Identification of Dominant Customer Behavior Patterns among Different Sectors over Time; A Case Study

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Abstract

Understanding and predicting customers' behaviors in customer-centric organizations such as banks are very critical. The aim of identifying customers is to recognize, make distinction, and maintain the high-value customers and to attract more beneficial customers. In the past, the separation of customers into different groups was based on customer requirements, whereas customer value has become more important as segmentation criteria in recent years. Offering cutting-edge banking services, banks' competition on market share, as well as the psychological and environmental factors of customers' behavior need to be analyzed over time. Transferring customers to different sectors over time and discovering the dominant models and their displacements between sectors are explored in this paper. We aim to identify the behavioral patterns and the leading characteristics of customer displacements with a focus on the customers of a private bank in Tehran, Iran. For this purpose, we propose a combined method based on clustering and association rules. Results show four dominant clusters of behaviors: "low-value customers with sustainable model", "low-value customer with unsustainable profitability model", "turned away customers with average profitability", "loyal customers with low profitability". We also analyze the relationships between these clusters. The outcomes of this study can play a remarkable role for top managers to take appropriate marketing strategies.

Keywords
segmentation, customer dynamic behavior, association rules, dominant pattern

1. Introduction

For decades, financial institutions have pursued strategies that focus on manufacturing and trading. With the exponential growth of technology and the development of competitive factors, the need to establish and maintain effective communication with customers has become more vital for firms. Banks will have to seek more knowledge of their clients in competition with other banks and financial institutions. The aim of identifying customers is to recognize, make distinction and maintain the high-value customers and also to attract more beneficial customers. The chance of withdrawing rewarding customers has increased due to the advancements of IT and e-banking services, marketing business growth, better customer relationship management, and growing competition among banks. Additionally, the environmental and psychological factors such as advertising, offering new services, etc. have caused unstable customer behavior in some situations. In order to have a better understanding of customers' needs and to make a more accurate prediction of customer behavior, we need to examine its dynamic nature. Customer relationship management is, therefore, an important and effective tool in competition among banks to provide better services and attract customers, see Silambarasan et al. (2018).

Customer relationship management is an infrastructure that reveals and increases the customer value. To have an effective customer relationship management, it is essential to gather and classify related information that answers customer's unique needs. Current competitive market is rapidly developing that has certain characteristics such as returning purchase intervals, the large volume of customers, valuable information about customer purchase behavior, and so on. In such markets, the goals of customer relationship management are to identify the customers, to understand and predict customer-purchasing patterns, to identify customers' needs, and to treat them in an appropriate manner according to customer demands and expectations. Therefore, customer relationship management can be used as a prerequisite for the implementation of marketing activities such as targeted customer segments, see Zahrotun (2017). Dynamic customer segmentation is one of the issues in the field of customer relationship management (CRM) and customer behavior analysis. In other words, regarding the strategic importance of customer segmentation in customer relationship management, it is necessary to examine the dynamic behavior of customers in this context. Available studies have often proved hostile clients yet, given the dynamic nature of customer and market changes in the environment, applying constant customer segments cannot provide worthy framework for accurate predictions of customer behavior, see Ha et al. (2002). There are two basic approaches in dynamic customer segmentation: 1) the study of customer switching between different sectors; and 2) customer segments change over time.

This study applies data mining techniques to answer the following questions:

1. What are the consumer behavior in different time intervals?
2. How customer behavior has been identified and grouped based on each group? What are their characteristics?
3. What are the dominant patterns of customer membership in different sectors over time?

A combination of K-means and association algorithms are used in order to answer the above questions. It also derives a sequence at which customers join to each cluster. Using association rules, the dominant patterns of each customer can be acquired. In the next section, we explore the literature. Next, we discuss the research methodology and the results of the implementation methodology and findings. Finally, conclusions and recommendations are presented.

2. Background

This section examines the concepts of segmentation, dynamic customer segmentation and then points out the research done on dynamic customer segmentation.

