prefer transacting through banks' card. ▪ Retention of these best customers is critical for the bank. ▪ These customers are most worthy of appreciation and special treatment. They must be treated specially through higher quality, special ATM services, informing about ATM services in a timely manner, and simplifying or increasing the relations of these customers by expanding the number and geographical spread to ensure convenient services. ▪ Mellat bank should to know why these customers prefer to use ATM services. This knowledge is useful for the bank in order to adopt proper and related strategies in the direction of making other customers to shift to this segment.
	Loyal	C1	45.15	R F M L	M H H H	▪ This segment involves customers who have high purchase amount, frequency and length but their last transactions are 4-10 days ago. So, churn probability of them is high, and thus retention of these customers is so important. ▪ Since this segment has the significant number of customers, the main focus of the bank for offering ATM services must be based on the behavior of this segment in addition to previous segment. ▪ These customers are at risk of falling from beneficial customers to non-beneficial customers. So, they must be treated on the way of transferring to golden segment. ▪ Recognizing the reason of decrease in purchase is the most helpful action that can be done for this segment. ▪ Proper strategy for increasing the number of purchase and amount of purchase must be adopted. This can be done by appreciation programs and informing about all services or giving special ATM services.
	Low-value	C2, C3	44.78	R F M L	L or VL L L L or VL	▪ CLV score of this segment is low because they have non-significant average recency, frequency, monetary, and length. So, it is considered as low-value customers of Mellat bank in using ATM services. ▪ Although the number of customers of this segment is remarkable, the bank should spend the least time and money. ▪ The best strategy to follow for these customers is to increase the average amount of using services via cross-selling and up-selling.
Internet banking	Golden	C1	18.5	R F M L	H VH VH H	▪ Customers of this segment are valuable for company because of their proven pattern of repeat Internet services; they purchase frequently and average frequency of their transactions is 7 times a day. ▪ These customers have positive tendency toward internet banking and they are doing their bank works through the Internet. ▪ In developing internet banking, the bank should use people of this segment in focus group researches. ▪ Bank should provide financial resources to promote new Internet banking services to this segment, and thus retain these valuable customers.
	Loyal	C4	34.19	R F M L	M H H H	▪ Loyal segment is the group of customers who do most of their banking activities via the Internet. These customers are valuable and beneficial for the bank but their value is lower than golden segment. They recently joined to Mellat bank to do their transactions through the Internet. So, if we want to have a long relation in future, we should be attending to them in order to not turn to other banks in future. ▪ Retention of this segment is the main point that should be considered because these customers have potential to become golden customers. The bank can advertise Internet banking services to them because of the considerable number of customers in this segment.
	Low-value	C2, C3	47.3	R	L or VL	▪ This segment has low level of revenue for the bank and these customers always spend little money on their online transactions. They use only small number of Internet banking services. ▪ Albeit the number of customers of this segment is more than the other segment, bank should be considered them in third-level and pay less time and money for online services advertisement. The strategies for these customers must be adopted carefully considering a trade-off between retention costs and their revenues. ▪ The cross-selling of other services can help to increase the money they spend in each purchase.

Table22. Characteristics and strategies of customer segments in each service group *(continued)*

Service Group	Name of Segment	Cluster No.	% of Each Group	Parameters	Para-meters' Value	Strategies
POS	Golden	C1, C4	11.85	R F M L	H VH VH H	▪ These customers are in the highest rating category of CLV in using POS. So, the bank must provide specific services for these valuable customers. ▪ We should consider this segment more than other segments to determine marketing strategy for POS services. ▪ Bank services with these customers cannot be limited to e-banking activities. In fact, these customers are the most valuable customers of the bank in the use of POS. They frequently obviate their requirements by Mellat card. So, they have potential to get other specific services of bank like ATM services. ▪ It is important to perform all of the efforts for retention of these customers.
	Loyal	C3	56.7	R F M L	M VL H M	▪ Recency of such customers is 1-3 days ago. Their frequency of using Mellat POS is at least 1 time in their relationship with the bank and their length of relations is 82-87 days. ▪ These are the customers who have a high average purchase amounts but very low average purchase frequency, and medium average recency and relation length. So, they are at risk of falling to low-value segment. The retention efforts for this segment must be reinforced. ▪ The most appropriate strategy for this segment is to build purchase frequency. This can be done by communication. We must encourage these customers by informing them about new POS services, capabilities and unique aspects of Mellat bank in a timely fashion. ▪ This segment is the loyal customers in using POS services. Because of the notable number of customers of this segment, bank should be propose specific options to create interest of using POS and therefore increase their frequency.
	Low-value	C2, C5	31.44	R F M L	L or VL L or VL L or M VL	▪ These customers have low length of relation and frequency low monetary value, and high distance between their transactions. Hence, CLV score of this segment is low. ▪ This segment involves low-value customers in using POS services but this is remarkable in numbers. So, bank should determine retention programs for them. ▪ These customers spend very little and rarely. They are at risk of leaving bank services. So, it is very important to investigate about the reasons and adopt proper strategies for them. One of the actions that we can do is promotion plans and some incentives or offers in order to make these customers more engaged. These offers must be adequate and profitable for Mellat bank. ▪ Special discounts and promotional plans have some cost for company. So, there must be some trade-off between costs and incomes of these plans. It is better to optimize our offer plans by using predictive models and more adequate analysis.
Virtual terminals	Golden	C2	21.21	R F M L	VH VH VH H	▪ By using lower commission rate, incentive schemes, and more features that Mellat bank offer for Mellat e-payment gateway, we can maintain use of Mellat bank virtual terminals. Thus, the bank can increase its customer transactions and retain their relationship with the bank.
	Loyal	C3	31.06	R F M L	H H H VH	▪ These customers are who frequently buy company's products or services by electronic payment gateway of Mellat bank. So, advertising the virtual terminal services for who has web site and providing online shopping channel for them can help to increase the number of customers. Also, there are many things for the bank to consider such as fees, recurring billing, and even currency support. By adopting these strategies, the customers of this segment will be migrated to golden segment. ▪ In order to join these customers to golden customers, bank should provide facilities of virtual terminal services for them.
	Low-value	C1	47.73	R F M L	L L H L	▪ This segment has the customers who have a high average monetary amount but a low average frequency. So, the most appropriate strategy for this segment is to build purchase frequency and increase relation length. If R, F, and L of these customers increase, it can be expected that they immigrate to loyal segment in future. This can be done by communication. We must encourage these customers by informing them about new virtual terminal services. ▪ Churn rate of this segment is high. The bank should specify retention program to keep these customers whereof the number of these customers is remarkable and they have high monetary value.

