International Journal for Quality Research 14(1) 163–182
ISSN 1800-6450

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Article info:
Received 12.04.2019
Accepted 11.09.2019

UDC – 004.738.5
DOI – 10.24874/IJQR14.01-11

STUDYING PRODUCT QUALITY BY EXPLORING CREDIT CARD CUSTOMERS BEHAVIOUR VIA DATA MINING TECHNIQUES

Abstract: *Recently, the competition has increased among Iranian-banks. This provides customer's satisfaction and quality-optimization. Nowadays, Credit-card is a new and significant product for Iranian-banks. Reports show customer's demand decreased by 21% in using credit-card in 2018. This study is aimed to identify high-quality customers of credit-card and develop the product quality through creating features in accordance with to their needs in order to increase customers' satisfaction. It was conducted on 1598 credit-card holders in two-phases. First, high-quality customers were selected using data-mining tools (K-means/C&RT algorithm); Results show 93 high-quality customers. Second, their data was studied the way of using credit-cards and its features from customers' perspective including how to pay installments, number of facilities documents, etc. Results show that 43% and 57% customers use the credit-card as a loan-card and revolving-credit respectively. Also, most customers of revolving-credit significantly consume allocated-credit in a transaction and start paying their debt in maximum-installments.*

Keywords: *Data-Mining; Credit-Card; Customer Satisfaction; K-means; Two-step.*

1. Introduction

Providing quality services is one of the essential components for the success and survival of business enterprises in today's competitive environment. Quality in business literature has different meanings and can be examined in different aspects. From a manufacturer's point of view, the quality is the ability of a product to carry out the work on which it was designed. From a customer's point of view, the quality refers to those features of the product or service that affect the ability to create satisfaction (Ladhari, 2010). Kano, a renowned quality theorist, believes that today quality is an integral part of any business, and is one of the main factors in global competition. He believes that due to the growing global competition, it is not possible to meet customer needs only through current products, but new products must be constructed to meet his/her expectations, this depends on an accurate understanding of the needs and requirements of customer. Therefore, he defines quality as "to meet the needs and expectations of a customer, and, even, going beyond his satisfaction" (Valdés et al., 2011).

Therefore, in order to achieve acceptable quality in products/services, customer expectations and needs must be considered

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for the products/services provided and their perception of the products/services that they have actually received. However, on many occasions, customer service needs are not taken into account in the design of products/services. Researchers believe that delivering quality services to customers not only satisfies their current needs but also predicts future customer needs. The ability to predict future customer needs encourages customers to reuse their services and increase their level of satisfaction and loyalty to the organization. Therefore, each organization must try to improve its customer satisfaction by improving the quality of its products and services (Hua et al, 2011). Banks as a service provider are not exception.

In the last two decades, banking sector in developing countries has undergone regulatory changes that have led to increased competition among banks. Banks play a key role in financial market operations and maintaining the economy of a country. On the other hand, the quality of banking services is one of the essential elements for increasing customer satisfaction and loyalty and are important factors in improving the performance and success of banks and increasing their profitability and market share (Anabila & Vitor, 2013). On the other hand, the highly competitive environment that banks have to work on, have made them to rethink their attitude and lead them to customer satisfaction and optimize service quality. Therefore, customer satisfaction is one of the key factors for business success in a competitive environment, and each organization strives to improve the quality of its products/services by providing customer satisfaction with a high level of achievement. The quality in services/products is only possible through the full recognition of the customer and the provision of products/services according to their needs. Credit-card is one of the new products that has been attracted the attention of Iranian banks in recent decade. Formal reports relating to credit-cards represent 21 percent decline in customer demand for using credit-card in 2018. Reducing the amount of credit-card usage indicates customer dissatisfaction. This problem is described further in the Problem Statement section.

1.1. Problem Statement

Credit card is one of the banking products that has been considered by Iran's banks for more than a decade. Promotion of this product due to its newness is possible through the improvement of the services quality related to this product. This requires improving the current features and creating new features tailored to customers' demands. Also, due to the limited resources of banks in the development of services quality related to credit-card, its profitability should be considered for the bank. To date, the features defined for a credit-card product have not been examined from the perspective of customers, in order to check its correspondence to their needs. Also the reports of credit-card in the bank in the last 3 years show that the number of demands of issuing credit-card in 2018 is less than that in 2016 (it has dropped 21%). Also, compared with the number of transaction made by credit-card in 2016, it has decreased in 32% in 2018. These results indicate that customers are not increasingly interested in using credit-cards. Table 1 shows the number of transactions and issued cards in studied bank in the last three years.

Table 1. Credit-card comparison over last three years

Year	Variables	
2016	Issued-card	195,882
	transaction	1,978,633
2017	Issued-card	179,525
	transaction	1,622,479
2018	Issued-card	153,438
	transaction	1,345,470

So, it is necessary to study on credit card in order to enhance customers' satisfaction and their willingness to use credit cards.

Also, the technology development has led to the accumulation of a large amount of data throughout the life-cycle of the product, including design, production, sales, and etc (He et al., 2016). The banking industry is no exception to this, and the expansion of e-banking has led to the recording of all customer data, including their transactions, which can be used to better understand the customers needs, allocate optimal resources to customers and boost bank productivity.
Data-mining is one of the successful tools used in various industries in designing products, supporting decisions, identifying customer behavior patterns, and etc (Xu et al., 2016). Data-mining is now becoming an important area for many industries, including the banking industry. This process analyzes data from different perspectives and ultimately summarizes it with meaningful information. This tool has various applications such as marketing and retail management, customer relationship management, market segmentation based on product and service, and etc in the banking industry (Farooqi & Iqbal, 2017). According to the above, this study was aimed at identifying high-quality, loyal credit-card customers and developing the quality of this product through the creation of features tailored to their needs. So the credit-card customers of one of Iran's state-owned banks were surveyed.
In order to identify high-quality banking customers, a list of related indicators was first identified by studying the research literature and interviewing experts in the banking industry. By analyzing customer behavior patterns in order to increase bank revenues from credit-card based on identified indicators, customers were divided into high quality customers, average quality customers and low quality customers. Then, the high-quality credit-card customer's behaviors were explored on how to use credit-card features. Finally, based on the analysis done to increase the quality of the credit-card product, designing and creating new features or modifying the existing features were proposed. These steps are presented in Figure 1.

