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Assessing Microcredit Eligibility Using LOGSTA Weighting and Comprehensive Distance-Based Ranking: A Multi-Criteria Decision-Making Approach

Desyanti[1*], Imam Ahmad[2], Sanusi[3]

[1]Department of Informatics, Institut Teknologi dan Bisnis Riau Pesisir, Riau, Indonesia
[2]Department of Information System, Universitas Teknokrat Indonesia, Lampung, Indonesia
[3]Department of Information Technology, Universitas Teuku Umar, Aceh, Indonesia

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ABSTRACT

This study aims to determine microcredit eligibility objectively and systematically through the integration of the logarithmic normalization and standard deviation (LOGSTA) weighting method with the comprehensive distance-based ranking method (COBRA) within a Decision Support System framework. LOGSTA is used to generate criterion weights objectively based on data variations, while COBRA is applied to rank alternatives by considering their comprehensive distance from the ideal conditions. The study involves several microcredit eligibility criteria and a number of prospective credit recipients analyzed quantitatively. The results indicate that the LOGSTA-COBRA integration can produce clear and measurable eligibility rankings, with Candidate A8 ranking first with a final score of 0.0345, followed by Candidate A2 with a score of 0.0319 and Candidate A7 with a score of 0.0280. Sensitivity analysis through various scenarios of changes in criteria weights shows that the main ranking structure is relatively stable, indicating the robustness of the method against variations in criteria importance. Furthermore, comparisons with several popular MCDM methods such as SAW, TOPSIS, MOORA, GRA, MAUT, and WASPAS using fixed LOGSTA weights show that the proposed method provides competitive and consistent results. These findings affirm that the LOGSTA-COBRA approach can be a reliable alternative to support more objective, transparent, and accountable microcredit eligibility decision-making.

I. Introduction

The determination of microcredit eligibility is very important because the micro-enterprise sector plays a strategic role in driving economic growth, especially in developing countries[1], [2]. Micro-enterprises often become the

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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backbone of the economy for lower-middle-class communities, providing jobs and increasing household income. However, limited capital is the main barrier faced by micro-entrepreneurs in developing their businesses. Therefore, access to financing through microcredit becomes a solution to support the sustainability and development of these businesses. In this context, determining microcredit eligibility is necessary to ensure that the capital assistance provided is targeted, effective, and capable of enhancing business productivity. In addition, determining the eligibility for microcredit is also an important aspect to maintain the sustainability of financial institutions that provide funding. Granting credit without proper selection poses the risk of default that can harm financial institutions and negatively impact the financial system more broadly. With the eligibility assessment process in place, financial institutions can identify the repayment capacity of prospective borrowers, evaluate business potential, and minimize the likelihood of default[3]. This not only protects the interests of financial institutions but also encourages the creation of a fair, healthy, and sustainable financing system, thus providing long-term benefits for the development of microenterprises and the national economy.

One of the problems that often arises in the assessment of microcredit eligibility is the subjectivity in the evaluation process. Many financial institutions still rely on manual assessments from credit officers, which can be influenced by perceptions, experiences, or even closeness to potential borrowers[3], [4]. This leads to assessment results that tend to vary among officers and do not accurately reflect the real conditions of prospective credit recipients. As a result, there is a possibility that businesses with real potential may not receive credit, while high-risk enterprises may be approved due to that subjective bias. In addition, the inconsistencies and limitations of conventional methods also pose challenges in determining the feasibility of microcredit. Inconsistencies arise due to the lack of uniform standards in evaluations[5], leading to differing criteria among branches or institutions. Meanwhile, conventional methods such as simple analysis based on payment history or interviews do not always capture the complexity of factors affecting borrowers' repayment abilities[6], [7]. This results in a less accurate assessment process and is prone to decision-making errors. Therefore, there is a need for a more systematic, objective, and data-driven approach so that the assessment of microcredit feasibility can be conducted fairly, consistently, and effectively.

