International Journal of Industrial Engineering & Production Research September 2021 Vol. 32, No. 3: 1-15
DOI: 10.22068/ijiepr.32.3.1

RESEARCH PAPER

Detecting Valuable Customers Using the Trade Patterns of Financial Transactions Applying Integrated RFM and OLAP

Shima Khalilinezhad[1]*, Hamed Fazlollahtabar[2], Behrouz Minaei-Bidgoli[3] & Hamid Eslami Nosratabadi[4]

Received 30 November 2020; Revised 10 February 2021; Accepted 17 July 2021;
© Iran University of Science and Technology 2021

ABSTRACT
One of the challenges that banks are faced with is recognition and differentiation of customers and providing customized services to them. Recognizing valuable customers based on their field of business is one of the key objectives and competitive advantages of banks. To determine guild patterns of the valuable customers based on their transactions and value of each guild for the bank, the banking tools on which the customer's transactions take place need to be surveyed. Using deeper insights into the value of each guild, banks can provide customized services to ensure satisfaction and loyalty of their customers. Study population was comprised of the holders of point of sale (POS) devices in different guilds and the transactions done through the devices in an 18-months period. Datamining methods were employed on the set of data and the results were analyzed. Data preparation and analysis were done though online analytical processing (OLAP) method and to find guild patterns of the bank customers, value of each customer was determined using recency, frequency, monetary (RFM) method and clustered based on K-means algorithm. Finally, specifications of customers in the most valuable cluster were analyzed based on their guilds and the rules were extracted from the model developed using C5 decision tree algorithm.

KEYWORDS: *Datamining; OLAP; RFM analysis; Valuable customers.*

1. Introduction

Banking is one of the highly competitive industries that naturally have moved toward using data mining tools as well as applying business intelligence approaches. Using data for marketing and spotting potential opportunities has been long practiced through databased marketing. The present study is an attempt to analyze the available data of customers in bank databases, combine the extracted knowledge with other data to generate more valuable data for intelligence marketing, and expand banking market. Customers' transactional patterns were identified using and taking into account the customer's class; so that the classes were analyzed according to the customers' characteristics and transactions. Recently a great deal of interest has been paid to customers clustering and ranking [1].

Diversity of the customers of banking system, their demands and needs, and the wide range of available services force the banking service to prioritize the customer on one hand and the available services on the other hand. Given the ever-increasing number of banks and finance institutes in Iran, Iranian banking industry is witnessing an increase in competition. In return, the banks have equipped themselves with datamining tools in an attempt to gain more competitive advantages and realize their goals. Categorization is one of the many applications of datamining. By categorizing their customers, banks can define a different customers' relationship policy for each category. In addition,

* **Corresponding author:** ***Shima Khalilinezhad***
sh.khalilinezhad@iaufb.ac.ir

1. *Department of Marketing Management, Firozkoh branch, Islamic Azad University, Firouzkoh, Iran .*
2. *Department of Industrial Engineering, School of Engineering, Damghan University, Damghan, Iran.*
3. *School of Computer Engineering, Iran University of Science and Technology, Tehran, Iran.*
4. *Department of Computer Science, University of Porto, Porto, Portugal.*

[Downloaded from www.iust.ac.ir on 2024-12-26]

the banks can make better decisions to convert their valuable customers into loyal customers or invaluable customer into valuable customers. Bank managers can decide which group of customers is more open to new services and what is the best way to make the relationship with customers more profitable based on the customer's transaction information [2].

Clustering customers based on datamining results in a common practice in banks. Guild-based clustering is a novel and profitable step for the banking industry. Adopting proper marketing approach to ensure the customer loyalty is easier if the bank knows which customer is more valuable and in which guild they are categorized. The present paper is in fact an introduction to recency, frequency, monetary (RFM) method to calculate value of each guild using datamining algorithms for clustering and finding top guilds customers. The innovative feature of this paper is studying customers' transaction based on their specifications and guild [3].

The present paper proposes a behavioral clustering method for the customers of Bank based on their activities and guild. Customer clustering method can be carried out using statistical and computational method, datamining methods, and RFM analysis and in this paper, the latter was adopted. K-Means, Two-step and neural networks algorithms are of the commonly used datamining models for clustering customers and the proposed model here is a combination of K-Means and RFM algorithm [4].

Results of the present study can create a competitive advantage in banks to find patterns in financial behavior of their customers and utilize the patterns to create a strategy in different fields such as marketing and attracting more customers. The first step to this end is to recognize the specifications of customers of each cluster and predict their behavior in the future.

To determine and categorize different groups of bank customers, datamining algorithms were employed on real data from POS devices, credit cards, and customers' database. The main problem, therefore, is if datamining methods can be used to categorize valuable bank customers [5].

The study tries to answer the questions "What are the main indices to evaluate customer clustering?", "What are the key specifications of valuable bank customer given the different guild patterns?", and "Which customers are more valuable for the bank based on their guild category?"

Guild patterns of the valuable customers of bank based on their transaction accounts were determined. Pertinent models for the valuable groups were determined based on their specifications and using datamining algorithms and techniques. The models can be used for development of better bank marketing programs.

Consumers in service sectors have to choose from a wide range of services while preferences in the market are fluctuating widely. One consequence of this fluctuation is higher ambiguity for decision makers and a great amount of data for decision-making. Having the required capacity to analyze the data in a timely and accurate manner, leads to a competitive advantage for businesses. Thanks to more powerful and multitask computers, increase in computation power, continues generation of large volume of data, and increase in competition, banks have adopted data analyzing techniques capable of analyzing and categorizing data from different aspects. These techniques can uncover hidden, interesting, unexpected, and valuable patterns that are usually neglected [6].

The rest of the paper is designed as follows. The next chapter discusses relevant studies followed by literature review. Then the methodology of study is represented and the data analyses afterward, where valuable cluster analysis, ranking analyses, and validity of the model are discussed. The paper is concluded with discussing the results.

2. Literature Review

In general, there are five methods of categorizing customers and these are defined based on customer clustering and business goal measures [4].

1. Categorization based on value, where the customers are categorized based on their values. This method is one of the main categorization methods to determine valuable and key customers, which also provides the opportunity to follow changes in value over time.
2. Categorization based on behavior where the customers are categorized based their behavioral pattern.
3. Categorization based on probability of future behavior, where the customers are categorized based on turning away, bankruptcy, or probability of failure to pay loan. The categories are estimated based on ranking models.
4. Categorization based on loyalty where the extent of loyalty of the customer is

[Downloaded from www.iust.ac.ir on 2024-12-26]

taken into account so that the loyal and disloyal customers are determined.

5. Categorization based on the customer's need, where the categorization relies on market research data and the customers are categorized based on their needs, demands, and interests.

