K-Mean Clustering Method For Analysis Customer Lifetime Value With LRFM Relationship Model In Banking Services

Mohsen Alvandi\textsuperscript{1}, Safar Fazli\textsuperscript{2}, Farzaneh Seifi Abdoli\textsuperscript{3}

1. Member of scientific board, Imam Khomeini International University, Iran, Qazvin
2. Member of scientific board, Imam Khomeini International University, Iran, Qazvin
3. Department of social science, Imam Khomeini International University, Iran, Qazvin

Corresponding Author email: seifi.management89@gmail.com

ABSTRACT: In today's businesses, achieving customers satisfaction have critical role in organization's goals. On the other hand, all of customers hasn't equal share in profitability of organization. Therefore, identification key customers will be more sensitive. Calculate the lifetime value assist organizations to rank customers based on their contribution to profitability. The purpose of this paper is to introduce a model to calculate customer lifetime value (CLV) based on LRFM customer relationship model which consists of four dimensions: relation length (L), recent transaction time (R), buying frequency (F), and monetary (M) in banking services. We proceed with this clustering analysis to classify customers in order to set marketing strategies. In this research, K-Mean clustering method as one of the main problems in unsupervised learning emphasizes. Achieving this, we used crisp method and implemented them on real data from an Iranian state bank. Validity of clustering process analyzed with R-Squared index. The results show nine cluster patterns between customers. Finally, in terms of this clustering, we proposed customer strategies. Thus, this study considers useful for customer relationship management.

Keywords: Crisp method, Customer lifetime value (CLV), K-Mean clustering, LRFM model, RS index

INTRODUCTION

Customers are ultimate source of growth in all businesses. Many organizations have come to the conclusion that understanding of their customers who are faced with is valuable and important. If all customers be similar, businesses would be so simple. However, Customers in various ways, such as preferences, price sensitivity, absorption rate, response to marketing tactics and sales and use appropriate communication paths are quite different (Elahi & Heidari, 2005). Some of organizations in rating their customers are wrong and in cases such as high investment on less valuable customers, low investment on high valuable customers, wasting critical resources and in attention to growth, profitability and competitive opportunities have mistakes. So more attention to customer relationship management (CRM) is required, because the main goal of CRM system is to understand profitable customers, to create and sustain relation with them (Gupta & Lehmann 2007). To cultivate the full profit potentials of customers, many companies already try to measure and use customer value in their management activities (Gloy et al., 1997).

In this paper we considered LRFM customer relationship model which consists of four dimensions: relation length (L), recent transaction time (R), buying frequency (F), and monetary (M) to cluster customers, analyzing and calculating CLV of different clusters. Then cluster with homogeneous CLV incorporate and construct a special cluster. Finally we ranking these cluster based on their CLV scores. There are two types of data in this study: transactional data, consist of relation length (L), recent transaction time (R), buying frequency (F), monetary (M) and customer lifetime value (CLV) and behavioral data, consist of: account number, customer type, account type, account status, first transaction and last transaction.
Literature review

This section will survey past research concerning customer relationship management and customer value analysis and RFM and LRFM models.

Customer Relationship Management

Linoff (1999) point out that the objective of CRM is to keep customers that contribute to the enterprise, which is also a continuous improvement process. Spengler (1999) proposes that CRM should really be called Contact Management, which represents the specific collection of all information on the interaction between the customer and the company. Swift (2001) explains that CRM is a behavior in which an enterprise tries to understand and reach customers through full interaction; moreover, it is a business strategy that enhances customer loyalty and profit gaining. Dong, Swain, and Berger (2007) shows that maximization of customer equity, which is a core objective of customer–company relationship management. Lin (2007) points out the customer satisfaction model and concept. Krasnikov and Jayachandran (2008) find that marketing capability has a larger influence than research and development ability on enterprise performance and management strategy of customer relationship, and maintenance are the main ability of marketing. Richards and Jones (2008) point out an intuition and general concept and claim that to increase customer relationship management should improve the business administration performance. King and Burgess (2008) point out some successes and failures factors influence customer relationship management.