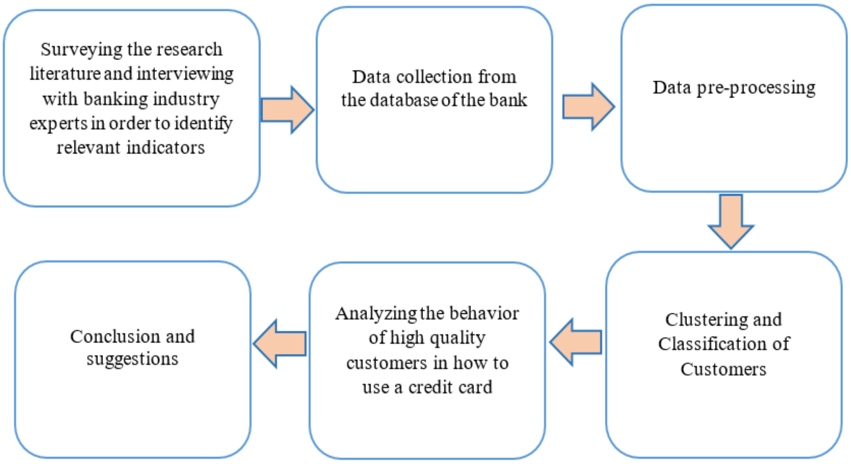


Figure 1. Research process

2. Literature Review

Considering the objectives of this research, this section examines the credit-card mechanism in Iran, studies on the provision of services in the banking industry focusing on the banking services quality and their relationship with customer satisfaction, also the data-mining application in identifying high-quality customers.

2.1. Credit Card in Iran

A credit card is a bank instrument issued by banks to individuals or legal entities, and the terms and conditions for each party are specified under a contract between a bank and a customer. This tool allows the card holder to buy goods or services from the seller. (Al-Qudah et al., 2012) In Iran, this product was designed with the purpose of increasing purchasing power and in accordance with international standards based on the moratorium contract and non-usury banking law, with the exception that the use of these cards in Iran is merely limited to buying from shopping malls and stores (while it is possible to receive cash from ATMs and transfer credit balances to international credit cards). Currently, three types of moratorium credit cards with regard to its credit limit (including the credit limit of 100, 300 and 500 million-Rials) are issued, and their features are as follows:

1. Possibility of debt installment of purchase and flexibility in the method of credit-card repayment taking into account different time frames.
2. Possibility of using the credit card as a fixed (loan credit card) or revolving credit card.

2.2. Credit card in other countries

Credit cards are also developed for the convenience of paying customers in other countries and credit-card holders use these cards in shopping daily necessities or in buying cars and house. For international cards, the cardholder is allowed to withdraw and shop from his/her account up to the credit limit assigned by the bank. After using credit and elapsing a certain period and in order to pay the debt, bank sends them the customer's statement. Some banks even take this debt from their customers in installments. Therefore, the main features of this card in other countries include:

1. Withdrawal and purchase up to the credit limit assigned by the bank.
2. A possibility to divide debt due to purchase and flexibility in the way of credit card repayment. (Khansari, 2016)

2.3. Services Quality

A study was conducted with the aim at examineing the satisfaction and loyalty of bank customers regarding the quality of the various services offered by the Pakistani banks. In this research, the questionnaire was used to assess the services quality provided to customers and then to examine its relationship SERVQUAL with customer satisfaction and loyalty. Study findings confirmed a positive relationship between service quality and customer satisfaction (Munawar Khan & Fasih, 2014). Also a study was conducted with the aim at evaluating the quality of perceived services provided by different Greek banks. The results showed that there was a significant difference between the perceived quality of banking services offered by different banks in Greece. Moreover, in this study, the relationship between customer service quality and customer loyalty was investigated, and the results confirmed a significant relationship between customer service quality and customer loyalty (Kraniasa et al., 2013). Another study investigated the relationship between the qualitative characteristics of Islamic banking products and customer satisfaction in Nigerian banks. Results showed a significant impact of the perceived quality of products on customer satisfaction. It was also found that there was a significant relationship between the cost of using products and the level of customer satisfaction, and customers tend to use less costly banking products (Baba et al., 2018). Also a study investigated the impact of service quality on customer loyalty and performance of Taiwan's financial institutions. Results showed that promoting the service quality could significantly influence the companies through the intermediary effect of customer loyalty (Liu & Wang, 2017). Another study investigated the effect of customer satisfaction on improving the performance of Scandinavian banks. Its results showed a positive effect of customer satisfaction on the profitability and financial performance of the bank (Eklofa et al, 2018). Another study investigated the impact of service quality, innovation, and technology and staff commitment on the performance of banks in Malaysia. The findings showed that the performance of Malaysian banks was heavily influenced by technology and innovation in products and services (Boon-Hui Chai et al, 2016). Another study examined the impact of service quality on customer satisfaction in Greek banks and the service quality was measured from two different aspects, namely, the quality of performance (how the bank operates effectively) and the relationship (intimacy between customers and the bank and employees of the bank). The findings showed that the performance quality did not affect customer satisfaction, while communication quality positively affected customer satisfaction. (Keisidou et al, 2013).

