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Research Paper

Presenting a Conceptual Framework to Increase the Return and Reduce Risk (A case study: customers of Mellat Bank of Arak)

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ABSTRACT

The objective of this study is to present a framework to increase the return and profitability and reduce the credit risk of Mellat Bank customers by developing the Recent frequency monetary value model (RFM). In this study, which was conducted as a case study in Mellat Bank of Iran, first the variables of the RFM model were identified. In the next step, relevant weights of RFM variables were calculated using the analytical hierarchy process (AHP) technique. In the next step, using the K-means algorithm, customers were clustered based on weighted RFM and extended RFM. The result included customer clusters. The results indicated that the three clusters 5, 1, and 7 obtained the highest scores for receiving facilities and the coefficients for receiving facilities were equal to 0.271, 0.173, and 0.556, respectively. By determining the facility coefficient for the cluster and consequently for the customers presented in these top groups, granting facility becomes more transparent and more purposeful, and therefore, it will help the company increase profitability, reduce the churn among high-efficiency customers, and create value for customers. This research demonstrates a systematic method for granting facilities to recognize the true value based on the capability and prevention of arbitrary acts.

1 Introduction

One of the necessary and effective tools for the economic development of the country is the existence of an efficient banking system. Investing in Banks as a way to earn money is of particular importance to investors [4]. Banks are in fact the pulse of financial activities and the situation governing them can have a significant impact on other economic sectors of society. By organizing and directing receipts and payments, banks will facilitate trade and commerce and promote markets, and, ultimately, bring economic growth and prosperity [1]. However, the banking industry has encountered a number of challenges in recent years for a variety of reasons, including the risk or cost of fluctuations in interest rate, inflation, currency, or non-refund of payment facilities. The continuity and intensity of such challenges for the banking industry in the world and various countries have resulted in numerous social crises. The

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existence of such consequences has led the officials of regulatory and executive institutions of financial systems to consider risk management for financial institutions, especially banks, more seriously and expertly [3]. Consequently, it is important to be aware of the impact of significant banking risks on the performance of the banking system in order to manage these risks and their adverse consequences. Therefore, in order to increase return and profitability and reduce credit risk in business, banks need to have a proper understanding of customers and their demands. Customer relationship management is an effective tool to obtain, maintain, and increase satisfaction in bank customers, as a result of the implementation of this method customer loyalty to the organization will be guaranteed. Financial and credit institutions and banks are among organizations that are in great need of customer relationship management processes because of the nature of their work. A large number of banks do not yet have a clear understanding of their customers and their expectations and do not know what service packages and through what channels should be provided to the customers to meet their needs. Also, not many banks have simply divided their customers into gold, silver and bronze categories to identify the small part of their customers (20%) that provide 80% of the organization's profit (according to the Pareto principle) [17]. Customer segmentation to identify more loyal customers is an unavoidable necessity in competitive markets, especially for financial and credit institutions and banks, in order to satisfy the organization better, including the bank, and increase its profitability by gaining customer loyalty, on the one hand, and in order to provide facilities to their customers, on the other hand, credit institutions and banks need to conduct a thorough review of the capability to repay and calculate the probability of non-refund of facilities and financing services to their customers; these investigations are generally called validation. According to a large number of experts, the credit system and banks apply traditional methods of decision-making for credit granting which are based on personal judgment, while these traditional methods will no longer work in today's competitive environment.

Therefore, using appropriate models for optimal credit allocation in order to manage (reduce) credit risk and, as a result, increase the efficiency and profitability of credit institutions and banks is inevitable in the current competitive environment [2]. One of the common models to measure and assess the credit risk of customers to provide facilities proportionate to the credit of customers and, consequently, manage (reduce) the credit risk and, eventually, increase the return is customer segmentation. One of the most common segmentation models is the RFM model [8]. This model has been applied so far in economies with low inflation rates and with relative stability in the time value of money and desired results have been achieved, but in the Iranian economy, which is affected by sharp fluctuations in inflation and a sharp decline in the time value of money, the indices of this model (especially the M index: the monetary average of the customer account) should be modified and optimized to include the time value of money in calculating the indices of the model mentioned. Therefore, this research aims to evaluate the compatibility of the RFM model with inflationary economies (such as Iran) by including the time value of money in the model calculations, which increases customer loyalty and reduces credit risk, as a result, and therefore, increases the return of the credit institution (bank) [6].

This study, which is a case study in Mellat Bank of Iran, it is attempted to develop a customer segmentation model by including the time value of money in order to achieve customer segmentation with the aim of increasing efficiency and profitability in the conditions of inflation in an optimal and more accurate manner. The reasons for selecting Mellat Bank as the case to study involve the possibility to access the customer data of this bank for the researcher and also the intense competition of Mellat and Saderat banks for occupying the second place after Melli Bank; consecutive shifts of the ranks in the second and third places between these two banks implied the very strong competitive situation between the two banks to maintain the second place among the banks in Iran. According to the experts in Mellat Bank, this goal could not be achieved unless a more accurate framework was developed to identify more loyal and profitable customers and to reduce customers' credit risk in the economic conditions of the recent decade with its several hyperinflations. Therefore, with the development of the RFM model, it was possible to include the time value of money in the index of this model in order to be able to solve the problem to a large extent (facing multiple hyperinflations and not including the time value of money in the most common segmentation model, the RFM model) with developing the RFM model and including the time value of money in the model indices.