Alfansi and Sargeant conducted a study titled "market segmentation in Indonesian banks" and examined demographical variables and compared them with expected profit from customers [7]. They carried out clustering based on hierarchical classification so that customers were clustered into two clusters at first based on their domicile. Afterward, the number "two" was used as input for K-means algorithm. They focused on the factors effective on categorization and found that the demographical variables and job were more effective and useful. In addition to the demographical variables other indices such as the number of transaction, the value of transaction, and customers' loyalty in terms of repayment of bank facilities were also effective on customer segmentation [7]. Tisai and Chio carried out a study titled "methodology of market segmentation based on purchase" assuming that the customers in a cluster tend to have similar behavioral patterns. They used genetics algorithm and RFM [8]. Kim et al performed a study titled "customer segmentation and strategy development based on lifetime of the customers." Their study was aimed at determining the current and potential values of customers and their loyalty [9]. Cheng et al. performed a study on customer segmentation and scoring, while their main area of focus was on marketing strategies to maximize customers' potential[10].

Kumar et al. [11] proposed a novel multimodal framework for rating prediction of consumer products by fusing different data sources, namely physiological signals, global reviews obtained separately for the product and its brand. Gorges et al. [12] presented the experimental validation of a road roughness classification method and an impact detection strategy for two-wheeled vehicles was proposed including a classification of service loads, mild special events, and severe special events. Product reviews are of great commercial value for online shopping market. The identification of customer opinions from product reviews is helpful to improve the marketing decisions of customers, sellers and producers. Hong and Wang [13] proposed a novel framework for summarizing customer opinions from product reviews.

Cheng et al. [10] published a paper on ranking value of the customer based on RFM model and RD theory for a Taiwanese company. They used a novel approach to connect value of RFM and K-means algorithm with RS theory to extract the rules [10].

Fouladifar et al. [14] studied market segmentation of bank industry a clustering model for bank. This study highlights the importance of segmentation model for retail banking internet-based services is applied upon

RFM and some demographic variables aiming to go more accurate through e-services market, in other to enable the marketers establishing new strategies and sample of 1478 E-banking customer is clustered via K-means. Finally, based on the clustering results recommendations and suggestions is offered to enhance customer relations and developing services [4]. Table1 showed some previous paper findings.

Tab. 1. Findings and methodologies in some paper

Authors/ Scholar	Year	Methodology	Findings
Minaei B, Asghari F.	1999	Scoring model & Market Segmentation	Bank customers risk analysis method.
Alfansi, L., & Sargeant, A.	2000	Clustering &K-means	Customers' loyalty in terms of repayment of bank facilities were effective on customer segmentation
Tsiptsis, K. K., & Chorianopoulos, A.	2011	RFM & Genetic Algorithm	Customers in a cluster tend to have similar behavioral patterns
Hong, T., & Kim, E.	2012	RFM &CLV	Potential values of customers and their loyalty
Cheng, C. H., & Chen, Y. S.	2009	RFM & market segmentation	Used a novel to connect value of RFM and K-means algorithm with RS theory to extract the rules
Gholamian M, Niknam Z.	2012	RFM & CLV	Identifying attracting customer with higher profitability through using scoring tools and presenting new model.
Fouladifar,A, Taghipour.E,. Hedayati	2016	RFM, K-means & market segmentation	Segmentation model for retail banking internet _based services is applied upon RFM and some demographic variables.

[Downloaded from www.iust.ac.ir on 2024-12-26]

Because it is critical for banks to determine guild patterns of their valuable customers and since, having a clearer picture of the customers based on guild activities is important for determining marketing strategies and providing services, and knowing that improving satisfaction of the customer is a competitive advantage for the bank, the present study is aimed at determining a proper guild patterns for the valuable customers.

3. Methodology

To determine guild patterns of the valuable customers using their financial transactions, the customer's behavioral specifications were summarized based on three variables of recency (R), frequency (F), and monetary (M); where, R stands for time interval between two transactions, F stands for total number of transactions in a period of time, and M stands for total value of transactions. Based on consultation with experts, all the variables were weighted equally.

RFM model was introduced by Arthur Hughes [15] based on which the key customers of the Organization are differentiated based on three variables R (recency), F (frequency), and M (monetary) (see Figure 1). The variables needed to categorize customer must be determine in advance. Based on literature review, we need three sets of variables including i) demographical data including gender, age, education, and marital status; ii) services provided by the bank including ATM, POST, telephone, mobile, and Internet bank; iii) customers' financial transactions indicating the value of transaction in specific time periods. Some of the terms have specific definition within the scope of RFM model.

1. Recency: Refers to the time period since the last business transaction; the lower this period the higher the value of R.
2. Frequency: Refers to the number of times a purchase is repeated and it is an indicator of the number of transactions in a given time period (e.g. two times a year, two times a month) the higher the frequency, the higher the value of F.
3. Monetary: refers to monetary value spent by the customer in their transactions in a specific time period. The higher the monetary value, the higher the value of M.

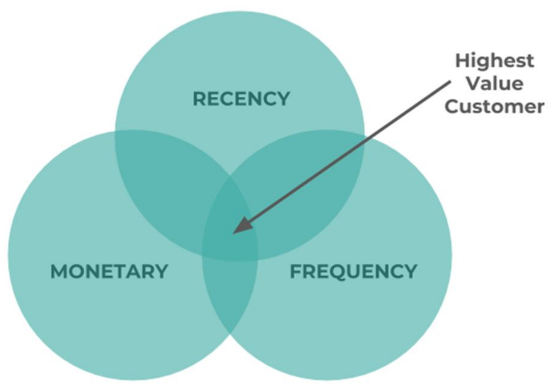

Fig. 1. RFM model

CRISP-DM is a standard datamining method introduced by three large companies Dimler Chrysler (Benz), SPSS, and NCR in 1996 [16]. Because the methodology is independent from data type, it can be used for analyzing almost all types of data.

The first stage of the process is the foundation of data analysis, where business goals in data analysis field are determined, discussed, and examined [17]. This stage is comprised of needs assessment, definition of problem scope, situation assessment, definition of the final goal, and preparation of program and procedures of data analysis.