2.4. Customer Classification

Of the major challenges in customer-based organizations are the recognition of the customer, an understanding of the difference between them and their ranking. Recently, customer value has been used as a measurable parameter for customer classification. Considering the importance of the issue, some research has been carried out in this area. A study presented a framework for classifying banking customers based on their value. So, customers' history in different periods was studied using K-Means and RFM techniques and their future behaviors was predicted (Khajvand & Tarokh, 2011). A study was conducted with the aim at identifying clusters key customers in order to create more efficient strategies for them. In this research, customers' data were analyzed using two-step and RFM clustering methods. The findings showed the distinction between bank customers' clusters based on the amount of loans, predetermined risk, inventory, loyalty and profitability for the bank (Ansari & Riasi, 2016). Another study was conducted with the aim at creating benefits to the bank such as attracting profitable customers, maximizing investment in sales and delivery channels, creating competitive advantage in the market, and improving their services to feature analysis. For this purpose, the investigated E-banking customers and their behavior by clustering methods of K-means and RFM. In this research, criteria such as access time, transaction and RFM, LTV and population-cognitive variables were investigated. (Kumar et al., 2012). Some of the studies used here are presented in Table 2.

Table 2. Litrerature Review

DATA-MINING Techniques				
No	Studies	Purposes and key findings	research design and analysis	limitations
1	(Doğan et al., 2018)	-Customer segmentation, detecting similarities and differences among customers, predicting their behaviors, proposing better options and opportunities to customers	-K-means -RFM technique	Not-mentioned
2	(Alborzi & Khanbabaei, 2016)	-Presenting a new hybrid model for behavioral scoring and credit scoring	-Data-mining technique -Neural networks -WRFMLCs analysis method	Not-mentioned

Table 2. Litreraturе Review (continued)

3	(Farokhi et al., 2016)	-Using the information gathered from Point of Sales (POS) for detecting the most profitable customer customers -Customer segmentation	-K-means -Kohonen	Not-mentioned
4	(Fouladifar et al., 2016)	-Clustering e-banking customers for enhancing customer relationship and developing services	-K-means -RFM technique	-accuracy
5	(Butaru et al., 2015)	-Risk and risk management in the credit card Industry	-Decision-tree -Regularized logistic regression -Random-forest models	Not- mentioned
Quality & Customer Satisfaction				
No	Studies	Purposes and key findings	research design and analysis	limitations
6	(Baba et al., 2018)	-Influencing of Islamic bank's products quality features on customer satisfaction	-Structural equation model	Not-mentioned
7	(Liu & Wang, 2017)	-Effecting of service quality on customer loyalty and corporate performance in financial industry.	-Multiple regression analysis	Not-mentioned
8	(Boon-Hui Chai et al., 2016)	-Effecting of service quality, innovation, technology and employee commitment on the bank performance	-Pearson correlation analysis -Multiple regressions analysis	-The result of this research is merely based on non-financial indicator , the result does not fully represent the bank performance as it would need both the financial and non-financial indicators to give a better picture -small sample size and accuracy
9	(Chochoľáková et al., 2015)	-Examining and quantifying the dependence of additional purchases of banking products from customer loyalty and dependence of bank clients' loyalty from their satisfaction with the bank's customer service.	-Pearson correlation coefficient	Not-mentioned
10	(Garvey Orji et al., 2017)	-Assessing the impact of new products development on the profitability of Nigerian deposit money banks	-Kendall coefficient	-Low response rate which lessens the generalisability of the findings to the entire population of Nigerian banks

With regard to what has been learned from previous researches, all of these researches have addressed the customers' classification and the impact of service quality on customer satisfaction separately. However, in this study, the results of the classification will be used to analyze the existing features of the credit card and provide a solution to increase its quality and thereby increase customer satisfaction.

3. Research Methodology

According to the large number of data of credit card customers and extracting useful patterns and information from the customers' database, data-mining method including clustering and classification is applied to analyze data. There are several fields in which data-mining can be used in the banking industry. They include customer classification in terms of their productivity, prediction of debt payment, marketing, fraud transactions detection, fund management and prediction operation, treasury asset optimization and investment rank. In general, banks can use data-mining to identify productive customer of credit-cards and high-risk loan applicants. (Liébana-Cabanillas et al, 2013) CRISP-DM and SEMM are methods of data-mining projects. In this study, CRISP-DM, a common data-mining method, is used. The main purpose of selecting CRISP-DM in this study is to be more widely used than other methods also more understandable than others for users, according to research conducted by the Data-Mining Research Association in 2007. This method consists of stages of business recognition, data perception, data preparation, modeling, evaluation and development. Therefore, after recognizing the business in the first stage, data on credit-card customers was collected from a database of one of the bank affiliated companies, whose field of work is "issuing and supporting credit-card". It should be noted that the data were extracted from the SQL database and then converted to an Excel format, and the Excel file was used for further analysis by Clementine software. Then the preprocessing data including data cleansing and converting were done. In the next step, to know more about the population, the clustering method was used. At this stage, demographic variables were separated from other variables. The reason for this separation is to eliminate the impact of customer demographic data on the clustering stage. In the modeling stage, the results obtained in the previous stage were used to classify customers into three classes of high quality, average quality and low quality customers and the rules were extracted. In the classification stage, the demographic data of customers were also added to other data. In the final stage, the results obtained from the previous step were reviewed to examine the features of the products and define the features that are tailored to the needs of high quality customers. Research conceptual model is shown in Figure 2.

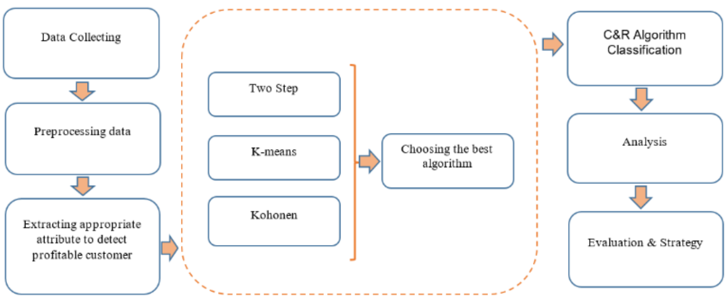


Figure 2. Conceptual Model

3.1. Sample Selection

Given that the purpose of the study was to investigate the behavior of credit-card holders in debt installment, how to use a credit-card, and etc, the population of this study includes all credit-card holders. In the same way, a sample of 1598 persons who have been issued a credit-card account in an Iranian bank who had the credit file date in the period from 2016/08/22 to 2016/10/22 were randomly selected. This information includes items such as non-overdue debt, overdue-debt, allocated-credits, interest, number of loan files, consumed credit, monthly consumption, etc. After consulting with industry experts, some of them related to the subject of the research were selected.