2 Theoretical Foundations

The history of risk in banking is as old as banking activity and despite the diversification of banking services, the risks have increased because of the expansion of banking activities, the inability of borrowers to repay debt, entry into international banking and financial crises, and new risks. Followed numerous definitions of risk can be found in various scientific sources, but each of these definitions, depending on their dimension or perspective, has provided a different definition of risk [9]. The word risk refers to the probability of loss, the degree of probability of loss and the degree of probability of loss. In this regard, risk includes the probability of risk and the probability of profit and the probability of loss. While net risk includes only the probability of loss and does not include the probability of profit. If there was sufficient certainty about the changes, certain changes were covered in the context of the anticipated benefits, while the impossibility of predicting the probability of the changes made it a risk of benefits. Risk management is a process that aims to reduce the possibility of harmful effects of activity through conscious action to predict unintended events and plan to avoid them [10]. The most important risks faced by the banking system are divided into the categories of credit risk, market risk, operational risk, legal risk, capital adequacy risk, rate of return risk, money or exchange rate risk and liquidity risk. However, risk as a threat has affected the activities of banks, and in the meantime, credit risk is doubly important due to arising from the most important banking operations, namely lending and facilities. Credit risk is one of the most important factors affecting the health of the banking system [5]. The risk related to losses due to non-repayment or repayment with a delay of the principal or sub-loan by the customer is called credit risk [19]. In another definition, credit risk is the probability of delay, doubtful receipt or non-receipt of the facilities provided to customers. In other words, credit risk is the risk according to which the borrower is not able to pay his principal and interest (loan) according to the terms of the contract; In other words, according to this risk, repayments are either delayed or not received. This causes problems in the bank's cash flow [18].

Four indicators are widely used to determine the level of credit risk for banks. A) The ratio of unrealized (outstanding) assets to total loans and leased assets; Unrealized assets Income-generating assets, such as loans, are over 90 days old. B) The net ratio of burnt loans to total loans and leased assets; Fuel loans are loans that are impossible for the bank to collect and are practically worthless, and the banks have removed them from their offices. C) The ratio of annual contingency reserve of loan losses to total loans and leased assets or total equity. D) The ratio of reserve doubtful receivables to total loans and leased assets. Failure to pay attention to credit risk reduces the liquidity and profitability of banks. Credit risk arises from the fact that the contracting party is unable or unwilling to fulfill its obligations. Traditionally, the impact of this risk is measured by the cost of the trial resulting from the default of the contracting party [7]. Credit risk losses may be incurred by the contracting party before the actual default occurs. Therefore, credit risk can be defined as the probable loss that occurs as a result of a credit event [22]. A credit event occurs when the ability of a party to a contract to fulfill its obligations changes. By this definition, a change in the value of the debt market due to a change in credit rating (or a change in the market's awareness of the contractor's ability to meet its obligations) can also be considered a credit risk. Accordingly, all banks face risks during their operations that they have not been able to eliminate but can be managed. Loan growth, defined as the difference between total loans at time t and total loans at time t-1, is one of the potential factors that can affect a bank's credit risk. To model credit risk, knowing the relationship between credit growth and risk is crucial and has been the basis of research by many researchers in this field [20].

In recent years, concerns about the growth of commercial lending by banks have increased due to the ease of lending and lending. Some researchers believe that banks have acquired new businesses and increased competition for lending customers by reducing lending rates and making it less difficult to lend on facilities. Others argue that while economic development is underway and records of past loan losses have not been forgotten, banks are more willing to take risks. Each of these explanations is correct; Accelerating loan growth can lead to sharp fluctuations in loan losses and reduced bank profits. It can also spark a new round of bankruptcies [14]. Gorinchas list the reasons for the rapid growth of lending as follows: The real trading period. Under this theory, the ultimate source of credit growth is technological shocks or various commercial shock conditions. One of the key features of this story is the higher GDP growth, one year before the sharp growth of loans. This theory can also well explain why banking indicators and payments balances in the post-lending crisis period are no more than periods of calm [11]. The fundamental approaches to the productive efficiency of banks are two; the non-structural understanding that considers the relations between performance indicators and the characteristics of the governance, and the structural perspective, which presupposes theory options around the optimization concept. In concrete, the older bank efficiency literature applies the traditional microeconomic theory of the production of non-financing companies to banking [13].

Recent economic research and experience have shown that a sharp boom in lending is one of the causes of financial and banking crises. Rapid lending growth often requires declining purchasing commitment standards and an overly optimistic assessment of customers' future ability to repay loans [12]. Furthermore, rapid lending growth may lead to an increase in asset prices (which can improve borrowers' balance sheets and apparent merit of facilities), move into a cycle of loan expansion, and increase asset prices [16]. In addition, the rapid growth of lending is associated with macroeconomic instability. A boom in lending facilities can lead to a sharp increase in consumption or investment, or both. The consequences may exacerbate or mitigate payment problems. However, in most loans, there is a credit risk, and the existence of such a risk can affect the performance of the banking system. One method for customer segmentation is based on latency, frequency and monetary value (RFM method), which is widely used in the banking industry.

