Analyzing Customers Credit Scoring Criteria in Banking Industry Using Fuzzy Cognitive Mapping Approach

Abstract
Credit scoring is one of the fundamental concepts in bank industry, used for analyzing and evaluating the customers who request for facilities. Because of its importance to its profitability, especially in the developing countries, this study aims to propose a fuzzy cognitive mapping approach for analyzing the potential criteria in credit scoring of legal clients. This research is applied in terms of purpose and survey in terms of method. This research has been conducted in several steps. In the first step, after reviewing the literature, the important factors for scoring the bank's legal clients were identified and 29 criteria out of them were selected. In the next step, a primal evaluation of these criteria by 16 experts, resulted in the 12 more important criteria (total debt ratio, return on assets, ratio of fixed assets to equity, average customer account, customer capital, the ratio of the deferred amount to current assets, ownership ratio (equity to total assets), amount of received facilities, borrowing capacity, amount of requested facility, type of guarantee and credit risk of the last period) were used in the modeling process. Due to the need for fuzzy logic regarding subjective judgments in cause-effect relationships between criteria, fuzzy cognitive mapping (FCM) method was used to visualize the relationships among these factors. The results show that the amount of requested facilities, customer capital, borrowing capacity and amount of received facilities, ratio of fixed assets to equity, and average customer account are the critical criteria in credit scoring of the legal clients.
Keywords: Credit Scoring, Banking Industry, Criteria, FCM

Introduction

Risk is considered as an important element in the economic decisions of financial institutions, and ignoring it can face decision-makers with critical challenges (Farre-Danesh and Homayounfar, 2015). Banks play the important role in modern financial affairs. These institutions are not only a suitable platform for monetary control; Rather, they are considered to be effective institutions in rebuilding the economy and ensuring the long-term stability of the macroeconomic stability. If these institutions face risks, they can have adverse and destructive effects on the economies (Bülbül et al., 2019). The banking profession is always susceptible to instabilities due to its unique features such as financial crises and sanctions. However, the factors that cause financial crises in the banking sector are structural in nature. These factors include sudden jumps in credit or irregular lending, rapid expansion of short-term guaranteed credit, asset mismatch, and debt, as well as weaknesses in liquidity management that make it difficult for the banking system to pay its debts. (Delafrooz et al., 2019).

In managing bank liquidity, inefficiency can create a risk of not being able to repay obligations, which can lead to further risk. To address this, the Basel Committee - the highest international body involved in banking supervision - has focused on creating a solid framework for managing risks in banks. Bank managers are obligated to continuously follow the process of identifying, measuring, monitoring, and controlling risk to ensure the desired level of liquidity is maintained. Failure to manage credit risk appropriately, which accounts for about 80% of a bank's balance sheet, is often interpreted as the cause of bankruptcy. Therefore, banks and financial institutions can take measures to eliminate or reduce credit risk using appropriate risk management. The importance of risk management has been highlighted by experts such as Tsiga et al. (2017). Credit risk management is an essential tool for evaluating customers to minimize the risk of value maximization. Its purpose is to assess the creditworthiness of customers and their financial ability to repay the received facilities. Banks use this process to grant facilities to customers who have a low risk and a return commensurate with the benefit of the granted facilities. Therefore, it is important for banks to properly identify their credit customers, both real and legal, and select customers based on their ability and willingness to fully and timely repay their obligations. This is achieved by investigating appropriate financial and non-financial criteria.

Banks consider risk as a failure to achieve goals. To remain profitable, banks use managed risk as a crucial tool. Credit risk, which includes unpaid debts and loans, is one of the primary types of risks in the banking industry. It signifies the inability of debtors to meet their financial obligations within the agreed-upon time frame. Banks face credit risk when this happens. Implementing customer credit risk management systems can help reduce direct and indirect costs, income diversity, and negative activities in financial markets. It can also improve the decision-making process for choosing the best investment opportunities. Credit risk and overdue bank claims are some of the manifestations of corruption in countries' economies. There have been a few studies conducted in the field of validating legal clients. However, none of them have taken a comprehensive approach like the one considered in the current research. Most of these studies used questionnaires to collect data from a specific point of view. By combining quantitative data from questionnaires that collect a wider community of opinions and qualitative data from interviews that explore the views and experiences of people related to the validation of legal clients, this study provides the possibility of a comprehensive analysis of the issue. The research focuses on the validation components of legal clients of private banks and uses the interpretative structural modeling as an analytical approach to analyze the relationships between the validation elements of legal clients. This approach enables us to stratify validation components and address them effectively.

This research aims to assist banking industry managers in standardizing the validation process for legal clients by identifying the criteria that affect the validation of such clients and exploring their relationships. The main research question is: What factors influence the validation of legal clients and how are they related? To address this question, the paper is structured as follows: Section 2 provides a review of the current literature on credit scoring, including various approaches to studying it. Section 3 explains the research methodology, data collection, and analytical approach. Section 4 describes the modeling steps used to translate the findings into practical outcomes. Finally, Section 5 presents the key results and recommendations based on the research.

