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Rating the Actual Customers of Banks based on Credit Risk using Multiple Criteria Decision Making and Artificial Intelligence Hyperbolic Regression

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ABSTRACT

This study wants to investigate the rating of the actual customers of banks based on credit risk using multiple criteria decision making and artificial intelligence hyperbolic regression. This is an applied research. The statistical population of the study includes the credit customers of Agriculture Bank in west branches of Mazandaran province, Iran in 2012-2016. A total of 100 cases have been evaluated. AHP method has been used in the case of elites' comments on the prioritized seven key factors using the corresponding weighting matrix. To model the classes of creditworthy and non-creditworthy customers and to predict the appropriate model based on the evidence in the customer's credit file, artificial intelligence hyperbolic regression has been employed. Using AHP method, the rating include customer revenue, credit in the market, customers' job, the duration of the relationship with the bank, the type of collateral, the value of collateral, average account balance to facilitate the credit risk of the actual customers, respectively. Using artificial intelligence hyperbolic regression, prioritization is based on the amount of credit in the market, customer revenue, the value of collateral, the duration of the relationship with the bank, the type of collateral and customers' job.

Keywords:

Credit risk, Actual customers, AHP artificial intelligence, hyperbolic regression, creditworthy customers

1. Introduction

The evaluation of the economic system at the international level highlights the fact that there is always a close relationship between the investment and the economic progress in countries (Tehrani et al., 2009). It means that countries with efficient model of allocating the capital to various economic sectors have high economic growth and, consequently, higher social welfare. Mobilization and allocation of investment resources to economic activities is done through financial market. Bank credit market is a part of this market. In the banking industry, one of the important issues that must be considered by credit policy makers is the credit risk management. Due to the development and dynamics of the credit industry, this industry has an important role in the national economy. Although the increasing competition and the creation of new channels in the new economy have created the new opportunities for the credit institutions, these institutions need new tools and methods as well. Therefore, the institutions require revision, empowerment and new technologies in the process of credit. Credit rating models are one of the most important and basic decision-making systems which provide much of the information required by the credit institutions on credit management.

The purpose of credit rating models is to predict the risk of non-repayment of credit by the client and to classify the applicants into two groups of creditworthy and non-creditworthy. In the other words, credit rating is a set of decision-making models and related methods which helps the credit institutions in granting the credit to customers (Tehrani et al., 2009). Among the risks which the bank faces in its vast performance, credit risk evaluation and measurement plays an important role. Reducing and controlling the risk, as one of the factors affecting the improvement of credit granting process and, consequently, banks performance, has a fundamental role in the continuation of providing the convenience and profitability and the survival of the banks and financial institutions. Studying the risk management, you will face various techniques, methods and tools which can be used after identifying the type of risk.

The development of banking activities having an efficient system will be very effective in the economic development of country. It will cause the bank survival in the competitive environment. In the other words, the success of banks and credit institutions in credit operations not only ensures the survival of banks and credit institutions in the long run, but also provides an economic growth and development for the Islamic homeland. One of the major activities which ensure the success of banks and credit institutions is the allocation of resources. Obviously, the national banking sources the major part of which consists of the people savings are a part of the national capital. The correct guidance this source to the economic activities through an efficient system of allocation of credit is essential in the banking industry of the country (Karami, 2004). Banks can allocate their resources to their customers optimally and effectively when they have a good system in valuation and classification of their customers in the time of credit granting. In many countries of the world a variety of strategies and solutions has been used in this regard. In our country, this issue is of great importance due to Islamic banking and allocation of the credit to natural and legal clients in Islamic contracts.

Therefore, the banking industry must try to design some appropriate systems to assess the clients for granting the financial facilities. This system will be efficient and effective when it has appropriate criteria for evaluation of customers before granting the financial facilities so that the banking facilities are allocated to the appropriate customers through this system. From the perspective of the bank, the appropriate customer is a customer who can return the received banking facilities to the banking system on time while spending these facilities in different economic sectors. Failure in timely repayment of loans will bring lack of success in receiving these banking facilities. In other words, the efficiency of the use of facilities was lower than bank interest. Therefore, these facilities will be converted to the bad loans. In addition to disruption in financial system and the economy, it causes some problems for banking system in the long run. The important issue for banking system and consequently for any country is to evaluate the ability of customers to repay before granting the financial facilities to them.