3 Research Hypotheses

Hypothesis A: The results obtained from the application of the conventional RFM model (excluding the time value of money) with the results obtained from the development of the RFM model (including the time value of money in the calculation of model indices) will be significantly different in inflation economies.

Hypothesis B: The profitability and return of the bank are significantly improved by using the developed model.

Hypothesis C: The results of using the conventional RFM model (excluding the time value of money) in comparison with the results of developing the RFM model (including the time value of money in the calculation of model indices) make a significant difference in customer credit risk management and a credit will do.

4 Research Methods

The present study is considered descriptive-exploratory research based on the purpose of the research. The conventional RFM model is one of the most widely used customer segmentation models in the world. Sometimes we compare the money in the M index (This index is equal to the average monetary value of the customer account over a specified period of time) and finally the results of the typical RFM with the developed RFM. For customer clustering, the K _means method (average K) will be used, which is based on the clustering of customers in a cluster based on the most similarities and the most differences with customers of other clusters. This algorithm is one of the most widely used clustering algorithms. In this segmentation process, first, all registered demographic data of customers and their transaction data are collected based on the RFM model classified. Also, the proper weighting of RFM indicators is done according to the agreement of the bank's experts based on one of the scoring methods such as AHP. Each customer is then assigned a score based on the RFM model. In the next step, sections must be created.

To do this, clustering techniques and data mining methods are used to segment the data. The clustering method used is also the mean K (average k) method. After identifying the clusters, the value of the clusters is determined, the loyal customers of the organization are identified, and an attempt is made to extract the specific characteristics of each department and analyze the departments in order to better understand them. Finally, in order to formulate marketing strategies and customer relationship management, taking into account the policies and strategies of the bank, practical suggestions are provided to provide better services to each segment of customers. The first step is to collect demographic data and customer transactions. The second step is to clear and refine the data to remove junk data. The AHP method was used before the clearance operation to extract the RFM variables. For this purpose, interviews were conducted with the bank's senior managers and a group of experts. The next step is to segment customers using RFM techniques and calculated weights with the help of segmentation algorithms such as K-Means. In the last stage, marketing strategies are presented and customer relationship management strategies are formulated for each segment of customers. Also, from the results of segmentation, the coefficient of facilities granted to the customers of each cluster can be obtained.

5 Descriptive Research Findings

This segmentation of customers is more important for Bank Mellat. According to the bank officials, customers whose average balance from the first day (2011/3/21) to the last day (2019/3/20) is equal to five hundred million rials are in the group of important customers of the bank. For this purpose, transactions of 96-month accounts of four hundred and fifty-one thousand customers with the value of Bank Mellat, whose average balance in the eight-year period (2012-2019) was equal to five hundred million rials were collected. The number of transactions of these customers was about four hundred and forty million records (four hundred and thirty-nine million, two hundred and seventy-seven thousand records). Thus, the accounts of customers whose information was incomplete were removed from the database for data mining operations. After the cleanup operation, the data and transactions of 450,000 customers were prepared for the next phase, which was about four hundred and thirty-nine million records. Therefore, at this stage, the variables R (Recently: The time of the customers' last transaction), F (Frequency: The number of times customers have carried out financial transactions with their account in a period of time) and M (Monetary: The average monetary value of the customer account over a period of time) were calculated for every 450,000 customers. So that four hundred and thirty-nine million records for the next stages became 450 thousand records that three new fields R, F and M were added to each record.

6 Analytical Findings of the Research

In order to test the research hypotheses through Microsoft Business Intelligence software, we compare the results in the first two columns of the following Table 1.

6.1 Test The First Hypothesis

Hypothesis A: The results obtained from the application of the conventional RFM model (excluding the time value of money) with the results obtained from the development of the RFM model (including the time value of money in the calculation of model indices) will be significantly different in inflationary economies. Considering the time value of money, the first cluster customers are the most loyal customers among the customers of other clusters, because its comprehensive ranking is the maximum value equal to 0/5123. The second cluster is in the second rank of loyal customers. Sixth cluster customers are also among the seven clusters in terms of loyalty.

Table 1: Calculating The Comprehensive Ranking and Determining the Loyalty Rating of Each Cluster by Considering the Time Value of Money and Comparing the Results with The Case Without Considering the Time Value of Money (Test of The First Hypothesis)

Ranking The Loyalty Of Clusters Based On The Time Value Of Money Loyalty Rating	Ranking The Loyalty Of Clusters Regardless Of The Time Value Of Money	C_I^j Considering The Time Value Of Money	C_I^j Regardless Of The Time Value Of Money	$W_F.C_F^j$	$W_R.C_R^j$	$W_M.C_M^j$	Calculate Comprehensive Ranking and Determine the Rank of Clusters / Clusters
1	3	0.5123	0.5238	0.0012	0.5218	0.0008	The first cluster
2	4	0.5008	0.5069	0.0005	0.5057	0.0006	The second cluster
5	2	0.4655	0.5301	0.0051	0.5228	0.0022	The third cluster
6	5	0.4321	0.4776	0.0003	0.4768	0.0005	The fourth cluster
3	7	0.4937	0.2457	0.0001	0.2449	0.0007	Fifth cluster
7	6	0.4123	0.4448	0.0002	0.4434	0.0012	Sixth cluster
4	1	0.4822	0.5404	0.0145	0.5232	0.0027	Seventh cluster

The results (as seen in the table above) confirm the first hypothesis of this study and make a significant difference in the results that are evident in the last two columns of the table.

