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A hybrid fuzzy-logic clustering framework for transparent credit risk assessment in microfinance lending

Serhii V. Popovskyi[1)]
ORCID: https://orcid.org/0009-0001-4305-0089; serhiipopovskyi1988@gmail.com
Victor E. Volkov[1)]
ORCID: https://orcid.org/0000-0002-3990-8126; viktor@te.net.ua Scopus Author ID: 57220703810
[1)] Odesa I. I. Mechnikov National University, 2, Vsevolod Zmiienko Str. Odesa, 65082, Ukraine

ABSTRACT

Relevance. The assessment of credit risk for short-term unsecured loans in microfinance institutions is a critical problem for financial stability and portfolio management. This segment is characterised by unstable client behaviour and limited credit history, creating challenges for traditional statistical and machine learning scoring models. Transparency and explainability are increasingly important due to regulatory requirements and the need for adaptive methods capable of handling incomplete and noisy data. This study **aims** to develop a methodology for applying fuzzy logic to enhance the accuracy, stability, and transparency of automatic credit decisions in the microfinance sector. The main **objectives** include constructing an interpretable fuzzy model, defining fuzzy sets for key variables, developing a transparent rule base built on clustering and BadRate profiles, and validating internal and external consistency, monotonicity, and transparency. **Methods.** The study uses a dataset of 601,092 issued and closed loans of a Ukrainian microfinance institution in 2024. The proposed approach combines clustering-based segmentation with fuzzy rule-based credit risk assessment. Clustering was performed using the K-Means method, with the optimal number of segments determined by the Elbow method. Fuzzy sets were constructed using trapezoidal membership functions, and rules were formed based on cluster combinations and normalised BadRate coefficients. Aggregation and defuzzification were performed using the Mamdani method to obtain a numerical RiskScore. Validation included checks for monotonicity, rule consistency, and decision transparency at the observation level. **Results.** The model identifies stable behavioural segments reflecting different risk levels. The RiskScore demonstrates strong consistency with empirical BadRates distributions and forms three interpretable risk categories: Low, Medium, and High. The proposed fuzzy model effectively predicts credit risk under incomplete and unstable data. **Conclusions.** The **scientific novelty** of the study lies in the integration of clustering, BadRate profiles, and rule-based inference into a unified interpretable scoring framework for credit risk assessment in microfinance lending. The proposed approach has **practical significance**, providing a transparent and interpretable decision-support tool for credit risk evaluation, applicable to risk management, portfolio monitoring, loan loss provisioning, and regulatory-compliant scoring systems.

Keywords: Fuzzy logic; credit risk; credit scoring; risk modeling; creditworthiness; consumer lending; computer modeling

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INTRODUCTION

Credit risk assessment is a key element in ensuring the financial stability of microfinance institutions operating in the short-term unsecured lending segment. In this sector, decisions must be made rapidly, often within minutes, while a significant proportion of clients lack a comprehensive credit history or provide minimal information. Data may be incomplete, fragmented, or unstable, and default rates are substantially higher than in traditional banking lending [1], [2], [3], [4]. Errors in scoring models lead to increased credit losses, higher interest rates, and reduced accessibility of financial products, highlighting the need for approaches capable of operating under conditions of uncertainty and limited information [5], [6].

The dynamism of the economic environment and frequent structural shifts in consumer behaviour further complicate risk modeling in the microfinance sector. Short credit cycles, variability in behavioural patterns, and rapid changes in external conditions result in historical data losing representativeness and failing to provide stable model accuracy. Under such circumstances, methods capable of adapting to instability and working with information of a gradational rather than discrete nature are required [7].

Traditional statistical models, such as logistic regression, as well as modern machine learning methods (XGBoost, Random Forest, neural networks) are widely used in credit scoring [8]. However, their application in the microfinance sector is often constrained by several factors. First, they rely on clear thresholds between classes, whereas borrowers' behavioural characteristics are inherently fuzzy [9].

Second, microfinance data contain missing values, anomalies, and non-standard entries, posing additional challenges for models that depend on structured inputs [10]. Third, high-accuracy ML algorithms often lack transparency, complicating audit, validation, and compliance with current regulatory requirements, particularly regarding explainability of algorithmic decisions [11], [12], [13].

In this context, fuzzy logic emerges as a promising approach for risk modelling under conditions of uncertainty and incomplete data. Fuzzy systems allow the formalisation of linguistic risk assessments, the description of gradational properties of behavioural variables, and the construction of interpretable IF-THEN rules [14], [15], [16]. Unlike black-box models, fuzzy systems provide transparency in decision-making logic; handle noisy (fuzzy) data, and naturally model non-linear relationships [17], [18], [19], [20]. Consequently, fuzzy logic is particularly suitable in environments, where data are unstable and the explainability of decisions plays a crucial role.

RELATED WORKS

Credit Scoring: Classical and machine learning approaches

Credit scoring is a fundamental tool for assessing borrowers' creditworthiness, designed to predict the probability of default and rank applicants according to risk level [21], [22]. Its scientific foundations were established in discriminant analysis and multifactor default prediction models. In contemporary systems, scoring is a continuous process that involves regular model updates within the CRISP-DM lifecycle (Fig. 1), with the resulting risk score employed to make credit decisions and determine loan pricing according to risk-based pricing principles.

However, modern financial markets, particularly the microfinance sector, are characterised by highly dynamic external conditions and variable consumer behavior [3], [11]. MFI (microfinance institution) data are often incomplete, unstable, contain missing or noisy values, and feature limited credit history. Under these conditions, classical statistical models – logistic regression, discriminant analysis, decision trees – exhibit limited robustness as they assume clear thresholds, linearity, and the absence of significant outliers [24], [25].

Machine learning (ML) models (Random Forest, XGBoost, neural networks) provide higher accuracy and better detect non-linear dependencies [26], [27], [28]; however, they are typically black-box in nature. This complicates auditing, regulatory compliance (GDPR, AI Act, Basel III), and explaining the logic behind credit decisions [12], [29], [30]. This issue is particularly critical in microfinance, where transparency and the ability to justify loan approvals or refusals are essential.

Fig. 1. **Stages of the CRISP-DM methodology for Data Mining (DM) processes**
***Source*: compiled by the [20]**

To address the lack of interpretability of ML models, post-hoc explainability techniques have been developed, including SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) [11], [12], [13], [26], [31], [32], [33]. These methods allow quantifying feature contributions to individual predictions and improving transparency of black-box models [31], [32]. However, their application in credit scoring remains limited in microfinance settings due to model complexity and the need for inherently interpretable alternatives [11], [13].

Thus, although classical and ML approaches remain effective for default prediction, they do not fully address the challenges posed by fuzzy, unstable, and incomplete MFI data and fail to provide sufficient explainability.

Fuzzy Logic in Credit Risk Modeling

Fuzzy logic, introduced by Lotfi Zadeh [34], provides a natural way to model fuzzy, gradational, and incomplete data. Unlike traditional methods, fuzzy systems allow the use of linguistic terms ("low risk", "moderate income"), the construction of IF–THEN rules, and the description of membership degrees in the [0,1] interval [35], [36].

In credit scoring, this offers several advantages [37], [38]:

– ability to work with incomplete, noisy, and non-standardised data;

– flexibility in modelling non-linear relationships;

– integration of expert knowledge via linguistic rules;

– high transparency and auditability.

The design of a fuzzy logic system involves fuzzification of variables, rule formulation, fuzzy inference, defuzzification, and calibration (Fig. 2) [39]. Modern fuzzy approaches employ ANFIS, fuzzy logistic regression, Takagi-Sugeno-type models, and Boolean-consistent fuzzy systems [15], [40], [41].

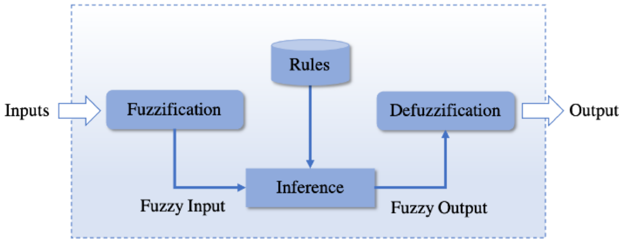


Fig. 2. **Fuzzy logic system**
***Source*: compiled by the [31]**

Recent studies have actively developed hybrid models [42], [43], [44], [45]:

– evolving fuzzy systems, capable of adapting to structural shifts;

– interval type-2 fuzzy systems, better suited for noisy data;

– q-rung orthopair fuzzy sets, enabling more flexible representation of uncertainty.

These approaches have demonstrated high effectiveness, but their implementation in the microfinance sector remains limited due to the lack of standardised procedures for constructing membership functions and insufficient research focused on short-term loans with a high proportion of new clients.