VI. DISCUSSION

We presented a framework for customer clustering based on the proposed GLRFM model and it was implemented on customers' data of Mellat bank. To analyze the usefulness of this framework, customer clustering was performed based on the traditional model too. In this section, we scrutinize outputs of two models to better understand their differences and analyze the usefulness of proposed framework. CLV score of cluster C5 in traditional clustering method is equal to one and therefore, the customers of this cluster are considered as valuable and loyal customers of business. We checked the placements of some of these customers in result of proposed clustering method as shown in Fig. 7. This comparison shows that some valuable customers in traditional method aren't valuable in using some services and they may even be have the worst CLV rates in proposed method. So, business cannot keep an eye on all of the customers.

According to Fig. 7, we examine two scenarios where the valuable customers may have:

1) It can be seen that some valuable customers in the traditional clustering model are used only one service group and they are valuable in this group. For instance, both c402 and c35 have been in the cluster C5 by traditional analysis and they are two valuable customers of business. But, when we look closer to their used services we discover that their preferences over the services are different. Customer c402 is used the services of retail terminals, while customer c35 is benefited from Internet banking services. Now, when the bank promotes Internet banking services to the valuable and loyal customers, it could attract only customer c34 and Internet banking advertisements most likely will not affect the customer c402. By proposed analysis method, these two customers have been placed only in the group of services that they used and they have the best CLV rate. So, with this analysis method, business can better develop marketing strategies for clusters of customers and don't waste business resources for advertisement.

2) Another case which is being investigated is valuable customers in traditional method who are valuable in one service groups and they aren't loyal among the other groups. With common analysis, we cannot understand why the customer has been part of our valuable customers, while proposed method provides more precise and detailed analysis. Detailed information about the customer can lead to a better plan for CRM. For example, customer c201 has the best CLV score in common clustering method, while his CLV score by proposed technique in the first service group is 4 and in the third service group is 1. He didn't use other services of business. So, in traditional method we recognize valuable customers, but we don't know which services they are valuable for?

In proposed method, customer c570 is only in the second group because he just used Internet banking services, and he has the best CLV score in it. Now, for specifying marketing strategies, we know that this person is one of the valuable customers which only use the Internet banking services. Therefore, using the proposed method we can see that which customers can participate in the advertising programs related to Internet banking or other services groups. However CLV score of this customer is equal to 1 in the traditional method, we cannot differentiate him from other customers and he gets involved in all promotional programs to our valuable customers. It may be only waste cost and resources of business.

While customer c479 is placed in cluster C5 with the best CLV score by traditional method, he is located in cluster C4 for first service group and in cluster C2 for third service group by using proposed method. This shows that he is considered as a valuable customer with traditional clustering methods, but it can be seen that he is valuable to the business actually because of being faithful in the use of ATM services. We discuss the reason by comparing score of RFML as shown in Table23. As mentioned before, the F and M parameters in traditional method equal to the sum of these two values in four service groups of proposed method; the value of the R parameter is equal to the lowest value of this parameter in each group.

Table24 reviews some customers whose CLV scores are two or more in traditional method and it shows their CLV scores in proposed analysis method.