4. Results and Discussion

4.1. Descriptive Statistics

As stated above, in order to reach the research purpose, 1598 people were selected. Table 3 describes the sample.

Table 3. Descriptive statistics

Variables		Frequency	Percent
Gender	Male	1097	68.6
	Female	501	31.4
	Sum	1598	100%
Age (years old)	20-30	216	13.5
	30-40	585	36.6
	40-50	424	26.5
	50-60	230	14.4
	60-70	83	5.2
	Older than 70	60	3.8
	Sum	1598	100%
Allocated-credits (million rial)	100	631	39.5
	300	434	27.2
	500	533	33.4
	Sum	1598	100%

4.2. Data Preprocessing

Data collected from the real world generally has problems such as noise, missing data, and data outside the acceptable range. If these data are used in data-mining before examination and preprocessing, they will not be able to provide acceptable results or create problems in the data-mining process. Therefore, data preprocessing is performed to prepare raw data. The steps for data preparation are described in Table 4.

Table 5 describes the operational definitions of some of the variables used in this research.

Table 4. Data preparation steps

1	Removing duplicate data	Finding and removing duplicate data from the data set by using the remove duplicates tool in Excel software
2	Creating new features	Converting and modifying variables and creating a new variable
3	Discretization	Converting continuous variables to discrete variables
4	Management Missing Value	Finding Missing Values and Removing or Replacing them. In this research, C&RT algorithm was used to replace missing data.
5	Management Extreme and Outlier	At this point, the anomaly detection method was used to identify and manage Extremes and Outliers. Difference between this method with other methods is the multidimensional look at Extreme and Outliers and to identify the values outside of the range in all variables.

Table 5. variables's operational definitions

NO	Variable name	Operational definition
1	Allocated-credits	The maximum amount of credit the Iranian-Banks grants to the applicant after validation.
2	Credit file	Includes all identity and customer debt information within a specified time period.
3	loan files	Debt instrument include information on facilities created during the use of credit-cards by the Card holder. In other words, each of the loan file includes the total amount of purchases made during a one-month period.
4	Customer status	This variable shows the different statuses of each customer credit file. For example, by paying the debt of credit-card, and at the request of the customer, the credit file is closed.
5	non-overdue debt	If less than 2 months has passed after the customer's installment, his debt will be called non-overdue debt.
6	overdue debt	If more than two months has passed after the customer's installment, his debt will be transferred to the overdue debt class.

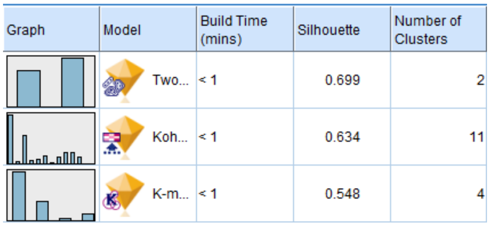
The titles and statistical data of the collected data from the database are shown in Figure 3 (see Appendix).

Figure 4 shows an overview of the preprocessed data used in the analysis (see Appendix).

According to industry experts, some variables including interest, annual percentage rate (APR) and customer debt, are not appropriate criteria for judgment and, depending on their nature, are dependent on allocated-credits and consumed Credit. In the initial analysis of the data and the clustering-stage, the above variables were used, but, for the customer classification, the indicators of "debt to consumed credit", "profit to consumed credit" and "APR to allocated-credits" were calculated and replaced the above mentioned variables.

4.3. Clustering Stage

We used clustering methods to identify the population. When there was not much knowledge of the data, different clustering-algorithms can be used to identify different groups of the study population. The whole sample (1595) was examined before clustering. The average debt and Interest-Paid before clustering were equal to 155,517,697 and 61,474,581 respectively. So the clustering-stage was done to select the group of key customers with the highest profitability and debt for the bank. At the clustering-stage, customers, in terms of profit, debt, allocated-credits, consumed-credit and APR, was examined. Different algorithms were used and the best algorithm was selected by comparing the algorithms of silhouette indices. (Rousseeuw, 1987) According to Figure 5, the Two-Step algorithm with 2 clusters had the highest silhouette, the results of which are described in more detail below.



Graph	Model	Build Time (mins)	Silhouette	Number of Clusters
	Two...	< 1	0.699	2
	Koh...	< 1	0.634	11
	K-m...	< 1	0.548	4

Figure 3. Algorithms Comparison

Figure 6 shows the results of the two-step algorithm. As you can see, the value of the silhouette of this algorithm is 0.7 and is acceptable. The data overview after the clustering is shown in Figure 6.

The variables were also considered regarding their importance, showing that the variables of allocated-credits, APR, and profit were more important than other variables (Figure 7).