The second stage deals with determining the data and it is comprised of activities like primary data gathering, data description, datamining, and validating data quality. At the next stage, data preparation is done followed by preparing and pre-processing the data for data analysis. When the model is developed, we need to ascertain if the data is suitable for decision making. Should the data set contain defective data, it is possible to decide about how to handle the default. This stage is about the processes that need to be done to make the data more suitable for datamining. Some of the best ideas and methods will be examined and compared relative to each other. This stage is comprised of selecting the data, refining the data, structuring the data, integrating the data, determining data format, and defining and choosing proper indices. Second and third

[Downloaded from www.iust.ac.ir on 2024-12-26]

phases usually are time-consuming, a feature that is a function of information infrastructure of the organization. One of the tasks performed at this phase is to standardize and normalize the data [18]. Doing these needs defining proper indices and standards based on which the proper way of data analysis and decision making based on the results is determined. Some of the ideas and methods utilized at this stage are aggregation, sampling, attenuation of aspects, and determination of a set of features, determining new features, and converting the variables into discrete and binary variables. In general, these tasks can be categorized into two categories; i) choosing the data items and specifications for further analysis; and ii) creating new features and modifying the already existed features. The common objective of these two categories of tasks is to improve datamining analysis based on time, cost, and quality. Modeling is done at the fourth stage so that the data is at first categorized as random and training data sets and each set is tested separately. Authenticity of the model is examined by creating predictive queries on the set of training data [19]. This phase is the main stage in analyzing the data, where different techniques and methods are used for data analysis and extraction of knowledge. This stage is comprised of tasks such as model development, test, and design techniques and mode assessment. The knowledge obtained at data survey phase is used to define and develop exploration model. After defining the exploration model, it is processed and the patterns are determined by implementing the datamining algorithms on the data. An exploration model consists of three elements of datamining structure, datamining model, and datamining algorithm [20]. There are several algorithms to develop any type of model and the algorithm can be modified using different parameters. The fifth stage in datamining process is to survey the development model and its effectiveness. Before implementing a model in actual environment, its performance must be examined. It is possible to create several modes and the best of them should be determined. Figure 2 shows the framework of the research.

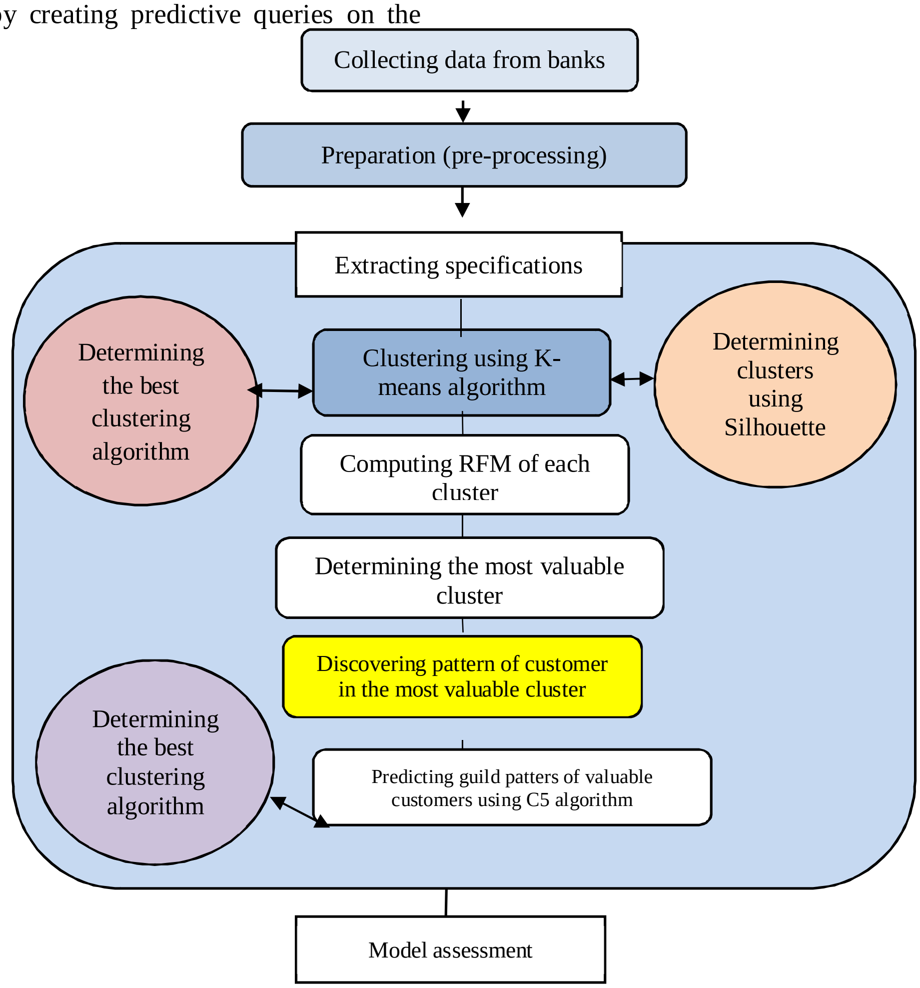

Fig. 2. The proposed research model

[Downloaded from www.iust.ac.ir on 2024-12-26]

In the case that none of the models meet the performance standards, the problem must be redefined and the data of the main dataset needs to be reexamined. When the model is developed, the data analysis results must be surveyed and analyzed to ensure that the model is helpful to realize the business objectives. The final stage in datamining method is to develop a model with highest performance and when it is done, the model is utilized in actual environment.

4. Data Analysis

Data preparation and analysis were done though online analytical processing or OLAP method (see Figure 3). To find the guild patterns of the bank customers, value of each customer was determined using RFM method and clustered based on K-means algorithm. Finally, specifications of customers in the most valuable cluster were analyzed based on their guilds and the rules were extracted from the model developed using C5 decision tree algorithm.

