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Fuzzy Inference System for Credit Scoring: Legal Clients in Banking Industry

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A B S T R A C T

Credit scoring is a fundamental concept in the banking industry, essential for analysing and evaluating all customers requesting financial facilities. Due to its significance for banks' profitability, particularly in developing countries, this study aims to propose a fuzzy inference system (FIS) model for the credit scoring of legal clients. Initially, after reviewing the literature, evaluation criteria for legal client appraisal were identified. From these, 29 criteria were selected by research experts using the Delphi method, and 12 critical criteria were organized into four categories (performance, leverage, borrowing, and credit risk measures) for FIS modelling. A researcher-developed questionnaire was then utilized to establish the rules for the main FIS and its four sub-FISs. The proposed system, designed based on the Gaussian membership function, was implemented in MATLAB. The model's validity was subsequently tested using the extreme condition test. A comparison of the results from the proposed FIS and the bank's validation system indicates that the proposed model is suitable for credit scoring.

1. Introduction

Banks play a crucial role in the intermediation of modern financial affairs [12, 16]. These institutions not only provide a suitable platform for monetary control but are also considered effective in rebuilding the economy and ensuring its long-term stability [9]. Practically, banks are responsible for financing enterprises and production companies [11]. In recent years, Islamic banks have garnered significant attention from various stakeholders. Several factors contribute to this trend: the increasing number of banks and branches, the emergence of new financial products and services along with associated risks, and the rise in bankrupt banks due to poor financial conditions during recent international financial crises [20]. Consequently, the proper

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functioning of the banking system plays a pivotal role in enhancing economic activities. The importance of banks in national economies is undeniable, as they offer diverse services to society, including account opening, issuing various types of guarantees, loan payments, financial supply, electronic banking, and more [34]. In Iran's economy, banking holds even greater significance due to the underdevelopment of the capital market [13].

Due to its unique characteristics, banking activities are always subject to various risks. One of the most significant risks arises from inefficiencies in managing bank liquidity [25]. The Basel Committee, as the highest international body involved in banking supervision, has emphasized creating a solid framework for risk management in banks and obligates bank managers to evaluate their customers [41].

Bank facilities are the primary outputs through which societal liquidity, which is otherwise stagnant, is injected into defined and targeted economic sources. A major challenge for decision-makers in banks is prioritizing loan applicants [27]. Credit loans come with inherent risks, and company profits are often adversely affected by clients who default on loans [1, 31]. Typically, 80% of banks' balance sheets pertain to aspects of credit risk. Therefore, banks and financial institutions must adopt appropriate risk management practices to eliminate or mitigate credit risk [7, 32, 33]. Risk management involves identifying, measuring, making decisions about, and monitoring various types of risks to control their harmful effects. Several risks, including changes and fluctuations in exchange rates, interest rates, and inflation, affect the performance of financial institutions. However, credit risk is the most significant risk associated with banking activities. This risk often results from inadequate credit standards, poor risk portfolio management, and a lack of attention to the economic conditions of loan applicants [7, 15]. Credit risk management has become increasingly important following the recent financial crisis and the bankruptcy of major banks and numerous financial and economic systems [4, 25]. Credit risk can be considered the primary cause of bank bankruptcy [28]. Disruptions in the banking system affect other economic sectors, creating a synergistic effect that exacerbates delayed claims [38]. Hence, it is crucial to investigate and identify the factors affecting the validation of legal clients from multiple perspectives.

Due to the high amount of overdue claims in the banking industry, the credit estimation of applicants is very important issue. Credit scoring is a set of decisions under statistical analysis patterns that help lenders make the right decisions to grant loans to applicants in order to reduce the risk of customers refusing to repay [6, 23]. Credit scoring is a crucial task within risk management for many financial institutions. First, it is the banks intention to avoid customers who probably default. Second, regulators require strict risk management systems from banks to protect their customers, to avoid bankruptcy and its negative impacts on economy [10]. Therefore, credit scoring accounts a necessity action through which banks acquire proper knowledge of the customer's status and financial ability in repaying facilities [2]. Attaining the required knowledge about their customers, both real and legal, banks will have the capability of using appropriate financial and non-financial criteria [9] in evaluation process.

In comparison to individual clients, few studies have been conducted to evaluate legal clients. Notably, most of these studies rely on questionnaires and address the issue from specific perspectives. Additionally, credit scoring is both expensive and time-consuming, making any method that increases its efficiency valuable [26]. Credit scoring systems are commonly used by numerous financial institutions worldwide. However, the application of an analytical fuzzy approach, such as Fuzzy Inference Systems (FIS), has not been widely published. FIS is particularly effective when a well-defined mathematical model is unavailable, especially for intuitive judgments. The formulation of this system requires more knowledge about the problem being modelled rather than data, making it a knowledge-based rather than data-based system. Developing and validating a fuzzy inference system provides a robust framework for incorporating qualitative data and managing uncertainty, ultimately leading to more accurate and reliable credit scoring. Furthermore, the use of linguistic variables in the form of words or sentences in natural language while formulating if-then rules distinguishes FIS from other mathematical models. The incorporation of linguistic variables enhances fuzzy sets by adding more dimensions to the system. These variables blur the gap between a fuzzy set and its extensions, such as intuitionistic fuzzy numbers or neutrosophic numbers, which are characterized by both degrees of membership and nonmembership. Therefore, a three-level fuzzy inference system is developed to investigate customers' credit scores. The primary question addressed is, “How can a fuzzy inference system be developed for evaluating a bank’s legal clients?”