The need for transparency in scoring models has increased under current regulatory standards – GDPR, AI Act, Basel II/III – which require explainability of automated credit decisions [46], [47]. In this context, Explainable AI methods such as SHAP, LIME, and rule extraction are widely used to improve transparency of machine learning-based credit scoring models. Combining Fuzzy Logic provides a hybrid framework for risk control and interpretable decision-making [5], [29].

The literature notes the advantage of fuzzy models in generating audit trails and integrating with blockchain to ensure data immutability [31], [32]. This is particularly valuable for MFIs subject to regulatory oversight, which must justify each loan approval or refusal.

Despite significant progress, key gaps remain in the literature that is critical for developing credit risk models in the microfinance segment. Methods for automatically constructing linguistic terms and membership functions based on real credit data, particularly considering Bad Rate, are insufficiently studied [25], [48]. Few studies combine clustering (K-Means, FCM), statistical risk characteristics (Bad/Good Rate), and fuzzy sets to form interpretable rules [49], [50]. There are no standardized approaches to creating transparent fuzzy rules for regulated financial decision-making processes [46], [47]. Insufficient attention has been paid to MFI data characteristics: instability, missing values, high proportion of new clients, and structural shifts.

While prior studies demonstrate the effectiveness of fuzzy and hybrid approaches for credit risk modelling, most existing research focuses either on improving predictive accuracy or on enhancing model interpretability as separate objectives. In contrast, only limited attention has been paid to the simultaneous integration of portfolio risk metrics, automatic segmentation, and transparent rule construction within a unified framework.

In particular, existing works rarely combine clustering-based behavioral segmentation with empirical risk indicators such as Bad Rate to construct membership functions and fuzzy rules directly from real credit portfolio data. Moreover, most fuzzy credit scoring models are validated primarily in traditional banking environments, whereas the microfinance sector is characterized by shorter loan cycles, a high proportion of new borrowers, and rapidly changing behavioral patterns. These characteristics require more adaptive and data-driven procedures for constructing interpretable fuzzy systems.

Therefore, the proposed research contributes to the literature by introducing an integrated methodology that links behavioral clustering, portfolio risk statistics, and fuzzy inference to produce a transparent and regulatorily compliant RiskScore. This approach aims to bridge the gap between theoretical fuzzy modeling and the practical requirements of automatic decision-making in microfinance institutions.

THE PURPOSE AND OBJECTIVES OF THE RESEARCH

The analysis of existing studies shows that classical and ML models are effective for default prediction but poorly suited to handling fuzzy and unstable MFI data. Fuzzy logic combined with

Explainable AI has the potential to overcome these limitations, providing interpretable, adaptive, and regulatorily compliant solutions. Nevertheless, methodological gaps remain in automatic membership function construction, transparent rule formation, and adaptation of fuzzy systems to portfolio metrics such as Bad Rate – precisely the issues addressed in this study.

The **aim** of this research is to develop and justify a methodology for applying fuzzy logic to improve the accuracy, stability, and transparency of automatic credit decisions in the microfinance sector. To achieve this aim, a fuzzy model has been constructed, which includes:

1. Formation of fuzzy sets for key variables (Credit Bureau Score, Usage Activity, Average Duration of Previous Loans) taking into account high asymmetry and outliers in the data.
2. Construction of a rule base built on clustering and empirical Bad Rate profiles, providing a transparent representation of the influence of borrower characteristics on the final RiskScore.
3. Implementation of fuzzy inference and defuzzification mechanisms, allowing point RiskScores to be obtained with interpretation at the level of individual observations.
4. Validation of the model through internal and external feasibility, monotonicity checking, rule consistency, and decision transparency.

Based on the identified research gaps, the following **hypotheses** are formulated:

H 1. Fuzzy sets for key variables provide stable ranking of borrowers.

H 2. The Fuzzy Logic rule base ensures transparent and statistically consistent RiskScore evaluation.

H 3. Interpretability of membership functions and activated rules allows credit decisions to be justified transparently and comply with regulatory requirements.

RESEARCH METHODOLOGY

Dataset Description and Variables

The study is based on data from one of the microfinance institutions (MFIs) in Ukraine and includes only issued and completed loan contracts during 2024, excluding applications that were rejected at the scoring stage. The final sample comprises 601,092 observations, allowing the unambiguous determination of the final status of each contract and assessment of repayment quality. The final default label (Status) was formed based on the actual repayment history of the contract: a loan was considered bad (Status = 0) if a delay of ≥30 days occurred; all other loans were classified as good (Status = 1).

The selection of variables was based on three criteria: (1) minimum data completeness, (2) relevance to credit risk, and (3) suitability for interpretation in fuzzy rules. The **dependent variable** is *Status*, used as the target to verify the consistency of fuzzy inference rules with empirical risk patterns.

Independent variables were selected to reflect different dimensions of credit behaviour:

1. Credit Bureau Score (CBS) – an aggregated index of the client's credit history, accounting for past delinquencies and the quality of previous credit interactions. It serves as a key reliability indicator and a basis for constructing fuzzy reliability levels.
2. Usage Activity (UA) – the number of authorisations on the platform over the last month. This indicator reflects the client's current engagement with the service and serves as a proxy for involvement and financial discipline.
3. Average Duration of Previous Loans (ADPL) – the average number of days clients used previous loans until full repayment. This variable allows the assessment of actual repayment discipline and the detection of atypical borrower behaviour patterns.

This combination of variables provides a comprehensive assessment of credit risk under conditions of incomplete, uneven, and non-linear data, typical of the microfinance sector.

Fuzzy Logic Model Design

The proposed system is a fuzzy-data-driven approach, where fuzzy membership functions are derived from clustering-based empirical partitions of the feature space.

The construction of the fuzzy credit risk model was carried out in five stages:

1. Fuzzification. The key variables CBS, UA, and ADPL($\{X_1, X_2, \dots, X_n\}$) were transformed into linguistic variables with risk levels using trapezoidal membership functions (trapmf). The number of clusters for each variable was determined by the Elbow method with K-Means [19], [51], [52]. For each cluster, the following were calculated: cluster centroid (1); inertia (2); Bad Rate (3); normalised risk coefficient (4).

$$c_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i, \tag{1}$$

where $|C_k|$ is the number of elements in cluster k; $x_i \in C_k$ is observation i, which belongs to cluster k.

$$\text{Inertia} = \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - C_k\|^2, \quad (2)$$

where K is the number of clusters for the given variable.

$$\text{BadRate}_k = 1 - \frac{\sum_{x_i \in C_k} 1_{Status_i = 1}}{|C_k|}. \quad (3)$$

$$\text{Coef}_k = \frac{\text{BadRate}_k - \min(\text{BadRate})}{\max(\text{BadRate}) - \min(\text{BadRate})}. \quad (4)$$

The boundaries of the trapezoidal membership functions (5) for each fuzzy term were computed based on the minimum and maximum values of the cluster and neighbouring clusters. The fuzzification stage transforms crisp cluster boundaries into overlapping linguistic sets. Each observation obtains a membership degree in multiple fuzzy sets, enabling gradual transitions between risk levels. A trapezoid is defined by 4 points: a (start), b (peak_start), c (peak_end), and d (end).

The membership degree $\mu_k(x)$ for a given input x is calculated as:

$$\mu_k(x) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ 1, & b < x \le c, \\ \frac{d-x}{d-c}, & c < x \le d \\ 0, & x > d \end{cases} \quad (5)$$

where a, b, c, d are parameters of the trapezoidal membership function.

These parameters (5a) are derived directly from cluster statistics, where the core support interval (b, c) is defined by the minimum and maximum values of the corresponding cluster, while the outer boundaries (a, d) are extended using the adjacent clusters to ensure smooth transitions between neighbouring fuzzy sets.

$$\begin{cases} a = \begin{cases} \min(C_k), & k = 1 \\ \min(C_{k-1}), & k > 1 \end{cases} \\ b = \min(C_k) \\ c = \max(C_k) \\ d = \begin{cases} \max(C_k), & k = K \\ \max(C_{k+1}), & k < K \end{cases} \end{cases} \quad (5a)$$

To ensure valid trapezoidal membership functions, a monotonicity-preserving adjustment is applied $a \le b \le c \le d$. If violations occur due to overlapping cluster distributions, parameters are corrected according to formula (5b).

$$\begin{cases} a = \min(a, b) \\ b = \max(a, \min(b, c)) \\ c = \max(b, \min(c, d)) \\ d = \max(c, d) \end{cases} \quad (5b)$$

After fuzzification, each input variable is represented by membership degrees to several fuzzy clusters. These fuzzy memberships are not used directly for final classification. Instead, they are used to activate combinations of cluster-level empirical risk coefficients.