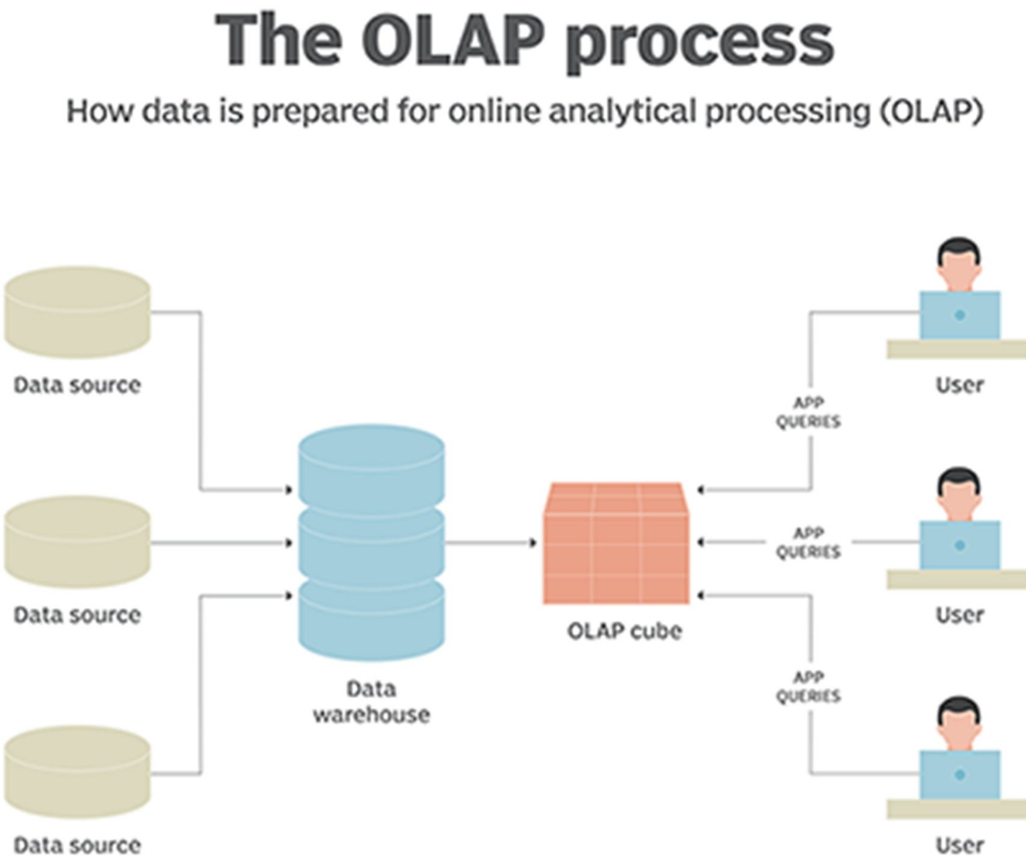

Fig. 3. OLAP structure

The data used in this study was about the customers from different guilds who used POS devices of Bank. Totally 98000 customers used the devices from June 2014 to November 2015 to have financial transactions with their accounts using electronic tools such as SMS Bank and Internet Bank. The data also included demographics of the customers including age, education, gender, and the time period of using the bank services. After implementation of OLAP method, the number of transactions reached 141 million records and the data of 5000 customers with 300000 records was included in the study. Data gathering was done in the Bank Database.

Surveys of the data showed that the garment guild had the highest education level and holders of high school diploma were the largest group of the participants in terms of education. ATM devices were the most popular devices and VPOS devices or Internet POS were the least common tool. Distribution Figure of the guilds in terms of gender showed that male constituted 94% of the participants group.

The highest RFM was obtained by real estate agency guild and the lowest FRM was obtained by kids' products guild. Notable is that only the vehicle guild used Internet-based bank services. K-means algorithm is the most common and

[Downloaded from www.iust.ac.ir on 2024-12-26]

simple algorithm to handle large data sets and given what mentioned above, K-means method was used as the proper clustering method for the bank data. This process is performed in a real-time manner as show in Figure 4.

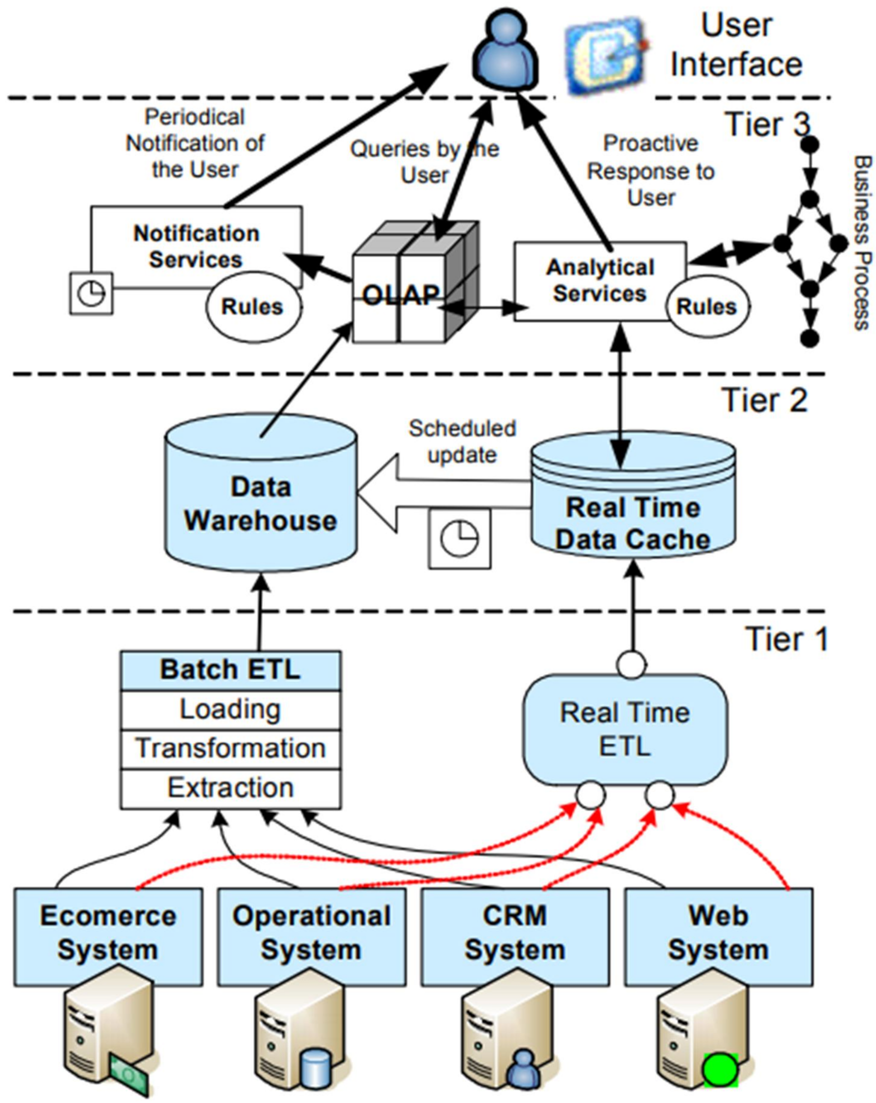

Fig. 4. Real-time data processing architecture

The number of clusters was determined using Silhouette index, which indicated that optimum number of clusters was two. At this stage, the customers were clustered using RFM index so that those with higher cluster score were more valuable customer for the bank. It is notable that the field amount was the most important factor in determining the number of clusters followed by number of transactions, and the medium. Figure 5 shows the number of cluster.