The remainder of the paper is structured as follows. Section 2 reviews the current literature and different approaches to studying credit scoring. Section 3 explains the research methodology, data collection, and analytical approach. Section 4 describes the modelling steps in real-world problems and presents practical findings. Finally, Section 5 concludes with key results and suggestions.

2. Literature Review

The purpose of credit scoring models is to predict the behaviour of applicants based on the past experiences of customers with similar characteristics. The primary task of these models is to distinguish between individuals who will repay their debts and those who will not [8, 30]. Consequently, several models have been proposed to expand the literature based on different concepts. Among recent research in this area, Xu et al. [39] considered parameter uncertainty in the development of credit scoring models. They proposed two novel metrics: the worst-case expected minimum cost and the worst-case conditional value-at-risk, to estimate the profit of credit scoring models with uncertain parameters and measure the loss incurred from employing a classification model in credit scoring under deteriorating cost parameters, respectively. Yang et al. [40] introduced a new hybrid ensemble model with feature enhancement and soft voting weight optimization to achieve superior predictive power for credit scoring. Experimental results demonstrate the superior performance, robustness, and effectiveness of the proposed model.

Kozodoi et al. [23] revisited statistical fairness criteria, examining their adequacy for credit scoring and cataloging algorithmic options for incorporating fairness goals in the machine learning model development pipeline. They empirically compared different fairness processors in a profit-oriented credit scoring context using real-world data. Yousofi Tezerjan et al. [41] applied the 5C (character, capacity, capital, collateral, and conditions) methodology to score customers. They developed a hybrid model predicting shocks in different stock market segments based on adaptive neuro-fuzzy inference systems (ANFIS) and recurrent neural networks (RNN). The results indicate the possibility of timely loan repayment for customers expected to do so, while loans for suspicious customers are either prevented or more closely monitored. Ehtesham Rasi et al. [10] evaluated bank customers based on credit risk using the Analytic Hierarchy Process (AHP) and artificial intelligence hyperbolic regression. The AHP method rated factors including customer revenue, market credit, job, relationship duration with the bank, type and value of collateral, and average account balance to facilitate the credit risk assessment of actual customers. Hyperbolic regression prioritized factors such as market credit, customer revenue, collateral value, relationship duration with the bank, type of collateral, and customer job. Maldonado et al. [26] proposed a two-step approach based on three-way decisions. In the first step, decisions are made for customers whose credit applications can be approved or rejected immediately. For the remaining customers, further analysis is conducted. Zhang et al. [42] proposed a cost-sensitive multiple-instance learning (MIL) approach to evaluate applicants’ credit scores by incorporating their dynamic transactional data and static individual information. Li et al. [24] addressed the credit scoring problem by incorporating networked information. They utilized a Bayesian optimal filter to provide risk predictions for lenders, assuming that published credit scores are estimated merely from structured financial data. Additionally, a recursive Bayes estimator was proposed to enhance the precision of credit scoring by integrating the dynamic interaction topology of clients. Additional information was gathered in a subsequent step, and a probabilistic rough set was applied for credit scoring. Blanco et al. [6] developed several non-parametric credit scoring models based on the multilayer perceptron approach and benchmarked their performance against other models employing traditional linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and logistic regression (LR) techniques. Mehrabi et al. [27] proposed a model for measuring customers' credit risk and prioritizing bank applicants in an Iranian bank. They utilized hesitant fuzzy data and a simple distance-based algorithm to rank loan applicants. A systematic review of credit scoring studies indicates that most research has concentrated on crisp methods, particularly discriminant analysis and multi-attribute decision-making (MADM) weighting methods. However, these studies tend to simplify evaluation models, thereby reducing their complexity for easier understanding and implementation. By employing a fuzzy inference system, this research aims to bridge the gap between mathematical models and judgmental decision-making, providing decision-makers with enhanced capabilities in the credit scoring process.