	Debt	Interest paid	Annual Percentage Rate	Allocated credit	Consumed credit	$T-TwoStep 1
1	25599902.0...	23383528....	1000000.000	100000000.000	100000000.000	cluster-1
2	90222053.0...	24850640....	1000000.000	100000000.000	300803409.000	cluster-1
3	45957691.0...	22464903....	1000000.000	100000000.000	100000000.000	cluster-1
4	33113655.0...	25558011....	1000000.000	100000000.000	129288000.000	cluster-1
5	0.000	22731717....	1000000.000	100000000.000	100000000.000	cluster-1
6	0.000	36291920....	1000000.000	100000000.000	99878000.000	cluster-1
7	0.000	22395040....	1000000.000	100000000.000	100000000.000	cluster-1
8	0.000	27731221....	1000000.000	100000000.000	129440000.000	cluster-1
9	15364784.0...	24520732....	1000000.000	100000000.000	99994200.000	cluster-1
10	42540246.0...	21858195....	1000000.000	100000000.000	109260000.000	cluster-1

Figure 6. Data Overview after clustering

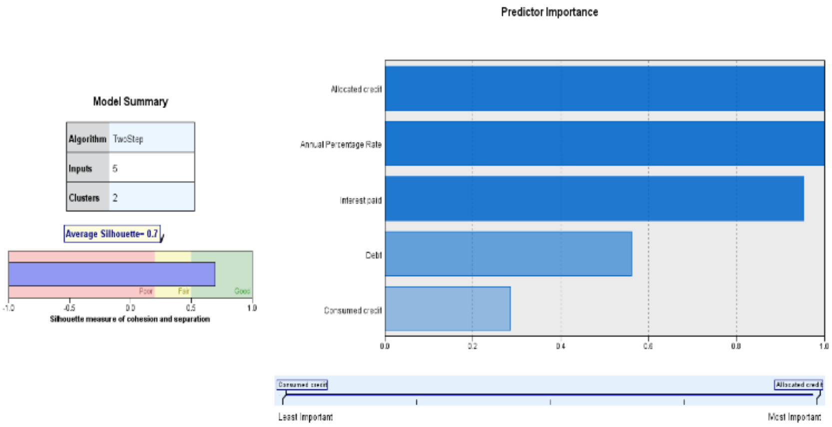


Figure 7. Variables Importance

The overview of each cluster and the variables distribution in each cluster are shown in Figure 8.

As it is known, the largest number of customers is located in cluster2; also this cluster has a better distribution than cluster1.

To further examine the data, the statistical characteristics of the two identified groups from the two-step algorithm were investigated, the results of which are shown in Table.6. According to the table, the average paid profit in cluster 1 and 2 were 24,008,731 and 98,940,431 million-Rials, respectively, so, the customers of the cluster.2 had higher profit. Also the average debt in cluster 1 and 2 were 42,036,834 and 268,998,559 million-Rials, respectively, indicating that cluster.1 customers' debt level was less than cluster.2. Given that customers in cluster.2 had higher profitability and more debt than customers in cluster.1, they had a higher priority than cluster.1 customer one, so, the information about cluster.2 customers are used as inputs of the decision tree.

Figure 9 shows the clearing model and data clustering.

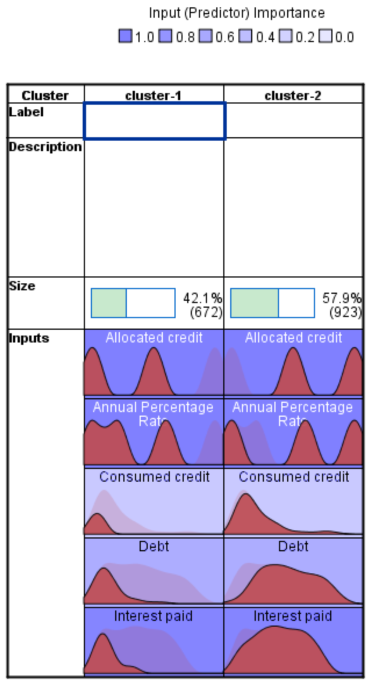


Figure 8. Clusters overview

Table 6. Clusters Comparison

		Debt	Interest-Paid	APR	Allocated-Credit	Consumed-Credit
Cluster 1	sample	672				
	mean	42,036,834	24,008,731	1,005,952	112,202,381	132,577,326
	median	23,134,806	24,003,754	1,000,000	100,000,000	100,000,000
	Minimum	0	0	0	100,000,000	5,682,000
	Maximum	450,870,138	90,159,176	3,000,000	300,000,000	801,150,000
Cluster 2	sample	923				
	mean	268,998,559	98,940,431	4,072,589	414,842,904	629,035,669
	median	260,958,145	92,333,653	5,000,000	500,000,000	500,000,000
	Minimum	0	0	0	300,000,000	51,300,000
	Maximum	754,846,988	203,423,477	5,000,000	500,000,000	6,192,771,538

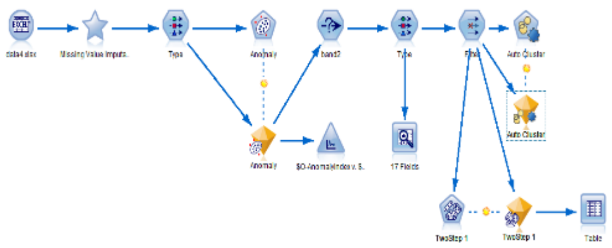


Figure 9. Model for preprocessing and clustering Stages

4.4. Customers Classification

At this stage, the data on cluster 2 were introduced into the model for classification. In this research, the C&RT classification algorithm was used to extract the rules. The input variables of these algorithms include the number of loan files, customer status of the credit file, age, gender, area, salary, "the ratio of debt to consumed credit","the ratio of profit to consumed credit" and "the ratio of APR to allocated-credits". The model for customer classification using decision tree is shown in Figure 10.

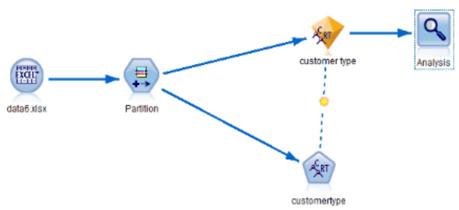


Figure 10. classification model

After the implementation of the model in order to ensure the model accuracy, the model accuracy was examined for the results obtained in the training and test data, which is shown in Table 7.