6.2 Test The Second Hypothesis

Hypothesis B: The profitability and return of the bank are significantly improved by using the developed model.

According to the experts' judgment, the new results can increase the bank's efficiency and profitability by up to 38%. However, according to experts at the Bank Mellat Research, Statistics and Information Center, the model developed in the face of hyperinflation showed more accurate results than the conventional model. It is considered for the development of the model and therefore the second hypothesis was confirmed.

6.2.1 Cluster Analysis (Sections)

Since our selected customers (according to a survey of bank experts) have a minimum balance of fifty million tomans. In terms of monetary value, the clusters are slightly different from each other, but in terms of latency and frequency, there are more differences between the clusters. For example, in the fifth cluster, the rate of customer delay is from forty-nine hundred to seventy-two percent, while no group or cluster, or category has a lag of forty-nine hundredths. The seventh category (cluster) of customers has a frequency of eight hundred (0.08) and no other group has this frequency. This means that the group of customers with the highest frequency is in the seventh cluster. In addition, the group of customers with the highest latency is in the fifth category of customers. Therefore, the characteristics and features of each customer segment can be easily analyzed by carefully looking at the shapes extracted from the software.

Using the capabilities of this software, another view of these seven clusters can be shown that the clusters have different colors according to their latency so that the seventh category (cluster) of customers is displayed less than all clusters (by software) and this indicates a lower concentration in the lag and the fifth category of customers has the highest concentration (according to Figure 1 about seventy-nine hundredths).

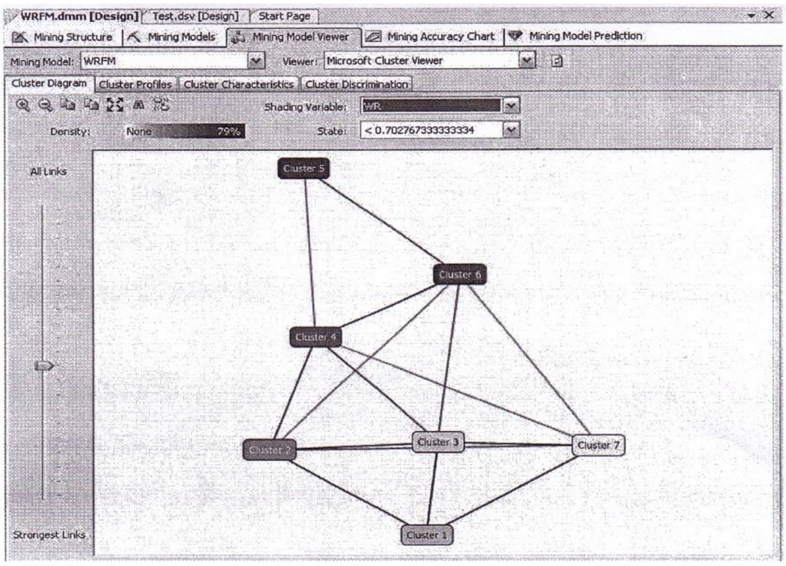

Fig. 1: Delay Variable (Novelty) And Display of Customer Clusters Based On It in the Software

For rotation and monetary value can also be done with the display software settings as shown above. Just select Shading Variable in the software, WF and then WM to have a display like the above display for rotation and monetary value. Therefore, Bank Mellat of the Arak city through the method presented in this study can segment its customers and by providing better and faster services to customers appropriate to each department in retaining and attracting new customers and ultimately more profitability of the bank can be very effective. Therefore, analytical customer relationship management with its efficient tool called customer segmentation has a very effective and efficient role in increasing profits by identifying valuable customers in the opposite industries, especially in the banking industry.

6.2.2 SOM Clustering On RFM Data

The behavioral scoring model in this study was first generated using the SOM algorithm and network in dimensions 4 × 4 and hexagonal neurons. Each of these neurons is regulated by synaptic weights that attach to the input vector during learning. The first phase of SOM is the rough estimation phase used to generate gross data patterns. The second phase is the configuration phase, which is used to configure the network map to model the good features of the data.

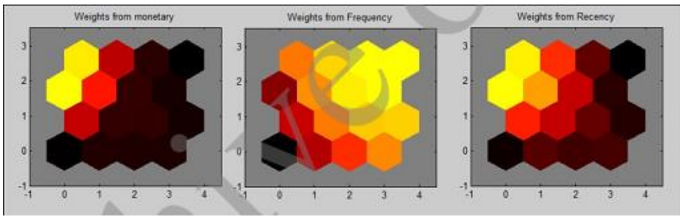

Fig. 2: Input Vectors

The clustering algorithm is used to identify groups of customers for ranking and granting facilities. The results of running the SOM algorithm in MATLAB software are shown in Figure 2. Figure 2 shows the number of clients divided into each neuron.