3. Methodology

This study applied a systems approach, specifically a fuzzy inference system (FIS), for credit scoring analysis (CSA) in the banking industry. Extracting experts' knowledge in the FIS modeling procedure enhances the reliability of the proposed model. While defining the number of expert group members is challenging, it is recommended to involve 10 to 15 experts. Therefore, in this phase of the research, a group of 11 experts was initially asked to participate. The selection criteria for the experts included their theoretical expertise, practical experience, willingness, and ability to contribute to the research. This number was subsequently increased to 14 experts using the snowball sampling method. To conduct the research, 29 evaluation criteria for assessing banks' legal clients were identified through a literature review and presented to the experts in the form of a fuzzy Delphi questionnaire [18]. After two rounds of the Delphi technique, 12 criteria (with an average rating of 0.7 or higher) were finalized as the scoring criteria. To design the fuzzy inference system, a custom-developed questionnaire was used to gather FIS rules. The steps of the research model are illustrated in Figure 1.

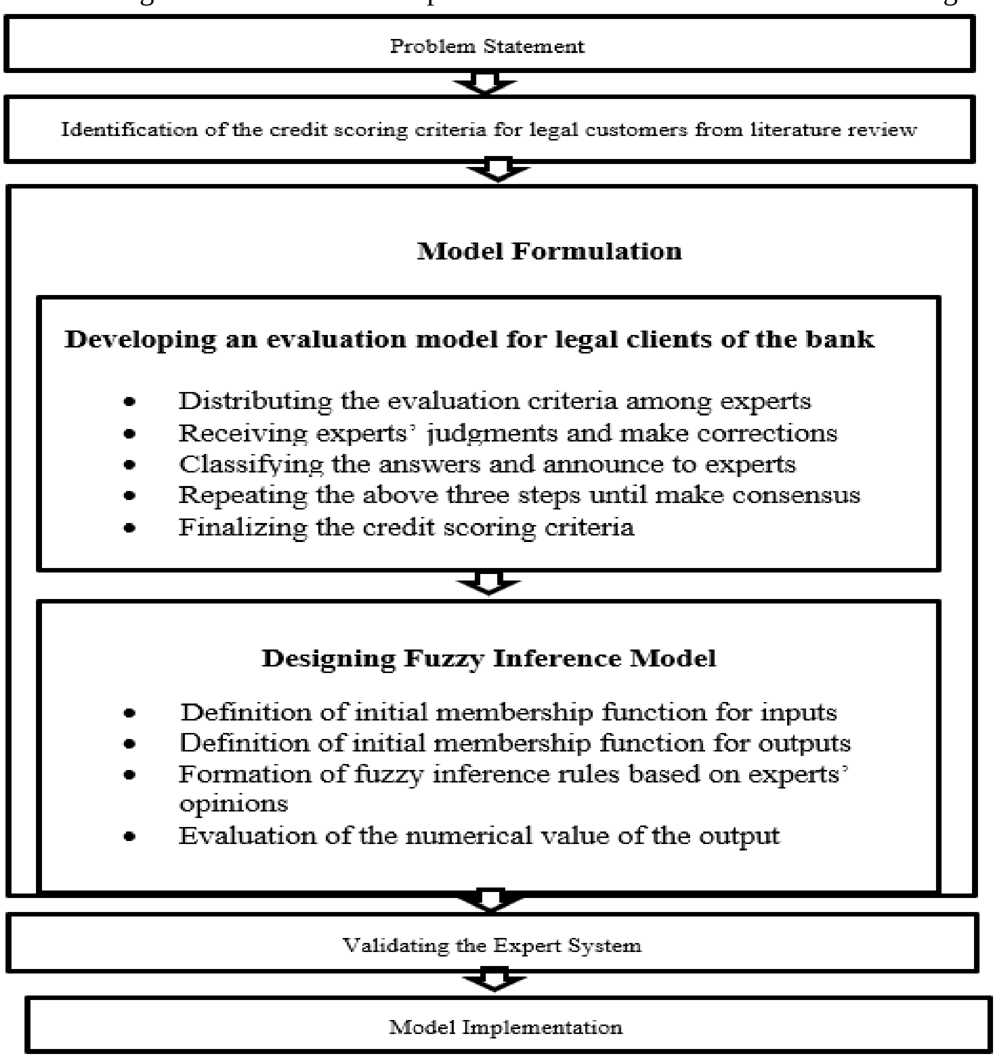

Figure 1. Steps of credit scoring of bank's legal customers

To determine the credit scoring criteria, a comprehensive literature search was conducted, identifying 29 important criteria as the primary evaluation metrics. These criteria were then distributed among experts in the form of a Delphi questionnaire. Experts provided their opinions based on a five-point linguistic scale ranging from very low to very high. The linguistic values were subsequently fuzzified and converted into crisp values using the Minkowski equation [5]. The average opinions of all experts were aggregated and redistributed to the experts for review. Through the implementation of the fuzzy Delphi method in two rounds and achieving consensus, the final evaluation criteria with scores greater than 0.7 were selected for further analysis. These criteria are illustrated in Table 1.