2.1 Segmentation

Since the early 1980s, the concept of relationship management has become important in the field of marketing. Assigning and retaining the most profitable customers are serious concerns for a company to performs more targeted marketing campaigns. In order to have an effective customer relationship management, the collection of information on customer value is important, see Lemmens et al. (2002). Perhaps the most powerful marketing tools are predicting the customer purchasing behavior and segmentation that differentiate the buyers from non-buyers, identify customer groups and provide high market opportunities. Customer segmentation concept is not new. Customer segmentation is a technique applied by marketers to target their customers and to allocate resources more effectively. It also identifies customers with similar characteristics, see Abdi and Abolmakarem (2018).

It is usually assumed that the market is relatively stable in designing customer segmentation and also the customer behavior does not change over time. Based on this assumption, most of the existing researches speculated that different customer segments have been stable over the time and the cluster in which the customer belongs to, does not change. But the remarkable point is that when the market is not sustainable or due to the influence of psychological factors, social instability, and external customer behavior, this assumption does not hold. In fact, needs, preferences, customer behavior, as well as market conditions change over time and the static assumption does not capture the real world situation, see Akhondzadeh and Al-badavi (2015). In most segmentation studies, the customer behavior was studied at specific and fixed intervals and as a result, customer behavior could not be predicted over the time. Therefore, static segmentation methods are not sufficient to understand and predict customer behavior for executive managers, see Ha (2007) and Cheng and Chen (2009). These methods are not compatible with future needs and demand of customers' feedback for different segments. While using the dynamic customer segmentation systems, a comprehensive understanding of customer behavior can be achieved and their behavior can be predicted as well, Akhondzadeh and Al-badavi (2015). Dynamic segmentation is the segmentation of customers so that customer displacements in different sectors and membership changes to these groups of customers during the period are considered. Monitoring the movement of customers from one sector to another, the dominant patterns of displacement, and predictions of these transfers are among the most important customer segmentation topics, see Zahrotun (2017). According to investigations, there is little research done in this field. For instance, see Zahrotun (2017).

Research in this area can be grouped into four areas 1) Modeling the movement of customers among different sectors over time 2) Analysis of the sectors changes over time. 3) Characteristics of segmentation over time. 4) Techniques and methods of dynamic customer segmentation.

Regarding the transport and movement of customers among different sectors, most of conducted studies have used the Markov Chains for modeling and forecasting. Netzer et al. (2008) is one of the most notable examples in this context that uses the Markov Chains for the customer portfolio management to predict the sector that attract customers in the future.

Customer segmentation literature provides both descriptive and predictive segmentations (purchasing behavior forecast). In general, the following variables are used in the descriptive segmentation:

- Statistical variables: based on data such as income, age, education records, marital status, ethnic group, religion, etc.
- Geographic variables: such as region - or country of the world, the size or the climate of the country.
- Psychographic variables: such as personal lifestyle and tendencies.
- Behavior variables: based on data such as the frequency of purchase, amount and type of products purchased, etc.
- Motivation variables: based on variables that describe reasons for customer purchases (e.g., satisfaction).

There are three approaches in customer segmentation. The first approach uses traditional customer segmentation by key variables such as statistical, geographical or organized mental psychographic. In the second approach, the customer segmentation is based on customer needs in addition to the costs of establishing and maintaining relationships with the customer. The third approach is based on deferment, frequency and amount of one or a combination of buying behavior patterns or motivation.

In this study, RFM variable is used for segmenting the customers. This model is one of the famous and efficient customer value analysis as it extracts the features of customers using clustering methods with less variables (i.e., only 3 dimensions), see Cheng and Chen (2009). This model is based on three factors; Recency (R), Frequency (F) and Monetary value (M). According to Bult and Wansbeek (1995) Recency measures the time of the last visit (purchase transaction). Frequency, captures the number of visits (purchase transaction) at a specified interval and monetary value represents the amount paid in a specific period of time.

2.2 Data Mining

Data mining is the process of discovering useful information from massive data sources. Data mining techniques, in an overall view, are divided into two categories: Descriptive and Predictive. Predictive methods acquire the value of a particular property based on other attributes. Predicted feature is called the goal which depends on other characteristics. Features that help to predict the goal are independent and explanatory variables. The purpose of applying descriptive methods is to extract the pattern so that it summarizes the communication between low level data layers. Forecasting techniques include classification, regression, and descriptive techniques such as clustering, anomaly detection etc. The clustering methods and association rules are used to extract and analyze customer behavior in this study.