Literature Review

Banks have faced several difficulties over the years due to reasons such as inadequate credit standards for facility applicants, poor risk portfolio management, and lack of attention to changes in economic conditions (Bara and Rogero, 2021). The control and management of credit risk are considered the primary problems of banks, which have gained double importance after the recent financial crises and the bankruptcy of large banks. It can be considered the primary cause of bank bankruptcy (Delafrooz et al., 2019). Banks that have better stability and health than others can better absorb negative economic effects and contribute to improving economic stability and growth (Aburime, 2009). Bank failure negatively affects economic growth (Hewitt and Liebenberg, 2011). The stability of the banking industry is vital for maintaining and improving economic stability and increasing customer confidence in the banking system. High levels of unrealized claims of banks and related institutions have created an unpleasant situation (Chamberlain et al., 2018). Continued refusal to repay loans by customers can make banks unable to pay their debts in the long run, reducing the level of investment and their ability to grant credit to customers. This situation disrupts the functioning of the banking system, affecting other economic sectors, creating synergy in the growth of delayed claims (Waeibrorheem and Sukri, 2015).

It is crucial to estimate the creditworthiness of borrowers in the banking industry due to the high number of overdue claims. This estimation helps to check the credit rating (Asteriou and Spanos, 2019; Vural-Yavas, 2020). Credit rating is a decision-making process that uses statistical analysis patterns to help lenders make informed decisions about loan applications. This process reduces the risk of customer defaults (Movahedi et al., 2023). Validation models aim to predict customer behavior based on data related to similar customers, within the framework of credit risk indicators (Yousfi Tzarjan et al., 2021). Several research studies have been conducted in the field of customer validation. For instance, Mousavi et al. (2013) developed a model based on machine learning algorithms and data envelopment analysis to differentiate between good and bad commercial customers of a bank. Modjtahedi and Daneshvar (2020) proposed a new method called NSGA-ELECTRE, which combines the NSGA algorithm with ELECTRE TRI to learn and elicit its parameters through an evolutionary process. This method was applied to six known credit risk datasets and demonstrated outstanding performance compared to the benchmark model, NRGA. Finally, Delafrooz et al. (2019) proposed a model for managing credit risk in banks using the DEMATEL-ANP combined approach. Their data analysis revealed that operational risk, particularly the quality of the facility review process, has the greatest impact on credit risk among the 17 criteria identified from the literature.

In a study by Zhu et al. (2024), the uncertainty of parameters in credit scoring models was considered. They developed two new metrics, worst-case minimum expected cost (WEMC) and worst-case conditional value-at-risk (WCVaR), to estimate the benefit of credit scoring models with uncertain parameters and the loss of using a classification model in scoring, respectively. The study conducted by Yang et al. (2024) proposed a new model for calculating credit scores by improving features and optimizing weights obtained from soft voting. Kozodoi et al. (2022) developed a profit-oriented credit scoring algorithm by examining credit scoring criteria. The proposed algorithm was found to meet multiple criteria simultaneously. Yousefi Tzarjan et al. (2021) used adaptive neural fuzzy inference systems (ANFIS) and recurrent neural network (RNN) based on 5C indicators (personality, capacity, capital, collateral and conditions) to measure the credit score of customers. Ehtsham Rasi et al. (2020) evaluated the credit rating of real bank customers using the AHP method and hyperbolic regression. The study identified customer income, credit in the market, customers' jobs, duration of relationship with the bank, collateral type, collateral value and average account balance as the most important indicators based on the AHP method. Using artificial intelligence regression, prioritization is, in order, the amount of credit in the market, customer income, value of collateral, duration of relationship with the bank, type of collateral and customers' occupation. Maldonado et al. (2020) developed a two-step approach to customer validation. In the first stage, customers whose credit requests can be approved or rejected immediately were identified. In the second stage, additional information was collected for the remaining requests and evaluated using the possible gray set. Zhang et al. (2020) proposed a cost-sensitive multi-sample learning (MIL) approach to assess the credit scores of loan applicants. This approach uses transaction data and individual customer information. Li et al. (2020) investigated the credit scoring problem by combining network information. They used an optimal Bayesian filter to predict loan default risk, assuming that credit scores are estimated based solely on financial data. Based on the research background and theoretical foundations, several factors have been used in credit evaluation, which are summarized in Table 1.