Table 1. Final criteria for legal customers' credit scoring

Main Category	Criteria	References
Performance Criteria	Return on assets	3, 4, 9, 10, 12, 32, 37
	Fixed assets to equity	3, 9, 10, 32, 34, 37
	Average customer account	12, 32
	Customer capital	3, 4, 9, 10, 30
Leverage Criteria	Total debt ratio (total debt to equity)	3, 4, 9, 10, 12, 32, 36, 37
	Ownership ratio (equity to total assets)	10
Borrowing Criteria	Ratio of deferred amount to current assets	4, 9, 10, 34, 37
	Amount of received facilities	3, 12, 37
	Borrowing capacity	4, 10, 36, 37
	Amount of requested facility	12, 37
Credit Criteria	Type of guarantee (collateral)	12, 15, 18
	Credit risk of the last period	7, 12, 15, 18, 34, 37

It should be noted that, all of the inferences, and evaluations related to the identification and initial evaluation of the criteria took place under consideration of the experts. The data collection tool was questionnaire, where its validity was checked using content and construct validity. Content validity was achieved by involving a panel of experts in the development and review of the questionnaire items. They assessed each item for its relevance and comprehensiveness in covering the evaluation criteria for legal client appraisal. Construct validity was addressed by ensuring that the questionnaire items accurately reflected the constructs they were intended to measure. The items were designed to capture various aspects of performance, leverage, borrowing, and credit risk measures.

4. Findings

Due to the lack of detailed information in the field under investigation, this research employs fuzzy inference systems (FIS) for credit scoring. FIS utilize expert opinions regarding the relationships between the model's inputs and outputs, expressed as a set of fuzzy if-then rules. This approach facilitates the aggregation of expert judgments and the derivation of rules from their assessments.

As shown in Table 1, four sub-fuzzy inference systems (Sub-FIS) and one overall fuzzy inference system (FIS) were designed to evaluate the bank's legal customers. Each Sub-FIS represents one of the main components of the evaluation system, while the main FIS integrates the four Sub-FIS to score the bank's legal clients. The performance measure (Sub-FIS1) includes four inputs: return on assets, fixed assets to equity, average customer account, and customer capital. The leverage measure (Sub-FIS2) incorporates two inputs: debt ratio and equity ratio. The borrowing measure (Sub-FIS3) comprises four inputs: the ratio of deferred amount to current assets, amount of received facilities, borrowing capacity, and amount of requested facilities. Finally, the credit risk measure (Sub-FIS4) includes two inputs: type of guarantee and the credit risk of the previous period (see Figure 2).

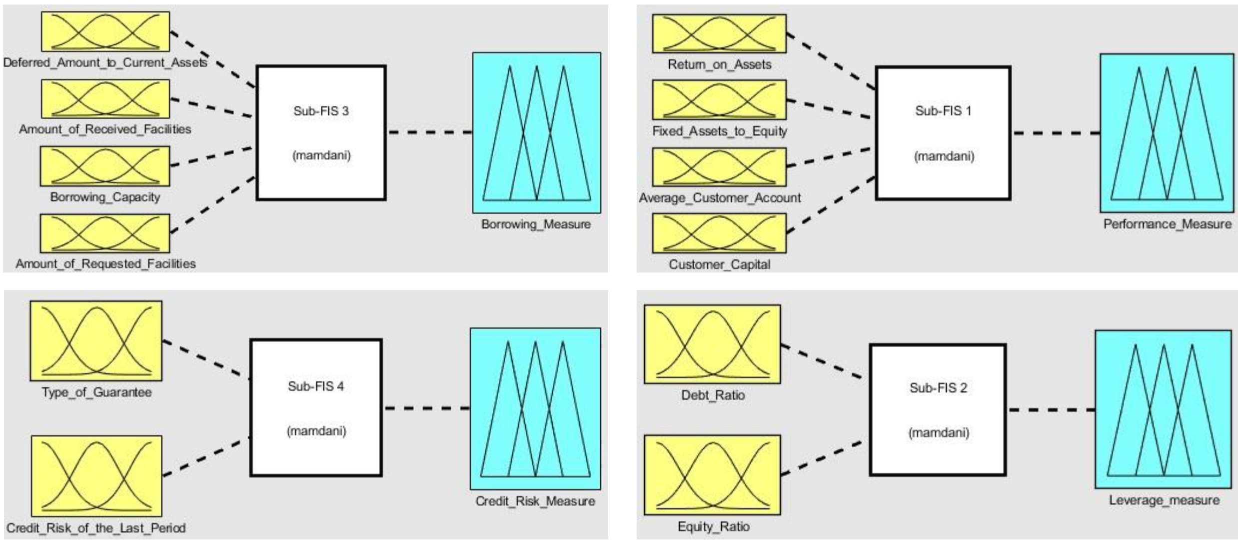

Figure 2. Sub FISs of the credit scoring criteria

Finally, the main FIS has four inputs, which are the outputs of the sub-FISs. As illustrated in Figure 3, these four inputs are: performance, leverage, borrowing and credit risk measures.