2.3 Clustering

Clustering divides an irregular population into a series of regular subgroups. In clustering, objects group based on the principle of maximum similarity with the members of each cluster and the least similarity with different clusters. Meaning that the clusters are adjusted in a way that the objects in each cluster are more similar to each other and have the greatest differences in data from other clusters. When all parameters are continuous, the similarity index is usually expressed in Euclidean distance, otherwise, a standard index will be defined, see Han (2007). Clustering methods contain two categories; partition and hierarchical. We use partition clustering in this study.

Assume a database containing n objects. A partition clustering method, makes K partition of the data so that any partition shows a cluster. Each group must have at least one object and every object should only belong to a group. However, the second condition can be flexible in fuzzy partition clustering methods. K-means algorithm is a common and efficient clustering technique that takes K (number of clusters) as an input and partition K clusters into a set of n objects. The algorithm works as follows:

1. Randomly selects K objects as the center of preliminary clusters.
2. Assigns each object to its most similar cluster center.
3. Update the cluster centers. This means that for each cluster, it calculates the average value of the cluster objects.
4. Return to Stage 2. Stop if no changes occur in clusters

2.4 Association Rules

Association rule is one of the unsupervised and descriptive data mining methods that searches for relationships among features in datasets. In fact, these methods study the mutual characteristics and seek to quantify the relationship between these mutual characteristics. Rules are in the form of if and when, which together with support and confidence factors, are expressed as: $x \rightarrow y$ (support, confidence).

3. Research Methodology

Since the objective of this study is to practically identify the customer behavior patterns using descriptive data type, the proposed framework for the study is consisted as the following phases:

Phase 1: Knowledge of business and data:
Corporate banking, retail banking, commercial banking, and business banking are different banking areas. Retail banking, among other areas has the highest customer facing with significant role in the composition and reputation management of banks. In retail banking, where banks are confronted with a large number of depositors and letter of credit (LC) applicants, they must have been designed with a well marketing strategy. Also, they need to specifically segment the market to carefully select the target markets, and to make clear and firm decisions on bank expected competitive position. Hence, the quality of the marketing strategy depends on market segmentation quality. This study is conducted on retail banking customers for all branches of a private bank in Tehran, Iran. Due to the large number of banking transactions done by customers, analyzing the behavior of this category of customers can have a significant effect in developing a smart marketing strategy.

Phase 2: Collection, preparation and preprocessing of data:
The required information is gathered over a period of two years and is aggregated in quarter intervals. Then, it goes through pre-processing and data preparation step where missing information, lack of some features, non-natural and replicated data are cleaned. This step improves data quality.

Phase 3: Customer clustering based on RFM variable:
Customers in any time interval are clustered using k-means algorithm. Variables of recentness, frequency, and monetary value of all deposits are used for this purpose. The clustering quality in each of the periods is done by the Dunn Index and the best clustering method is extracted in each period. Then the clusters are labeled based on the obtained optimal number.

Phase 4: Extraction of customer behavior groups:
After labeling the clusters, the sequences of individual customers are extracted and the customer membership in different sectors are generated. The obtained sequences are clustered using K-means method and then the best cluster are selected using Dunn Index and different behavior groups are extracted.

Phase 5: Rules for each of the clusters:
Finally, obtained clusters are analyzed, interpreted, and various behavioral groups are extracted. Based on the results, new variable that indicates different groups of behaviors is defined and its relationship with demographic characteristics is analyzed using Association Rules and Apriori Algorithm. Association Rules are efficient methods in data mining that explores the relationship between features provided with descriptive approach. Yet, Apriori Algorithm is more efficient to discover association rules than other algorithms. This allows us to define rules based on gender, sexual groups on the basis of the dominant features of each sector and test the generality and reliability of results using support and confidence indices.

4. Results of Study

This section conveys the proposed and implemented process of extracting customer behavior patterns together with its results.