[Downloaded from www.iust.ac.ir on 2024-12-26]

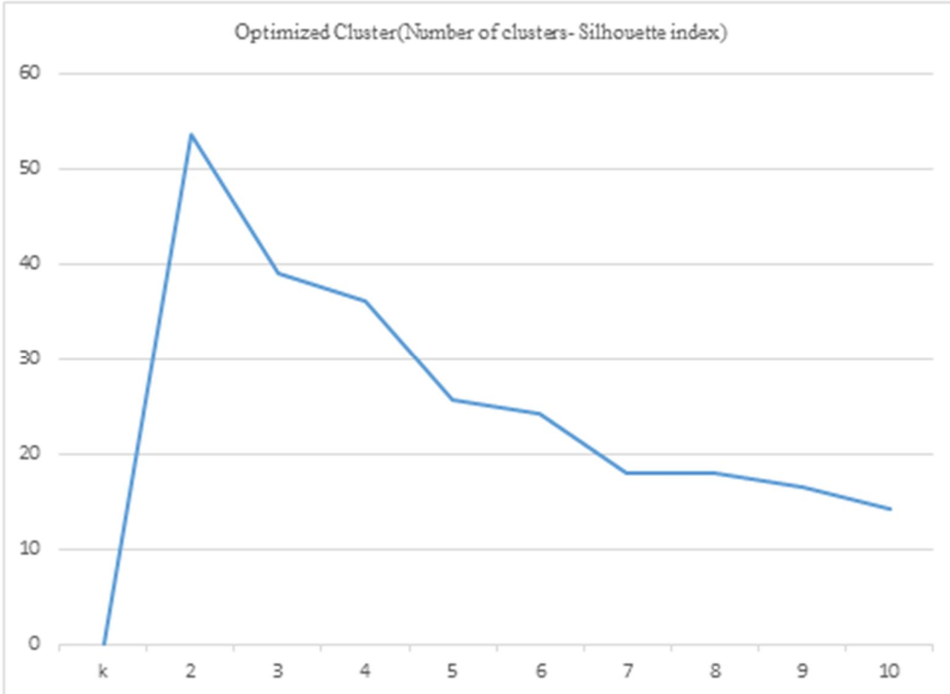

Fig. 5.Optimum number of clusters

5. Analysis of Valuable Cluster

Cluster one comprising 53.6% of the sample group was the best cluster from the experts' point of view, given RFM index, which was higher than that of the other clusters. The use of electronic devices with f-value of 27% in cluster one was pertinent to ATM devises; while in the cluster two, f-value of 28% was pertinent to POS. In addition, 61% in the customers in the cluster one had high school diploma and average age of customers in this cluster was 41. Average term of business relationship with the bank in the cluster one was six years. Additionally, most of the customer did not have VPOS and men were the majority (94%).

The highest RFM score was obtained by cultural guild and the lowest RFM was obtained by industries and whole seller guilds, which represented B2B relationship with the bank. The average age of users of SMS bank was the highest and equal to 49 years and that of the users of VPOS devices was the lowest and equal to 42 years.

Figure 4 illustrates value of each age group in the valuable cluster of bank customers in terms of the guilds. The highest average age belongs to reception and ceremony services and cultural guild and the lowest average age belongs to customers in kids' products guild.

Figure 5 represents the term of business relationship between the valuable bank customers based on their guild. The longest term of business relationship with the bank was obtained by the vehicle guild followed by cultural, and reception and ceremony services guild. Additionally, the shortest business relationship was observed in beauty and health care guild.

[Downloaded from www.iust.ac.ir on 2024-12-26]