Customer Value Analysis

Berger and Nada (1998) explain the importance of maintaining a customer by comparing customer lifetime value and the necessary cost of attracting a new customer. Mani, Drew, Betz, and Datta (1999) and Crowder, David, and Wojtek (2007) regard that the customer lifetime value is composed of two independent factors: tenure and value. They point out that CLV is an important concept in the work of customer classification, selection, and retention, because different strategies may apply to different customers. Brown (2000) proposes that not all customers are worth keeping, and uses value-based segment theory to determine the limitation resources and efforts to maintain a specific customer's loyalty. He claims that customer value analysis is the foundation of customer relationship management. Kotler (2000) defines Customer Lifetime Value (abbreviated as CLV) as the profit net present value (NPV) that one can obtain in a customer's lifetime. Kim, Jung, Suh, and Hwang (2006) define customer lifetime value as the net income amount of the business during the entire life cycle of a customer. He emphasizes long-term continued income and cost, instead of the profits from a specific trading activity. Siddharth S. Singh, SharadBorle, and Dipak C. Jain (2009) proposed a flexible Markov Chain Monte Carlo (MCMC) based data augmentation framework for forecasting lifetimes and estimating customer lifetime value (CLV) in such contexts. Dries F. Benoit and Dirk Van den Poe (2009) show that in the common situation where interest is in a top-customer segment, quantile regression outperforms linear regression. The method also has the ability of constructing prediction intervals. Combining the CLV point estimate with the prediction intervals leads to a new segmentation scheme that is the first to account for uncertainty in the predictions. Reinartz and Kumar (2000) propose the idea of customer relation length, and examine its influence on customer loyalty and profitability. They suggest increasing relation length to improve customer loyalty. Benoit and den Poel (2009) led to an interest in understanding and estimating customer lifetime value and relation method. Gladys, Baesens, and Croux (2009) propose the approach for predicting customer lifetime value with the Pareto/NBD model.

RFM AND LRFM MODELS

RFM model is a well-known customer value analysis method widely applied to segment customers (Chang et al., 2010). Some literature has attempted to develop new RFM models to test whether they perform better than the traditional RFM models by taking additional variables into account (Hosseini et al., 2010). For example, Ching-Hsue Cheng, You-Shyan and Chen (2009) firstly utilizes RFM model to yield quantitative value as input attributes; next, uses K-means algorithm to cluster customer value; finally, employs rough sets to mine classification rules that help enterprises driving an excellent CRM. Miglautsch (2000) and Kaymak (2001) use the RFM model as a way to measure customer lifetime value, and made extensive use of estimated customer value at present. Before carrying out database marketing, enterprises must focus research on the customers’ historical trade records in order to obtain references for prediction and as the basis of decisions. Yeh et al. (2008) selected targets for direct marketing from a database using a modified RFM model, namely RFMTC, by adding two parameters, i.e., time since first purchase (T) and churn probability (C). Also Hsiao-ping tsai (2011) propose a new frame work called GRFM (for group RFM) analysis to alleviate the problem. The new measure method takes into account the
characteristics of the purchased items so that the calculated the RFM value for the customers are strongly related to their purchased items and can correctly reflect their actual consumption behavior. In this regard, in this paper, RFM model is extended as LRFM model by taking length (L) into account.

**Theoretical background**

**Customer lifetime value**

The value of a customer is the value the customer brings to the firm over his/her lifetime. Some recent studies (Kumar & Reinartz, 2006) have shown that past contributions from a customer may not always reflect his or her future worth to the firm. Hence, there is a need for a metric which will be an objective measure of future profitability of the customer to the firm (Berger & Nasr, 1998). Customer lifetime value takes into account the total financial contribution- i.e., revenues minus costs- of a customer over his or her entire lifetime with the company and therefore reflects the future profitability of the customer. Customer lifetime value (CLV) is defined as the sum of cumulated cash flows discounted using the Weighted Average Cost of Capital (WACC) of a customer over his or her entire lifetime with the company (Grover & Vriens, 2006).