4.1 Data collection and data preprocessing

Before the implementation of the method, data preparation and data preprocessing for improving data quality is completed in this phase. Since this research is intended to elicit the customer behavior pattern over a period of two years, the required data tables was gathered for calculation of RFM variable in a basis of quarter in eight months period for 10,000 actual customers of this private Bank. The data tables include customer ID, gender, age, number of port service transactions (including branches, ATMs, POS and terminals), the balance of current accounts, savings accounts, deposit rate, and time of the last transaction. Incomplete data and missing values, erroneous values, inconsistent and the bias data were assessed and data were converted to a format suitable for implementation. Data was normalized using min-max technique.

$$v' = \frac{v - min_A}{max_A - min_A} \tag{1}$$

4.2 Clustering customers based on RFM variables

In this section, the RFM value of customers in each time interval is obtained and then clustered using K-Means Algorithm. Since the banks financial statements are published every three months, the number of clusters are considered 3, 6, 9, and 12, respectively.
The quality assessment of clustering for each time interval is then performed using Dunn Index, which includes two criteria; the maximum inter-cluster distance and the minimum outer-cluster distance. This index helps analysts to have dense clusters with fixed boundaries.

$$D_{nc} = \min_{t=1,2,\ldots\ldots nc} \left\{ \min_{j=t+1,\ldots\ldots,nc} \left(\frac{d\left(c_i, c_j\right)}{\max_{k=1,\ldots\ldots,nc} diam\left(c_k\right)} \right) \right\} \tag{2}$$

Table 1 shows the results of customer clustering intervals.

Table 1: Dunn Index values for different clusters of time intervals

		Time Intervals							
		T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8
No. of Clusters	K=3	0.430	0.462	0.448	0.413	0.466	0.420	1.226	0.467
	K=6	0.380	0.585	0.507	0.550	0.621	0.544	1.151	0.452
	K=9	0.487	0.406	0.491	0.454	0.342	0.356	0.224	0.506
	K=12	0.639	0.399	0.481	0.522	0.160	0.420	0.280	0.485
Optimal Clusters		12	6	6	6	6	6	3	9

After determining the optimal number of clusters for each interval, the proposed model by Akhondzadeh and Al-badavi (2015) is used to label the clusters. R, F, and M factors with respect to their mean interval are labeled High (H) and Low (L). In other words, if the average of each of these variables for a cluster is greater than the mean of this variable in the relevant time period, it is labeled H otherwise considered as L. Based on the proposed model, all behavioral patterns of clusters are extracted that contain eight patterns of LLL, LLH, LHL, LHH, HHH, HHL, HLH, and HLL.

Behavioral patterns of each sector are listed in Table 3. As it can be seen, the LLL pattern of behavior exists in all time intervals and the HLH pattern of behavior exists only in interval 8 while HLL occurs in all periods except in interval 7. The following lines indicate the labeling concept for each of the behavior groups using the insight of experts:

LLL: Includes those customers that have recently used banking services. But the number of their transactions is less than total average in the relevant period. They are called ordinary customers with low profitability.

HLL: Explains the behavior of customers with low number of transactions and a long time since their last transaction. This category is known as turned away customers.

LLH: Represents the behavior of customers who have recently used banking services. But the number of their transactions is more than total average in the relevant period. They are called ordinary customers with high profitability.

LHH: Includes customers who have recently used banking services with higher than average number of transactions. These customers are labeled profitable golden customers.

HLH: Contains customers with less number of transactions than average and a high balance. Moreover, a long time has passed since their last transaction. These customers are called turned away customers with high profitability.

HHL: Refers to the behavior of customers with more number of transactions than average and a low balance than total average in the relevant period. They have passed a long time since the last transaction and are called turned away customers with low profitability.

HHH: Represents the behavior of customers who have not recently used banking services. But the number of their transactions is more than total average in the relevant period. They are called turned away customers with high profitability.

LHL: Contains customers who have recently used banking services more than average frequency. But their balance is less than total average. These customers are labeled as loyal customers with low profitability.

In Table 2, the numerical value of 1 indicates the presence of behavior group and the numerical value of 0 shows its absence in any time intervals.