Currently, in the banking system of our country, failure to repay the loans has become one of the biggest issues. Due to the lack of a proper system for optimal allocation of facilities, they face a lot of problems including the allocation of funds, the inability to repay the loans of the central bank and a high content of financial facilities compared to the repayments. Customer credit rating is one of the ways to solve this problem. It means that banks and credit institutions give some points to their customers based on some valid criteria and determine their rate for granting financial facilities according to these points. In the last decade, researchers have used various systems to advance this strategy. These systems also have some problems. Therefore, multiple criteria decision making and artificial intelligence hyperbolic regression systems can solve the problems in wider range and improve the e effectiveness and efficiency of the solution to these problems.

The main objective of the study are as following:

Rating the actual customers based on credit risk and estimating their financial power to repay their debts in due date according to Agriculture Bank clients' information.

1) The secondary objectives of the study To determine the credit point of each customers receiving the facilities in the studied branches.
2) To determine the probability of repayment and none-repayment of customers receiving the facilities in the studied branches.

To group the existing customers and to predict the desired group for new customers in the studied branches.

To predict the credit point and the probability of creditworthiness for new customers in the studied branches

The main research question: What is the point of the actual customers receiving the facilities in the studied branches?

The secondary research questions:

- How is the grouping process of the existing customers in the studied branches?
- How is the prediction of the desired group for new customers in the studied branches?

In this study, credit risk has been considered as the dependent variable. The independent variables related to the natural persons are as follows:

1. The applicant income 2. Occupation 3. The type of collateral 4. The value of collateral 5. The duration of the relationship with the bank 6. The average account balance 7. The consumer credit in the market

2. Literature Review

Shamspour and Weil (2019) used a large sample of firms from nine European countries; this study examined the relationship between bank efficiency and the cost of credit for borrowing firms. They hypothesize that bank efficiency – the ability of banks to operate at lower costs – is associated with lower loan rates and thus lower cost of credit. Combining firm-level and bank-level data, they find support for this prediction. The effect of bank efficiency on the cost of credit varies with firm and bank size. Bank efficiency reduces the cost of credit for SMEs, but does not exert a significant influence for either micro companies or large firms. Furthermore, the effect is driven by large banks, where improvements in bank efficiency tend to be strongly associated with lower cost of credit. They also found that lower bank competition facilitates the transmission of greater bank efficiency to lower cost of credit. Overall, their results indicated that measures that increase bank efficiency can foster access to credit. Azvedo et al., (2019) founded that credit portability is frequently advocated as a mechanism to foster competition in the banking industry, to lower spreads and to contribute to the development of financial intermediation. Yet there were no empirical studies that measured the effect of this policy on spreads. This article evaluated the effect of the portability resolution in the Brazilian credit market that was intended to facilitate borrowers to change from one financial institution to another whenever they have access to better credit conditions. By lowering switching costs, the portability resolution promotes competition among incumbent banks and consequently reduces credit spreads. Using difference-in-differences with matching estimation for 231 Brazilian financial institutions, they found that credit spreads for types of credit susceptible to portability become significantly lower than credit spreads for other types of credit that were not benefited by the new law. Wang et al., (2018) showed that if the market credit status is relatively poor, the supplier prefers to adopt only the screening mechanism. Otherwise, the supplier attains more leeway to decide whether to transfer risk via the insurance mechanism or to undertake risk via the screening and checking mechanisms based on the tension between the credit incentive effect and the default risk gap effect. According to Rosen and Saunders (2009) believed that Multi-factor credit portfolio models are used widely today for managing economic capital and pricing collateralized debt obligations (CDOs) and asset-backed securities. Commonly, practitioners allocate capital to the portfolio components (sub-portfolios, counterparties, or transactions).

The hedging of credit risk is generally also focused on the 'deltas' of underlying names. Rosen and Saunders (2009) presented analytical results for hedging portfolio credit risk with linear combinations of systematic factors, based on the minimization of systematic variance of portfolio losses. They solved these problems within a multi-factor Merton-type credit portfolio model, and applied them to hedge systematic credit default losses of loan portfolios and CDOs.

Mousavi and Gholipour (2007) have conducted a research entitled ranking the validation criteria of bank customers by using Delphi approach. 5C variables including the character, capacity, capital, collateral and conditions each of which has some subcategories have been investigated. The results showed that there is difference between 5C criteria in terms of importance according to experts. The most important criterion is collateral. Capacity, character, capital and conditions are less important, respectively.