Based on the approach of estimating CLV, there are different definitions for this term. Some researchers have recommended CLV as a metric for selecting customers and designing marketing programs (Blattberg & Deighton, 1996). However, there is no empirical evidence as to the usefulness of CLV compared with that of other customer based metrics. Jain and Singh determined that many models have been proposed in CLV literature dealing with all kinds of issues related to CLV. The following selection of models provides summaries of some key models addressing some major research opportunities in CLV research and applications. Based on the threefold stream of research related to CLV, they divided them into three corresponding categories (Jain & Singh, 2002):

1. **Models for calculation of CLV:** This category includes models that are specifically formulated to calculate the CLV and/or extend this calculation to obtain optimal methods of resource allocation to optimize CLV. These are applied models and more relevant to practitioners who wish to use CLV as a basis for making strategic or tactical decisions.

2. **Models of customer base analysis:** Such models take into account the past purchase behavior of the entire customer base in order to come up with probabilities of purchase in the next time period. These models take into consideration the stochastic behavior of customers in making purchases and therefore these models look at each customer individually in order to compute the probability of purchase in the next time period. Models in this category can provide input for the calculation of CLV.

3. **Normative models of CLV:** These models have been proposed and used mainly to understand the issues concerning CLV. Managers depend on many commonly held beliefs in making decisions regarding CLV. As an example, it is believed that long lifetime customers are more profitable. Numerous researchers and practitioners have provided many reasons in support of this belief. Normative models provide us an opportunity to explore this issue without the “noise” encountered by empirical studies. Such models provide valuable insight for policy-making.

This paper works on normative model of Der-Chiang Li, Wen-Li Dai, and Wan-Ting Tseng (2011). Gupta et al. described six modeling approaches in CLV issue (Gupta et al., 2006):

1. **RFM modeling:** RFM models create “cells” or groups of customers based on three variables- Recency, Frequency, and Monetary value of their prior purchases.

2. **Probability modeling:** The focus of the model-building effort is on telling a simple paramorphic story that describes (and predicts) the observed behavior instead of trying to explain differences in observed behavior as a function of covariates (as is the case with any regression model).

3. **Economic modeling:** Many econometric models share the underlying philosophy of the probability models. Specifically, studies that use hazard models to estimate customer retention are similar to the NBD/Pareto models except for the fact that the former may use more general hazard functions and typically incorporate covariates.

4. **Persistence modeling:** The major contribution of persistence modeling is that it projects the long-run or equilibrium behavior of a variable or a group of variables of interest.

5. **Computer science modeling:** These models are based on theory (e.g., utility theory) and are easy to interpret. In contrast, the vast computer science literature in data mining, machine learning, and nonparametric statistics has generated many approaches that emphasize predictive ability.

6. **Diffusion/Growth Modeling:** Based on customer equity (CE).

In this study we uses LRFM modeling (advanced of RFM modeling) of Gupta’s categories.
LRFM model

This study uses transaction data as the basis for the work of data mining (DM). It applies the LRFM customer relationship model (Chang & Tsay, 2004) to cluster customers into meaningful groups. Where four attributes are included as: (1) recent transaction time: referring to the time of the customer’s last transaction; (2) frequency of buying; (3) monetary value: the total value bought during a period; and (4) relationship length. The definition of the LRFM model used in this study shows in Table 1.

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Data content</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Transaction length</td>
<td>The interval is between the first and last exchange with a customer</td>
</tr>
<tr>
<td>2 Recent transaction time</td>
<td>From the last transaction time until now measured in years</td>
</tr>
<tr>
<td>3 Annual frequency</td>
<td>The average number of transactions a customer had per two year</td>
</tr>
<tr>
<td>4 Average monetary value</td>
<td>The average monetary value is in each transaction in two year</td>
</tr>
</tbody>
</table>

METHODOLOGY

This study is a applied research aspect of purpose and a descriptive-survey aspect (Khaki, 1390) of method of research. The case study concerns a state bank of Iran. Data were collected at two-year period.