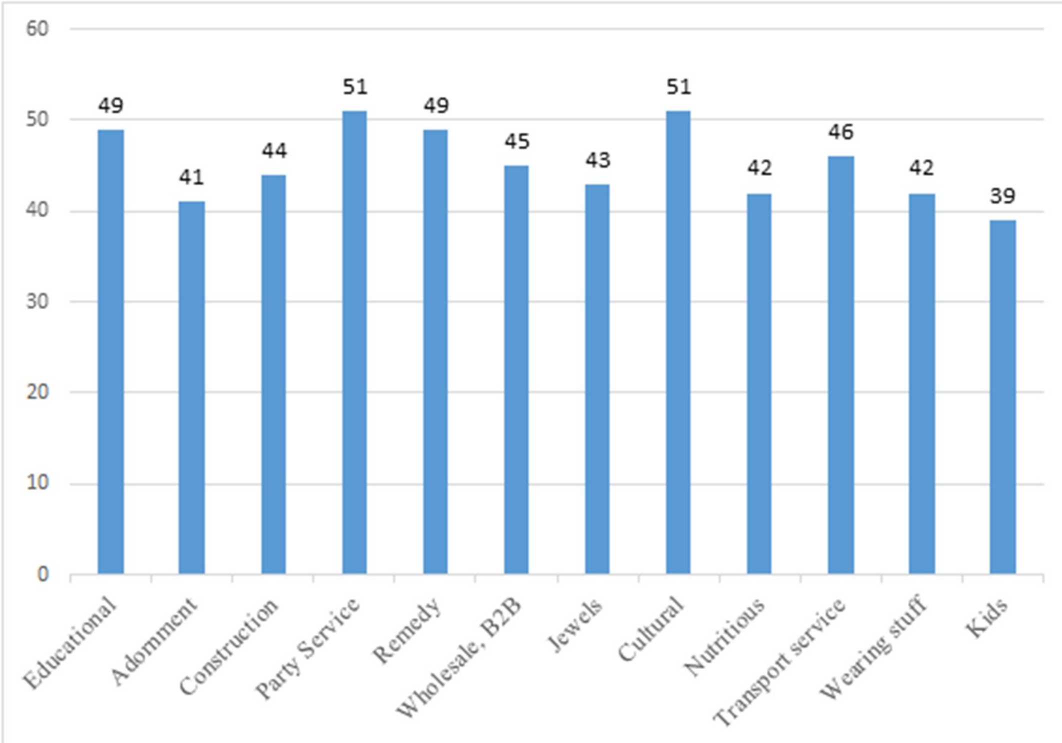

Fig. 4. Average age in the valuable cluster based on guild

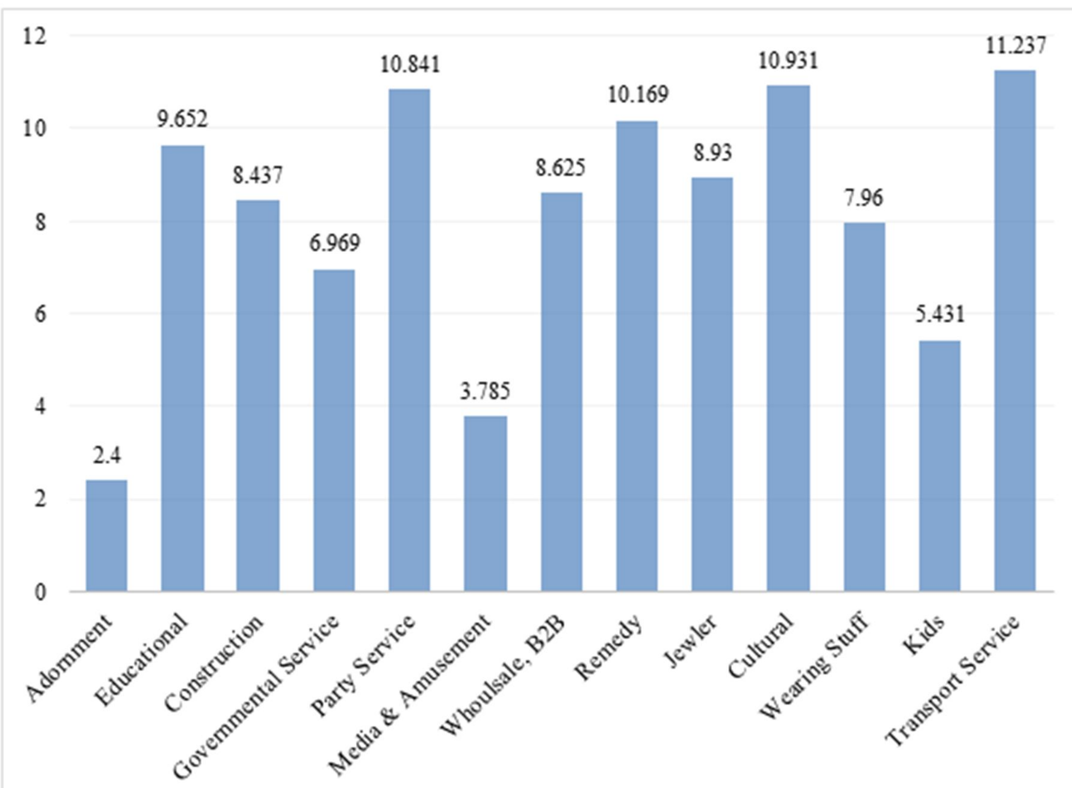

Fig. 5. Average term of business relationship with the bank in the valuable cluster based on the guilds

[Downloaded from www.iust.ac.ir on 2024-12-26]

6. Analysis of Obtained Categories

Customers ranking is one of the common methods in datamining. Here, C5 algorithm was used as a ranking algorithm taking into account the available data. One of the models of ranking is decision tree, where one question is asked at each node and each data is led to one of the children of that node based on its value and the question in the node. The questioning and segmentation of information is continued until the information reaches the leaf of a specific group where the group of data is determined. The decision tree structure is a quasi-flowchart tree structure, where each internal node is a test based on the features of the data and each branch that is projected from the node is an achievement of the test. The nodes of leaf determine the classes. The highest node is the root of the tree. Since C5 decision tree guarantees more than 93% optimality, the detected patterns based on the tree would be the most possibly reliable tree obtained from the data. This data analysis is performed through an integrated sense and response service architecture as presented in Figure 6.

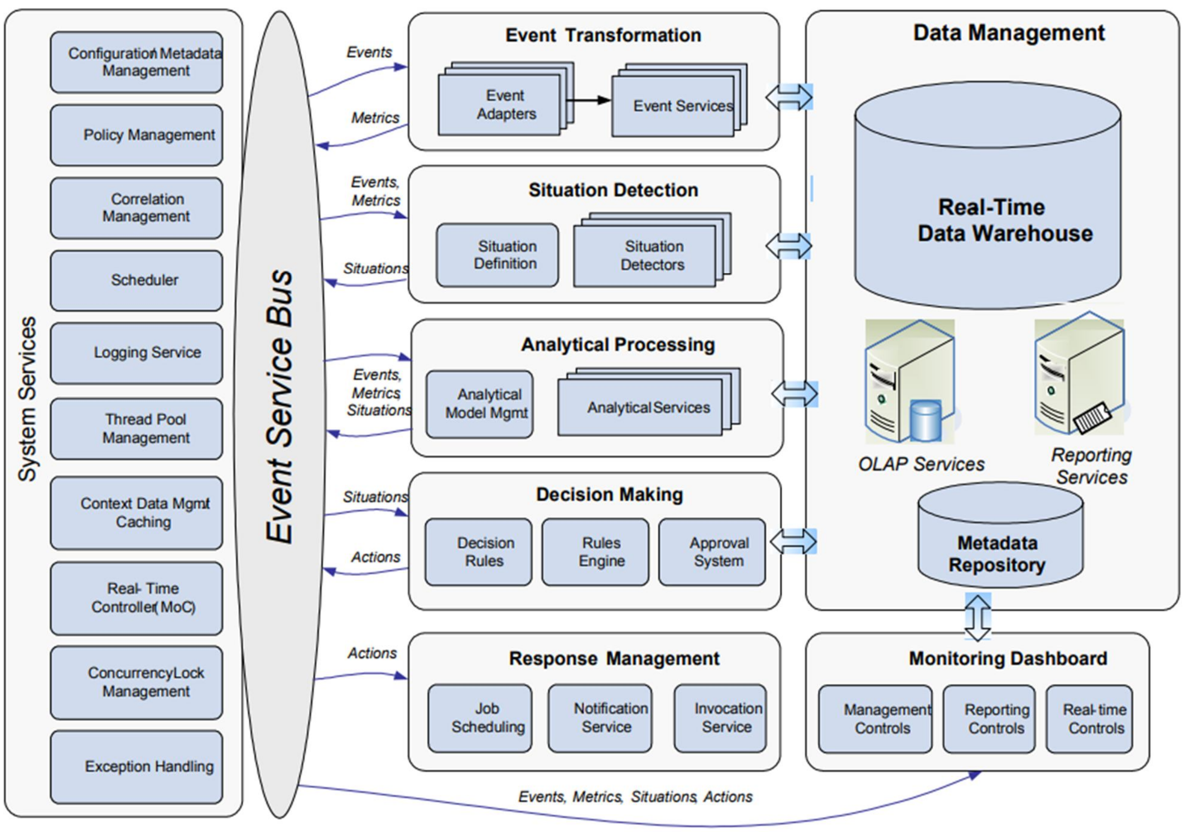

Fig. 6. Configuration of sense and response architecture

Based on the results, the most important indices in the algorithm were education, age, and term of cooperation and the least important indices were the medium and VPOS.

Some of the rules yielded by the proposed model:

- Men with bachelors' degree, younger than 41 years old and with business relationship term of less than six years constituted the largest group of customers in real estate guild.
- Men with bachelors' degree, older than 41 years old and with business relationship term of less than three years constituted the largest group of customers in education guild.
- Men with high school diploma, older than 53 years old and with business relationship term of less than nine years constituted the largest group of customers in tourism and travel services guild.
- Men with Masters' degree with business relationship term of less than eight years constituted the largest group of customers in real estate guild. However, men with business relationship term of more than eight years and age of less

[Downloaded from www.iust.ac.ir on 2024-12-26]

than 48 year had the highest majority in administrative services field, and if the age is more than 48 years, those in medical guild are in majority.