To address the issues of subjectivity, inconsistency, and limitations of conventional methods in assessing microcredit eligibility, a new approach can be proposed that integrates Logarithmic Normalization and Standard Deviation (LOGSTA) Weighting and Comprehensive Distance-based Ranking (COBRA). LOGSTA weighting is an objective weighting technique designed to capture the real contribution of each criterion in multi-criteria decision-making by combining logarithmic normalization with statistical dispersion analysis[8]. The LOGSTA weighting approach eliminates subjective bias by relying entirely on data characteristics rather than expert judgment, making it suitable for financial feasibility analysis, risk evaluation, and credit assessment problems[9], [10]. Moreover, the integration of logarithmic normalization and standard deviation weighting enhances robustness against scale effects and data heterogeneity, ensuring that the resulting weights reflect both data distribution and decision relevance. As a result, LOGSTA weighting supports more transparent, consistent,

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and empirically grounded decision outcomes in complex evaluation environments involving multiple and often conflicting criteria.

COBRA method is used to carry out the ranking process of alternatives based on comprehensive distance to the ideal solution, thereby producing more consistent and measurable decisions[9], [11], [12]. This method considers the proximity of each alternative (candidate borrower) to both the ideal condition and the worst condition, making the ranking more accurate and reflective of reality. The COBRA method is a ranking method in multi criteria decision-making based on the calculation of comprehensive distance between each alternative and the ideal and anti-ideal conditions. The basic concept of COBRA is that an alternative is considered better if its position is closer to the ideal solution (best solution) and further from the worst solution (worst solution)[11]–[13]. By considering both sides simultaneously, COBRA is able to provide a more balanced, objective ranking that reflects the reality of various factors influencing the decision[12], [14], [15]. Through this distance-based approach, each alternative is evaluated comprehensively without relying solely on one aspect. The result is a consistent, transparent ranking that minimizes inconsistencies in the decision-making process. Thus, the use of the COBRA method can assist financial institutions in targeting microcredit more precisely and reducing the risk of problematic credit.

The integration of the LOGSTA weighting method with COBRA not only produces an objective and consistent decision-making framework but also offers a number of significant advantages in multi-criteria evaluation. LOGSTA ensures that the criteria weights are determined rationally based on variations in actual data, thereby reducing subjective bias and enhancing the representation of information for each criterion. When this weighting is applied in COBRA, the process of comprehensively measuring the distance to the ideal solution becomes more accurate because the contribution of each criterion has been adjusted according to its actual level of importance. Another advantage of this integration is its ability to handle heterogeneous and differently scaled data without losing sensitivity to performance differences among alternatives. Additionally, the clear and systematic structure of the method facilitates the interpretation of ranking results, thus supporting transparent, consistent, and empirically accountable decision-making in various multicriteria application contexts.

The purpose of this study is to determine the feasibility level of granting microcredit objectively and accurately by utilizing the integration of the LOGSTA weighting method and COBRA. This approach is designed to address the problem of credit assessment, which has so far tended to rely on subjective weights and partial evaluations of both financial and non-financial criteria of prospective borrowers. With LOGSTA, the criteria weights are determined based on actual data variations, reflecting the importance level of each criterion empirically, while the distance-based ranking method is used to evaluate the closeness of each applicant to the ideal feasibility conditions comprehensively. The main contributions of this study are summarized as follows:

a. Proposing a novel decision-support framework for microcredit borrower selection by integrating the LOGSTA weighting method with the COBRA ranking approach to improve decision-making effectiveness in complex credit assessment environments.
b. Developing an objective weighting mechanism based on the combination of logarithmic normalization and standard deviation, enabling more balanced

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criterion weight determination while reducing the influence of extreme values in the evaluation data.

c. Conducting a comparative performance analysis by benchmarking the proposed LOGSTA-COBRA approach against established MCDM methods to evaluate its ranking capability, consistency, and decision quality.

d. Performing sensitivity and validation analyses to assess the robustness and stability of the proposed model under varying criterion weight scenarios, thereby ensuring the reliability of the generated ranking results.

Therefore, the proposed LOGSTA-COBRA model is expected to provide a more objective, robust, and transparent decision-making tool for microcredit evaluation while contributing to the advancement of multi-criteria decision-making methodologies.