Table 2: SSE Parameter Rate per Number of Clusters in SOM

Number Of Clusters	SSE
8	17.70969
9	15.75831
10	14.61389
11	18.61049
12	19.50487

Table 3: Scattering of Clusters

10	10	10	9
10	10	8	7
10	4	6	5
4	3	2	1

6.2.3 Scoring Points

After determining the clusters, we now want to get the value of each cluster in order to determine the ranking of the clusters. Therefore, in the following, we will perform the operations related to granting facilities to the superior clusters. The weight of the clusters was determined using the opinion of experts. Due to the importance of the monetary value index for the bank, which indicates the amount of money in the transactions of individuals, the weight of this variable is more than the other two variables and the value was considered 0.5 for the frequency variable 0.3 and for the delay variable 0.2 is considered. The results for each cluster are shown in Table 2. As you can see, clusters 5, 1, and 7. Have the highest scores, respectively. Since the focus of this study is on valuable customers, the clusters that have the highest rank in the scoring model have been considered. Therefore, these three clusters are examined in the following. Cluster five. There are customers with a turnover of over 25 million who usually have a relatively good range. The number of months they have a transaction is between 9 and 12 times and the number of negative balances under 5 months means that they have a great presence in the market. The volume of transactions per month is relatively good and they have a good settlement. The number of customers in this cluster is 24 people.

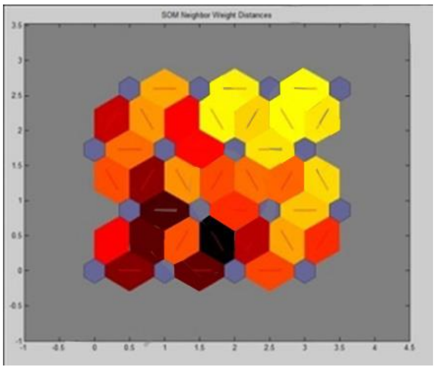

Fig. 3: Number of Members of Each Neuron

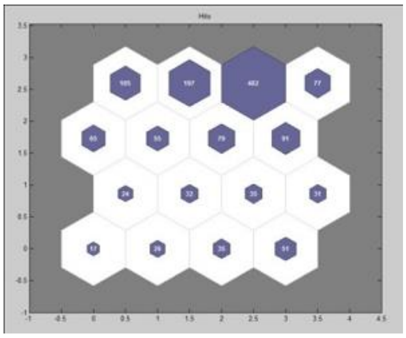

Fig. 4: The Distance of the Neurons

Table 4: Evaluation of Clusters

Cluster	Average Money	Value Average Fre-Quency Value	Average Delay Value	Cluster Value	Number of Cluster Members
5	0.67393	0.94097	0.75394	0.77064	24
1	0.68137	0.96078	0.33824	0.69657	17
7	0.37681	0.78333	0.80256	0.58392	65
8	0.25606	0.56667	0.94394	0.48682	55
6	0.18821	0.45573	0.74479	0.37978	32
2	0.26107	0.53526	0.44231	0.37958	26
9	0.14639	0.36349	0.95714	0.37367	105
10	0.03909	0.10615	0.97762	0.24691	957
4	0.04854	0.14923	0.50194	0.16942	86
3	0.01126	0.03571	0.10238	0.03682	35

Cluster one. There are customers with an average turnover of 50 million or more, the number of months they have a transaction is between 10 and 12, which is great, but the number of negative balances is between 6 and 11 months, which is because the transaction volume is high. This amount is negligible. The number of customers in this cluster is 17 people. Cluster seven. There are customers with a turnover of between 25 million and 750 million who have a relatively good range. The number of months they have a transaction is between 8 and 12 times and the number of negative balances is less than 5 months; This means that they have an excellent presence in the market. The volume of transactions per month is relatively good and they have a good settlement. The number of customers in this cluster is 65 people. From each other, the three clusters, which were ranked higher in terms of scoring, accounted for 80% of the total volume of debt and credit turnovers. As a result, it can be confirmed that the members of the three clusters 5, 1, and 7 have the highest volume of transactions and turnovers. As a result, more attention should be paid to them in order to make the bank more profitable. The results for turnover percentage are shown in Figure 4.

6.2.4 Scoring Members of Top Clusters to Provide Facilities

After determining the top clusters in the previous step, now it is time to somehow allocate the desired facilities to the members of these clusters. In order to be able to assign these credits to the superior customers in the next stage, it is necessary to first determine the coefficient of facilities granted to these three superior clusters. To do this, the value of customers in these top three clusters must be calculated. Using the customer value calculation formula mentioned in this Section, the operations related to customer scoring in these three clusters are performed.