- Men with PhD degree, younger than 45 years old and with business relationship term of 16 years constituted the largest group of customers in medical guild.
- Men with elementary education and younger than 36 years old constituted the largest group of customers in food products guild. In the age range above 36 years old, men in garment guild had the highest frequency.
- Women with bachelors' degree, younger than 41 years old constituted the largest group of customers in administrative services guild; and at the age range higher than 41 years old, members of education guild were in majority.
- Women with associates' degree with business relationship term of more than seven years constituted the largest group of beauty and health care guild. And women with business relationship term of less than seven years constituted the largest group of garment guild
- Men who used VPOS with bachelors' degree and younger than 43 years old and term of business relationship of less than 6 years constituted the largest group of customers in industry and whole sale guild and for the business relationship term of more than six years, men in computer guild had the highest frequency.
- Men who used VPOS with bachelors' degree and younger than 43 years old and term of business relationship of less than 6 years constituted the largest group of customers in industry and whole sale guild (B2B) and for the business relationship term of more than six years, men in computer guild had the highest frequency.
- Men who used VPOS with high school diploma and younger than 38 years old constituted the largest group of customers in industry and whole sale guild (B2B) and if the age is older than 38 years old, men in real estate and construction guild had the highest frequency.

Men who used VPO,S older than 43 years old and term of business relationship of less than five years constituted the largest group of customers in culture guild and for the business relationship term of less than five years, men in whole sale guild (B2B) had the highest frequency.

7. Model Validation

Given the necessity of examining the methodology, validity and reliability of the model were examined through dividing the sample into two sets of training and test sets. Validity level was measured using the new data and the test data was used to monitor the algorithm and examine authenticity of the results. Validity and reliability of the model was tested based on authenticity of the clustering or segmentation of the data. Reciprocal validity with 10 iterations was used so that the data was divided into 10 sets and in each iteration, 80% of the training data and 20% of the test data were used to measure accuracy of clustering. Final accuracy of the model was obtained after 10 iterations. C5 decision tree with accuracy of 93.34% is more accurate than other ranking algorithms while it is featured with lower complexity. Meanwhile, received accuracy with other used algorithms was neural net 67%, Bayesian net 72%. On the other hands, to guarantee the trust of the transaction and analysis a fraud detection event processing model is co-implemented in the overall system as shown in Figure 7.

[Downloaded from www.iust.ac.ir on 2024-12-26]

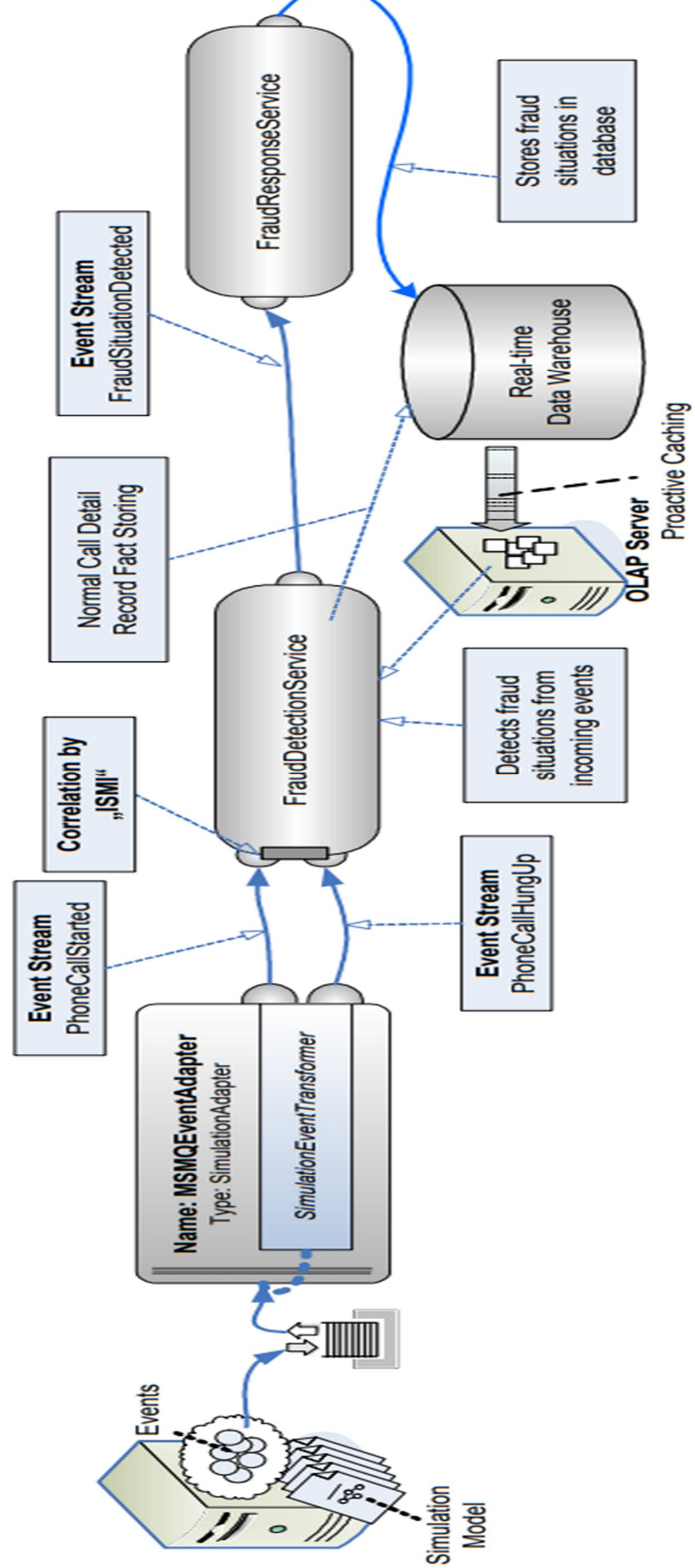

Fig. 7. Fraud Detection Event Processing Model

[Downloaded from www.iust.ac.ir on 2024-12-26]

8. Results and Discussion

Guild patterns of the valuable customers of bank based on their transaction accounts were determined. Pertinent models for the valuable groups were determined based on their specifications and using datamining algorithms and techniques. The models can be used for better development of bank marketing programs.

A framework to determine guild patterns of the customer using their financial transactions was proposed. To do so, a set of transactions consisting of 98000 customers in the time period from June 2014 to November 2015 with 141million records was extracted. The samples (5000 customers) were selected directly from a bank database and then their records including 300000 transactions were extracted. To determine guild patterns of the customer, each record was clustered in one of the clusters based on three indices of recency, frequency, and monetary using K-means clustering method. The preferred number of clusters was two, which was determined using silhouette index. Afterward, specifications of the customers in the valuable cluster were examined based on their guild, a model was proposed using C5 decision making tree and the rules were extract.

The study is an applied-developmental work in nature and in terms of method it is a descriptive work. Data gathering was done through Internet surfing, and library review (books, articles, and dissertations). The data needed to develop the models was collected from the Bank. The determinant specifications of valuableness of the customers are based on guild pattern, education, and age. Based on RFM indices, the most valuable guilds from bank point of view were cultural services guild (based on their term of business relationship), real estate guild, garment and food products, and industry and whole sale (B2B) guild. So far, no research has been done about the patterns of businesses with regard to transactions, and value for the bank, and other more potential.