2. Rule Base Construction. For each combination of clusters across the input variables, a composite empirical risk indicator (6) is calculated by aggregating the normalized cluster risk coefficients. This stage represents rule aggregation, where cluster assignments determine which coefficients participate in the final risk evaluation.

The aggregation is performed as the arithmetic mean of the corresponding cluster coefficients.

$$\text{avg\_coef}_{\text{combo}} = \\ = \frac{1}{n} \sum_{v \in \{X_1, X_2, \dots, X_n\}} \text{Coef}_{\{v,\ cluster\}} \quad (6)$$

where n is the number of independent variables; $\text{Coef}_{\{v,\ cluster\}}$ is the normalised empirical risk coefficient for variable v in the corresponding cluster.

This step defines a rule-based linguistic discretization of an empirically derived aggregated risk coefficient obtained from cluster-level risk indicators. The aggregated coefficient is mapped into linguistic risk categories (Low, Medium, High) using a deterministic thresholding function (7). These labels define the consequent part of fuzzy rules and serve as intermediate interpretable outputs of the rule base.

$$\text{Rule\_Consequent\_Label} = \\ = \begin{cases} Low, & 0 \le avg\_coef \le 0.33 \\ Medium, & 0.33 < avg\_coef \le 0.66 \\ High, & 0.66 < avg\_coef \le 1 \end{cases}. \quad (7)$$

The proposed model thus represents an approach that combines fuzzy data representation with rule-based risk assessment.

The general form of rules (8):

$$\begin{pmatrix} X_1 \in Cluster_a \land X_2 \in Cluster_b \land \dots \\ \dots \land X_n \in Cluster_z \end{pmatrix} \Rightarrow \\ \Rightarrow Risk_{Category} = \text{Low/Medium/High}. \quad (8)$$

3. **Fuzzy Logical Inference**. The degree of rule activation (9) was determined as the minimum membership degree of the antecedents:

$$\text{RuleStrength} = \min\{\mu_{\text{antecedent}_i}(X_i)\}_{i=1}^{n} \qquad (9)$$

where $\mu_{\text{antecedent}_i}(X_i)$ is the membership degree of the i-th input observation X_i to the corresponding fuzzy set defined in the rule antecedent.

Rule aggregation was performed using the Mamdani method [34]. The membership degrees of all activated rules were combined using the maximum operator (10).

$$\mu_{\text{aggregated}}(x) = \max\{\mu_{rule_m}(x)\}_{m=1}^{M_{\text{active}}}. \qquad (10)$$

where x is the value on the RiskScore output axis for which the membership is calculated; M_{active} is the number of rules activated for a particular observation.

4. **Defuzzification**. The point RiskScore was calculated using the centroid method (11).

$$\text{RiskScore} = \frac{\sum_i x_i \cdot \mu_{\text{aggregated}}(x_i)}{\sum_i \mu_{\text{aggregated}}(x_i)}. \qquad (11)$$

where x_i is the value on the RiskScore axis, and $\mu_{\text{aggregated}}(x_i)$ is the membership degree after rule aggregation.

The RiskScore was then normalised to the 0-100 range for integration into the scoring system (12).

$$\text{RiskScore}_{norm} = \text{clip}(\text{RiskScore}, 0, 100). \qquad (12)$$

The defuzzified value RiskScore serves as a single continuous representation of aggregated fuzzy inference results and is used as the basis for final risk classification.

5. **Integration into the Decision-Making System**. The normalised RiskScore is described by three fuzzy sets (Low, Medium, and High) with trapezoidal membership functions, ensuring smooth transitions between risk levels. A final crisp decision is obtained via deterministic thresholding of the normalised RiskScore. Each customer j is assigned to a discrete risk category based on the normalized defuzzified score $\text{RiskScore}_{norm}^{(j)}$. This step represents the final decision layer of the scoring system.

$$Final\_Risk_{Category}(j) = \\ = \begin{cases} Low, & 0 \le \text{RiskScore}_{norm}^{(j)} \le 33 \\ Medium, & 33 < \text{RiskScore}_{norm}^{(j)} \le 66 \\ High, & 66 < \text{RiskScore}_{norm}^{(j)} \le 100 \end{cases}. \qquad (13)$$

Model Testing and Validation

The model validation included several aspects [7], [15], [44].

1. Internal Feasibility – assessment of the complexity and non-linearity of the empirical data, coherence of the clustering, and correctness of the membership function construction.
2. External Feasibility – comparison of the formed clusters with the actual default distribution to evaluate the model's consistency with real-world data.
3. Monotonicity Check (H1) – verification of the increase in Bad Rate across ordered clusters.
4. Rule Coherence (H2) – evaluation of the frequency of rule activation and their conformity with empirical credit risk patterns.
5. Transparency Analysis (H3) – assessment of the overlap of membership functions, clarity of linguistic level boundaries, and the traceability of activated rules for each decision.

Sample limitations

The study is limited to data from a single microfinance institution (MFI) and covers only the year 2024. The sample includes only issued and completed loans, which may introduce selection bias. Socio-demographic and detailed financial variables of borrowers are not available. Despite these limitations, the data allows for the construction of a comprehensive fuzzy credit risk model and the assessment of clients' behavioural and financial characteristics.

RESEARCH RESULTS

Descriptive Statistics

The overall default rate in the sample is 13.72 % (Status = 1 – 518,620 cases; Status = 0 – 82,472 cases). Such a low share of Status = 0 is typical for the microfinance institution (MFI) segment, where default is defined strictly based on actual arrears of ≥30 days.

The three selected independent variables provide a comprehensive representation of different aspects of credit behaviour: formal credit history, current interaction with the service, and actual repayment discipline. Correlation analysis (Table 1) revealed weak but statistically significant relationships between the variables, confirming their informational independence and suitability for the fuzzy risk model.

Table 1. **Correlation**

	CBS	UA	ADPL
CBS	1	0.051***	0.005***
UA	0.051***	1	-0.086***
ADPL	0.005***	-0.086***	1

Note: *** – p < 0,01; ** – p < 0,05; * – p < 0,1

Source: **compiled by the authors**

The weak but statistically significant correlations between CBS, UA, and ADPL are consistent with findings in prior studies indicating that credit bureau indicators, behavioural activity measures, and repayment dynamics capture partially independent dimensions of borrower risk [2], [4]. Such low-correlation structures are consistent with research emphasising heterogeneous feature complementary in explainable credit scoring systems, where predictive strength is derived from complementarity heterogeneous features rather than redundancy [11].

Descriptive statistics (Table 2, Fig. 3 and Fig. 4) show high levels of skewness, large standard deviations, and the presence of outliers, justifying the use of fuzzy logic for the interpretation of behavioural patterns. CBS exhibits a substantial difference in mean values between defaulters and non-defaulters (88.611 versus 133.776), with 37.5 % of observations having no credit history (value = -1). UA shows pronounced positive skewness (1.052-1.430), with a lower mean for defaulters, reflecting non-linear behavioural patterns. ADPL is characterised by extremely high skewness and kurtosis, with higher values for defaulters (23.787 versus 15.396), indicating atypical repayment discipline patterns.

The observed non-normality, strong skewness, and presence of outliers across key variables are consistent with empirical evidence in credit risk modelling [8], [9], where behavioural and transactional credit data typically exhibit skewed and nonlinear patterns. These distributional properties are widely documented in the literature and are frequently associated with the suitability of hybrid and fuzzy-based approaches in credit scoring [51], [52].

Clustering Results and Formation of Fuzzy Sets

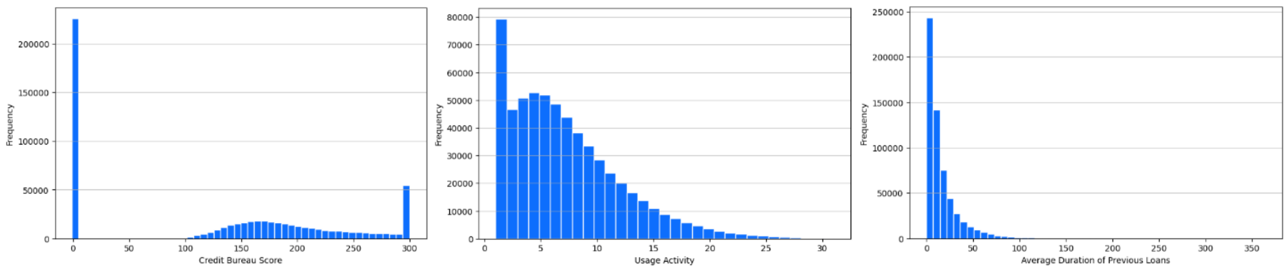
The application of K-Means clustering to CBS, UA, and ADPL allowed the identification of stable segments for the formation of fuzzy sets. The optimal number of clusters was determined using the Elbow method (Fig. 5a, 5b and 5c).