RESEARCH METHOD

Data mining and crisp methodology

There are different methodologies for implementing data mining projects but one of the powerful methods is CRISP (Cross Industry Standard Process for Data Mining) methodology. As a process model, CRISP provides an overview of the data mining life cycle. CRISP uses six phases to describe the process from gathering business requirements to deploying the results (Larose, 2006):

1. Business Understanding: This phase typically involves gathering requirements and meeting with expert personnel to determine goals rather than working with data.
2. Data understanding: The data understanding phase of CRISP involves taking a closer look at the data available for mining. This phase includes collecting initial data, describing data, exploring data, and verifying data quality.
3. Data preparation: Data preparation is one of the most important and often time consuming aspects of data mining projects and includes selecting data, cleaning data, constructing new data, and integrating data.
4. Modeling: The data which was spent time preparing are ready to bring into data mining algorithms, and the results begin to shed some light on the business problem posed. Selecting modeling techniques, generating a test design, building the models, and assessing the model construct this phase.
5. Evaluation: In this phase, evaluating the results, review process, and determining the next steps are done.
6. Deployment: Deployment is the process of using the new insights to make improvements within the organization.

Data formation for establishing the LRFM model

This study uses customer lifetime value as the quantitative indicator, and principally uses the LRFM (Chang & Tsay, 2004) model to do the measurement. The definition of the LRFM model used in this study shows in Table 1. The source data is the real transaction data in the bank, which has 298 observed values collected in the file. In order to avoid periodic LRFM difference, we standardize the data first, and then calculate weights of the customer relationship length, recent transaction time, buying frequency, and monetary values with Shannon entropy.

Clustering analysis

This paper applies a K-Mean method of cluster analysis to the case bank data to group customers. The first stage is separate raw data into 16 clusters as favorite. Second stage consist of calculate the distance of each customer to the center of its cluster and Calculate the error function. This process stop with No getting changed in cluster members or not getting reduced the error function. For this we used apersonal computer with a Pentium 4 processor and SPSS software.

Group description
Marcus (1998) proposes a customer value matrix, shown in Figure 2, which uses customer buying frequency (F) and monetary value (M) as the two axes. Two other indicators are customer relationship length (L) and customer recent transaction time (R); these two indicators relate to customer loyalty, and therefore this is defined as the customer loyal matrix.

Figure 1 illustrates research methodology of this study regarding crisp methodology.

Figure 2. Customer value matrixes (Marcus, 1998)

Marcus (1998) claims that the longer a customer relationship, the higher the loyalty; and the shorter the recent transaction time, the greater the customer loyalty. Through buying frequency and monetary value one can form four quadrants in the first plane; and customer relation length and customer recent transaction time, one can form another four quadrants in the second plane. Consequently, using the customer value and customer loyal matrices one can form 16 quadrants to explain the result of clustering.
This study refers to Sung and Sang’s (1998) customer segment description and uses the up symbol (↑) to represent when the group’s average value is larger than the total average value; and the down symbol (↓) to represent when the group’s average value is smaller than the total average value.

Chang and Tsay (2004) further propose customer classification by summing the 16 groups to five kinds of customer groups, as Figure 3 shows, including: (1) core customers: including high value loyal customers (LRFM↑↓↑↑), high frequency buying customers (LRFM↓↑↑↑), and platinum customers (LRFM↓↓↓↑); (2) potential customers: including potential loyal customers (LRFM↑↑↑↑), potential high frequency customers (LRFM↓↑↑↑), and potential consumption customers (LRFM↓↓↓↑); (3) lost customers: including high value lost customers (LRFM↑↓↑↑), frequency lost customers (LRFM↓↓↓↑), consumption lost customers (LRFM↓↓↓↑), and uncertain lost customers (LRFM↓↓↓↑); (4) new customer groups: including high value new customers (LRFM↓↑↑↑), frequency promotion customers (LRFM↓↓↓↑), spender promotion customers (LRFM↓↓↓↑), and uncertain new customers (LRFM↓↓↓↑); (5) consuming resource customers: including low consumption cost customers (LRFM↓↓↓↑), high consumption cost customers (LRFM↓↓↓↑).