Table 1. Criteria for credit scoring of bank legal clients

Factors	Resource
Debt ratio (total debt to equity)	Wang and Ma (2011), Zhang et al. (2018), Mousavi et al. (2023)
Return on assets	Wang and Ma (2011), Zhang et al. (2021), Mousavi et al. (2023)
Profitability of the last three years	Zhang et al. (2021), Mousavi et al. (2023)
Assets (fixed assets to total assets)	Wang and Ma (2011), Zhang et al. (2021), Mousavi et al. (2023)
History of customer relationship with bank	Ehtesham Rasi et al. (2021), Mousavi et al. (2023)
Average customer account	Wang and Ma (2011), Mousavi et al. (2023)
Customer capital	Delafrooz et al. (2016), Maldonado et al. (2020), Zhang et al. (2021),
Net working capital (assets minus liabilities)	Ullah et al. (2019), Maldonado et al. (2020), Mousavi et al. (2023)
Current ratio (ratio of current assets to current liabilities)	Wang and Ma (2011), Zhang et al. (2018), Zhang et al. (2021)
The ratio of deferred amount to current assets	Wang and Ma (2011), Zhang et al. (2021)
Sales return ratio (net profit to net sales)	Wang and Ma (2011), Maldonado et al. (2020), Zhang et al. (2021)
Ownership ratio (equity to total assets)	Fernandes and Artes (2016), Delafrooz et al. (2016), Ehtesham Rasi et al. (2021)
Activity ratio (current capital turnover ratio)	Wang and Ma (2011), Ehtesham Rasi et al. (2021), Mousavi et al. (2023)
Cash ratio (cash balance to total assets)	Wang and Ma (2010), Delafrooz et al. (2016), Maldonado et al. (2020)
The amount of received facilities	Zhang et al. (2020), Ehtesham Rasi et al. (2021)
Borrowing capacity	Wang and Ma (2011), Zhang et al. (2020)
Current debt to net sales	Wang and Ma (2010), Mousavi et al. (2023)
Short-term loan to net sales	Zhang et al. (2021), Zhang et al. (2020)
Facility period (repayment period)	Zhang et al. (2020), Mousavi et al. (2023)
Rate of rrequested facility	Zhang et al. (2020), Maldonado et al. (2020), Ehtesham Rasi et
The amount of requested facility	al. (2021), Mousavi et al. (2023)
Type of requested facility	Zhang et al. (2020), Zhang et al. (2021)
Type of guarantee (collateral)	Fernandes and Artes (2016), Mousavi et al. (2023)
The amount of the installment on the income	Zhang et al. (2020)
Macroeconomic variables	Chamberlain et al. (2018), Vural-Yavas, C. (2020), Ceylan (2021)
Interest rate	Ehtesham Rasi et al. (2021), Mousavi et al. (2023)
Credit risk of the last period	Mousavi et al. (2023)
Bank profitability	Ehtesham Rasi et al. (2021), Mousavi et al. (2023)
Company size	Ehtesham Rasi et al. (2021), Mousavi et al. (2023)

According to a systematic review conducted on credit scoring studies, most research focuses on crisp methods, specifically discriminant analysis and MADM weighting methods. However, these studies tend to simplify evaluation models to make them easier to understand and implement. This research proposes the use of fuzzy cognitive mapping to bridge the gap between mathematical models and judgmental decision-making. By doing so, decision-makers will be able to improve the credit scoring process.

Methodology

This study applied systems approach namely, fuzzy cognitive mapping, for credit scoring analysis (CSA) in the banking industry. In developing fuzzy cognitive map, using expert knowledge leads to improving the reliability of the final model (Yaman and Polat, 2009). Although determining the exact number of expert group members is challenging, it is recommended that the researcher be in contact with a small number of experts (Ferreira et al.,

2017). Therefore, in the third phase of the research, among all of the experts, a group of 16 experts at Iran Central Bank participated in this study. The index for selecting research experts were their theoretical expertise, practical experience, willingness, and ability to participate in the research. The research process is described in three phases as follows:
The research aimed to identify the important criteria in credit scoring for the banking sector. To achieve this, a literature review was conducted, which found 29 key criteria that are presented in Table (1). Next, experts were asked to share their opinions on these criteria through a Delphi questionnaire, using a five-point scale. The results were then aggregated to determine the average opinion of all experts. Finally, a fuzzy cognitive map was created to model the relationships between the identified criteria. This helped to determine the influence, susceptibility, and priority of each factor through static analysis. It should be noted that, all discussions, inferences, and evaluations related to the identification and comparison of the criteria were determined under consideration of these experts. The data collection tools were interview and questionnaire, where its validity was checked using content validity.

Fuzzy Cognitive Maps (FCM)
Fuzzy Cognitive Map (FCM) was first introduced by Kosco in 1986 as an improvement to Cognitive Mapping. FCM uses a neuro-fuzzy system to analyze complex systems related to decision-making, modeling, and simulation. It consists of a set of neural processing entities called concepts (neurons) and the causal relations among them. The activation value of these neurons ranges from 0 to 1, where the higher the value, the greater the impact on the network. The strength of the causal relation between two neurons is quantified by a numerical weight, Wij ∈ [-1, 1], denoted via a causal edge from Ci to Cj.
In an FCM, causal relationships between neural units can be of three types: positive, negative, and neutral. If Wij has a positive value, it indicates a positive causality between the concepts i and j; whereas a negative value indicates negative causality, and a neutral value means there is no causality.
Kosko's activation rule is illustrated by Equation (1), with A(0) being the initial state. At each step t, a new activation vector is calculated, and after a fixed number of iterations, the FCM will be at one of the following states: (i) equilibrium point, (ii) limited cycle, or (iii) chaotic behavior. The FCM is said to have converged if it reaches a fixed-point attractor; otherwise, the updating process terminates after a maximum number of iterations T is reached. Thus, FCMs can be categorized into three types of relationships and can reach different states depending on the activation rule and number of iterations.

$$A_i^{(t+1)} = f\left(\sum_{j=1, j\neq i}^{M} w_{ji} \times A_j^{(t)}\right) \tag{1}$$

Subsequently, the values A_i^{t+1} and A_i^t, respectively, provide the value of the conceptual variable Ci at discrete times t+1 and t. In this case, A_j^t will be the value of the concept Cj in the t-th iteration of the simulation. In the equation (1), f (0) denotes a monotonically non-decreasing function to clamp the activation value of each concept to the allowed intervals [0,1] or [-1,1]. The function which are more popular are Bivalent, Trivalent, Hyperbolic, Saturation and Sigmoid functions, among them Sigmoid function is used in this paper:

Sigmoid function $$f(x) = \frac{1}{1 + e^{-\lambda(x-h)}} \tag{2}$$

In activation functions, t represents the number of repetitions or simulation steps, and wji indicates the influence value of the conceptual variable Ci from the variable Cj.
Stylios and Groumpos (2004) proposed a modified inference rule for Kosko's activation rule, which considers the neuron's previous value. This rule is preferable when updating the activation value of independent neurons, i.e., neurons that are not influenced by any other neural processing entities.

$$A_i^{(t+1)} = f\left(\sum_{j=1, j\neq i}^{M} w_{ji} \times A_j^{(t)} + A_i^{(t)}\right) \quad (3)$$

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$$A_i^{(t+1)} = f\left(\sum_{j=1, j\neq i}^{M} w_{ji}\,(2A_j^{(t)} - 1) + (2A_i^{(t)} - 1)\right) \quad (4)$$

The first step in the modeling process involves coding and analyzing the adjacency matrix. Once the results of the static analysis have been verified, Fuzzy Cognitive Maps (FCM) are created. In the next stage, the FCM model is executed and simulations are carried out using one of the common activation functions based on the principles of the neural network method. These calculations continue until the system converges, as described by Venhonshoven et al. (2020).
In equation (2), λ is a real and positive number, which determines the slope of the threshold function; x also represents the value of $A_i^{(t)}$ at the equilibrium point. Often, the sigmoid function is used as the activation threshold function; to show that the value of concepts is in the range [0,1]. In this function, the value of λ is generally assumed to be "1"; This value is an estimate for the linear function and has shown better performance than other functions in various studies (Felix et al., 2017). The simulation process continues until the condition presented in equation (5) is met and the modeled system enters the state of equilibrium or convergence. The difference between the next two output values should be equal to or less than epsilon (ε=0.001) (Vanhoenshoven et al., 2020).

$$\left|A_i^{(t+1)} - A_i^{(t)}\right| \leq \varepsilon \quad (5)$$

The FCM network can be characterized by different concepts, including density, input degree, output degree, and centrality index (Kharaghani et al., 2023). Density is a useful measure of connectivity that counts the number of existing connections between mapping concepts as a ratio of all the possible connections. The input degree, which is the degree of influence, for a given concept i is the sum of the values in the column related to that variable i. The output degree, which is the degree of being influenced, is the sum of the values in the row related to variable i in the adjacency matrix. The centrality index is obtained from the sum of the input and output degrees of a given concept, as described in equation 2.

$$Cen(C_i) = \sum_{i=1}^{n}\left|w_{ij}\right| + \sum_{i=1}^{n}\left|w_{ij}\right| \quad (6)$$

In general, using fuzzy cognitive mapping, it is possible to evaluate the impact of concepts on each other, as well as the whole system. By designing "what-if" questions, it’s also possible to simulate different scenarios and evaluate the impact of changes in some concepts on the whole system. The development stages of fuzzy cognitive mapping modeling are presented in eight steps as follows:

- *Step 1. Identification of the factors related to the problem*
- *Step 2. Evaluation of causal relationships among related factors by experts*
- *Step 3. Evaluation of the causal relationships’ intensity among the factors (concepts).*

In this step, the experts were asked to determine the causal relationships' intensity using a linguistic scale (Table, 2). It should be noted that before determining the relevant intensities, a consensus on the direction (sign) of all system effects was reached by experts. In this way, the degree of causality between two concepts will be in the range of [-1,1].

Table 2. Linguistic variables and the equivalent fuzzy triangular numbers (Lin, 2013)

Linguistic Variable	Fuzzy Triangular Numbers
Element i has a crucial influence on element j	(0.75, 1, 1)
Element i has high influence on element j	(0.5, 0.75, 1)
Element i has moderate influence on element j	(0.25, 0.5, 0.75)
Element i has low influence on element j	(0, 0.25, 0.5)
Element i has no influence on element j	(0, 0, 0.25)

Step 3. De-fuzzification of the individual fuzzy influence matrixes. In this step, the fuzzy influence matrixes is fuzzified using equation (7):

$$x_{ab}^{k}=\frac{(\tilde{x}_{ab}^{k}-min\tilde{x}_{ab}^{k})}{\Delta_{min}^{max}},y_{ab}^{k}=\frac{(\tilde{y}_{ab}^{k}-min\tilde{y}_{ab}^{k})}{\Delta_{min}^{max}},z_{ab}^{k}=\frac{(\tilde{z}_{ab}^{k}-min\tilde{z}_{ab}^{k})}{\Delta_{min}^{max}}. \quad (7)$$

Where $\Delta_{min}^{max}=\max(\tilde{z}_{ab}^{k})-\min(\tilde{x}_{ab}^{k})$. The right and left normalized values also are calculated using equation (8).

$$Left_{ab}^{k}=\frac{y_{ab}^{k}}{(1+y_{ab}^{k}-\tilde{x}_{ab}^{k})},\quad Right_{ab}^{k}=\frac{z_{ab}^{k}}{(1+z_{ab}^{k}-\tilde{y}_{ab}^{k})}. \quad (8)$$

The final normalized deterministic value is also obtained from equation (9):

$$W_{ab}^{k}=\frac{\left[Left_{ab}^{k}\left(1-Left_{ab}^{k}\right)+(Right_{ab}^{k})^{2}\right]}{(1-Left_{ab}^{k}+Right_{ab}^{k})}. \quad (9)$$