Mohammad Khan and colleagues (2007) have conducted a research entitled designing the evaluation model of credit risk of bank customers using logistic regression. The research variables included liquidity ratios, activity ratios, investment ratios and profitability ratios. The results based on the findings of this study showed that the logistic regression model can predict the probability of bank customers' failure in a suitable. It covered the goodness test and related processing. It has shown that it can be used for deciding on customers applying for a loan. Mohtashami and Salami (2007) have conducted a research entitled the factors distinguishing the low-risk and high-risk legal customers: Case Study of Agriculture Bank by using the Diagnostic Analysis. The results of this study show that, among the factors influencing the credit characteristics of the company's management, bank account number, the guarantor and the number of bad cheques are very important in make a distinction between the borrowers who will repay and those who will not.Saberi, Esmail (2007) has conducted a research entitled the credit risk management and its implementation in Karafarin Bank using the Spearman test and discriminant analysis. The variables are liquidity ratios, activity ratios, leverage ratios, profitability ratios, company work experience, number of bad cheques, commitment to other banks and last year profit. The results showed that A) there is a significant relationship between the indices of credit risk and performance of obligations by customers, B) the original audit function method could predict 67 percent of delayed members and 91 percent of on time customers correctly and C) cross-validation method based on U method could predict 100 percent of delayed members and 91 percent of on time customers correctly.

Sabzevari, Hamid (2007) has conducted a research entitled designing and explaining the credit risk model in the banking system using linear probability model, logistic regression and perceptron model neural networks. The variables included customer credit history, type of loan, the loan amount, loan due time, deferred payments number, accounting and financial ratios and company activities. The results showed that A) there is no significant relationship between the credit rate and credit risk, B) there is a direct relationship between the loan due time and failure to repayment, C) there is a significant relationship between the financial ratio and failure to repayment, D) there is a significant relationship between industrial activity and credit risk and E) perceptron model and logistic model are more efficient.

In a study entitled the factors affecting the credit risk of bank customers, Arabmazar and Rouyintan (2006) have conducted a case study of Agriculture Bank. The purpose of this study was to identify the effective factors and develop a model for assessing the credit risk of legal customers of Iran Agriculture Bank using logistic regression method. For this purpose, the qualitative and financial information of a random sample of 200 companies which receive credit facilities from Agriculture Bank branches in Tehran during the years 2012 to 2016 have been investigated. In this study, 36 descriptive variables including qualitative and financial variables have been determined and investigated. Among the available variables, 17 variables which had a significant effect on credit risk and separation of creditworthy and non-creditworthy customers were selected using the logistic regression analysis. The final model was processed by them. In addition to endorsement of the economic and financial theories regarding the factors affecting the credit risk, the results show that the factors affecting the credit risk of legal customers of Agriculture Bank have a large overlap with factors affecting the credit risk of legal customers of other banks (including Mellat Bank and Export Development Bank).Tehrani and Falah Shams (2005) have conducted a research entitled designing and explaining the efficient model of allocation of banking facilities using neural networks and linear and logistic regression. The research variables include type of activity, activity history, registered capital, the company's management activity history, total current assets, total fixed assets, total assets, total current liabilities, total turnover of the debtor in the branch, total turnover of creditor in the branch and return on investment. The results of the study showed that neural networks behave like the logistic regression model in the estimation of binary variables. In the case of estimating the credit capacity, the artificial intelligence processed hyperbolic regression model is more efficient. In addition to suitable slope, it has high coefficient of determination compared to the linear regression model. In a study entitled ranking the banks and credit institutions according to the decision making models Khalili Araghi and Asgharpour (2005) wanted to improve the decision making regarding the granting of credit to the bank customers. They use the credit risk management to rank the banks. The majority of businesses of financial institutions such as banks, insurance companies, pension funds and companies financing are to give a loan. Moreover, to earn more profit, these institutions must be successful in the full repayment of their loans by customers. In other words, their credit risk must be low. In the absence of paying attention to credit risk management and its reduction, the behavioral risk may occur. It has been concluded that the regression model prediction is more accurate compared to other models of decision-making. It is closer to reality. Glantz (2004) have called the risk of non-repayment or the payment of the principal and interest of facilities granted by banks and other debt instruments by client "the credit risk". Designing a model to measure and rate the credit risk was performed by John Murray on the bonds for the first time in 1909.