**Experimental analysis**

The case study is a status bank in Iran over 32 years of financial history. This case bank as a development bank, is one of the main instruments and institutions to contribute to economic growth and economic development through the development of the mining industry. This study aim finding answers for the following question: 1) How are K-Mean clustering of customers with LRFM model?, 2) How is CLV rank of each cluster customers and integrity rate of them? and 3) what are appropriate strategy in face of each cluster of customers?

**CLV ranking**

Integrity rate of each cluster calculated with this formula:

\[
C_i = \frac{C_i^{L} + W_R C_i^{R} + W_F C_f^{I} + W_M C_m^{I}}{N}
\]

Where \(C_i^{L}, C_i^{R}, C_f^{I}, C_m^{I}\) are mean values of the four variables.

**RS index**

Since clustering is an unsupervised process in data, It is necessary to validate the clustering process by a variety of criteria that are evaluated in order. We used RS index to this process. The motivation RS (R Squared) index (sabhash, 1996), described on Equation 2, index is to measure the dissimilarity of clusters. Formally it measures the degree of homogeneity degree between groups. The values of RS range from 0 to 1 where 0 means there are no difference among the clusters and 1 indicates that there are significant difference among the clusters.

\[
RS = \frac{SS_b}{SS_T} = \frac{SS_T - SS_W}{SS_T} (2)
\]

\[
SS_W = \sum_{i=1}^{k} \sum_{x \in C_i} \sum_{j=1}^{d} (x_{ij} - \bar{x}_{ij})^2 (3)
\]
\[ SS_t = \sum_{i=1}^{n} \sum_{j=1}^{d} (x_{ij} - \bar{x}_j)^2 \] (4)

Where,

- \( SS_b = \) referring to the sum of squares between groups,
- \( SS_w = \) referring to the sum of squares within group,
- \( SS_t = \) referring to the total sum of squares, of the whole data set,
- \( d = \) the number of variables (data dimensionality),
- \( n = \) is the number of data values of \( j \) dimension,
- \( \bar{x}_j = \) is the mean of data values of \( j \) dimension.

### RESULTS

This study used K-Mean clustering method for grouping customers and with providing a comprehensive picture of customer lifetime value, ranked customers of bank. so it can assist managers of bank branches to identification profitable customers and prioritize them. The final cluster centers after 35 consecutive iterations are shown on table 2.

<table>
<thead>
<tr>
<th>cluster</th>
<th>L</th>
<th>R</th>
<th>F</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1834429</td>
<td>0.0071719</td>
<td>0.0043396</td>
<td>0.0047112</td>
</tr>
<tr>
<td>2</td>
<td>0.0412785</td>
<td>0.0001319</td>
<td>0.0021698</td>
<td>0.0039162</td>
</tr>
<tr>
<td>3</td>
<td>0.0134534</td>
<td>0.0026100</td>
<td>0.0070688</td>
<td>0.0036759</td>
</tr>
<tr>
<td>4</td>
<td>0.0027874</td>
<td>0.0021631</td>
<td>0.0010345</td>
<td>0.0038519</td>
</tr>
<tr>
<td>5</td>
<td>0.0093057</td>
<td>0.0110043</td>
<td>0.0066300</td>
<td>0.0049880</td>
</tr>
<tr>
<td>6</td>
<td>0.0006827</td>
<td>0.0065170</td>
<td>0.0063648</td>
<td>0.0044124</td>
</tr>
<tr>
<td>7</td>
<td>0.1076133</td>
<td>0.0013023</td>
<td>0.0104151</td>
<td>0.0030387</td>
</tr>
<tr>
<td>8</td>
<td>0.0009689</td>
<td>0.0012160</td>
<td>0.0063913</td>
<td>0.0034294</td>
</tr>
<tr>
<td>9</td>
<td>0.0010655</td>
<td>0.0142945</td>
<td>0.0048885</td>
<td>0.0040380</td>
</tr>
<tr>
<td>10</td>
<td>0.0009539</td>
<td>0.0094711</td>
<td>0.0014322</td>
<td>0.0026405</td>
</tr>
<tr>
<td>11</td>
<td>0.0187203</td>
<td>0.0048839</td>
<td>0.0077631</td>
<td>0.0021583</td>
</tr>
<tr>
<td>12</td>
<td>0.0080197</td>
<td>0.0141767</td>
<td>0.0017840</td>
<td>0.0030004</td>
</tr>
<tr>
<td>13</td>
<td>0.0200477</td>
<td>0.0139977</td>
<td>0.0040664</td>
<td>0.0038396</td>
</tr>
<tr>
<td>14</td>
<td>0.0171184</td>
<td>0.0009818</td>
<td>0.0011434</td>
<td>0.0026324</td>
</tr>
<tr>
<td>15</td>
<td>0.0151221</td>
<td>0.0078715</td>
<td>0.0020010</td>
<td>0.0046523</td>
</tr>
<tr>
<td>16</td>
<td>0.0006360</td>
<td>0.0070661</td>
<td>0.0017264</td>
<td>0.0042633</td>
</tr>
</tbody>
</table>