- *Step 4. Aggregation of the expert opinions.* After de-fuzzification of the individual fuzzy influence matrixes, the average of the experts' judgements, called "aggregated adjacency matrix" will be computed using equation (10)." The elements of the main diameter of matrix are considered equal to zero, which means that no measure leads to its formation.

$$\overline{W}_{ab}=\frac{\sum_{a,b=1}^{k}\left(W_{ab}^{k}\right)}{k},k=1,2,3\ldots,n. \quad (10)$$

- *Step 5. Developing the fuzzy cognitive map*. The analysis of the adjacency matrix from the fourth step, provides important information such as input degree, output degree, centrality index and density of fuzzy cognitive map to analyze the network structure.
- *Step 6. Implementation of the simulation process.* In order to check the dynamic state of the system and using relations (2) and (4), the values of the factors are calculated during the simulation and the new values will repeatedly replace the previous values.
- *Step 7. Checking the termination conditions.* In this step, if one of the conditions presented in relations (5) is satisfied, it means that FCM has provided the last state of all concepts and this is called a uniform state. Otherwise, step 6 needs to be repeated again. After the convergence of the system, it will be possible to present the final values of the concepts (Movahedi et al., 2023).

Findings

As previously mentioned, a review of recent literature on "credit scoring" and consultations with experts from the Iran Central Bank resulted in the identification of 29 important factors (shown in Table 1). These factors were sent to 16 experts in the form of a Delphi questionnaire, and they were asked to determine their importance. Through two rounds of the Delphi technique, a consensus was reached among the experts, and 12 criteria were identified as critical (total debt ratio, return on assets, ratio of fixed assets to equity, average customer account, customer capital, ratio of deferred amount to current assets, ownership ratio, amount of received facilities, borrowing capacity, amount of requested facility, type of guarantee, and credit risk of the last period).

After identifying the 12 critical credit scoring criteria, a questionnaire was designed to include these criteria in the first row and column of a table. The experts were asked to determine the intensity of causal relationships between the factors based on the linguistic variables mentioned in Table 2. Because the judgments of the experts were uncertain and ambiguous, the linguistic variables were converted to triangular fuzzy numbers. The fuzzified matrices of the experts' judgments were then collected, and their average was calculated to form an "aggregated adjacency matrix," as shown in Table 2

Table 2. Aggregated adjacency matrix for credit scoring criteria

Factors		F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}
Debt ratio (total debt to total property)	F_1		-5.76			-7.45		-7.22		-8.45		-4.15	
Return on assets	F_2			-7.1			-5.35	8.17	4.44	6.07		2.86	
Ratio of fixed assets to equity	F_3	-4.72	-7.33			3.88	5.96	6.57	5.34	4.95	6.77	4.97	-5.86
Average customer account	F_4		4.55	3.75		8.59	4.35		6.98	7.29	6.78	4.91	-7.07
Customer capital	F_5		6.14	5.87	7.85			6.74	7.55	8.06	7.32	5.16	-8.01
The ratio of deferred amount to current assets	F_6									-8.50	-8.19	-5.29	
Ownership ratio (equity to total assets)	F_7	7.27					-7.08			6.10	5.62	4.15	
The amount of received facilities	F_8	-7.62		5.39		4.74	-4.27	-6.16				5.33	
Borrowing capacity	F_9								6.86		8.64		
The amount of requested facility	F_{10}						-5.39		9.11	7.06		7.84	
Type of guarantee (collateral)	F_{11}									6.15	8.44		
Credit risk of the last period	F_{12}								-6.57	-5.84	-7.73	-6.99	

During the modeling process, the fuzzy cognitive mapping model's structure was analyzed using the FCM Expert software. The FCM static analysis output, which is based on graph theory principles, was studied. The results of this analysis were presented as the degree of input, degree of output, and centrality index of the credit scoring criteria. Table 3 ranks the affecting actors based on the centrality index, in descending order. It's important to note that factors with higher centrality index scores have more influence and impact on the network and play a more central role in the fuzzy cognitive mapping.

Table 3. Ranking the affecting factors in credit scoring

Factors	Indicator	Input	Output	Centrality
Amount of requested facility	F_{10}	5.949	2.94	8.889
Customer capital	F_5	2.466	6.27	8.736
Borrowing capacity	F_9	6.847	1.55	8.397
Amount of received facilities	F_8	4.685	3.351	8.036
Ratio of fixed assets to equity	F_3	2.211	5.635	7.846
Type of guarantee	F_{11}	5.165	1.459	6.624
Ownership ratio (equity to total assets)	F_7	3.486	3.022	6.508
Average customer account	F_4	0.785	5.427	6.212
Return on assets	F_2	2.378	3.399	5.777
Ratio of deferred amount to current assets	F_6	3.24	2.198	5.438
Debt ratio (total debt to total property)	F_1	1.961	3.303	5.264
Credit risk of the last period	F_{12}	2.094	2.713	4.807

The results have shown that the "Amount of requested facility" has the highest interaction with the system, with a centrality score of 8.889. "Customer capital", "Borrowing capacity", and "Amount of received facilities" have taken the 2nd to 4th place for the total influence point of view. The column related to the degree of output shows the total influence of each concept on other related concepts. The concepts "Customer capital", "Ratio of fixed assets to equity", and "Average customer account" have the highest impact on system factors with an output grade of 6.270, 5.636, and 5.427, respectively. The input degree column provides the total influence of other concepts on a specific concept. "Borrowing capacity", "Amount of requested facility", and "Type of guarantee" have received the greatest influence from the system factors, with input grades of 6.847, 5.949, and 5.427, respectively. Table (3) provides other information on the static analysis of fuzzy cognitive mapping of this research.