Table 2: Different Customer Segments and Time Intervals

HLL	HLH	HHL	HHH	LHH	LHL	LLH	LLL	Customer Segments / Time Intervals
1	٠	1	٠	٠	1	1	1	1
1	0	1	1	0	1	1	1	2
1	0	0	1	1	0	0	1	3
1	0	0	1	1	0	0	1	4
1	0	0	1	1	0	0	1	5
1	0	0	0	1	1	1	1	6
0	0	0	1	0	0	1	1	7
1	1	0	1	1	1	0	1	8

Extracting the Customer Behavior Groups

To extract the customer behavior groups, the membership sequences of each customer are calculated at different time intervals. The obtained sequences are then clustered using K-Means algorithm. Applying experts' opinions, number of clusters are considered as 3, 6, 9 and 12. In the next step, clustering quality assessment is preformed using Dunn Index and the results are shown in Table 3.

Table 3: Various Behavioral Patterns Comparison Using Dunn Index

No. of Clusters	Dunn Index Value
k=3	0.7338
K=6	0.739
K=9	0.7281
K=12	0.7237

According to the results, the optimal number of clusters is equal to 6. Examples of sequences of each cluster are shown in Table 4. In order to interpret the obtained clusters, a new variable is defined as “Cluster” and the relationship between gender and age of each cluster and the dominant rules of each cluster are analyzed and interpreted.

Table 4: An Example of Sequence Patterns

Gender	Age	Sequence Pattern	Cluster
Women	27	LLL in-active in-active in-active in-active in-active in-active in-active	cluster-1
Men	28	in-active in-active LLL LLL LLL LLL LLL in-active	cluster-2
Men	35	in-active in-active in-active LLL LLL LLL LLL in-active	cluster-2
Women	55	LLL LHL in-active in-active in-active in-active in-active LHL	cluster-3
Men	41	HHL LLH in-active in-active in-active in-active in-active LLL	cluster-3

Men	29	in-active HLL in-active in-active in-active in-active in-active HLL	cluster-3
Women	39	LLL LLL LLL LLL LLL LLL LLL LLL	cluster-4
Men	50	LLL LLL HLL HLL HLL HLL LLL LLL	cluster-4
Men	33	in-active in-active LHH LHH LHH LHL LLL in-active	cluster-4
Men	35	HLL in-active in-active in-active in-active in-active in-active in-active	cluster-5
Women	54	LHL LHL in-active HLL LLL in-active in-active LHL	cluster-6
Men	42	in-active LLL in-active in-active in-active in-active in-active LLL	cluster-6

Afterward, Apriori Algorithm is used to analyze the behavior of clusters and to determine and extract the behavior groups with the minimum confidence level of 80% and support of 2.
Cluster-1: This cluster contains 153 customers. The rules obtained from this cluster represent that customers in most of the time intervals were in the LLL and in active sectors which means they were in LLL sector in the first interval and then disabled for multiple time intervals and finally returned to LLL. This cluster is called low-value customers with a sustainable pattern.
Cluster-2: This cluster includes 602 customers that were mostly in LLL, HLL and LHH sectors. It means that customers were consistently in LLL (regular customers with low profitability) over time, and alternately moved to the parts of LHH (profitable golden customer) or HLL (turned up). This cluster is recognized as customers with unstable profitability pattern. The rules obtained from Apriori Algorithm of this cluster are as follows:
1. Those customers who have been inactive for the first and second period and then turned to customer with low profitability (LLL) are100% likely to be elected as turned away over a few intervals.
2. HLL customers in the first and second intervals are 95% likely to remain in the same situation until the last interval. In other words, customers will have little sustainable profitability. Meaning that, customers with Monetary (M) and the Frequency of transactions (F) below the average in the first and second intervals out of 8 intervals, will have the same status during the latter interval with a distinct possibility. Their Recentness of last transaction (R) also will be long and they will not have desire to continue cooperation with bank.
Cluster-3: This cluster includes 973 customers that in most of the time intervals were in LLL, HLL, and LHL. The customers of this cluster had a below average balance of total during the time intervals. This shows that Clister-3 customers do not tend to deposit in the bank largely. These customers only did their everyday banking and in some occasions they increased the number of banking transactions. Hence this cluster can be called customers with low and stable profitability:
1. Customers who were non-active for more than one interval at the beginning of it are 100% likely to remain non-active in the last interval.
2. Those customers who were LHL and then reduced the number of transactions to LLL and then deactivated, will remain LHL in the last interval. Furthermore, those customers who were HLL

and then reduced the number of transactions to LLL and then deactivated, will remain HLL in the last interval.