The use of clustering as a preprocessing step for fuzzy set construction is consistent with recent hybrid credit risk approaches, in which unsupervised segmentation is applied to derive interpretable risk partitions prior to fuzzy inference [24], [51]. Such frameworks are reported in the literature as supporting the interpretability of credit scoring structures by providing empirically grounded segmentation that facilitates subsequent rule-based modelling [52].

Table 2. **Descriptive Statistics**

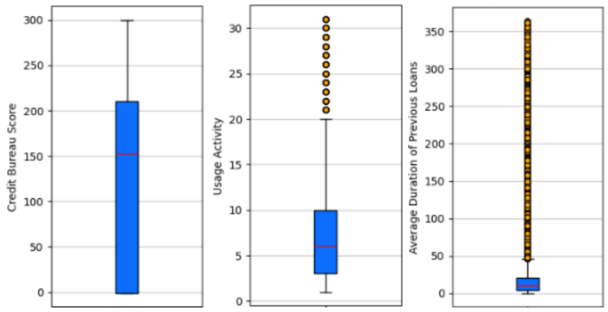
Variable	Credit Bureau Score			Usage Activity			Average Duration of Previous Loans		
Group	All	Status=0	Status=1	All	Status=0	Status=1	All	Status=0	Status=1
Count	601092	82472	518620	601092	82472	518620	601092	82472	518620
Mean	127.579	88.611	133.776	6.919	5.478	7.148	16.548	23.787	15.396
Median	153.000	120.000	159.000	6.000	4.000	6.000	9.750	13.750	9.417
SD	109.379	88.380	111.105	5.058	4.443	5.112	22.377	32.099	20.170
Min	-1	-1	-1	1	1	1	0	0	0
Max	300	300	300	31	31	31	364	364	364
Skewness	0.004	0.205	-0.067	1.096	1.430	1.052	3.915	2.993	4.007
Kurtosis	-1.434	-1.434	-1.452	1.192	2.450	1.072	26.871	14.088	29.841

***Source*: compiled by the authors**



a b c

Fig. 3. **Frequency distribution**
a – Credit Bureau Score (CBS); b – Usage Activity (UA); c – Average Duration of Previous Loans (ADPL)
***Source*: compiled by the authors**



a b c

Fig. 4. **Box plots**
a – Credit Bureau Score (CBS); b – Usage Activity (UA); c – Average Duration of Previous Loans (ADPL)
***Source*: compiled by the authors**

The statistical profiles of the clusters are presented in Table 3. Each cluster is described by a value range, mean indicator, and an empirical default probability proxy (Bad Rate). For CBS, four clusters were identified (Absent, Low, Average, High). The Absent cluster is the largest (225,679 observations), while the High cluster has the lowest BadRate and therefore represents the least risky borrower segment. UA is defined by four clusters reflecting increasing activity intensity, with Bad Rate varying between 0.073 and 0.185. For ADPL, five clusters were identified: Short and Average represent elevated risk, while Long and Suspicious Long represent the highest risk, reflecting unreliable borrower behaviour due to prolonged repayment of previous loans.

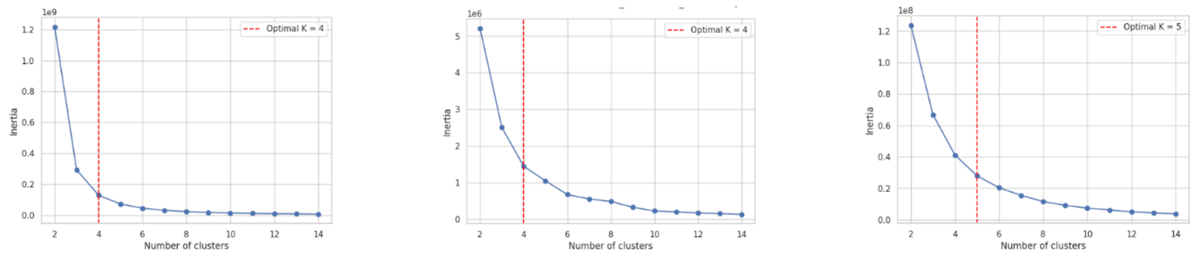
The application of fuzzy logic aligns with established research demonstrating its suitability for modelling gradual transitions between risk categories in financial datasets characterised by uncertainty and behavioural heterogeneity [14], [15]. Fuzzy inference systems are widely used in credit risk applications, particularly for handling borderline cases where crisp classification approaches may be overly restrictive [9]. [17].

Bad Rate profiles (Fig. 6) demonstrate the discrete nature of transitions between segments, justifying the use of fuzzy sets with smooth membership functions (Fig. 7).

Table 3. **Cluster summary**

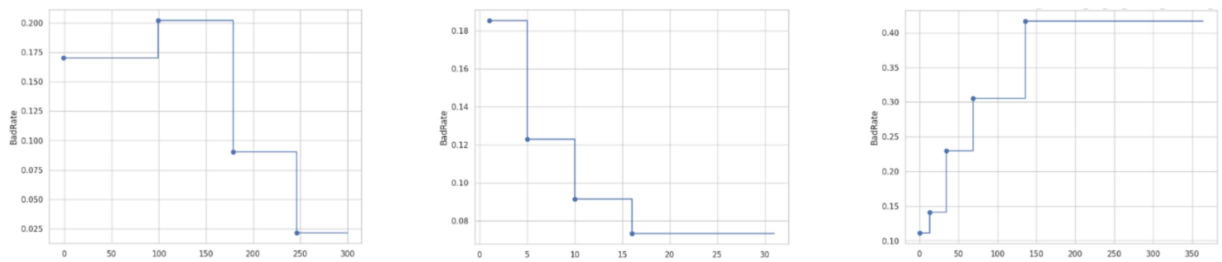
Va-riable	Cluster ID – label	Interval	Count	Mean	Bad-Rate	Coef
CBS	0 – Absent	(-1; -1]	225679	-1.000	0.170	0.825
	1 – Low	(99; 178]	151516	150.596	0.202	1.000
	2 – Average	(179; 245]	124518	206.785	0.090	0.382
	3 – High	(246; 300]	99379	285.235	0.021	0.000
UA	0 – Absent	(1; 4]	229643	2.336	0.185	1.000
	1 – Low	(5; 9]	216087	6.781	0.123	0.442
	2 – Average	(10; 15]	113872	11.971	0.091	0.161
	3 – High	(16; 31]	41490	19.142	0.073	0.000
ADPL	0 – Short	(0; 13]	363151	5.125	0.111	0.000
	1 – Average	(13; 34]	161798	21.044	0.141	0.099
	2 – Sufficient	(34; 68]	56958	47.000	0.230	0.388
	3 – Long	(68; 135]	16063	89.695	0.305	0.636
	4 – Suspi-cious Long	(135; 364]	3122	180.213	0.416	1.000

***Source*: compiled by the authors**



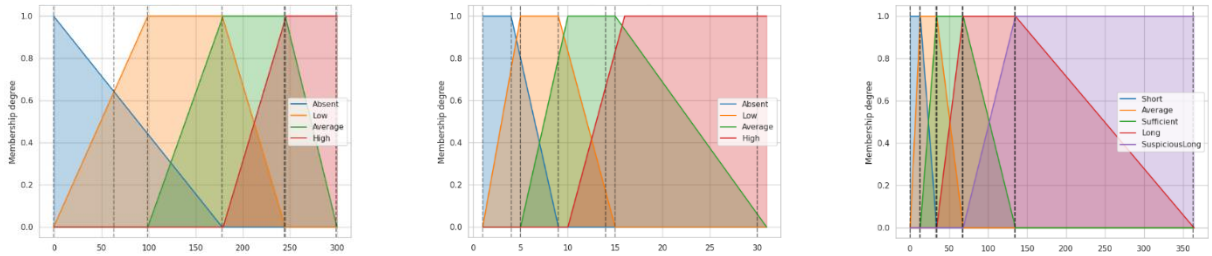
a b c

Fig. 5. **Optimal Number of Clusters Elbow method**
a – Credit Bureau Score (CBS); b – Usage Activity (UA); c – Average Duration of Previous Loans (ADPL)
***Source*: compiled by the authors**



a b c

Fig. 6. **Step functions BadRate by cluster**
a – Credit Bureau Score (CBS); b – Usage Activity (UA); c – Average Duration of Previous Loans (ADPL)
***Source*: compiled by the authors**



a b c

Fig. 7. **Membership functions**

a – Credit Bureau Score (CBS); b – Usage Activity (UA); c – Average Duration of Previous Loans (ADPL)

***Source*: compiled by the authors**

The intersection points of adjacent membership functions (Table 4) define characteristic zones of gradual transition between categories. ADPL exhibits the most complex structure, with several triple and quadruple intersections due to its wide range of values.