Altman (1968) has conducted a research entitled the credit risk measurement of released bonds using multivariate scoring which is known as Z score model. Altman's Z score model is a discriminant analysis model which tries to distinguish the companies with financial distress by using key financial ratios. Due to the fact that the non-repayment of loans is mainly related to the companies which will have financial distress in the future, it will be possible to predict the credit risk by using this model. The results showed the 75 percent prediction of the model. To achieve the above-mentioned model, Altman select the following five variables among 22 variables (financial ratios) after discriminant analysis. The relationship between these five variables in Altman Z model to predict the credit score of the borrower is estimated as follows:

$$Z = 1/2X_1 + 1/4X_2 + 3/3X_3 + 0/6X_4 + 0/999X_5$$

Desaei and colleagues (1998) have conducted a study entitled classification of international loans customers through using some techniques such as the linear analysis of audit and logistic regression. The customers (from America, Germany and Australia) of this study have been divided into three categories of good, poor and bad. It has been concluded that classification into two categories of good and bad is preferred. The determined variables and collected data from artificial intelligence hyperbolic regression have been used to classify the customers into two categories of good and bad. The results showed that the prediction and accuracy of artificial intelligence hyperbolic regression are more than linear audit analysis techniques and logistic regression.

3. Methodology

The present study is an applied research in terms of the objective. It can be used to make the credit risk theory practical in Agriculture Bank of West Mazandaran, Iran. Based on the method used to obtain the required data, scientific researches can be divided into descriptive and experimental researches. Therefore, given the description of the studied conditions and phenomena, it is a descriptive research. It has been conducted for better understanding of the situation and helping the decision-making process. The data will be used to provide a reasonable plan to amend or modify the existing conditions. In terms of the relationship between the variables, it is a comparative research since it wants to compare the relationship between independent variables and the dependent variable.

In this research, the aim is to achieve an equation which can be used to predict the customers' behavior for their obligations according to the identified indices. In terms of collecting the information, it is a cross sectional study which has been conducted in the years 2012 to 2016. Given that it investigated the issue in an organization, it can be called a field study.

3.1. Statistical population

Before providing any statistical model, it is necessary to identify the target statistical society accurately. In this case, an appropriate sampling method can be used according to the qualitative and quantitative dimensions. Therefore, the credit regulation of the bank which has a direct impact on the structure of the population must be investigated. According to the existing regulations in the banking system, after the loan due date, two-month deadline is given to the borrower to settle the account. After this period, in the case of non-repayment of obligations by the borrower, the contracted facilities will be transferred to another headline named past due repayment. In the absence of implementation of commitments, the contracted facilities will be transferred to another headline named delayed commitments. This procedure divides the population into two groups of creditworthy and non-creditworthy. Creditworthy clients are these who settle the loan on due date and non-creditworthy clients are these who underdo their loan obligations.

This study evaluates the actual customers. The studied population include about 100 actual customer's credit file of Agriculture Bank in West Mazandaran, Iran. The bank is now considered a pioneer bank in offering variety of banking services through its 1,914 branches nationwide, including 476 rural branches, 1182 urban branches, and 72 branches based in other organizations. For the past decade, the bank has been successful in meeting its objectives, especially financing the agriculture sector through active participation in monetary and financial markets and relying on adequate resources mobilization. Considering the evaluation indicators, only 80 cases have had complete information. These cases have been divided into two groups of creditworthy (having no delayed commitments) and non-creditworthy (having delayed commitments) clients.

3.2. Data collection method

At the beginning of the work, the required information is collected using the resources available in the library and articles in accredited journals. By finding the necessary indicators through consulting with experts and assessors of Agriculture Bank, the issue will be investigated using the multi-criteria decision-making and artificial intelligence hyperbolic regression methods.

3.3. The data collection tool

The required information is gathered in two ways. First, the required indicators to assess the credit risk will be identified through interviews with experts. The most important parameters and coefficients will be obtained by using Spss 20 through pairwise comparisons questionnaire. Then, the required information will be collected from the available cases and analyzed via appropriate software.

3.4. Data analysis method

In this study, the purpose of the analysis is to determine whether the customer will be able to repay its debt to the bank or not. To achieve this goal, the following two methods will be used:1.Multi-Attribute Decision Making ;2.Artificial Intelligence Hyperbolic regression.

3.5. Indicators related to actual customers

Given the fact that the actual customers have no attributable financial reports in the bank, a trusted source that can be used is the banking forms. In addition to the information regarding the account balance and the account turnover of applicants, the bank will ask the applicant to fill the forms when requesting the banking facilities. Based on these two sources of information and experts' views, 17 criteria were identified as follows:

1.The year of using the facilities 2. The amount of granted facilities 3. The duration of facilities repayment 4. The applicant's revenue 5. Education 6. Occupation 7. Work experience 8. The age of customer 9. Gender 10. Customer credit rate 11. Marital status 12. Type of collateral 13. The value of collateral 14. The duration of the relationship with the bank 15. The number of taken loans 16. Average account balance 17. Loan type Given that a number of identified factors are not very important in the field of research, 7 indicators were considered for this research in coordination with professors and experts of Agriculture Bank:

1. The applicant's revenue 2. Occupation 3. The consumer credit in the market 4. Type of collateral 5. The value of collateral 6. The duration of the relationship with the bank 7. Average account balance.