At this stage, due to the importance of the monetary value index, the coefficient of this variable is considered 0.5, and also the periodicity variable with a coefficient of 0.3 and the latency variable with a weight of 0.2 is applied in the formula. A total of 106 customers are in these 3 clusters, for all of which the value is determined. Then, the weight of each customer is determined by dividing the value of each customer by the sum of the value of the top 106 customers. The sum of the weights assigned to the customers of each cluster at the end determines the coefficient of granting facilities to the members of that cluster. The results are shown in Table 6. By doing so, we determine how much of the facility is allocated to these top clusters. According to Table 5, for clusters 5, 1 and 7 of the number of facilities, 1/27%, 3/17% and 6/55%, respectively, are considered. Cluster 5, which is the highest cluster, allocates fewer facilities than cluster 7, which is in third place, and the reason is that the number of members of cluster 7 is more than cluster 5. As a result, this amount of facilities is relatively less divided among the members of cluster 7, so the number of members of the cluster that have the highest rank is allocated to them in proportion to the greater amount of facilities.

Table 5: Facility Coefficient for Superior Clusters by Linear Weighting Method

Cluster	Facility Coefficient
5	0.271
1	0.173
7	0.556

In order for the researchers to complete their model for validation, they use the coefficient (weight) of the cluster produced in the previous step. The process is such that for each cluster, first the sum of the values of all their customers is calculated, then for each person, the value of the customer is divided by the total amount obtained, thus determining the initial coefficient of granting facilities for each customer. The weight of that cluster is determined by the weight of each customer, the coefficient of granting customer facilities. The relevant results are shown in Tables 6, 7 and 8. As shown in the table, the coefficients for the members of the top clusters were determined separately based on the customer value of each cluster. The coefficient obtained for each customer can also be considered as a separate coefficient for receiving facilities. At present, the amount of credit that the company can allocate to its customers in each period is an amount of 100 billion.

Table 6: Coefficient and Amount of facilities For Cluster 5 By Linear Weighting Method

Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Amount of Customer Facilities	Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Amount of Customer Facilities
c1	0.0464897	0.0125908	1259082589	c13	0.041656427	0.011281824	1128182373
C2	0.0382968	0.01037218	103721786	c14	0.039608421	0.010727162	107271679
C3	0.0416154	0.01127073	1127073049	c15	0.050258049	0.013611404	1361140385
C4	0.041082985	0.011126518	1112651839	C16	0.043786352	0.011858672	1185867214
C5	0.036782174	0.009961728	996172832	C17	0.051363971	0.013910921	1391092129
C6	0.038420578	0.010405458	100545787	C18	0.039977062	0.010827001	0108270094
C7	0.038830179	0.01051639	1051639026	C19	0.036413533	0.009861889	986188917.9
C8	0.036003932	0.009750957	975095679.2	C20	0.036741214	0.009950635	955063508.8
C9	0.042557549	0.011525875	1152587498	C21	0.041328746	0.011193078	1119307782
C10	0.046448759	0.012579733	125793265	C22	0.044564594	0.012069444	1206944367
C11	0.042475629	0.011503689	1150368850	C23	0.04292619	0.011625714	1162571413
C12	0.044073073	0.011936325	1193632481	C24	0.03829768	0.010372178	1037217816

Table 7: Coefficient and Amount of Facilities for Cluster 1 By Linear Weighting Method

Customer Number	Customer Value Coef-Ficient	Customer Facility Coefficient	Amount of Customer Facilities	Customer Number	Customer Value coef-Ficient	Customer Facility Coefficient	Amount Of Customer Facilities
C25	0.055018873	0.009540185	954018525.7	C34	0.065190967	0.01130401	1130401021
C26	0.050540592	0.008663659	876365855	C35	0.05169215	0.008963337	896333684.6
C27	0.060200883	0.010438738	1043873759	C36	0.061032563	0.01058295	1058294969
C28	0.06570277	0.011392756	1139275612	C37	0.076002815	0.013178767	131786754
C29	0.055402725	0.009606745	960674468.9	C38	0.063527605	0.011015586	1101558600
C30	0.06110514	0.010605136	1060513617	C39	0.053611413	0.009296134	929613400.6
C31	0.065190967	0.01130401	1130401021	C40	0.064679163	0.011215264	1121526430
C32	0.055146824	0.009562372	956237173.4	C41	0.049516985	0.008586167	858616673.1
C33	0.046382189	0.008042598	804259803.6				

Table 8: Coefficient and Amount of Facilities for Cluster 7 By Linear Weighting Method

Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Customer Number	Customer Value Coefficient	Customer Facility Coefficient
C42	0.015249501	0.008475234	C64	0.013752495	0.007643241	C86	0.014710579	0.008175717
C43	0.017844311	0.009917355	C65	0.01493014	0.008297743	C87	0.0149501	0.008308836
C44	0.015209581	0.008453048	C66	0.015588822	0.008663819	C88	0.014151697	0.007865106
C45	0.014211577	0.007898386	C67	0.013832335	0.007687614	C89	0.016387226	0.009107549
C46	0.015189621	0.008441955	C68	0.017245509	0.009584558	C90	0.01259481	0.006999834
C47	0.015169661	0.008430861	C69	0.014650699	0.008142437	C91	0.01510978	0.008397582
C48	0.016706587	0.009285041	C70	0.015209581	0.008453048	C92	0.016926148	0.009407066
C49	0.016327345	0.009074269	C71	0.0150499	0.008364302	C93	0.013932136	0.007743081
C50	0.015568862	0.008652726	C72	0.013752495	0.007643241	C94	0.018962076	0.010538577
C51	0.014810379	0.008231183	C73	0.014650699	0.008142437	C95	0.016706587	0.009285041
C52	0.017325349	0.009628931	C74	0.014730539	0.00818681	C96	0.014471058	0.009285041
C53	0.013872255	0.007709801	C75	0.017185629	0.009551278	C97	0.01740519	0.009673304
C54	0.017145709	0.009529092	C76	0.014750499	0.008197903	C98	0.014451098	0.008031505