Table 4. **Intersection points between fuzzy sets across all variables**

Variable	Cluster label from	Cluster label to	Intersection x
CBS	Absent	Low	63; 244
	Low	Average	-1; 178; 299
	Average	High	99; 245
UA	Absent	Low	4; 14
	Low	Average	1; 9; 30
	Average	High	5; 15
ADPL	Short	Average	12; 13; 67
	Average	Sufficient	0; 33; 34; 134
	Sufficient	Long	13; 67; 68; 363
	Long	SuspiciousLong	34; 134; 135

***Source*: compiled by the authors**

To verify the external validity of the identified clusters, an analysis of the relationship between Bad Rate and cluster coefficients (Coef) was conducted for CBS, UA, and ADPL (Fig. 8). The results demonstrate that the segments are statistically distinct in terms of mean indicators and risk levels, confirming the adequacy of the clustering procedure as a basis for fuzzy set construction. This verification supports the rationale for the subsequent formation of fuzzy sets and the construction of the Rule Base for credit risk assessment.

Moreover, the clustering outcomes indicate stable segmentation patterns across variables with different distributions and behavioural characteristics. Identified structures remain stable across variables with different distributions and behaviours. This consistency shows that the derived fuzzy sets are capable of representing both typical and atypical behavioural profiles, strengthening the foundation for subsequent fuzzy inference and model calibration.

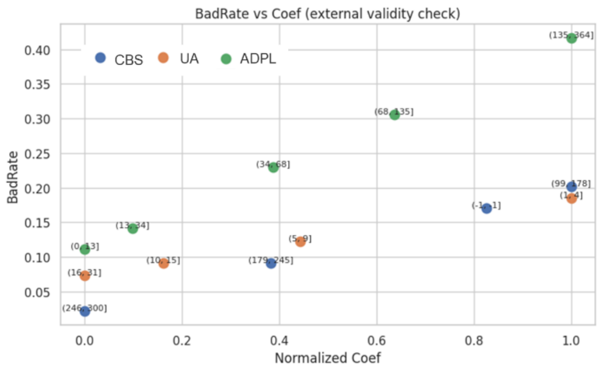


Fig. 8. **External validity check**

***Source*: compiled by the authors**

Rule Base: Empirical assignment of risk categories

After the formation of fuzzy sets for CBS, UA and ADPL, a comprehensive Rule Base was constructed to assign credit risk categories to all possible combinations of clusters. The three-dimensional aggregated membership surface μ_aggregated (Fig. 9) reflects the interaction between behavioural and historical indicators. Peaks in the surface correspond to cluster combinations associated with well-defined borrower profiles and clearly differentiated risk levels.

The heatmap representation in Fig. 10 provides further insight into the distribution of aggregated membership across cluster combinations. Segments with low CBS and long ADPL durations consistently activate rules corresponding to High Risk, reflecting the higher proportion of bad loans. Conversely, clusters with stronger credit histories or shorter/moderate loan durations tend to trigger Medium or Low Risk rules.

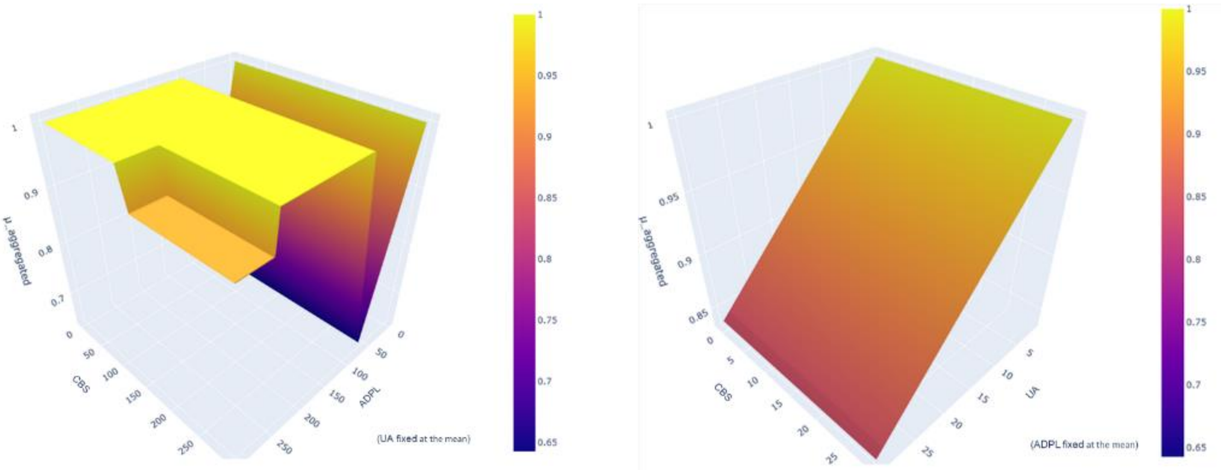
Table 5 presents a sample of the Rule Base, showing cluster combinations and their corresponding Risk Category. Rules with high avg_BadRate_combo form High Risk, medium values correspond to Medium Risk, and low values indicate Low Risk. The

Rule Base includes all possible combinations of the clusters across CBS, UA, and ADPL, resulting in total of 80 rules (4 × 4 × 5).

The proposed fuzzy rule base provides full combinatorial coverage of empirically derived clusters across CBS, UA, and ADPL variables, supporting structural completeness of the inference mechanism. This design enables consistent interpretation of borrower profiles across the entire segmentation space and provides a stable basis for potential extensions, including adaptive or time-dependent rule updating.

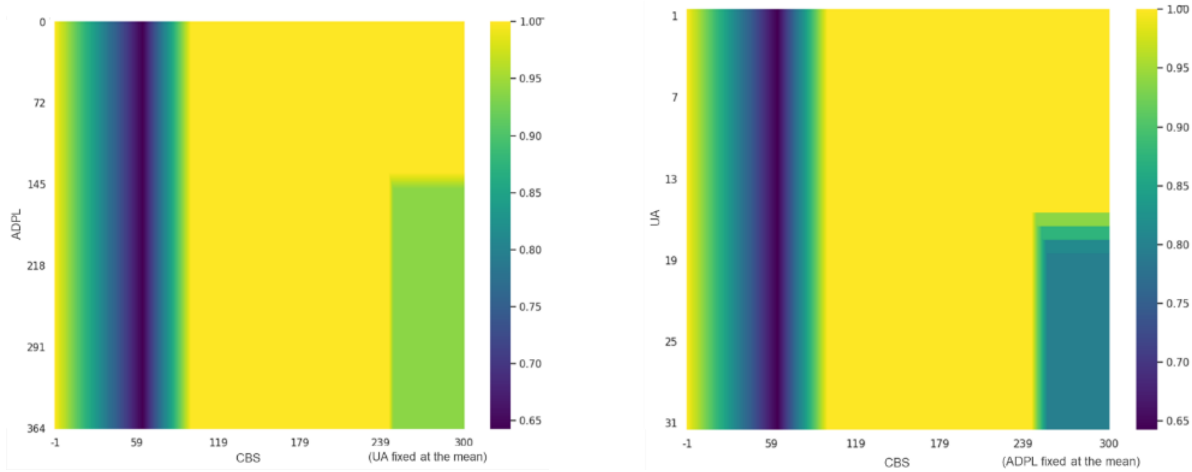
Overall, these observations confirm that the constructed Rule Base formalises the mapping between behavioural clusters and risk categories while preserving the empirical structure of the data. The fuzzy inference system remains both interpretable and aligned with actual portfolio dynamics.

The Rule Base demonstrates internal coherence and empirical validity: frequent patterns correspond to intuitive behavioural categories, and rare but high-risk combinations are properly represented due to the continuous structure of μ_aggregated. This ensures that both typical and atypical borrower profiles are adequately considered in risk scoring.



a b

Fig. 9. **Aggregated Membership μ_aggregated Surface**
a – for Credit Bureau Score (CBS) vs Average Duration of Previous Loans (ADPL), Usage Activity (UA) fixed at the mean; b – for Credit Bureau Score (CBS) vs Usage Activity (UA), Average Duration of Previous Loans (ADPL) fixed at the mean
***Source*: compiled by the authors**



a b

Fig. 10. **Heatmap of μ_aggregated**
a – for Credit Bureau Score (CBS) vs Average Duration of Previous Loans (ADPL), Usage Activity (UA) fixed at the mean; b – for Credit Bureau Score (CBS) vs Usage Activity (UA), Average Duration of Previous Loans (ADPL) fixed at the mean
***Source*: compiled by the authors**

Table 5. **Fuzzy Rule Base: Overview of Cluster Combinations and Consequents (sample rows)**