3.6. Inferential analysis

The main question: How is the actual customers' rating based on credit risk? To rate the actual customers based on credit risk, artificial intelligence hyperbolic regression model is used. Using the part related to the artificial intelligence hyperbolic regression in the SPSS 20 software, the output tables will be analyzed. Table 4-1 summarizes the process of observations related to the artificial intelligence hyperbolic regression

Table 1: The process of observation

Percent	Number	sample observations
52/5	42	Training
47/5	38	Testing
	80	Total

As seen in the table above, 42 (52.5%) cases of observation include the training part of the artificial intelligence hyperbolic regression and 38 (47.5%) cases include the learning principles of the artificial intelligence hyperbolic regression. Diagram 1-4 represents the learning principles and the commands of classification function for defined indices related to the actual customers of Agricultural Bank, the west branches of Mazandaran province in Iran.

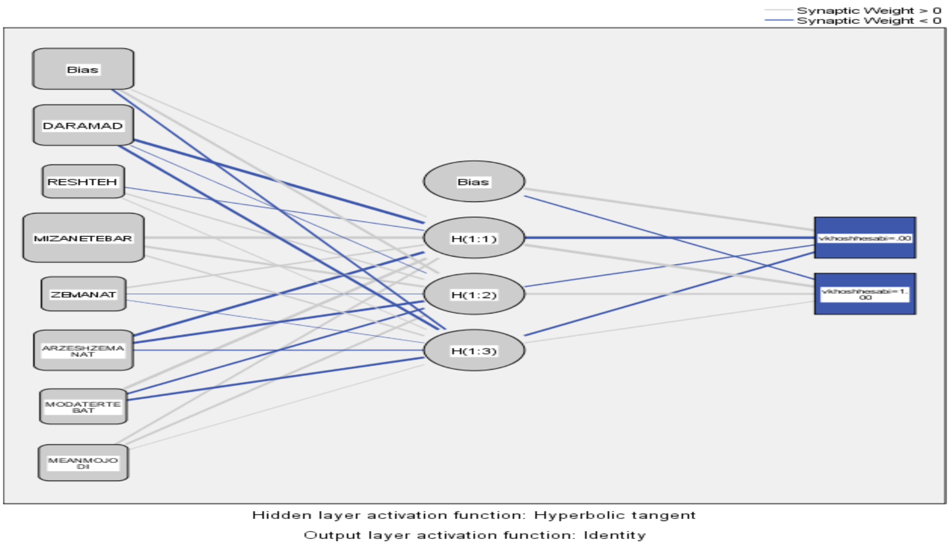

Diagram 1: the learning principles and the commands of classification function for defined indices related to the actual customers of Agricultural Bank, the west branches of Mazandaran province in Iran

The active function of classified layers includes 4 layers with a layer of bias on the basis of hyperbolic effects. The dependent variable levels are defined as 0 (for non-creditworthiness) and 1 (creditworthiness). Table 2-4 represents the classification of the type of customer account and predicted values in both training and testing groups.

In the above table, in 7 cases of the training group, the clients were non-creditworthy. By using the learning principle of the artificial intelligence hyperbolic regression, they are called non-creditworthy. The predicted values called them creditworthy. The correct percentage in the training sector for 0 which shows the non- creditworthiness is equal to 87.5% which is more than 80%. Therefore, the non-creditworthiness is desirable and significant. It shows that the learning principles are appropriate and based on the defined performance. It is related to the creditworthy part of the artificial intelligence hyperbolic regression which performs very well and presents the creditworthy clients as creditworthy in all cases.

Table 2: The classification of the type of customer in training and testing groups

Predicted values			observed	Sample
Percent of correctness	**Creditworthy**	**Non-creditworthy**		
87/5	1	7	Non-creditworthy	Training
100	24	0	Creditworthy	
91/7	1	11	Non-creditworthy	Testing
100	26	0	Creditworthy	
%97/4	%71/1	%28/9	Total Percent	

In the testing part of the artificial intelligence hyperbolic regression, 12 cases were studied. In 11 (91.7%) cases, the non-creditworthy clients were presented as non-creditworthy. In 1 case, the non-creditworthy client was presented as creditworthy. The predicted value for non-creditworthy clients is 28.9% and for creditworthy clients is 71.1%. Therefore, according to the above table, in 97.4% of cases, the correct percentage of training and testing parts of the artificial intelligence hyperbolic regression is related to the clients' creditworthiness.