Table 8: Coefficient and Amount of Facilities for Cluster 7 By Linear Weighting Method

Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Customer Number	Customer Value Coefficient	Customer Facility Coefficient	Customer Number	Customer Value Coefficient	Customer Facility Coefficient
C55	0.016327345	0.009074269	C77	0.012075848	0.006711409	C99	0.017285429	0.009606745
C56	0.01261477	0.007010927	C78	0.015349301	0.008530701	C100	0.015269461	0.008486328
C57	0.016866267	0.009373787	C79	0.013532934	0.007521216	C101	0.015329341	0.008519607
c58	0.0150499	0.008364302	C80	0.016646707	0.009251761	C102	0.014830339	0.008242276
C59	0.0149501	0.008364302	C81	0.014011976	0.007787454	C103	0.016487026	0.009163015
C60	0.016846307	0.009362693	C82	0.017125749	0.009517999	C104	0.015648703	0.008697099
C61	0.015309381	0.008508514	C83	0.015449102	0.008586167	C105	0.017065868	0.009484719
C62	0.013772455	0.007654335	C84	0.014650699	0.008142437	C106	0.014231537	0.007909479
C63	0.01742515	0.009684397	C85	0.015129741	0.008408675			

6.3 Comparison of Validation Results for Granting Facilities Once Considering the Time Value of Money and Once Without Considering the Time Value of Money

The results without considering the time value of money are shown in the table below:

Table 9: Facility Coefficient for Top Clusters Regardless of Time Value of Money

Cluster	Facility Coefficient
5	0.271
1	0.173
7	0.556

The results are given in the table below, taking into account the time value of money:

Table 10: Facility Coefficient for top Clusters Considering the Time Value of Money

Cluster	Facility Coefficient
2	0.159
4	0.108
8	0.402

6.4 Test The Third Hypothesis

Hypothesis C: The results of using the conventional RFM model (excluding the time value of money) in comparison with the results of developing the RFM model (including the time value of money in the calculation of model indices) make a significant difference in customer credit risk management and a credit will do. As can be seen from the comparison of the two tables above, when we consider the time value of money in the model, the top clusters will change from clusters 5, 1 and 7 to clusters 2, 4 and 8, respectively, and the coefficient of facilities granted to the top clusters will be significantly different. Therefore, based on the results, the third hypothesis is also confirmed. So by considering the time value of money in customer credit risk management has changed up to 24% in improving the resulting accreditation results, which also shows the correctness of entering the time value of money in management Customer credit (validation) is at the time of granting the facility.

7 Conclusions

Customer accreditation is an important issue for the banking industry, and you will be able to identify and gain an accurate perception of the existing customers through customer clustering, and you can also provide customer behavioral rankings to state the best part of customers through scoring methods. In a final conclusion, it can be said that four hundred and fifty thousand customers were segmented into seven clusters so that the first cluster consisted of one hundred and eighty-seven thousand customers, the second cluster consisted of eighty-seven thousand customers, the third cluster contained one hundred and eleven thousand customers, the fourth cluster consisted of fifteen thousand customers, the fifth cluster included twelve thousand customers, the sixth cluster involved eleven thousand customers, and the seventh cluster consisted of twenty-seven thousand customers. Customers of the seventh cluster have the highest transaction among other clusters, just as the average monetary value of the customers in this cluster is higher than the rest of the clusters. The fifth cluster has the lowest transaction (frequency) among the other clusters, and the average monetary value of the customers of this cluster (fifth cluster) is the lowest value among other clusters; also, the highest rate of WR delay belongs to the customers of this cluster. Considering the points mentioned above, the fifth cluster occupies the last rank, i.e. the seventh rank of clusters in terms of triple variables.

Also, the second rank belongs to the third cluster, the third rank goes to the first cluster, the fourth rank is occupied by the second cluster, the fifth rank belongs to the fourth cluster, and finally, the sixth rank is related to the sixth cluster. After the seventh cluster, the third cluster is in the second place in terms of frequency, monetary value and delay, and after the third cluster, the first cluster is in the third place in terms of the triple variables. The research findings are consistent with the findings of Alfansi & Sargeant, Maenpaa, Case and Machauer & Morgner. Frances Case divides credit rating models into two clusters, parametric evaluation and classification tree. The idea of separating clusters in a population was introduced by Fisher in 1995. In 1995, Altman developed the first credit application evaluation system using three criteria. Noel’s studies have shown that RFM variables are very efficient for ranking customers. Yeh et al Used RFM variables to select the direct marketing method, which expands the RFM pattern by adding two variables, time of first purchase and probability of loss.