Rule No.	CBS_ cluster_ID	UA_ cluster_ID	ADPL_ cluster_ID	avg_BadRate_ combo	avg_coef_ combo	Rule_Consequent_ Label	Support (n)
0	0	0	0	0.793	0.608	Medium	63894
1	0	0	1	0.790	0.641	Medium	15517
2	0	0	2	0.673	0.738	High	8518
3	0	0	3	0.590	0.820	High	3003
4	0	0	4	0.477	0.942	High	673
5	0	1	0	0.887	0.423	Medium	40976
6	0	1	1	0.837	0.455	Medium	26182
7	0	1	2	0.753	0.552	Medium	8714
8	0	1	3	0.666	0.635	Medium	1859
9	0	1	4	0.566	0.756	High	219
10	0	2	0	0.916	0.329	Low	27673
11	0	2	1	0.859	0.362	Medium	10722
12	0	2	2	0.754	0.458	Medium	2353
13	0	2	3	0.680	0.541	Medium	437
14	0	2	4	0.607	0.662	High	28
15	0	3	0	0.934	0.275	Low	11661
16	0	3	1	0.868	0.308	Low	2612
17	0	3	2	0.783	0.404	Medium	540
18	0	3	3	0.618	0.487	Medium	89
19	0	3	4	0.667	0.608	Medium	9

***Source*: compiled by the authors**

The structure of the rule base is consistent with findings in interpretable AI literature, where fuzzy rule-based systems provide explicit mappings between input conditions and output classes, supporting explainability in decision-making processes [20], [21], [22], [23], [24], [25], [26], [27], [34]. In credit risk applications, such systems are widely recognised for their ability to maintain interpretability while preserving practical predictive usefulness relative to more opaque modelling approaches [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44].

Activation of fuzzy rules for individual observations

This section demonstrates how the model evaluates the behaviour of individual clients based on the set of rules established after the segmentation of CBS, UA, and ADPL indicators. Unlike the general characterisation of rules, which describes the structure and stability across the entire sample, the assessment of RuleStrength reflects the model's performance at the level of a single observation. RuleStrength indicates the extent to which a specific rule has been "activated" for a given client, i.e., how closely the client's indicator values match the pattern described by the rule. This measure allows the identification of the specific combinations of factors that determined the client's risk level.

To illustrate the model's operation for different types of clients, Table 6 presents three examples belonging to different final risk categories: Client A – Low Risk, Client B – Medium Risk, and Client C – High Risk. For Client B, the full list of activated rules is provided in Table 7, which demonstrates how the model generates the overall risk assessment considering the entire Rule Base structure.

The strongest activation was observed for Rule No. 20 (RuleStrength = 1), which corresponds to a High-Risk pattern. Subsequent activation include Rule No. 40 (Medium Risk) with RuleStrength = 0.888 and Rule No. 45 (Low Risk) with RuleStrength = 0.500. This combination of rules results in an overall Medium credit risk for Client B, reflecting a balanced profile with mixed behavioural signals across the loan portfolio.

For Clients A and C, Table 8 presents the three most strongly activated rules. This illustrates how different CBS, UA, and ADPL values form risk patterns within the client base and how these patterns relate to credit risk. Client A's high CBS and moderate ADPL result in activation of Low-Risk rules, while Client C's low CBS and extreme ADPL values lead to activation of High-Risk rules.

The application of RuleStrength allows the model not only to classify clients but also to assess the probability of default at the level of specific factor combinations. For instance, for Client B, the average BadRate values of the rules (avg_BadRate_combo) and the cumulative activation intensity indicate a medium portfolio risk, which can inform the calculation of loan loss provisions and risk management strategy. Similarly, high activations for Client C indicate a potentially significant portfolio burden, while low activations for Client A reflect stable borrower behaviour.

Table 6. **Example clients: input and output data**

Client ID	Value			Centroid	Final_ Risk_ Category	Number of activated rules	TOP 1		
	CBS	UA	ADPL				No rule	Rule Strength	avg_BadRate_ combo
A	290	25	7	18.57 (1.00)	Low	8	75	1.000	0.992
B	170	3	6	56.97 (0.77)	Medium	12	20	1.000	0.786
C	150	2	200	73.90 (0.80)	High	12	24	1.000	0.536

***Source*: compiled by the authors**

Table 7. **Activated rules for Client B**

Rule No.	CBS_ cluster_ID	UA_ cluster_ID	ADPL_ cluster_ID	avg_BadRate_ combo	avg_coef_ combo	Rule_Consequent_ Label	support_ n	Rule Strength
20	1	0	0	0.786	0.667	High	35123	1
40	2	0	0	0.900	0.461	Medium	20670	0.888
45	2	1	0	0.952	0.275	Low	21718	0.500
25	1	1	0	0.837	0.481	Medium	23538	0.500
26	1	1	1	0.810	0.514	Medium	20736	0.462
41	2	0	1	0.883	0.494	Medium	12798	0.462
46	2	1	1	0.911	0.308	Low	18305	0.462
21	1	0	1	0.761	0.700	High	13759	0.462
0	0	0	0	0.793	0.608	Medium	63894	0.045
1	0	0	1	0.790	0.641	Medium	15517	0.045
6	0	1	1	0.837	0.455	Medium	26182	0.045
5	0	1	0	0.887	0.423	Medium	40976	0.045

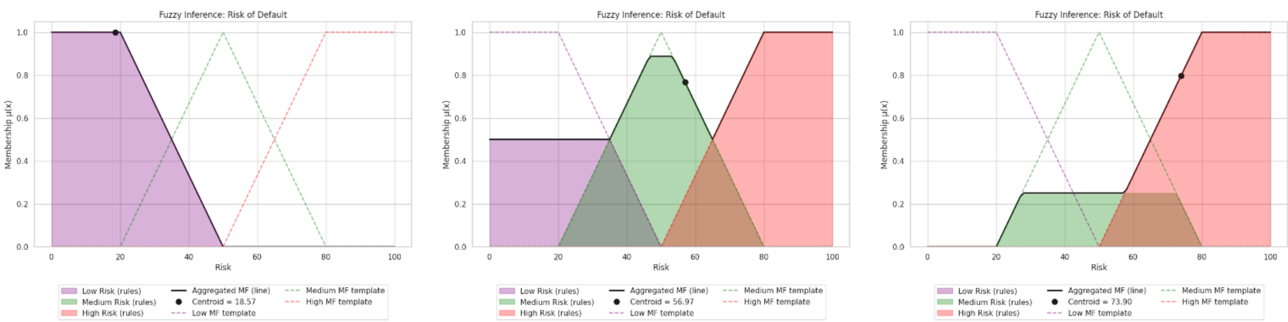
***Source*: compiled by the authors**

Table 8. **Activated rules (TOP 3) for Clients A and C**

Client A					Client C			
Rule No.	avg_BadRate_ combo	Rule_Consequent_ Label	Rule Strength		Rule No.	avg_BadRate_ combo	Rule_Consequent_ Label	Rule Strength
75	0.992	Low	1.000		24	0.536	High	1.000
76	0.968	Low	0.538		23	0.633	High	0.716
70	0.989	Low	0.375		44	0.631	High	0.638

***Source*: compiled by the authors**

For a more visual illustration of the fuzzy inference system at the level of individual clients, Fig. 11 presents the aggregated membership functions for the “Risk” variable for Clients A, B and C. The centroid of the aggregated membership function indicates the final RiskScore assigned to each client. By visualising the degree of activation across risk categories, the figure highlights how specific combinations of client indicators influence the overall credit risk assessment.



a – Client A b – Client B c – Client C

Fig. 11. **Fuzzy inference for selected clients**
***Source*: compiled by the authors**

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The rule activation mechanism is conceptually aligned with post-hoc explainability approaches such as SHAP and LIME, which decompose model predictions into contributions of input features [31], [32]. However, unlike model-agnostic methods, fuzzy rule-based systems provide intrinsic interpretability through explicit inference structures, eliminating the need for external approximation of feature importance. Recent comparative analyses suggest that both approaches can offer useful explanatory insights, although fuzzy systems provide stronger structural transparency and direct traceability of decision logic [13], [48].

Defuzzification Results and RiskScore

After applying fuzzy logic and activating rules for all clients, defuzzification was performed to obtain an individual RiskScore for each observation. The distribution of RiskScore within the sample is shown in Fig. 12. The histogram reveals three main risk groups formed by the model based on the behavioural variables CBS, UA, and ADPL. Most clients are concentrated within the medium RiskScore range (≈ 47.90-52.10), corresponding to the Medium Risk category, while lower (≈18.57-24.85) and higher (≈75.14-81.43) values reflect Low and High-Risk borrowers, respectively.