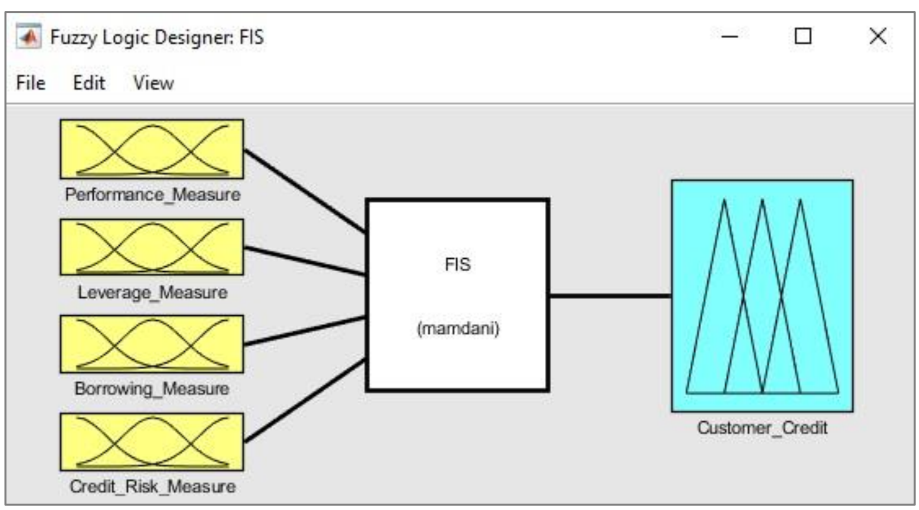

Figure 3. Fuzzy inference system for Legal customers' credit scoring in banks

4.1. Definition of Membership Functions (MFs)

The membership function (MF) of a fuzzy set, denoted as A, represents the set of membership degrees assigned to its elements. The MF of a fuzzy set is a mapping of the members of set A onto the interval [0, 1], described as [0, 1] → A: y. Essentially, any function capable of implementing such a mapping can serve as the MF of a fuzzy set.

In this study, Gaussian functions have been employed as the MFs for both the input and output variables of the fuzzy inference system. Gaussian functions are chosen due to their derivability, a prerequisite for FIS systems. Additionally, this class of functions offers the flexibility to adjust the σ (standard deviation) parameter, allowing them to span a wide range of values [9]. Empirical evidence from similar studies supports the widespread use of Gaussian functions for MFs in fuzzy inference systems.

$$gussian\ (x,\sigma,c)=exp(-((x-c)/\sigma)^2 \quad (1)$$

In Equation (1), the parameter c signifies the symmetry center, while σ determines the degree of openness of the function. Gaussian functions exhibit smooth curves, and their parameters can be adjusted to reflect linguistic variable characteristics. Notably, the range of changes for both input and output variables are defined between 0 and 10. Figure 4 illustrates the initial membership functions (MFs) for the linguistic variables of the inputs and outputs of the fuzzy inference system for validating the legal clients of the bank.

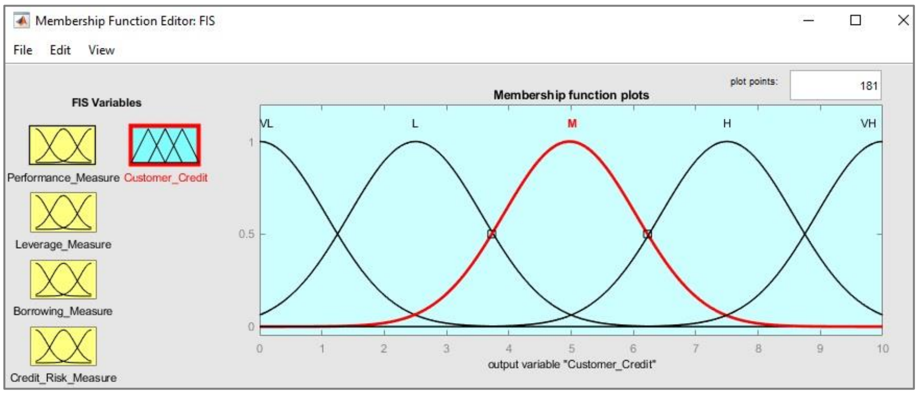

Figure 4. Membership function of the model’s elements

4.2. Structuring fuzzy inference rules

The rule base constitutes a crucial component of a fuzzy system, comprising a set of logical if-then rules that guide the mapping of input variables to output variables. Various methods, such as direct use of expert knowledge, clustering methods, and fuzzy methods, are employed to construct the rule base. There are primarily two types of fuzzy inference systems: (i) Mamdani type and (ii) Sugeno type. Although both systems share similarities, the determination of outputs differs between them. In the Sugeno type fuzzy inference system, the output is computed as the weighted average of the rules’ consequents, without employing fuzziness. On the other hand, in the Mamdani fuzzy inference system, a fuzzy membership function (MF) is utilized to determine the value of an output variable. The Mamdani system, due to its incorporation of fuzziness, offers easier interpretability. Moreover, formulating a model using the Mamdani fuzzy inference system is straightforward and intuitive. Consequently, in our work, we have opted for the Mamdani-type fuzzy inference system. In the current research, experts’ knowledge in validating legal clients of the bank has been leveraged to design inference rules. Experts were requested to provide judgments on the output variable by considering different values for the input variables based on their experiences.