We anticipated that have 16 clusters between customers of bank, but after K-Mean clustering results showed that the pattern of some clusters are completely equal so customers of this group merged and changed to a unique and new cluster. Table 3 shows results. For example cluster numbers of 3, 8 and 11 followed L R F M pattern, so after merging them we have a new cluster (C) with 67 customers.

According to the results of clustering that was presented on table 2, data were divided into 9 clusters (A, B, C, ..., I). we should ranking CLV score of these clusters regard as equation 1. Table 4 shows results of ranking CLV after calculating integrity rate.

For testing validity of clustering RS index was calculated followed by equations 2, 3 and 4. So results show that value of this index is 0.85.

\[
RS = \frac{0.058273077}{0.007448088} = 0.85
\]

This value is near to 1, so reliability of data clustering is high.

### DISCUSSIONS

For the first time we studied the LRFM customer relationship model in Iran and especially in banking industry. Also for the first time weighting variables be happened with Shannon entropy. On the other hand, validation of clustering process with RS index is one of the other innovations of this study. In this section first wediscuss results of ranking customers and then appropriate strategy for each of cluster.
Customers with L1R1F1M1 pattern: These customers are in the highest rating category of CLV, so bank must provide specific services for these valuable customers. Cluster A called potential loyal customers.

Customers with L1R1F1M1 pattern: These are valuable customers for bank but their loyalty is low, so maybe in the future turn to other banks. CLV score of this group is high between our customers. Cluster B is called platinum customers.

Customers with L1R1F1M1 pattern: This pattern show that these customers have low length of relation and frequency, high distance between transaction and monetary value is low also. CLV score of this group is low, so these customers are not valuable for bank. Cluster C called uncertain lost customers.

Customers with L1R1F1M1 pattern: these customers have long length of relationship but recency, frequency and monetary value of them does not follow a specific pattern. Lowest score of CLV belong them in this study. These customer recently joined to bank, so should be protect if want to have a long relation in future. Cluster D called low consumption cost customers.

Customers with L1R1F1M1 pattern: according to high L, R and F, if monetary of these customers increase can be expected that CLV score increase until highest in future. Cluster E called potential high frequency customers.

Customers with L1R1F1M1 pattern: these customers have highest CLV after cluster A, so are valuable for bank. Although length of relation and frequency are low but recency and monetary are high. Cluster F called consumption lost customers.

Customers with L1R1F1M1 pattern: these customers join us recently so have L, R, F and M in the lowest value. CLV score of this group is low also. Bank should have some persuasive plans for preserve of them. Cluster G called uncertain new customers.

8- Customers with L1R1F1M1 pattern: these customers have high loyalty but for low monetary and length of relationship CLV score of them is very low. So bank should propose specific options for increase their monetary. Cluster H called frequency promotion customers.