Table 7. Accuracy of the C&RT algorithm

	Training		Testing	
Correct	531	97.6%	371	97.9%
Wrong	13	2.4%	8	2.1%
Total	544	100%	379	100%

Results show the accuracy of C&RT algorithm was above 97% in the training and test data, which indicates the high model accuracy. The results also showed that the variables "amount of debt to consumed credit", "amount of consumer profit to consumed credit" and "debt type" had the highest role in choosing customers with high, medium and low quality, and demographic variables such as region, age and etc are of no significant importance. In Figure 11, the results of the variables importance are displayed.

Figure 12 and Table 8 refer to the rules extracted from the decision tree for credit card customers.

Some variables have different states and values. For example, the “debt type” variable has three states (No-debt, Non-overdue debt, overdue debt). So we consider a code for each state and value. The codes for each state and value used in the classification model, is shown in Table 9.

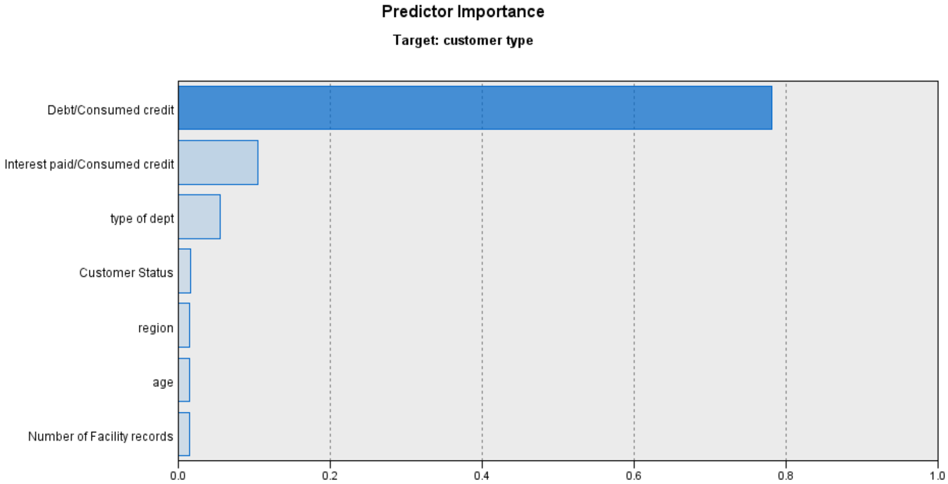


Figure 11. Variables Importance

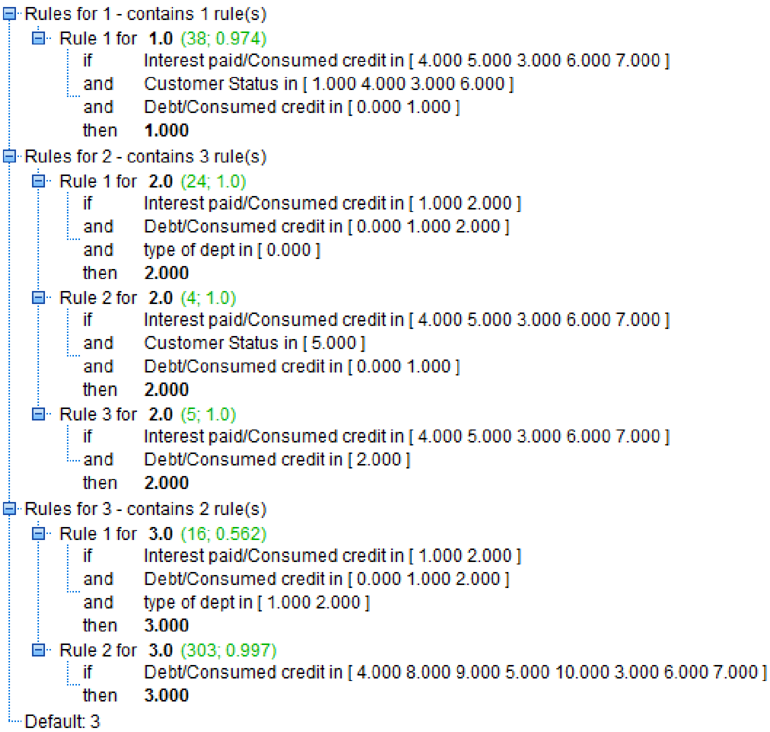


Figure 12. Rules derived from C&RT

Table 8. Rules derived from C&RT

Customer Class	Rules Number	Rules derived from C&RT algorithm	Confidence
High-quality customers	Rule 1	If Interest paid/Consumed credit in [4,5,3,6,7] and Customer Status in [1,4,3,6] and Debt/Consumed credit in [0,1] then 1,	97%
Middle-quality customers	Rule 2	If Interest paid/Consumed credit in [1,2] and Debt/Consumed credit in [0,1,2] and type of debt in [0] then 2	100%
	Rule 3	If Interest paid/Consumed credit in [4,5,3,6,7] and Customer Status in [5] and Debt/Consumed credit in [0,1] then 2	100%
	Rule 4	If Interest paid/Consumed credit in [4,5,3,6,7] and Debt/Consumed credit in [2] then 2	100%
Low-quality customers	Rule 5	If Interest paid/Consumed credit in [1,2] and Debt/Consumed credit in [0,1,2] and type of debt in [1,2] then 3	56%
	Rule 6	If Debt/Consumed credit in [4,8,9,5,10,3,6,7] then 3	99%

Table 9. variables Code

Variable name	states and values	Variable code in the model
Interest paid/Consumed credit	0	0
	Between 1% to 5%	1
	Between 6% to 10%	2
	Between 11% to 15%	3
	Between 16% to 20%	4
	Between 21% to 25%	5
	Between 26% to 30%	6
	More than 30%	7
Debt Type	No-debt	0
	Non-overdue debt	1
	Overdue debt	2
Debt/Consumed credit	0	0
	Between 1% to 10%	1
	Between 11% to 20%	2
	Between 21% to 30%	3
	Between 31% to 40%	4
	Between 41% to 50%	5
	Between 51% to 60%	6
	Between 61% to 70%	7
	Between 71% to 80%	8
	Between 81% to 90%	9
	Equal or More than 30%	10
Customer Status	Closed	1
	Inactive due to debt	2
	Inactive	3
	Active	4
	Blocked due to debt	5
	Expired	6

After identifying 93 quality customers, the information of these customers was investigated in terms of how to use the credit card, how to payout the installments, the number of loan files, allocated credits, and etc. Its results are displayed in Table 10.