Table 3-4 represents the parameters related to prediction function of the artificial intelligence hyperbolic regression. The dependent variable of creditworthiness is based on indices of revenue, occupation, the credibility of the type of collateral, the duration of the relationship with the bank and the average account balance of six months.

Table 3: Parameters estimation

Output layer Code = creditworthiness type	Predicted H (1,3)	H (1,2)	H (1,1)	Predictive variables
	-0/272	0/475	0/116	The amount of bias (Bias)
	-0/506	-0/028	-0/87	Revenue
	0/086	0/174	-0/06	Job
	0/194	0/627	2/139	Credibility
	-0/025	-0/055	0/279	Collateral
	-0/125	-0/639	-0/641	Value of Collateral
	-0/515	-0/351	0/682	validity duration
	0/057	0/467	0/320	Average account balance
0/831				Bias
-1/039				H (1,1)
0/126				H (1,2)
-0/421				H (1,3)

In the above table, the predictive factors have been predicted based on three functions of hyperbolic effects related to training and testing the artificial intelligence hyperbolic regression. In function of H (1, 1), the fixed value or the bias of the variables in the artificial intelligence hyperbolic regression is equal to 0.116. In the functions of H (1, 2) and H (1, 3) are equal to 0.475 and 0.272, respectively. The coefficient of revenue in the functions of H (1, 1), H (1, 2) and H (1, 3) is -0.87, -0.028 and -0.506, respectively. The minus sign for non-creditworthy code indicates that the actual customers with higher income are less creditworthy.

In the case of occupation in the function of H (1, 1), the coefficient of occupation in the artificial intelligence hyperbolic regression is equal to -0.06 which has an inverse relationship with non-creditworthiness. There is an inverse relationship between the value of the collateral and non-creditworthiness. According to the training and testing parts of the artificial intelligence hyperbolic regression, the lower collateral value makes the clients more creditworthy. The average account balance and credibility in functions of H (1, 1), H (1, 2) and H (1, 3) is positive. It shows that the average account balance plays an important role in clients' creditworthiness and non-creditworthiness.

Table 4-4 represents the classification of the independent variables of the artificial intelligence hyperbolic regression based on importance index.

Table 4: The classification of the predictive variables of the artificial intelligence hyperbolic regression

Normalized importance index	Importance indicator	Predictive variables
%48/1	0/198	Revenue
%3/3	0/0140	Field
%100	0/412	Credibility
%8/9	0/037	Collateral
%46/1	0/190	validity duration
%15/1	0/062	Average account
%21/5	0/088	balance

As seen in the above table, the validity has one hundred percent importance. To prioritize the actual customers, it is classified based on the credit risk.

The second important factor in prioritizing the customers based on credit risk is the monthly income of the customers. The third factor is the value of the collateral which is defined by bank and the client while performing the banking transactions and granting the loans. The fourth factor is the average account balance of six months. The validity duration of the collateral and the client's occupation are the last priorities.

Diagram 2-4 represents the column chart related to the importance of predictive variables for the variable of the type of creditworthiness.

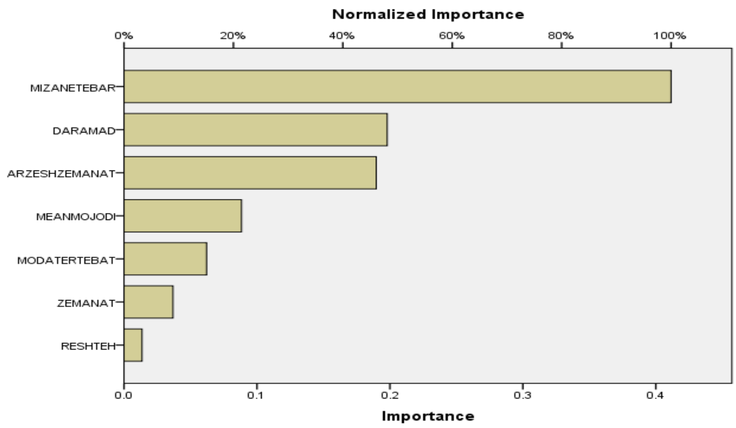

Diagram 2: The column chart related to the importance of predictive variables for the variable of the type of creditworthiness

3.7. AHP method

In order to use the method of AHP for the research question, the research problem is divided into some easier parts. Then, the specified options and indicators between the indices of pairwise comparisons are ranked. These indices are gathered according to the responses of questionnaire given to the experts and assessors of Agriculture Bank. Therefore, they follow the following algorithm:

a) Normalizing the pairwise comparison matrix after defuzzification
b) Using the arithmetic mean of each row of normalized matrix of pairwise comparison
c) Multiplying the relative weights of indicators in the arithmetic average of the options
d) Ranking the options

The secondary question: Who are the actual clients based on the receiving credits and how can we rank them?