9- Customers with L1R1F1M1 pattern: customers of this group have high transaction with bank but monetary and recency value of them are low. This group has high CLV score in our study so Bank need to provide better services for maintenance them. Cluster I called high frequency buying customers.

Table 3. Merged cluster with similar pattern

<table>
<thead>
<tr>
<th>Cluster No</th>
<th>Cluster name</th>
<th>L</th>
<th>R</th>
<th>F</th>
<th>M</th>
<th>Number of customers</th>
<th>pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,5</td>
<td>A</td>
<td>0.0047112</td>
<td>0.0043396</td>
<td>0.0071719</td>
<td>0.1834429</td>
<td>3</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>2</td>
<td>B</td>
<td>0.0039162</td>
<td>0.0021698</td>
<td>0.0011319</td>
<td>0.0412785</td>
<td>1</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>11-8-3</td>
<td>C</td>
<td>0.0030080</td>
<td>0.00070740</td>
<td>0.0029030</td>
<td>0.0110480</td>
<td>67</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>4</td>
<td>D</td>
<td>0.0038519</td>
<td>0.0010345</td>
<td>0.0021631</td>
<td>0.0027874</td>
<td>11</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>9-6</td>
<td>E</td>
<td>0.0044794</td>
<td>0.0056111</td>
<td>0.0106152</td>
<td>0.0036846</td>
<td>44</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>7</td>
<td>F</td>
<td>0.0030387</td>
<td>0.0104151</td>
<td>0.0013023</td>
<td>0.1076133</td>
<td>1</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>10-14</td>
<td>G</td>
<td>0.0026364</td>
<td>0.0012878</td>
<td>0.0009644</td>
<td>0.0090361</td>
<td>128</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>12</td>
<td>H</td>
<td>0.0030004</td>
<td>0.0017840</td>
<td>0.0141767</td>
<td>0.0080197</td>
<td>2</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>13-15-16</td>
<td>I</td>
<td>0.0042517</td>
<td>0.0059729</td>
<td>0.0096451</td>
<td>0.0119352</td>
<td>41</td>
<td>L1R1F1M1</td>
</tr>
<tr>
<td>Total average</td>
<td></td>
<td>0.0037030</td>
<td>0.0043260</td>
<td>0.0060210</td>
<td>0.0275760</td>
<td>298</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Ranking of CLV

<table>
<thead>
<tr>
<th>Cluster name</th>
<th>Number of customers</th>
<th>Integrating rate</th>
<th>Percent %</th>
<th>CLV ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>0.0517037</td>
<td>40.158998</td>
<td>9</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>0.0122477</td>
<td>9.512961%</td>
<td>7</td>
</tr>
<tr>
<td>C</td>
<td>67</td>
<td>0.0061078</td>
<td>4.744014%</td>
<td>3</td>
</tr>
<tr>
<td>D</td>
<td>11</td>
<td>0.0024485</td>
<td>1.901785%</td>
<td>1</td>
</tr>
<tr>
<td>E</td>
<td>46</td>
<td>0.0070771</td>
<td>5.496883%</td>
<td>5</td>
</tr>
<tr>
<td>F</td>
<td>1</td>
<td>0.0316380</td>
<td>24.57368%</td>
<td>8</td>
</tr>
<tr>
<td>G</td>
<td>128</td>
<td>0.0035451</td>
<td>2.753529%</td>
<td>2</td>
</tr>
<tr>
<td>H</td>
<td>2</td>
<td>0.0067953</td>
<td>5.278005%</td>
<td>4</td>
</tr>
<tr>
<td>I</td>
<td>41</td>
<td>0.0071843</td>
<td>5.580147%</td>
<td>6</td>
</tr>
<tr>
<td>Total</td>
<td>298</td>
<td></td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

REFERENCE

Quality & Quantity, 44(4), PP. 807–815.
155.
Hosseini SMS, Maleki A, Gholamian MR. 2010. Cluster analysis using data mining approach to develop CRM methodology to assess the
PP. 34-46.
review;74(4), PP. 136-144.