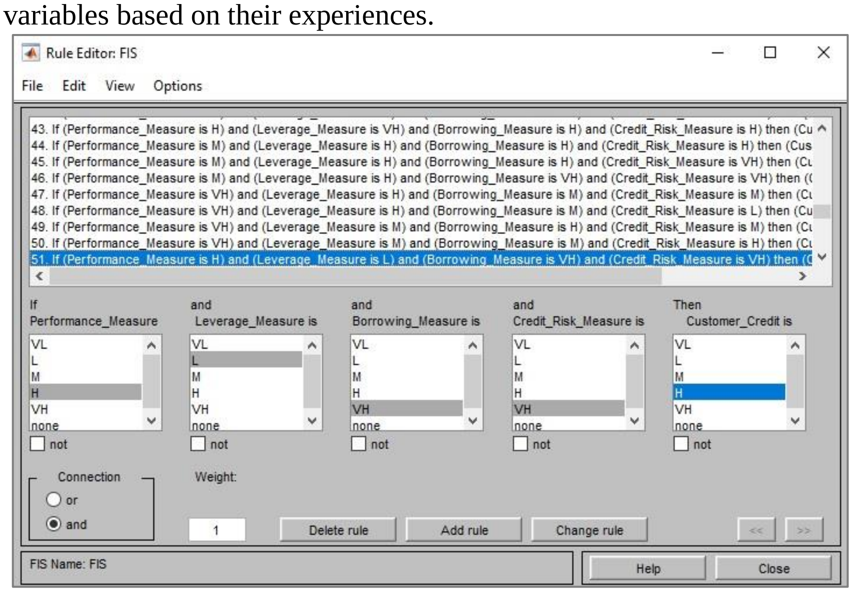

Figure 5. Credit scoring rules for banks’ legal customers

For example, Figure 5 depicts the designed fuzzy inference system (FIS) for credit scoring of the bank's legal clients. This FIS comprises four inputs, namely performance, leverage, borrowing, and credit indicators, and one output, namely clients' credit score. In this section, experts are tasked with evaluating the output variable (client credit) by considering various values for the input variables. The main system consists of 72 inference rules, as illustrated in Figure 5.

It should be noted that for all the designed Sub-FISs, the fuzzy rules are constructed in a similar manner. For further interpretation, we utilize three-dimensional diagrams to illustrate the decision levels created by the designed FISs. These diagrams depict the impact of input component values on an output component.

Figure 6 presents the three-dimensional view of the validation of legal clients of the bank, based on paired combinations of performance and leverage as inputs and the client's credit score as the output. In part A, performance and leverage; in part B, performance and borrowing; in part C, performance and credit; in part D, leverage and borrowing; in part E, leverage and credit; and finally, in part F, borrowing and credit are represented as the length and width of the diagrams, respectively. In all diagrams, the legal clients' credit index is depicted as the height .