Target level: Prioritizing the actual customers of Agriculture Bank

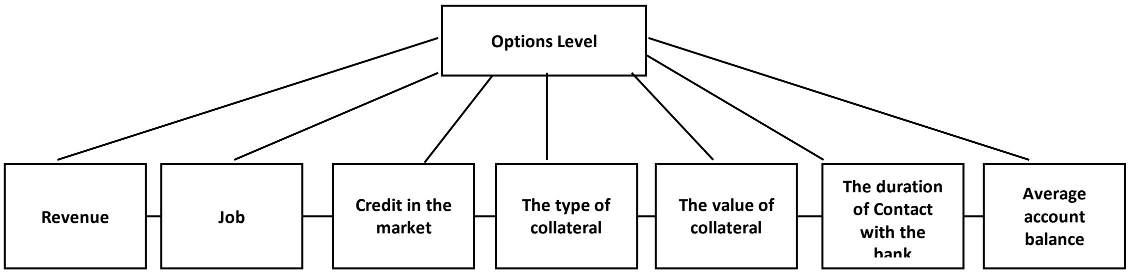

Figure 1. Hierarchical tree of research

Table 5: Index matrix based on the repayment of the facilities

Repayment of customers	A1	A2	A3	A4	A5	A6	A7	The degree of importance
A1	1	3	2	5	4	3	3	0/295
A2		1	0/33	2	3	0/5	0/33	0/103
A3			1	2	2	2	4	0/205
A4				1	2	3	0/5	0/097
A5					1	2	4	0/111
A6						1	2	0/092
A7							1	0/097

Table 6: Index matrix based on the credit risk regarding the customers

Credit risk	A1	A2	A3	A4	A5	A6	A7	The degree of importance (EX.C Software)
A1	1	6	0/11	3	4	0/142	5	0/163
A2		1	0/33	2	1	0/5	0/33	0/097
A3			1	3	2	2	4	0/299
A4				1	3	5	0/5	0/132
A5					1	4	3	0/107
A6						1	6	0/155
A7							1	0/046

Customer commitments	A1	A2	A3	A4	A5	A6	A7	Average
A1	1	0/5	0/33	4	3	0/166	0/142	0/096
A2		1	0/33	5	6	0/33	0/5	0/152
A3			1	4	3	5	3	0/274
A4				1	2	4	2	0/120
A5					1	0/5	3	0/073
A6						1	0/5	0/149
A7							1	0/136

Table 7: Weight matrix of indicators

Indicators	Repayment of the facilities	The credit risk	Customer commitments	The degree of importance
Repayment of the facilities by the customers	1	7	3	0.659
The credit risk to the customers		1	0/25	0/079
Customer commitments			1	0/263

Thus, the weighted average of indicators will be as follows:

Table 8: AHP index weighted average

Repayment	0/659
Credit risk	0/079
Commitment	0/263

Table 9: AHP options weighted average matrix

Credit Factors	Repayment of the facilities 0/659	Credit risk 0/079	Commitments 0/263
A1	0/295	0/163	0/096
A2	0/103	0/097	0/152
A3	0/205	0/299	0/274
A4	0/097	0/132	0/120
A5	0/111	0/107	0/073
A6	0/092	0/155	0/149
A7	0/097	0/046	0/136

Now, the weight of indices similarity is multiplied in the relative weighting matrix of options according to each index. The options will be ranked accordingly. Therefore, there is:

Table 10: The final weight vector matrix of AHP options importance

Options	The final weight	Weight row
A1	0/23259	1
A2	0/115516	3
A3	0/230778	2
A4	0/109403	5
A5	0/104797	6
A6	0/11206	4
A7	0.103325	6

4. Results

To prioritize the actual customers based on credit risk was used the artificial intelligence hyperbolic regression model. The learning principles of the artificial intelligence hyperbolic regression have been tested and evaluated. Creditworthiness has been defined as 1 and non-creditworthiness has been defined as 0.According to the multiplication of the ab normalized matrix (table10), the options are ranked.

Accordingly, the actual customers will be prioritized so that the customers' income with the weight of 0.23259 is the best option and the first priority, credibility in the market with the weight of 0.230778 is the second priority, customers occupation with the weight of 0.115516 is third priority, the duration of the relationship with the bank with the weight of 0.11206 is the fourth priority, the type of collateral to obtain the bank loans with the bank with the weight of 0.109403 is the fifth priority, the value of collateral with the weight of 0.104797 is the sixth priority and the average account balance with the weight of 0.103325 is the seventh priority.