Figure (2) presents the FCM graphic structure of the credit scoring. The fuzzy cognitive mapping has 12 concepts connected by 65 arcs that express the causal relationships between the related concepts. The transfer function is considered "Sigmoid", the activation rule is "Kosko's activation rule with self-memory", and the epsilon (Convergence) index is equal to 0.001.

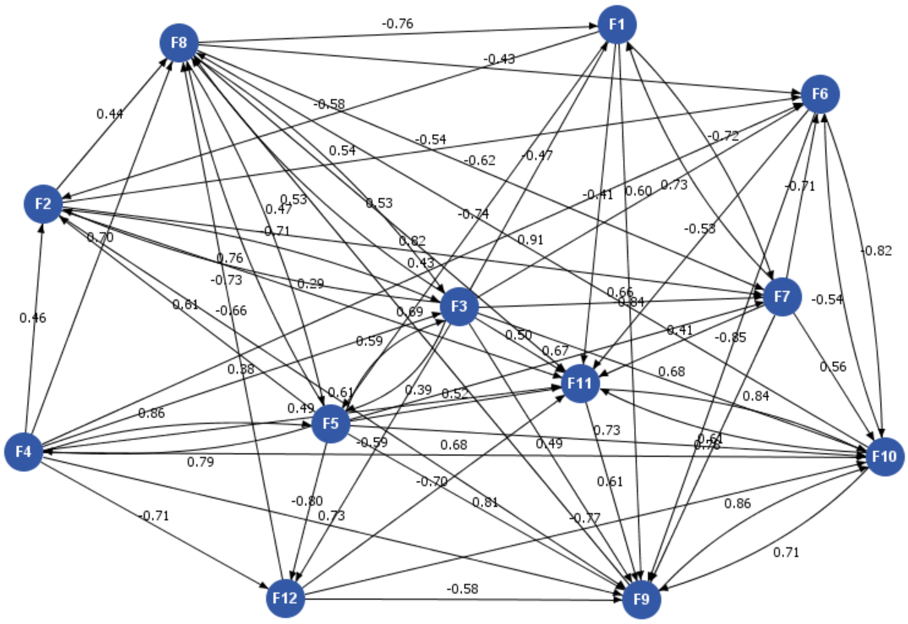

Figure 2. Graphical structure of the criteria for credit scoring

In order to visually understand the fuzzy cognitive mapping in Figure (2), after eliminating the causal relationships with weights less than |±0.7|, the corresponding fuzzy cognitive mapping was again presented in Figure (3); In this way, only the most important causal relationships are displayed and a more accurate understanding of FCM is obtained for the viewer.

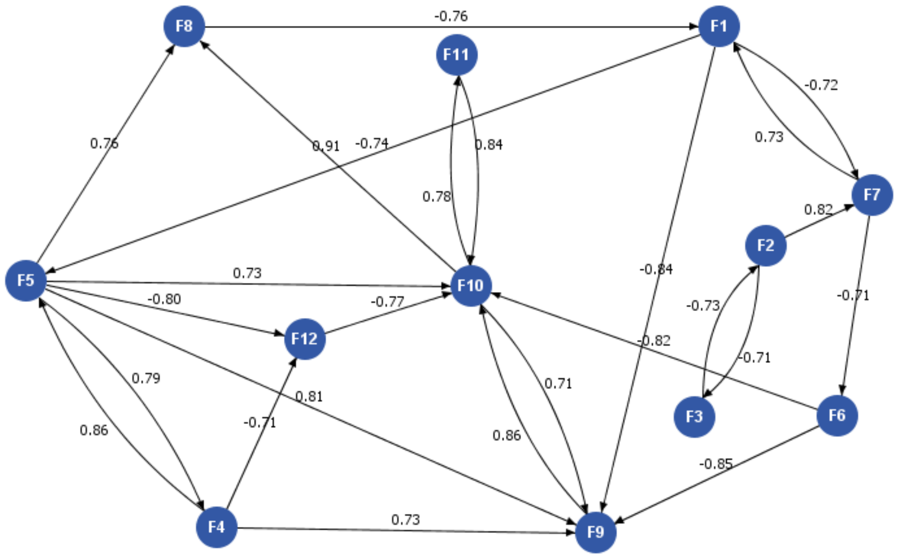

Figure 3. Graphical structure with important causal relationships

The model interface provides a way to perform reasoning using the activation values that are provided. However, before starting the inference process, the user needs to specify the activation values of input concepts that are used to activate the FCM-based system. This can be done by editing the concepts. Once this is done, the results of the inference process can be summarized through a chart and a table that display the activation values of concepts for each iteration. Please refer to Figure 4 for a better understanding.