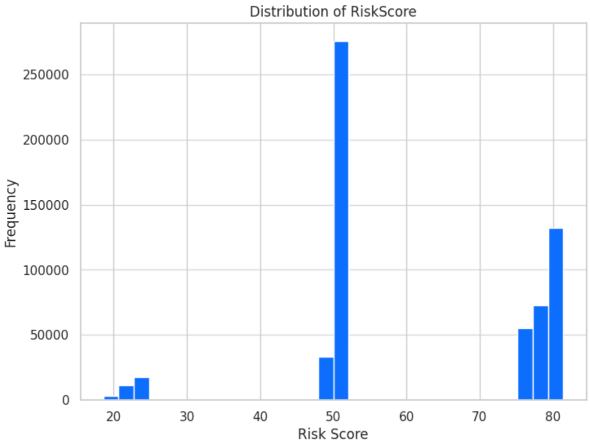

Fig. 12. **Distribution of RiskScore**
***Source*: compiled by the authors**

Analysis of RiskScore by risk category confirms the classification logic. For the Low-Risk category, RiskScore values range are characterised by minimal activation of high-risk rules. The Medium Risk category shows a sharp concentration around 50, reflecting a balanced combination of medium-risk and partially high-risk rules. For the High-Risk category, RiskScore ranges corresponding to strong activation of high BadRate rules and RuleStrength intensities typical for clients with potentially problematic repayment behaviour.

Fig. 13 illustrates the distribution of RiskScore across RiskLevel categories. Boxplot statistics show clearly separated clusters for Low, Medium, and High Risk. Notably, the Low and High-Risk categories have well-defined boundaries with no significant outliers, while the Medium Risk category shows very consistent RiskScore values around 50, with a few negligible deviations. This confirms the stability of the model and the adequacy of the membership functions used in the fuzzy inference system.

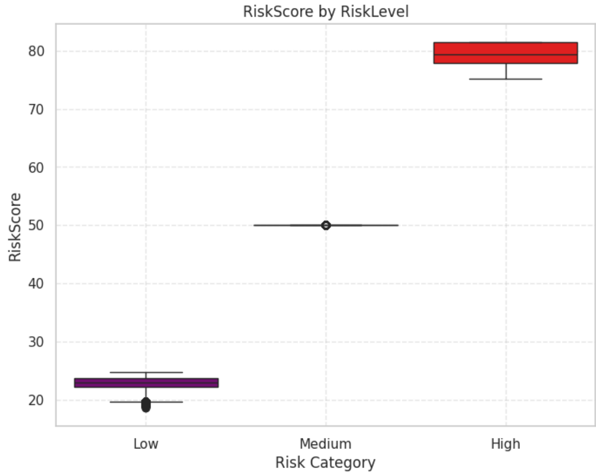

Fig. 13. **RiskScore by RiskLevel**
***Source*: compiled by the authors**

Thus, the defuzzification results demonstrate the effective operation of the fuzzy inference system, with RiskScore providing a numerical representation of credit risk based on multidimensional behavioural patterns. These values can be used for credit scoring, portfolio management, and the determination of loan loss provisions, supporting informed risk management decisions.

The observed separation of RiskScore distributions across risk categories is consistent with findings from fuzzy credit scoring literature, where centroid-based defuzzification produces stable and interpretable risk gradients that align with underlying default risk patterns [46], [52]. Similar behaviour has been reported in fuzzy inference-based credit rating systems, confirming the robustness of defuzzified risk outputs for decision-making applications [18].

Monotonicity Check (H1)

To verify the internal consistency of the constructed model, a monotonicity analysis of the relationship between BadRate and cluster ID was conducted for each variable (CBS, UA, ADPL). Fig. 14 demonstrates that as cluster IDs increase (from categories with the lowest indicator values to the highest), BadRate changes sequentially, reflecting a logical trend of increasing credit risk.

For CBS, BadRate drops from 0.170 in the Absent cluster to 0.021 in the High cluster, indicating the expected dependence between credit history and default risk. For UA, there is a gradual decrease in BadRate from 0.185 (Absent) to 0.073 (High), confirming the inverse relationship between user activity and risk. For ADPL, the trend is more complex: Short and Average durations show lower BadRate (0.111-0.141), while Sufficient, Long, and Suspicious Long durations correspond to higher risk (0.230-0.416), indicating non-linear behaviour.

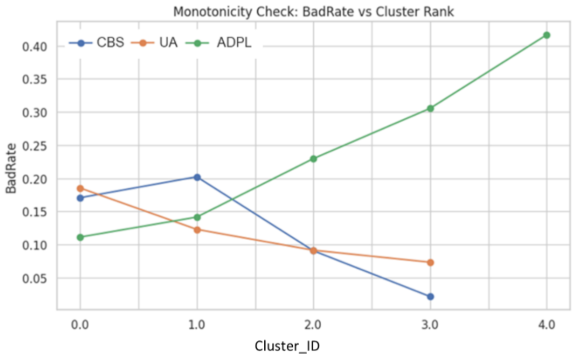

Fig. 14. **Monotonicity Check – BadRate vs Cluster ID**
***Source*: compiled by the authors**

Thus, the monotonicity analysis confirms the correctness of cluster formation and fuzzy sets and supports their subsequent use in the Rule Base for determining RiskScore.

The monotonic relationship between cluster progression and BadRate is consistent with theoretical expectations in credit scoring systems and has been widely documented in both classical and fuzzy credit risk modelling studies [17], [51]. Consistent risk ordering is considered an important property of interpretable credit scoring models, ensuring that segmentation reflects coherent differentiation of borrower risk across behavioural profiles [52].

Rule Coherence & Activation Analysis (H2)

Following the monotonicity check, an analysis of rule coherence and activation was performed to evaluate client behavioural patterns. The purpose of this stage is to confirm that the constructed Rule Base responds consistently to combinations of CBS, UA, and ADPL clusters, and accurately reflects the differentiation between defaulters and non-defaulters.

Fig. 15 shows that the strongest rules are concentrated in areas corresponding to higher-risk ADPL and lower CBS clusters, whereas rules for lower risk are activated more locally, corresponding to clusters with high CBS and low ADPL. Sequential variations in activation across CBS and ADPL cluster_ID are observed, confirming the internal consistency of the fuzzy inference system.

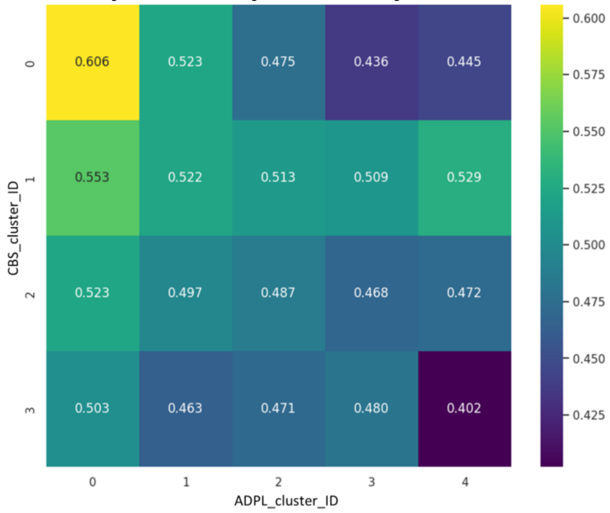

Fig. 15. **Heatmap of all Rule Activation**
***Source*: compiled by the authors**

This analysis provides additional validity for the Rule Base, demonstrating that the system not only classifies clients by RiskScore but also captures the logical interactions among risk factors at the level of specific indicator combinations. The distribution of RuleStrength across cluster_IDs ensures that both typical and atypical client profiles are appropriately represented in the credit risk assessment.

Transparency Analysis (H3)

The final stage of model evaluation focuses on assessing the transparency of the constructed fuzzy inference system. Transparency Analysis illustrates the extent to which the model's logic can be interpreted and which factors influenced the specific RiskScore for each client. Unlike conventional "black-box" machine learning models, the proposed fuzzy model provides a complete audit trail – from membership function levels to specific activated rules and defuzzification.

The transparency of the proposed fuzzy inference system stems from its explicit rule structure and direct mapping between input clusters and risk outcomes, which enables full traceability of decision logic without auxiliary post-hoc approximation methods. This structural property ensures that each risk assessment can be reconstructed through the underlying membership functions and rule activations, thereby supporting auditability in credit risk applications.

Key elements of model transparency include.

1. Visualisation of Membership Function (MF) Intersections. The intersection points of neighbouring trapezoidal membership functions (Table 4 and Fig. 7) indicate characteristic zones of gradual transition between CBS, UA, and ADPL categories. This allows assessment of how changes in input variable values affect the strength of rule activation and, ultimately, RiskScore formation. ADPL exhibits particularly complex intersection structures, including triple and quadruple intersection zones, reflecting the high flexibility of the model and its ability to accurately capture atypical borrower behavioural patterns.