To determine value of bank customer in different guilds, RFM model was used. The customers were segmented after obtaining value of the customers and the parameter and given the value of each group, two clusters of customers were obtained, which were named as valuable and invaluable customers clusters.

9. Concluding Remarks and Suggestions

Development of electronic communications between individuals and organizations creates a reliable ground for establishing business and economic relationships. Electronic banking provides faster and less-expensive access for the customer to several channels of carrying out banking activities. Using electronic tools enables banks and finance institutes to keep their customers regardless of the location and opens new areas for finding new customers in target markets. Geographical expansion of services, establishment of complete business relationship, and improving reputation are other advantages of electronic communications for banks. According to Data Monitor, the main advantages of electronic banking are concentration on new distribution channels, provision of reformed services, and utilization of electronic commerce approaches. It is notable that advantages of e-banking can be approached to from short/mid/long-term perspectives.

The study was not free of limitations; such as the fact that securing data from the banks in Iran is not easy. The authors spent a great deal of time trying to convince the marketing team of the bank to cooperate. Another limitation was the great volume of the data and that processing them was time-consuming even with powerful processing system. To deal with this challenge, a part of the data was selected randomly and the study was carried out based on it.

One of the main issues of banking industry i.e. determining accurate patterns of the customer and their behavioral habits- was examined. Banks today collect more information of their customers and they can provide better services depending on the customer needs using the information. Thereby, along with keeping old customers, banks have more opportunity to attract new customers.

One of the most important applications of this article is to explain the specific marketing policies for each customer cluster. The extracted rules about the customer enable the banks to develop better policies based on the discovered patterns and achieve better perception of the current and future expectation of the customer based on their guilds. There has been no similar study to segment and survey specifications of the valuable customers based on the guild in Iranian banks.

References

[1] S. Monalisa, P. Nadya, and R. Novita, "Analysis for customer lifetime value categorization with RFM model," *Procedia Computer Science*, Vol. 161, (2019), pp. 834-840.

[Downloaded from www.iust.ac.ir on 2024-12-26]

[2] R. G. Martínez, R. A. Carrasco, J. García-Madariaga, C. P. Gallego, and E. Herrera-Viedma, "A comparison between Fuzzy Linguistic RFM Model and traditional RFM model applied to Campaign Management. Case study of retail business," *Procedia Computer Science*, Vol. 162, (2019), pp. 281-289.

[3] M. Mohammadzadeh, Z. Z. Hoseini, and H. Derafshi, "A data mining approach for modeling churn behavior via RFM model in specialized clinics Case study: A public sector hospital in Tehran," *Procedia computer science*, Vol. 120, (2017), pp. 23-30.

[4] X. Zhou, Z. Zhang, and Y. Lu, "Review of Customer Segmentation method in CRM," in *2011 International Conference on Computer Science and Service System (CSSS)*, (2011), pp. 4033-4035.

[5] S.-C. Wang, Y.-T. Tsai, and Y.-S. Ciou, "A hybrid big data analytical approach for analyzing customer patterns through an integrated supply chain network," *Journal of Industrial Information Integration*, Vol. 20, (2020), p. 100177.

[6] S. Tahanisaz, "Evaluation of passenger satisfaction with service quality: A consecutive method applied to the airline industry," *Journal of Air Transport Management*, Vol. 83, (2020), p. 101764.

[7] L. Alfansi and A. Sargeant, "Market segmentation in the Indonesian banking sector: the relationship between demographics and desired customer benefits," *International Journal of Bank Marketing*, (2000).

[8] K. K. Tsiptsis and A. Chorianopoulos, *Data mining techniques in CRM: inside customer segmentation*. John Wiley & Sons, (2011).

[9] T. Hong and E. Kim, "Segmenting customers in online stores based on factors that affect the customer's intention to purchase," *Expert Systems with Applications*, Vol. 39, No. 2, (2012), pp. 2127-2131.

[10] C.-H. Cheng and Y.-S. Chen, "Classifying the segmentation of customer value via RFM model and RS theory," *Expert systems with applications*, Vol. 36, No. 3, (2009), pp. 4176-4184.

[11] S. Kumar, M. Yadava, and P. P. Roy, "Fusion of EEG response and sentiment analysis of products review to predict customer satisfaction," *information fusion*, Vol. 52, (2019), pp. 41-52.

[12] C. Gorges, K. Öztürk, and R. Liebich, "Impact detection using a machine learning approach and experimental road roughness classification," *Mechanical Systems and Signal Processing*, Vol. 117, (2019), pp. 738-756.

[13] M. Hong and H. Wang, "Research on customer opinion summarization using topic mining and deep neural network," *Mathematics and Computers in Simulation*, (2020).

[14] A. Fouladifon, E. Taghipour, and A. Hedayati, "Marketing segmentation for marketing of banking industry products constructing a clustering model for bank pasargad" s e-banking customers using RFM technique and K-means algorithm," *International Business Management*, Vol. 10, No. 6, (2016), pp. 1106-1119.

[15] T. P. Hughes, "Catastrophes, phase shifts, and large-scale degradation of a Caribbean coral reef," *Science*, Vol. 265, No. 5178, (1994), pp. 1547-1551.

[16] P. Chapman *et al.*, "CRISP-DM 1.0: Step-by-step data mining guide," *SPSS inc*, Vol. 9, (2000), p. 13.

[17] A. Nadali, E. N. Kakhky, and H. E. Nosratabadi, "Evaluating the success level of data mining projects based on CRISP-DM methodology by a Fuzzy expert system," in *2011 3rd International Conference on Electronics Computer Technology*, Vol. 6, (2011), pp. 161-165.

[18] B. Noh, H. Yeo, "SafetyCube: Framework for potential pedestrian risk

[Downloaded from www.iust.ac.ir on 2024-12-26]

analysis using multi-dimensional OLAP", *Accident Analysis & Prevention*, Vol. 155, (2021), p. 106104.

[19] J. Dong, H. S. Du, S. Wang,, K. Chen, and X. Deng, "A framework of Web-based Decision Support Systems for portfolio selection with OLAP and PVM", *Decision Support Systems*, Vol. 37, No. 3, (2004), pp. 367-376.

[20] L. Shen, S. Liu, S. Chen, X. Wang, "The Application Research of OLAP in Police Intelligence Decision System, *Procedia Engineering*,, Vol. 29, (2012), pp. 397-402.

Follow This Article at The Following Site:

Khalilinezhad S, Fazlollahtabar H, Minaei-Bidgoli B, Eslami Nosratabadi H. Detecting Valuable Customers Using the Trade Patterns of Financial Transactions Applying Integrated RFM and OLAP. IJIEPR. 2021; 32 (3) :1-15
URL: http://ijiepr.iust.ac.ir/article-1-1169-en.html

[Downloaded from www.iust.ac.ir on 2024-12-26]