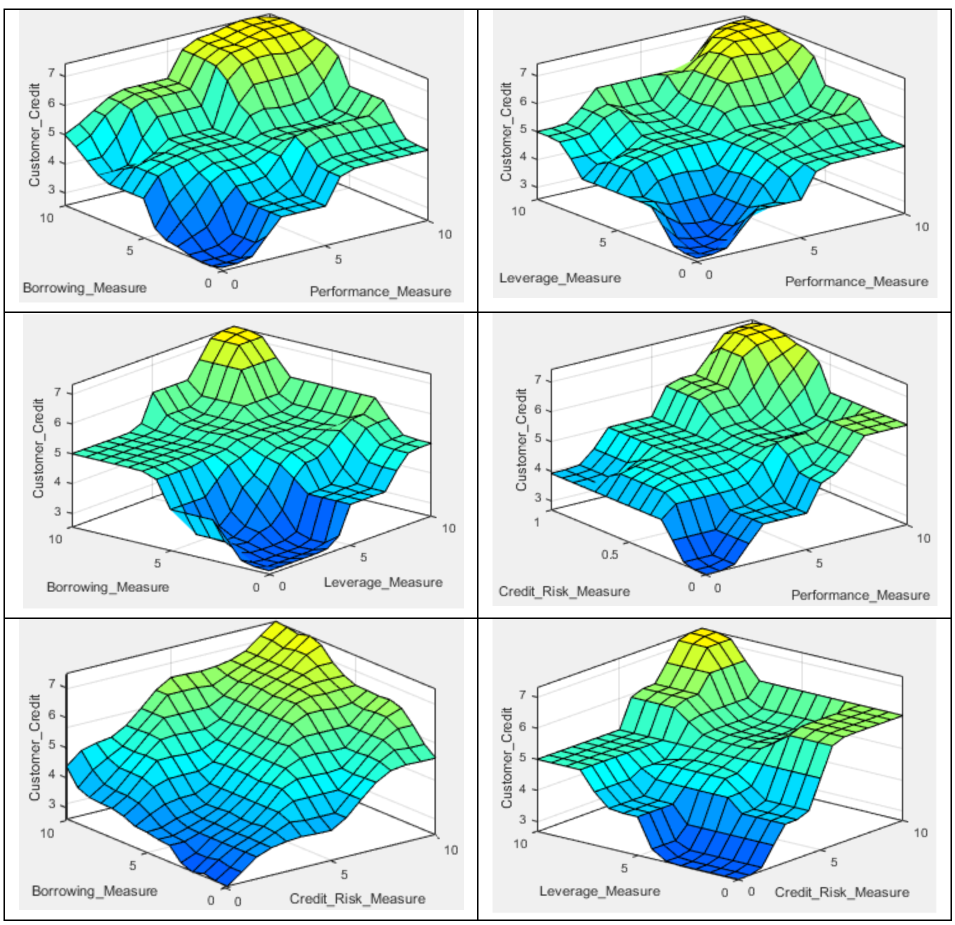

Figure 6. Three-dimensional credit scoring diagrams based on different inputs

4.3. Model validation

Testing and validating the model are crucial steps to ensure its applicability and reliability. Various tests are available for validation, among which the extreme condition test was used to validate the mathematical model. This test involves altering each of the input values to their highest and lowest possible numbers to check the sensitivity of the output to these changes. The extreme condition test assesses whether the model behaves appropriately under extreme conditions. To conduct the extreme condition test, all the model outputs should be examined for feasibility when the input values are at their minimum (zero) or maximum (infinite). In this research, the input variables range from a minimum value of 1 to a maximum value of 10. This test, also referred to as a reality check by Pearson and Eberlin, ensures the model's robustness. As illustrated in Figure 7, the model demonstrates completely reasonable behavior when the input components vary from very low (1) to very high (VH).

Figure 7. Effect of simultaneous changes of inputs on output

The summary of the extreme condition test is presented in Table 2. As shown, the clients' credit score after fuzzification ranges between 1.16 and 8.84.

Table 2. Results of extreme condition test

Inputs				Output
Performance measure	**Leverage measure**	**Borrowing Measure**	**Credit risk Measure**	**Client Credit**
0	0	0	0	1.16
5	5	5	5	5
10	10	10	10	8.84

The extreme condition test was also conducted for all four Sub-FISs, and each demonstrated reasonable behavior in response to the extreme values of the inputs. This outcome confirms the validity of the proposed model. Due to limitations in providing similar content, the outputs of these fuzzy inference systems are not included here.

4.4. Results of the Model Implementation

To validate the bank's legal clients, the designed FIS model needs to be applied to a real-world scenario, and the results must be examined. For this implementation, experts were asked to assess a sample of clients based on the bank's customer validation system using a 1-10 scale. Since the questionnaire used in this stage is interval-based, the geometric mean was employed to combine the experts' opinions. By inputting the values from the second row, the outputs of the Sub-FISs were calculated. These outputs were then used as inputs for the main FIS, resulting in the calculation of the credit scores for the bank's legal clients, as shown in Table 3.

As shown in Table 3, the final credit scores of the four legal clients of the bank were calculated using the proposed FIS. By applying Gaussian MFs, the clients' credit scores were determined to be 6.71, 6.36, 7.02, and 6.84, respectively. Additionally, each client's score was calculated based on the bank's existing validation system (right column). By comparing the results of the FIS with the bank's validation system, it can be concluded that the proposed FIS is suitable for credit scoring.

Table 3. Credit scores of the banks' legal clients

Client	Performance measure				Leverage measure		Borrowing Measure				Credit risk Measure		FIS Score	Bank score
	Return on assets	Fixed assets to equity	Average customer account	Customer capital	Total debt ratio (total debt to equity)	Ownership ratio (equity to total assets)	Ratio of deferred amount to current assets	Amount of received facilities	Borrowing capacity	Amount of requested facility	Type of guarantee (collateral)	Credit risk of the last period		
1	8.75	8.51	5.84	6.52	4.66	7.49	6.13	5.77	8.21	7.27	6.10	5.94	6.65	6.71
	7.28				6.19		7.33				6.00			
2	9.21	7.57	4.87	8.22	8.16	4.50	5.36	8.74	8.38	5.96	5.52	4.62	6.36	6.19
	7.62				6.04		6.80				4.96			
3	7.30	9.12	6.81	8.52	6.93	5.13	5.10	7.66	4.70	5.30	5.47	5.28	7.02	6.89
	8.25				5.86		5.42				5.35			
4	6.94	8.44	5.84	8.63	5.88	6.19	4.60	6.55	7.99	6.26	6.63	6.66	6.84	6.75
	7.38				5.92		6.62				6.65			