Table 11: Comparative Table of Monetary Value of Customers in Each Cluster

Clusters	Number Of Customers Per Cluster	The Total Weighted Monetary Value Of Each Cluster At The End Of Segmentation	The Total Weighted Monetary Value Of Each Cluster After One Month Of Segmentation	Percentage Of Growth In Monetary Value Before And One Month After Segmentation
First Cluster	187000	0.1829	0.1997	9.0 %
Second Cluster	87000	0.0666	0.0724	8.71 %
Third Cluster	111000	0.294	0.3216	9.42 %
Fourth Cluster	15000	0.0091	0.0093	2.32 %
Fifth Cluster	12000	0.0107	0.0106	1.29 %
Sixth Cluster	11000	0.0154	0.0156	1.45 %
Seventh Cluster	27000	0.0888	0.0983	10.78 %

In consultation with experienced, proficient and scientific experts and managers of Mellat Bank regarding their research results, they stated that customers should explore the clusters in terms of the growth of monetary value in one month so that they can judge the accuracy of research results better and more accurately. Therefore, after the segregation of the valuable customers of Mellat Bank, considering the fact that the monetary value was introduced as the most important variable from the point of view of bank managers and experts, the monetary value of segmented customers was re-examined in another one-month deadline and once again, the monetary value of these customers was calculated over the period of one month. These calculations are shown in Table 11. In this table for each cluster, the total weighted monetary value (before and after the segmentation) as well as the percentage of growth of the weighted monetary value of the customers in each cluster are displayed. As shown in Table 11, the monetary value of the customers of the seventh cluster (category) increased by about 10.78 % during this period. On the other hand, the monetary value of the customers of the fifth cluster decreased by about 1.29%. Diagram 1 below shows the percentage of monetary value growth for seven customer clusters over this one-month period.

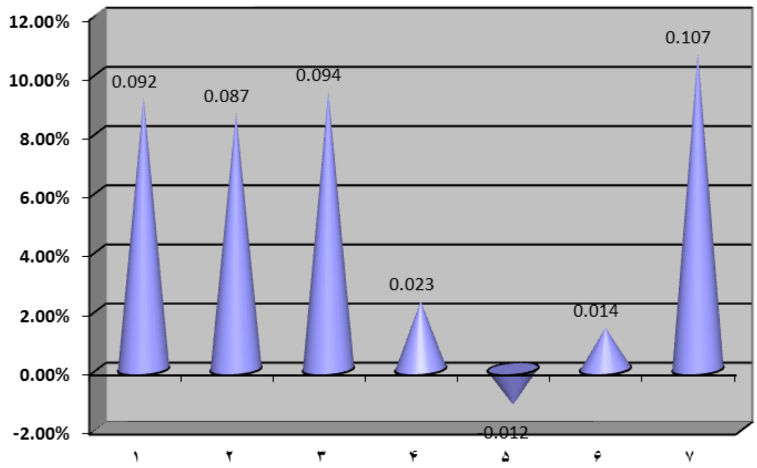

Diagram. 1: Comparative Results of Monetary Value as A Percentage of Monetary Value Increase Over a One-Month Period

According to the obtained results, customer segmentation is calculated correctly, which was approved by the experts and managers of Mellat Bank, and the experts' feedback on the accuracy of the research results confirms the accuracy of the findings. By determining the facility coefficient for the cluster and consequently for the customers presenting in these top groups, granting facilities becomes more transparent and more purposeful and this will help the company to increase profitability, reduce the attrition of return customers and enhance value creation for customers. The results of accreditation for granting facilities, once considering the time value of money and another time regardless of the time value of money, also indicated that considering the time value of money in managing the customer credit risk can change accreditation results by up to 24% and using this factor can be appropriate in the validation of facilities.

Based on the research findings, the following suggestions are provided:

Reducing costs of transactions and providing services and fixed costs throughout the institution.

Quick implementation of services, ease of access to services using electronic banking services through broadband or mobile communication facility. Providing guarantee for customers that, with continuous training, all sections of the organization are focused on and committed to providing the highest quality services to customers. Customer relationship management is the core of integrated customer software. Software such as Cordiant can help financial and credit institutions and banks to establish efficient interactions with their customers. Using SAP consultants to design, implement and support customer relationship management systems with this company software known as SAPR3 and MYSAP; the former is applied for human resource planning and the latter for marketing, sales, order management, managing customer service functions and interactions. These systems can also be procured and implemented by other major CRM vendors, such as Sibel and Nuttle / Clarify and PeopleSoft / Vantio and Oracle. Using the choice board the customized services are determined based on the customers' tastes. Customization for service goods and intangible information is easier and more applicable compared to physical goods, of course. This method will turn customers into service makers and designers, rather than service recipients. The limitations of the research also involve the following cases: Data collection of customers' transactions was of the difficulties of this research. Convincing the bank officials and going through the relevant administrative cycles and providing the requested information by the bank occupied a great amount of time in this research and in reviewing the data in each stage, the data had to be retrieved, too; only in the last stage was the data and information provided complete and conformed to the research requirements.

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