3. If the customer was LLL in the first interval and remain the same in the rest of the intervals, will remain in the same situation. In other words, if the customer is a loyal customer with low profitability and does not change this pattern in the last period, will remain the same.
4. If the customer is turned away (HLL) at the initial time and then only improves its Recentness (R) of services over the time, the likelihood of becoming a loyal customer in the last period is 100%. But if the customer cannot improve its attributes in the following intervals, it will be remained as turned away customer with the probability of 93% during the last interval.
5. Those customers that were loyal customers with low profitability (LHL) in the first and second intervals, after turning to LLL, will remain loyal customers with low profitability (LHL). These groups may be considered as loyal customers with sustainable value trend.

Cluster-4: The cluster includes 1213 customers of LLL, HLL, and LHH dominant behavior patterns over time. Customer behavioral characteristics of this sector show a falling value trend so that they can be called turned away customers with average value. Customers in this cluster were in LHL or LHH in the initial intervals but after a period did not have any activities in the study timeframe and changed to turned away. The following rules have obtained using Apriori Algorithm implemented in the cluster:

1. Customers with low profitability (LLL) in the first interval, that have no transactions later on, will deactivate and, thus, known as turned away customers with 100% chance during the last interval.
2. Loyal customers with low profitability (LHL) after transitions between sectors of LLL and LHL, will remain LHL with 100% chance during the last interval.

Cluster-5: This cluster has 168 customers which all of them were with low profitability in the first interval and after no activities, referred as to turned away customers with low value. The behavior of this cluster can be described as low and stable value pattern.

Cluster-6: This cluster includes 901 customers, mostly in intervals LHL, LLL, and HLL, where majority of them were in LHL in the last interval. they are called loyal customers with low value. The most important rules of the Apriori Algorithm analysis of this cluster are as follows.

1. Customers in HLL sector in the first interval and LLL in the second, are 89% likely to be known as loyal customers with low profitability.
2. Those LHL (loyal customer with low profitability) customers in the first interval are displaced to LLL sector. Finally, they will turn into LHL with likelihood of 81% during the last interval.

Table 5: Examples of Rules for Each Cluster

No	Antecedent	consequent	Support	Confidence
1	in-active in-active LLL LLL LLL LLL LLL in-active	in-active	15.26	100
2	HLL HLL HLL HLL LLL LLL LLL HLL	HLL	6.89	95
3	HLL HLL LLL LLL LLL LLL LLL HLL	HLL	6.7	95

4	in-active in-active LLL LLL LLL LLL LLL in-active	in-active	4.83	100
5	LHL LLL in-active in-active in-active in-active in-active LHL	LHL	1.31	88
6	HLL HLL in-active in-active in-active in-active in-active HLL	HLL	1.45	91
7	LHL LHL LLL LLL LLL LLL LLL LHL	LHL	4.15	100
8	HLL LLL LLL LLL LLL LLL LLL LLL	LLL	2.5	100
9	HLL HLL LLL LLL LLL LLL LLL HLL	HLL	1.98	93
10	LHL LHL LLL LLL LLL LLL LLL LHL	LHL	1.78	100
11	LLL in-active in-active in-active in-active in-active in-active in-active	in-active	2.11	100
12	LHL LHL LLL LLL LLL LLL LLL LHL	LHL	2.25	100
13	HLL LLL in-active in-active in-active in-active in-active LLL	LLL	2.33	100
14	LHL LLL LLL LLL LLL LLL LLL LHL	LHL	2.44	81