In prioritization based on the artificial intelligence hyperbolic regression model, customer credibility in the market is very important. It has been classified based on the credit risk. The second important factor in prioritizing the customers based on the credit risk is related to the customers' monthly income. The third factor is the value of collateral which is determined by the bank and the client while performing the banking transactions and granting the loans. The fourth factor is the average account balance of six months. The validity duration of the collateral and the client's occupation are the last priorities. In AHP algorithm, according to the multiplication of the abnormalized matrix, the options are ranked. Accordingly, the actual customers will be prioritized so that the customers' income is the best option and the first priority, credibility in the market is the second priority, customers' occupation is third priority, the duration of the relationship with the bank is the fourth priority, the type of collateral to obtain the bank loans is the fifth priority, the value of collateral is the sixth priority and the average account balance is the seventh priority.

5. Discussion and Conclusions

Using the artificial intelligence hyperbolic regression, it can be concluded that, in terms of ranking the actual customers in providing the banking facilities, considering the customer credibility in the market is the highest priority. Evaluation of reputation and credibility of the applicant as well as his rectitude in the financial operations and activities of the market are the best indicators to reduce the credit risk. It can be concluded that the customers monthly income along which their credibility in the market is another important priority. The financial power of the customers to pay bank loan reduces the bank's risk. The second priority in ranking the actual customers according to the artificial intelligence hyperbolic regression is the value of the collateral. The average account balance, duration of customers relationship with the bank and their occupation are the next priorities and extend the atmosphere of trust. It is worth mentioning that the prioritization of the artificial intelligence hyperbolic regression has been done using the clients documents available in the banks. In AHP method, it is done according to the experts views. Therefore, according to the research findings, it can be concluded that the customers who try to increase their honesty and trustworthiness in performance of obligations will be more successful in getting the bank credits.

According to findings of research, we suggest for future research based on first question as following:

1) It is recommended to the senior bank managers to control the bank's risk by classifying the customers according to their credibility in the market in order to ensure the collection of receivables and to provide more banking facilities and services.
2) It is recommended to the senior bank managers to study the customer turnover thoroughly in order to provide more banking facilities and services. The amount of collateral should be determined according to customers received facilities.
3) It is recommended to the senior bank managers to implement this system in order to achieve effective and appropriate decisions with respect to credit policies and credit strategic programs of financial institutions as well as considering the lending priorities in terms of risk and return.

Further above, we suggest for future research based on the second question as following:

1) It is recommended to the senior bank managers to prioritize the natural and legal customers based on the amount of credibility in the industry market in order to create turnover and fair banking facilities. Classification of companies and private individuals into two groups of high credit risk and low credit risk or creditworthy and non-creditworthy can provide the financial security and capital return based on the credits provided by the banks.
2) It is suggested to the bank managers and officials to classify the financing facilities payment guarantee based on the economic activity of the customers. The client’s turnover power must be considered as the basis.
3) It is suggested to the bank managers and officials to evaluate the possibility of repayment before granting facilities. Base on the customers' average account balance of six months, monthly income and their credibility the market, the customers must be ranked.
4) It is suggested to the bank managers and officials to create classified cards in order to classify the facilities. In other words, banking facilities are mostly granted to creditworthy
5) It is suggested to the bank managers and officials to grant the facilities based on the credibility of the applicant and his accuracy in the financial operations and past actions.
6) It is suggested to the bank managers and officials to define the credit domain based on the risk coefficients obtained for clients. Out of this credit domain, the safety margin must be extended.

In this study, like other studies, there are some limitations. Some of them can be stated. Researches which are done using the questionnaire or records are very time consuming. They must be conducted more accurately. Regarding the topic of this paper, the researcher tries to design the questionnaire so that the matrix form of the questionnaire determines the prioritization. Explaining to respondents and the answers were the main limitations regarding the matrix form of the questionnaire and the short time.

The wide extent of the topic related to the factors influencing credit risk is one of the limitations of this study. Regarding the questionnaire distributed and the trustworthy guidance of supervisor, adviser, experts and assessors of the bank, the indicators which have the greatest impact on the credit risk have been selected.

1) Collecting the financial information of actual customers increased the period of investigation. It was tried to reduce the period of investigation by the help of trusted colleagues.

Due to the time-consuming nature of the investigation, a database of 100 cases has been formed for the actual customers. This database should be expanded in the future to include more information in order to increase the accuracy of model predictions

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