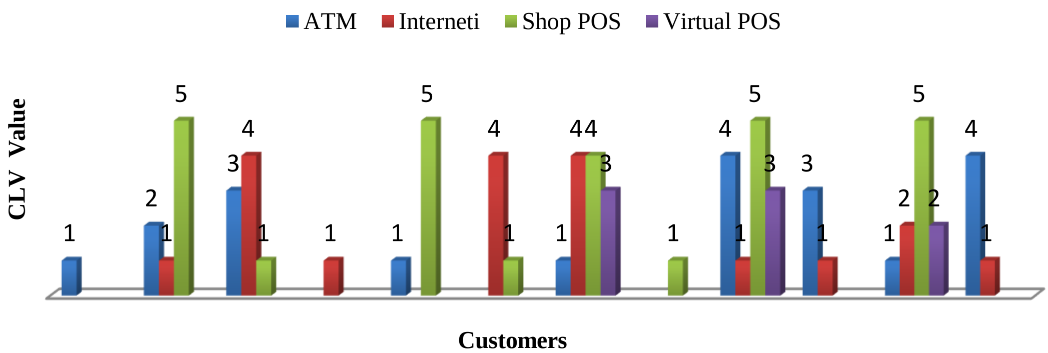

Fig.7. Comparison of clustering results - CLV values of some customers in proposed method, who have the best CLV rate in traditional method

Table23. Comparing a customer who has CLV=1 in traditional method with his/her score in proposed method

Parameter / Method	L	M	F	R	RFML Analysis
Traditional LRFM	88	849790750500	782	1	**4553**
Proposed method (in ATM service group)	88	849650000500	778	1	**5555**
Proposed method (in POS service group)	3	140750000	4	55	**1121**

Table24. Comparing CLV scores of some customers who have CLV≥2 in traditional method with their CLV scores in proposed method

Customer ID	CLV Score in Traditional Method	CLV Score in Proposed Method			
		ATM	Internet Banking	Shop POS	Virtual Terminals
117	2	3	2	3	-
610	2	3	-	2	-
421	2	-	2	3	3
435	2	2	-	2	-
143	3	2	2	3	1
16	3	2	4	3	-
113	3	2	-	4	-
330	3	2	-	5	-
153	3	-	2	-	-
223	3	2	-	3	3
608	3	2	2	3	2
4	3	3	-	3	-
26	4	3	2	۵	3
515	4	3	3	4	1
144	5	4	-	5	-

It should be noted that cluster C1 and C4 in the third service group are same in terms of RFML scores. So, they can be considered as a segment. Cluster C3 and C5 in the traditional method can also be combined together due to this reason.

According to what was said, traditional analysis does not give us an accurate result and cannot be clearly identified that why the customers are loyal for business or for using which services. Moreover, we are not recommended a service to a customer who did not use this service because his acceptance probability of this offer is too low. In fact, we are not looking to attract new customers, but we're looking to maintain our current customers since the cost of attracting a new customer is 5 times of maintaining current customer's cost.

Although the proposed method requires more time to implement, it has advantages that give it superior to the traditional method. One of its advantages is determining the value of each customer according to the used products/services. This advantage itself leads to many benefits and it offers effective information to promote special products/services. Also, it causes more accurate and more convenient analysis. So, business can provide appropriate marketing strategies for each cluster by the proposed method of this research and offer the right strategy to the right person in order to retain their existing customers and increase the effectiveness of their performance.

VII. Conclusion

The main purpose of this study is research on customer clustering based on CLV and suggestion of a new framework in this field. In this paper, we presented a new CLV model called GLRFM. GLRFM model is based on the basic RFM model with considering the customer relation length parameter and also the idea that CLV value must be calculated according to the customers' used products/services. Our aim of proposing this model was reflection of the customers' actual consumption behavior and improvement of analysis. GLRFM modeling consists of five phases: (1) hierarchy of business products/services, (2) grouping customers' data based on the used products/services, (3) definition of the four variables required for the model, (4) variables scaling for estimation of each customer GLRFM value, and (5) variables normalization for calculating CLV rate.

The results of this study could be as a guideline with further understanding of customers for marketing plan formulation, formulating retention programs for each valuable group, and also developing and cross selling of new products for the low-value customers according to the obtained value of each group and the acceptance and use of each group of various services. Indeed, the main findings of this paper include:

- Reviewing the existent research articles in the scope of clustering based on CLV;
- Proposing GLRFM model with consideration of products/services used by customers in the measurement of CLV parameters - Loyalty and value of customers shall be measured as for used products/services because the parameters, which affect the calculation of customer value, are varied between different products/services. For instance, frequency of using Internet banking is lower than ATM;
- Presenting a novel framework for customer clustering based on the combination of GLRFM model and k-means clustering algorithm - Proposed method exactly specifies "What are the consumption interval, frequency, relation length, and money amount of a customer over a particular services?", "Who are potential consumer of a

certain services?, and "What services are they valuable for? ";

- Implementing both proposed framework and traditional method on a banking data set in the field of e-banking and comparing the outputs - The comparison of clustering results shows that proposed method provides more precise information for cluster analysis than traditional methodology. So, if the CLV is calculated with respect to used services, customer needs can be met better, and an effective personalized management system can be developed to further improve customer relationships;
- As a result, organizations can use this framework to create clear sales and marketing policies and recommend right product to right person with the purpose of enhancing customer utility and firm profitability. Finally, it should be noted that it is much better for business to try to determine and retain profitable and loyal customers using data mining techniques, rather than paying heavy costs for attracting new customers.

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