5. Conclusion

Increase in bankruptcies among credit financial institutions, even in developed countries, has underscored the importance of evaluating the financial ability of clients seeking loans. Central banks are increasingly concerned about the banking industry's stability due to the rapid transmission of banking crises to other economic sectors, potentially leading to widespread financial turmoil. Over-reliance on regulatory mechanisms alone may not adequately address these concerns. Banks play a critical role in collecting financial resources and allocating them to various economic sectors. They must balance the need to meet their own financial requirements with the optimal allocation of limited resources to productive economic activities. Therefore, banks strive to extend credit to companies that are low-risk and offer returns that align with the interest rates on the granted facilities. Achieving this balance requires banks to accurately identify and classify their credit customers—both individuals and legal entities—based on their ability and willingness to repay obligations fully and on time, using a combination of financial and non-financial criteria.

An effective validation system enables banks to allocate credit facilities to applicants with lower credit risks, thereby increasing the likelihood of timely debt repayment. Regulatory bodies such as the central bank, the Ministry of Economy, and other oversight institutions can mitigate financial risks by implementing robust validation systems. This, in turn, helps stabilize the banking sector. To enhance the validation process, the country's banking system should focus on key indicators such as the ratio of deferred amounts to current assets, the number of facilities received, borrowing capacity, the number of requested facilities, and the type of guarantee. These indicators are crucial for accurately assessing clients' creditworthiness.

From the managerial and practical perspective, it is recommended that banks adopt advanced validation systems incorporating both financial and non-financial criteria to better assess the creditworthiness of clients. These systems should be dynamic and adaptable to changes in the economic environment. They should regularly review and update their validation criteria to reflect current economic conditions, regulatory changes, and innovations in financial technology. This ensures that the validation process remains relevant and effective. On the other hand, banks should work closely with regulatory bodies to ensure that their validation systems comply with current regulations and standards. This collaboration can also help in sharing best practices and improving the overall stability of the financial sector.

For the future researches, it's recommended to other researchers to explore the integration of artificial intelligence (AI) and machine learning techniques in risk prediction and client validation. AI can provide more accurate, data-driven insights and adapt to changing conditions in real-time. They can also design an ANFIS model, which combine the learning capabilities of neural networks with the reasoning capabilities of fuzzy inference systems. ANFIS can incorporate feedback and continuously learn from new data, improving the accuracy of client validation.

The primary constraint of this study lies in the process of selecting and extracting initial indicators solely through a literature review. Furthermore, it's important to acknowledge that indicators and factors associated with the validation of legal clients are subject to variability over time, often in response to environmental shifts. These changes may be attributed to fluctuations in financial regulations, economic landscapes, advancements in financial technology, and alterations in market conditions.

6. Managerial Implications

The implementation of fuzzy inference systems for customer validation offers significant managerial benefits, including improved evaluation accuracy, integration of expert knowledge, comprehensive risk assessment, and enhanced credit risk management. These advantages support better-informed decision-making and strategic planning within the banking sector. In the following, several important implications for bank managers and financial institutions are proposed.

- *Enhanced Customer Evaluation*: The application of fuzzy inference systems (FIS) in this research highlights a sophisticated method for validating bank customers in the absence of detailed information. Managers can adopt this approach to improve the accuracy and reliability of customer assessments, which is critical for making informed credit decisions.
- *Integration of Expert Knowledge*: By integrating expert opinions into the FIS through fuzzy if-then rules, managers can leverage the collective expertise of their teams. This method ensures that subjective judgments are systematically incorporated into the evaluation process, thereby enhancing the overall robustness of customer validation.
- *Comprehensive Risk Assessment*: The use of multiple sub-fuzzy inference systems (Sub-FIS) allows for a detailed analysis of various risk components, such as performance, leverage, borrowing behavior, and credit risk. Managers can benefit from this detailed segmentation by identifying specific areas of concern and addressing them proactively.
- *Holistic Scoring System*: The aggregation of the Sub-FIS into a main FIS provides a comprehensive scoring system for legal clients of the bank. This holistic approach ensures that all relevant factors are considered in the final assessment, leading to more balanced and informed decision-making.
- *Customization and Flexibility*: The structure of FIS allows for customization based on the specific needs and criteria of the bank. Managers can tailor the inputs and rules within each Sub-FIS to reflect the unique risk profiles and strategic priorities of their institution, providing flexibility in the evaluation process.
- *Improved Credit Risk Management*: By incorporating specific measures such as the type of guarantee and previous credit risk into the FIS, managers can enhance their credit risk management practices. This approach enables the identification of high-risk clients early on, allowing for timely interventions and risk mitigation strategies.
- *Strategic Resource Allocation*: The insights gained from the FIS can inform strategic decisions regarding resource allocation. Managers can prioritize their efforts and resources towards clients who present the most potential value or risk, optimizing the bank's overall performance and stability.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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