2. Rule Tracing and RuleStrength as Explainability Tools. The use of RuleStrength for individual observations enables precise reconstruction of the logical chain leading to credit risk assessment. For Clients A, B, and C (Table 6, Table 7 and Table 8, Fig. 11 and Fig. 12), it is evident which rules were activated, with what intensity, and how these rules aggregated into the final RiskScore. For example, Client B activated both medium-risk and partially high-risk rules, resulting in assignment to the Medium Risk category. This level of transparency allows the model to be employed even in environments with heightened regulatory requirements.

3. Integration with the Rule Base and Defuzzification. Transparency Analysis combines information on activated rules (Fig. 15), the MF structure (Fig. 7), the aggregated surface μ_aggregated (Fig. 9 and Fig. 10), and the final stages of defuzzification (Fig. 11, Fig.12 and Fig. 13). The centroid of the aggregated membership function produces the final numerical RiskScore, making each model outcome fully reproducible – an analyst can explain the final score by reviewing the sequence of rule activations.

Table 9 summarises the main aspects of transparency, coherence, and validity of the constructed fuzzy model, alongside their practical implications and remaining methodological limitations.

Thus, the Transparency Analysis confirms that the constructed FIS is not only effective in classifying borrowers but also interpretable for analysts and credit specialists. It allows the model's logic to be traced at all levels – from individual trapezoidal membership functions to aggregated RuleStrength for specific clients – providing interpretability and fostering trust in the resulting RiskScore.

CONCLUSIONS

The results of this study demonstrate that the application of fuzzy logic in credit scoring for microfinance organisations is an effective method for risk modelling under conditions of incomplete data, noisy observations, and behavioural instability of clients. The constructed model provides comprehensive support for all three tested hypotheses:

1. High internal consistency (H1) – BadRate consistently increases with the cluster_ID of CBS, UA, and ADPL (Fig. 14). This confirms the correctness of the constructed fuzzy sets and the logical relationship between behavioural patterns and credit risk.

2. Transparent and coherent Rule Base (H2) – Heatmaps of rule activation (Fig. 15) show structural coherence of the Rule Base, appropriate responses to all cluster combinations, and absence of contradictory or inactive rules. Consequently, the Rule Base generates a stable and logically consistent RiskScore assessment.

3. High interpretability and transparency of the model (H3) – A key advantage of the proposed fuzzy model is its full transparency: from MF intersections (capturing the logic of transitions

Table 9. **Summary of Transparency, Validity and Model Coherence**

Aspect	Key Findings	Implications	Remaining Gaps
Fuzzification	CBS, UA, and ADPL form stable fuzzy sets	Adequate ranking of borrowers	Standardisation of membership functions (MF) across different MFIs
Rule Base	100% of cluster combinations present in rules	Enhanced interpretability and transparency	Automatic of Rule Base updates
RiskScore	Corresponds to actual default patterns	Usable for credit scoring and provisioning	Need for adaptation to changes in client behaviour
Monotonicity	BadRate logically increases with cluster_IDs	Confirms model correctness	Handling of extreme behavioural patterns
Transparency	RuleStrength, MF intersections, RuleTracing provide an audit trail	High transparency for audit and explainable AI	Integration of alternative data sources
Model Validity	Internal and external validity verified	Ensures model stability	Limited to a single year of data

***Source*: compiled by the authors**

between segments), through RuleStrength (indicating why each rule was activated), to the final defuzzification centroid (explaining how the RiskScore was determined).

In summary, the proposed fuzzy model: (1) provides an interpretable alternative to conventional machine learning models while maintaining stability and transparency of decisions; (2) enables tracking of the contribution of each input variable, facilitating audit, and risk modelling; (3) exhibits flexibility in capturing complex nonlinear client behaviour patterns, particularly for ADPL; (4) demonstrates significant potential for scaling to other microfinance organisations, additional years of data, and different lending segments.

Nevertheless, remaining challenges include standardising the methodology for constructing membership functions across different data segments and lending scenarios, incorporating alternative data sources (e.g., mobile data, open banking), implementing adaptive rule update mechanisms, and integrating the fuzzy model with machine learning frameworks (hybrid fuzzy-ML architectures).

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Гібридна система кластеризації на основі нечіткої логіки для прозорої оцінки кредитного ризику в сфері мікрофінансування

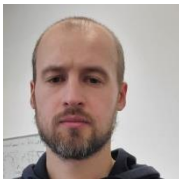
Поповський Сергій Валерійович[1)]
ORCID: https://orcid.org/0009-0001-4305-0089; serhiipopovskyi1988@gmail.com
Волков Віктор Едуардович[1)]
ORCID: https://orcid.org/0000-0002-3990-8126; viktor@te.net.ua Scopus Author ID: 57220703810
[1)] Одеський національний університет імені І. І.Мечникова, Всеволода Змієнка, 2, Одеса, 65082, Україна

АНОТАЦІЯ

Актуальність. Оцінка кредитного ризику в мікрофінансових установах, що надають короткострокові незабезпечені кредити, має вирішальне значення для фінансової стабільності та управління портфелем. Цей сегмент характеризується нестабільною поведінкою клієнтів та обмеженою кредитною історією, що створює виклики для традиційних статистичних моделей та моделей машинного навчання. Прозорість та зрозумілість стають дедалі важливішими через регуляторні вимоги та потребу в адаптивних методах, здатних працювати з неповними та зашумленими даними. **Метою** цього дослідження є розробка методології застосування нечіткої логіки для підвищення точності, стабільності та прозорості автоматичних кредитних рішень у секторі мікрофінансування. Основні завдання включають: побудову інтерпретованої нечіткої моделі, визначення нечітких множин для ключових змінних, розробку прозорої бази правил на основі кластеризації та профілів BadRate, а також валідацію внутрішньої та зовнішньої узгодженості, монотонності та прозорості. **Методи.** Дослідження використовує дані про 601 092 видані та закриті кредити української мікрофінансової організації у 2024 році. Запропонований підхід поєднує сегментацію на основі кластеризації з оцінкою кредитного ризику на основі нечітких правил. Кластеризацію виконано за допомогою методу K-Means, а оптимальну кількість сегментів визначено методом Elbow. Нечіткі множини побудовано з використанням трапецієподібних функцій належності, а правила сформовано на основі комбінацій кластерів та нормалізованих коефіцієнтів BadRate. Агрегацію та дефуззифікацію виконано методом Mamdani для отримання RiskScore. Валідація включала перевірку монотонності, узгодженості правил та прозорості рішень на рівні спостереження. **Результати.** Модель ідентифікує стабільні поведінкові сегменти, що відображають різні рівні ризику. RiskScore демонструє високу узгодженість з емпіричними розподілами BadRates та формує три інтерпретовані категорії ризику: низький, середній та високий. Запропонована нечітка модель ефективно прогнозує кредитний ризик в умовах неповних та нестабільних даних. **Висновки. Наукова новизна** дослідження полягає в інтеграції кластеризації, профілів BadRate та правил на основі нечіткої логіки у єдину інтерпретовану систему оцінювання кредитного ризику в мікрофінансуванні. Запропонований підхід має **практичну значущість**, забезпечуючи прозорий і інтерпретований інструмент підтримки прийняття рішень для оцінювання кредитного ризику, придатний для управління ризиками, моніторингу портфеля, формування резервів під кредитні збитки та розробки регуляторно сумісних скорингових систем.

Ключові слова: нечітка логіка; кредитний ризик; кредитний скоринг; моделювання ризиків; кредитоспроможність; споживче кредитування; комп'ютерне моделювання

ABOUT THE AUTHORS



Serhii V. Popovskyi - Postgraduate Student, Department of Mechanics, Automation and Information Technology. Odesa I.I. Mechnikov National University, 2, Vsevolod Zmiienko Str. Odesa, 65082, Ukraine
ORCID: https://orcid.org/0009-0001-4305-0089; serhiipopovskyi1988@gmail.com
Research field: Credit scoring; data science; machine learning

Поповський Сергій Валерійович - аспірант, кафедра Механіки, автоматизації та інформаційних технологій. Одеський національний університет імені І. І. Мечникова, Всеволода Змієнка, 2. Одеса, 65082, Україна

Victor E. Volkov - Doctor of Engineering Sciences, Professor, Department of Mechanics, Automation and Information Technology. Odesa I. I. Mechnikov National University, 2, Vsevolod Zmiienko Str. Odesa, 65082, Ukraine
ORCID: https://orcid.org/0000-0002-3990-8126; viktor@te.net.ua Scopus Author ID: 57220703810
Research field: Gas Dynamics; Mathematical Theory of Combustion and Explosion; Mechanics; Physics; Automation; Information Technology; Computer Science

Волков Віктор Едуардович – доктор технічних наук, професор, кафедра Механіки, автоматизації та інформаційних технологій. Одеський національний університет імені І. І. Мечникова, Всеволода Змієнка, 2. Одеса, 65082, Україна

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