Table 10. customer’s credit card information

Variable name		frequency	percent
Fixed Credit		40	43%
Revolving Credit		53	57%
Allocated Credits	300 million	37	40%
	500 million	56	60%

43% of "high-quality customers" only had one loan file, which indicates that 43% individuals have used credit-cards once (loan card) and the revolving credit was not important to them. 57% of them had more than one loan file (between 2 and 23 cases), which shows that 57% of customers use revolving credit.

Regarding allocated-credits, 40% of the customers had allocated-credits of 300 million Rials and 60% of them had allocated-credits of 500 million Rials and none of them had allocated-credits of 100 million Rials.

Examining the behavior of these customers in using a credit-card during a one-month period showed that 50% of the loan files were comprised of between 10 and 50 million-Rials, and that the files had the highest rating than other loan files. Therefore, it can be concluded that most of the transactions carried out by these customers over a one-month period ranged from 10 to 50 million Rials, which indicates the use of a credit card in retail purchases. On the other hand, the highest amount of loan files made by the customers was equal to the total of allocated-credits (300/500 million Rials), accounting for 20% of these customers.

One of the features of credit cards is the flexibility in its payout method, with different time periods (once payout, 3, 6, 12, 18, 24 and 36 months payout). In the sample, it was found that the method of payout of 39% of customer loan files was 36 months, and this method had the highest rank in comparison with other methods of payout. The method of payout of 27% of the loan files was payout at once. The high percentage of the once payout is due to 2 reasons. The first reason is the use of credit-cards in payments less than 500 thousand-tomans because debts installment cannot be paid for less than 500 thousand tomans to the customer and the second reason is the high interest of card holders in choosing the once payment method. On the other hand, the method of payout with 18 month installments had the lowest rank in the sample (0.1% of the loan files).

5. Conclusions

This study was conducted to investigate the behaviors of profitable customers of credit card and to find the appropriate model for creating new strategies, introducing new products and improving existing products. So, after collecting data, high-quality customers were selected using data-mining tools (clustering/classification). Thus, from the results obtained from rule.1 of the C&RT algorithm (Table 8), 93 high-quality customers were identified, accounting for about 10% of customers in cluster 2. The information of these customers was investigated in terms of how to use the credit card, how to payout the installments, the number of loan files, allocated-credits, and etc. The results of the analyses showed that 43% of high-quality customers use a credit card as the loan card and 57% of high-quality customers use revolving credit of card credit. Moreover, surveys showed that most customers, who use revolving credit cards, used the highest amount of allocated credits during a transaction, and start payout with their maximum installment (36 months). Then, by payout the debt, the credit card is recharged to the exact amount of the installment, and due to the low installment amount, it will only be possible for the customers to use cards in retail payments. Furthermore, given the low transaction cost, there is no possibility of installing debts to customers, which leads to the choice at once payout in many credit files. On the other hand, the number of customers who used the credit-card as a loan card (fixed credit) and payout their debt with 36 month installments is significant. Given the above, creating a variety of credit card features and delivering different products will make it more profitable for the bank and bring more customer satisfaction. In order to improve, creating variety in products and higher profitability, the followings were suggested:

1. Providing a product with a fixed credit considering important allocated credits and a 36 month payout method.
2. Providing a product with the revolving credit, a low amount of allocated credits, and considering the number of installments less in the payout method.

In doing so, there were limitations such as lack of access to more sample numbers and the lack of investigating some demographic features of customers such as their education and job. These suggested that future research should be conducted with larger samples and using fuzzy-logic to compare it with this research in terms of accuracy. Also some of the studies conducted in classification are looking for increased accuracy and sensitivity in classification. This study combine fuzzy-methods and optimization-algorithms such as combining “optimized rough set theory and fuzzy-logic” algorithms (Thippa Reddy & Khare, 2017b). The results indicate an increased accuracy and sensitivity in classification. Another study on classification was done to decrease the features through locality preserving projection. It showed that decrease in features does not lead to reduce accuracy in classification. Also, a combination of Firefly, BAT and rule-based fuzzy-logic causes to decrease complication and increase accuracy in classification (Thippa Reddy & Khare, 2017a). Therefore, it is recommended that optimization-algorithms and fuzzy-logic will be used in future studies in order to increase the accuracy to classify credit-card customers.

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Appendix:

Field	Graph	Measurement	Min	Max	Sum	Range	Mean	Mean Std. Err.	Std. Dev	Skewness	Kurtosis	...	Valid
Consumed credit		Continuous	5682000.0...	6192771538.000	676456485292.000	6187089538.000	423314446.365	13451475.983	537722647.248	5.302	39.975	--	1598
Number of Facility records		Continuous	0.000	25.000	4889.000	25.000	3.059	0.115	4.608	2.196	5.122	--	1598
Debt		Continuous	0.000	754846988.000	277435163489.000	754846988.000	173613994.674	4494670.752	179674428.161	0.918	-0.056	--	1598
gender		Continuous	1.000	2.000	2099.000	1.000	1.314	0.012	0.464	0.805	-1.354	--	1598
Interest paid		Continuous	0.000	203423477.000	107729497023.000	203423477.000	67415204.645	1226773.455	49040259.256	0.617	-0.817	--	1598
region		Continuous	0.000	3.000	2422.000	3.000	1.519	0.016	0.655	0.538	-0.290	--	1594
Allocated credit		Continuous	100000000...	500000000.000	459800000000.000	400000000.000	287734668.335	4260313.440	170305996.475	0.117	-1.612	--	1598
Annual Percentage Rate		Continuous	0.000	5000000.000	4450000000.000	5000000.000	2784730.914	43943.251	1756631.132	0.117	-1.558	--	1598
Customer Status		Continuous	1.000	6.000	5610.000	5.000	3.511	0.046	1.832	0.042	-1.682	--	1598
age		Continuous	13.000	1377.000	2135009.000	1364.000	1352.127	1.500	59.615	-21.577	482.892	--	1579