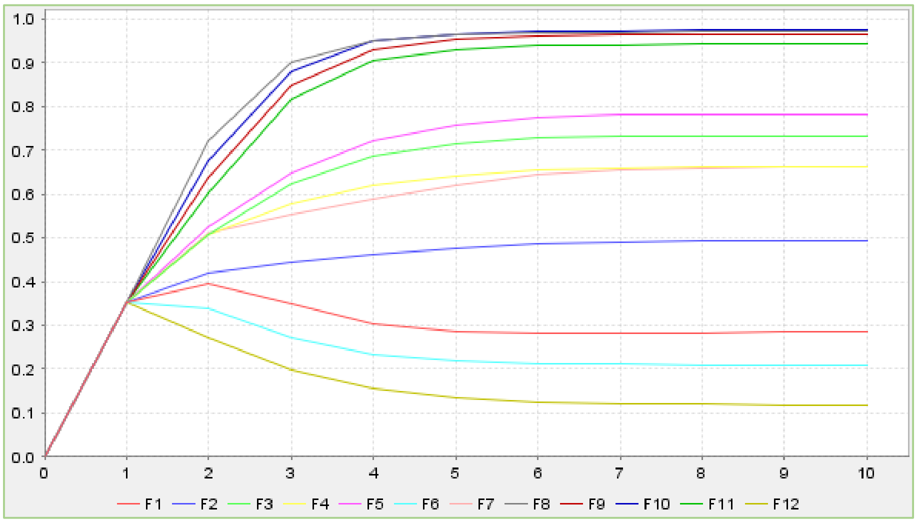

Figure 3. The graphical interface results

The graphical interface visualizes the response vector obtained after adjusting the weights. It should be mentioned that the convergence index (ε) in this research considered 0.001.

Conclusions

Banks need to prioritize risk assessment to evaluate a borrower's ability to repay a loan. This can be achieved by analyzing financial statements, cash flow projections, business plans, and other relevant factors. By considering these factors, banks can better determine the borrower's creditworthiness and minimize lending risks. Some of the most important criteria in credit scoring include the total debt ratio, return on assets, ratio of fixed assets to equity, average customer account, customer capital, ratio of deferred amount to current assets, ownership ratio, amount of received facilities, borrowing capacity, amount of requested facility, type of guarantee, and credit risk of the previous period.

To evaluate customers accurately, banks need to understand these factors. The centrality index values in FCM indicate that the critical criteria in credit scoring can be ranked in terms of their importance. The amount of requested facility has the most significant impact on the credit scoring system. Banks should balance assessing the amount of requested facility with evaluating other critical factors. Customer capital is another essential criterion that banks should consider. They can take an innovative approach to lending by moving towards cash-flow financing, which looks at the future cash flow of a business, rather than customer capital. This approach can help small businesses, startups, or entrepreneurs who may have limited customer capital but strong cash flows. Banks should also thoroughly assess the borrower's borrowing capacity to determine their ability to repay loans. This includes analyzing income sources, debt obligations, savings, and overall financial health. Conducting comprehensive financial assessments will provide a more accurate picture of the borrower's ability to repay loans and help determine their borrowing capacity. Finally, banks should determine the amount of received facilities and provide more specific information about the type of facilities received. For future studies, the credit scoring system could be studied as a dynamic system.

References

1. Aburime, U. T. (2009). Impact of political affiliation on bank profitability in Nigeria, African Journal of Accounting. Economics, Finance and Banking Research, 4(4), 61-75.
2. Asteriou, D., & Spanos, K. (2019). The relationship between financial development and economic growth during the recent crisis: Evidence from the EU. Finance Research. Finance Research Letters, 28, 235-248.
3. Barra, C., & Ruggiero, N. (2021). Do microeconomic and macroeconomic factors influence Italian bank credit risk in different local markets? Evidence from cooperative and non-cooperative banks. Journal of Economics and Business, 19(114),141 – 169.
4. Bekhet, H.A., & Eletter S.F.K. (2014). Credit risk assessment model for Jordanian commercial banks: Neural scoring approach, Review of Development Finance, 4, 20-28.
5. Bülbül, D., Hakenes, H., Lambert, C. (2019). What influences banks' choice of credit risk management practices?" Theory and evidence. Journal of Financial Stability, 40, 1-14.
6. Ceylan, O. (2021). Time-Varying Risk Aversion and its Macroeconomic and Financial Determinants: A Comparative Analysis in the U.S. and French Financial Markets. Finance Research Letters, 41, 101804.
7. Chamberlain, T.W., Hidayat, S., & Rahman Khokhar, A. (2018). Credit Risk in Islamic and Conventional Banking. International Atlantic Economic Society, 24 (1), 99-100.
8. Delafrooz, N., Homayounfar, M., Taghipour Tamijani, M. (2019). Credit risk management in banks using a hybrid approach. Financial Engineering and Portfolio Management, 10 (38), 94-116.
9. Ehtesham Rasi, R., Karimipour, M., & Azad, M. (2020). Rating the Actual Customers of Banks based on Credit Risk using Multiple Criteria Decision Making and Artificial Intelligence Hyperbolic Regression. International Journal of Finance & Managerial Accounting, 4(16), 51-63.
10. Farre-Danesh, K. & Homayounfar, M. (2015). Ranking the affecting factors in performance evaluation of banking sector based on fuzzy AHP. Universal Journal of Management and Social Sciences 5(4), 9-18
11. Fernandes, G.B., & Artes, R. (2016). Spatial dependence in credit risk and its improvement in credit scoring. European Journal of Operational Research, 249 (2), 517-524.
12. Felix, G., Nápoles, G., Falcon, R., Froelich, W., Vanhoof, K. & Bello, R. (2017). A review on methods and software for fuzzy cognitive maps. Artificial Intelligence Review, 52, 1707-1737.
13. Ferreira, F. A. F., Ferreira, J. J. M., Fernandes, C. I. M. A. S., Meidute- Kavaliauskiene, I., Jalal, M. S. (2017). Enhancing Knowledge and Strategic Planning of Bank Customer Loyalty Using Fuzzy Cognitive Maps. Technological and Economic Development of Economy, 6, 860-876. https://doi.org/10.3846/20294913.2016.1213200
14. Ghane, F., Gilaninia, S., Homayounfar, M. (2016). The effect of cloud computing on effectiveness of customer relation management in electronic banking industry: a case study of eghtesad novin bank. Kuwait Chapter of the Arabian Journal of Business and Management Review 5 (8), 52-105.
15. Kharaghani, M., Homayounfar, M., & Taleghani, M. (2023). Value Chains Analysis: Application of Fuzzy Cognitive Map in Pharmaceutical Industry. Journal of System Management, x, xx-xx.
16. Koford, K., & Tschoegl, A.D. (1997). Problems of Banking Lending in Bulgaria: Information Asymmetry and Institutional learning, Financial Institutions center, The Wharton School University of Pennsylvania, Philadelphia, P. A.
17. Koso, B. (1986), Fuzzy cognitive maps. International Journal of Man-Machine Studies, 24, 65-75.
18. Kozodoi, N., Jacob, J., & Lessmann, S. (2022). Fairness in credit scoring: Assessment, implementation and profit implications. European Journal of Operational Research, 297 (3), 1083-1094.
19. Li, Y., Wang, X., Djehiche, B., & Hu, X. (2020). Credit scoring by incorporating dynamic networked information. European Journal of Operational Research, 286 (3), 1103-1112.
20. Maldonado, S., Peters, G., & Weber, R. (2020). Credit scoring using three-way decisions with probabilistic rough sets. Information Sciences, 507, 700-714.
21. Modjtahedi, A. & Daneshvar, A. (2020). A New Credit Risk System Using Hybrid ELECTRE TRI and NSGA-II Methods, Journal of System Management, 6 (4), 1-25.
22. Mousavi, S.F., Eskandari, N., Abtahi, S.A.R. & Gazri Neishaburi, A. (2023). Providing a model to validate legal clients applying for working capital facilities of a commercial bank. The 5th National Conference and the 2nd International Conference on New Patterns of Business Management in Unstable Conditions, Tehran.