Conclusion

In this paper, we presented a new hybrid K-Means and association rule method that identifies behavior groups of customers over time and analyzes characteristics of these group. Majority of previous studies applied markov chains to model customers' movement among different sectors and few studies have been conducted in the context of dominant displacement patterns. In previous researches, the dominant patterns were extracted using the maximum number of available sequences and frequency without any systematic and qualitative approach. In this paper, we developed a new extraction and clustering sequence approach as a general way of identifying dominant behavioral patterns of different customer groups among sectors. Identification and analysis of behavioral groups can come handy in developing productive marketing strategies. In addition to the cases mentioned in this paper, the behavioral characteristics of different customer groups were evaluated in order to explore the dominant patterns pertaining to the demographic characteristics of customer groups.

According to the proposed method, four groups of customer behavior were identified as; "Low-value customers with a sustainable pattern", "Low-value customers with stable profitability pattern", "Turned away customers with average value", and "Loyal customers with low profitability". Using the results of this study, we can provide a decent insight into the customer behavior patterns, regarding membership and transfer to different sectors over the time. These insights led us to propose and improve businesses and their marketing strategies. The following strategies can be recommended for each of the fields defined: 1. Low-value customers with stable pattern: Due to their stable behavior, they can be encouraged to use the services of the bank with new services and promotions. 2. Low-value customers with unstable profitability pattern: It's necessary to study the reasons of their behavior instability to provide the basics to attract and retain them. 3. Turned away customers with average profitability: Due to the volume of their balance and transactions, electronic banking can be used to provide distinguished services to improve and return those consumers. 4. Loyal customers with low profitability: Given the level of their loyalty, incentive plans for special customer can intensify their loyalty, profitability, and their willingness to increase their deposits and transactions.

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Biographies

Shaya Sheikh obtained his Ph.D. from Case Western Reserve University in 2013. He worked as scheduling and optimization scientist at Lancaster Laboratories and as visiting assistant professor at University of Baltimore prior to joining New York Institute of Technology. He is currently serving as assistant professor of supply chain management at NYIT school of management. His research interests include energy supply chain, multiple criteria decision making, and application of state-of-the-art heuristics and data driven methods in variety of business problems.

Shaya has published dozens of research papers in peer-reviewed journals such as *International Journal of Production Research*, *Applied Mathematical Modeling, Computers & Industrial Engineering, Journal of Intelligent Manufacturing, International Journal of Advanced Manufacturing Technology, International Journal of Communication Systems, Journal of Wireless Networks, and Operations Research Perspective*. Professor Sheikh has served as editorial board of journals and as ad-hoc reviewer for more than 10 technical journals in systems, energy, and supply chain management field and as speaker and session chair for international conferences.

Vahid Kayvanfar has received his PhD in industrial engineering from Amirkabir University of Technology in 2016. His expertise mainly falls within supply chain, healthcare, soft computing, and applied operations research. He is member of Iran's National Elite Foundation from 2012 up to now and has published more than 20 peer reviewed ISI-indexed journal papers accompanied by 20 peer reviewed conference proceedings as well as one book, so far. Also, he serves as reviewer in more than 30 ISI-indexed peer reviewed journals (Publons). His other honors are winner of ARAP scholarship from A*STAR (Agency for Science, Technology and Research) in Singapore in 2016 and winner of the National Elite Foundation's award of Iran for superior PhD talent students in 2015-2016.

Iman Gharib received his PhD in industrial management from science and research branch of Islamic Azad University in 2018. His dissertation was about simulation of customer behavior with approach of agent base modeling (case study in private banking sector). His special areas of interests are data mining, quantitative methods, developing mathematical modeling and solution approaches. He also has served as the manager of Research and Development (R&D) department in banking industry for more than 8 years.

Sahar Bigdeli got her PhD in the field of industrial management from Islamic Azad University of Tabriz in 2018. Her research areas of interests are system dynamic, performance management, knowledge management, training and development. Her PhD dissertation was about collecting of dynamic strategic map for creating value in power projects (case study in power plant industry). Also, she has served as a training and development manager in power plant holding for 8 years. She is fluent in Farsi, Turkish, English, and has working knowledge of Deutsch language.