Figure 4. Primary Data Statistics

	Debt	Interest paid	Annual Percentage Rate	Allocated credit	Consumed credit	Number of Facility records	Customer Status	gender	age	region
1	25599902.0...	23383528....	1000000.000	100000000.000	100000000.000	0.000	5.000	2.000	1362....	1.000
2	90222053.0...	24850640....	1000000.000	100000000.000	300803409.000	11.000	2.000	1.000	1361....	2.000
3	45957691.0...	22464903....	1000000.000	100000000.000	100000000.000	0.000	2.000	1.000	1374....	2.000
4	33113655.0...	25558011....	1000000.000	100000000.000	129288000.000	6.000	5.000	2.000	1369....	1.000
5	0.000	22731717....	1000000.000	100000000.000	100000000.000	0.000	1.000	2.000	1352....	1.000
6	0.000	36291920....	1000000.000	100000000.000	99878000.000	0.000	1.000	1.000	1354....	1.000
7	0.000	22395040....	1000000.000	100000000.000	100000000.000	0.000	5.000	1.000	1365....	1.000
8	0.000	27731221....	1000000.000	100000000.000	129440000.000	2.000	6.000	1.000	1357....	1.000
9	15364784.0...	24520732....	1000000.000	100000000.000	99994200.000	2.000	5.000	1.000	1355....	1.000
10	42540246.0...	21858195....	1000000.000	100000000.000	109260000.000	3.000	5.000	1.000	1351....	3.000
11	0.000	25622944....	1000000.000	100000000.000	222327030.000	10.000	1.000	2.000	1376....	1.000
12	53903872.0...	19484816....	1000000.000	100000000.000	100000000.000	0.000	2.000	1.000	1364....	1.000
13	0.000	27734062....	1000000.000	100000000.000	159207398.000	9.000	6.000	2.000	1364....	1.000
14	24205927.0...	25234630....	1000000.000	100000000.000	103465293.000	2.000	5.000	1.000	1347....	1.000
15	143386039....	0.000	0.000	100000000.000	100000000.000	0.000	2.000	2.000	1373....	2.000
16	43404490.0...	25897878....	1000000.000	100000000.000	100000000.000	0.000	2.000	2.000	1328....	1.000
17	27296286.0...	24898557....	1000000.000	100000000.000	100000000.000	0.000	5.000	2.000	1367....	2.000
18	41755563.0...	22914010....	1000000.000	100000000.000	99996000.000	0.000	2.000	2.000	1374....	1.000
19	10058090.0...	24210649....	1000000.000	100000000.000	100000000.000	0.000	5.000	2.000	1365....	1.000
20	73464084.0...	18900434....	0.000	100000000.000	99900000.000	0.000	2.000	1.000	1362....	2.000
21	135126109....	6532213.000	1000000.000	100000000.000	116046700.000	7.000	2.000	1.000	1330....	1.000
22	0.000	34133917....	1000000.000	100000000.000	299375000.000	4.000	1.000	1.000	1357....	1.000
23	79135962.0...	24487299....	1000000.000	100000000.000	100000000.000	0.000	2.000	1.000	1353....	2.000
24	64824921.0...	29304281....	1000000.000	100000000.000	200000000.000	2.000	2.000	2.000	1355....	2.000
25	59365774.0...	19468921....	1000000.000	100000000.000	100000000.000	0.000	2.000	2.000	1367....	2.000
26	77357627.0...	27044553....	1000000.000	100000000.000	227300000.000	4.000	5.000	2.000	1362....	2.000
27	15220023.0...	23777001....	1000000.000	100000000.000	100000000.000	0.000	5.000	2.000	1366....	1.000
28	8298762.000	23958902....	1000000.000	100000000.000	100000000.000	0.000	5.000	2.000	1367....	1.000
29	96930538.0...	14063306....	1000000.000	100000000.000	99995000.000	0.000	2.000	2.000	1366....	2.000
30	74924925.0...	21863617....	1000000.000	100000000.000	199809221.000	4.000	2.000	1.000	1376....	0.000
31	0.000	20852192....	1000000.000	100000000.000	105289128.000	4.000	1.000	1.000	1334....	2.000
32	26011282.0...	26447252....	1000000.000	100000000.000	100000000.000	0.000	5.000	1.000	1371....	2.000
33	58993062.0...	28447466....	1000000.000	100000000.000	124370000.000	5.000	5.000	1.000	1365....	0.000
34	124381276....	9730327.000	1000000.000	100000000.000	114000000.000	2.000	2.000	2.000	1334....	2.000
35	15574990.0...	33674696....	1000000.000	100000000.000	99978900.000	0.000	2.000	2.000	1370....	2.000
36	140983766....	2085703.000	1000000.000	100000000.000	99960000.000	0.000	2.000	1.000	1361....	1.000
37	56061895.0...	33242201....	1000000.000	100000000.000	275659798.000	11.000	6.000	1.000	1359....	1.000
38	0.000	32059362....	1000000.000	100000000.000	99960000.000	0.000	1.000	2.000	1348....	2.000
39	0.000	28686645....	1000000.000	100000000.000	100000000.000	0.000	1.000	2.000	1359....	1.000
40	4992392.000	23294404....	1000000.000	100000000.000	104056000.000	4.000	6.000	1.000	1361....	1.000

Figure 5. Preprocessed data overview