23. Movahedi, M., Homayounfar, M., Fadaei Eshkiki, M., Soufi, M. (2023). Development of a model based on fuzzy cognitive map to analyze the performance of stock exchange firms. Journal of Securities Exchange, 16 (61), 41-60
24. Stylios, C. D., Groumpos, P. P. (2004). Modeling complex systems using fuzzy cognitive maps, IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans, 34(1), 155–162.
25. Tsiga, Z., Emes, M. & Smith, A. (2017). Implementation of a risk management simulation tool, Procedia Computer Science, 121, 218–223
26. Ullah, S., Wang, Zh., Stokes, P., & Xiao, W. (2019). Risk perceptions and risk management approaches of Chinese overseas investors: An empirical investigation. Research in International Business and Finance, 47, 470-486.
27. Vanhoenshoven, F., Nápoles, G., Froelich, W., Salmeron, J.L. & Vanhoof, K. (2020). Pseudoinverse learning of Fuzzy Cognitive Maps for multivariate time series forecasting. Applied Soft Computing, 95,106461.
28. Vural-Yavas, C. (2020). Corporate risk-taking in developed countries: The influence of economic policy uncertainty and macroeconomic conditions. Journal of Multinational Financial Management, 54 (124), 17-41
29. Waeibrorheem, W., & Sukri, S. (2015). Bank Specific and Macroeconomics Dynamic Determinants of Credit Risk in Islamic Banks and Conventional Banks. International Journal of Economics and Financial Issues, 5(2), 476–481.
30. Wang, G., & Ma, J. (2011). Study of corporate credit risk prediction based on integrating boosting and random subspace. Expert Systems with Applications, 38 (11), 13871-13878.
31. Witzany, J. (2017). Credit Risk Management Pricing, Measurement and Modelling. Springer.
32. Yaman, D., Polat, S. (2009). A fuzzy cognitive map approach for effect-based operations: an illustrative case. Information Sciences, 179(4), 382–403.
33. Yang, D., Xiao, B., Cao, M., & Shen, H. (2024). A new hybrid credit scoring ensemble model with feature enhancement and soft voting weight optimization. Expert Systems with Applications, 238, 122101.
34. Yousofi Tezerjan, M., Safi Samghabadi, A., & Memariani, A. (2021). ARF: A hybrid model for credit scoring in complex systems. Expert Systems with Applications, 185, 2021, 115634.
35. Zaker Nia, Ehsan, Khadem Alizadeh, Amir. (2016). Principles Governing Validation in Credit Risk Management of Islamic Banking from the Perspective of the Quran, 6 (2), 5-34.
36. Zhang, W., Xu, W., Hao, H., & Zhu, D. (2020). Cost-sensitive multiple-instance learning method with dynamic transactional data for personal credit scoring, Expert Systems with Applications, 157, 113489.
37. Zhang, X., Yang, Y., & Zhou, Z. (2018). A novel credit scoring model based on optimized random forest. In 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 60-65).
38. Zhang, W., Yang, D., Zhang, S., Ablanedo-Rosas, J.H., Wu, X. & Lou, Y. (2021). A novel multi-stage ensemble model with enhanced outlier adaptation for credit scoring. Expert Systems with Applications, 165, 113872.