II. Methodology

The research method used in this study is designed to produce a more objective, consistent, and comprehensive microcredit feasibility assessment model through a combination of the LOGSTA and COBRA methods. This research is quantitative with an MCDM approach, as the main focus lies on the analysis of numerical data to determine the weights of criteria and rank the alternatives[16]-[19]. Figure 1 is the research method used and applied in this study.

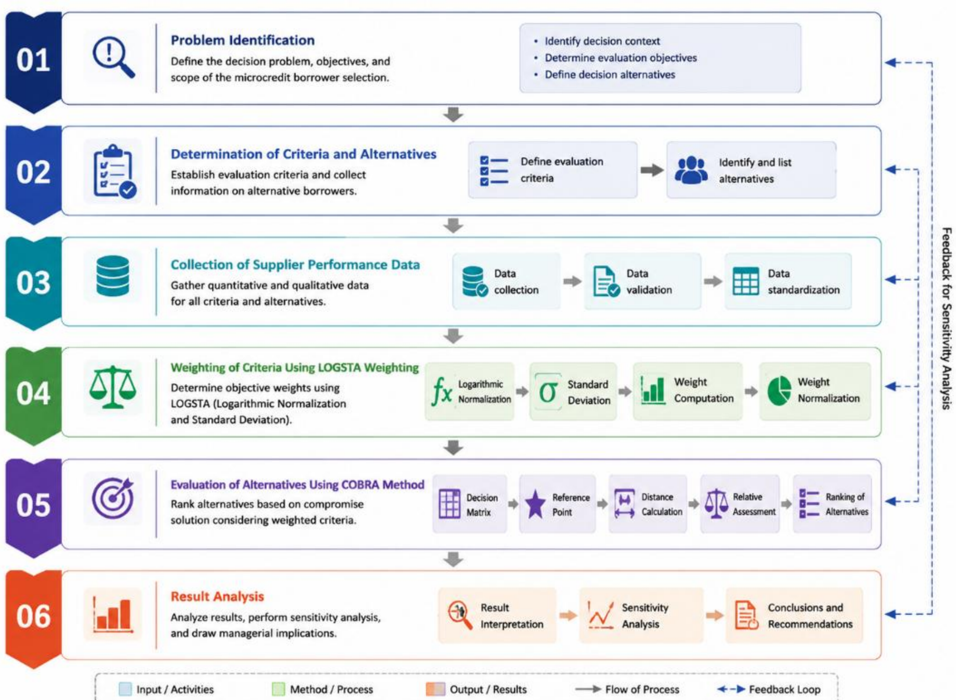

Figure 1. Research Stages

The diagram in figure 1 explains the research stages in determining the feasibility of microcredit using a combination of the LOGSTA and COBRA methods. The process starts with identifying the criteria for

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assessing microcredit, where important factors that affect the eligibility of borrowers are determined, such as income, credit history, assets, and non-financial aspects. After the criteria are established, data collection of potential borrowers is conducted as the basis for analysis. The next stage is the determination of criterion weights using the RECA method, which aims to provide an objective importance value for each criterion based on its influence on credit eligibility. The weights obtained are then used in the alternative assessment stage using the COBRA method. This method calculates the comprehensive distance of each potential borrower from both the ideal and worst-case conditions, allowing for a thorough evaluation. The final stage is the ranking of alternatives, where potential borrowers are ordered based on the assessment results so that financial institutions can determine who is most eligible to receive microcredit facilities.

2.1. Logarithmic Normalization and Standard Deviation (LOGSTA) Method

The logarithmic normalization and standard deviation (LOGSTA) method serves as a weighting method for objective criteria in multi-criteria decision making, combining logarithmic normalization techniques and standard deviation measurement to determine the relative importance of each criterion[8]. The criterion weights in LOGSTA are determined based on the magnitude of this variation, so that criteria with higher value dispersion receive greater weight. With this approach, LOGSTA produces criterion weights that are rational, data-driven, and free from decision-makers' subjectivity.

The first stage is the formation of a decision matrix, which represents the relationship between alternatives and criteria in the form of a decision matrix. Each row represents an alternative, while each column represents an evaluation criterion. The values in this matrix come from initial data, which can be quantitative data or the results of measuring the performance of alternatives against each criterion. At this stage, the data is still on its original scale, so the differences in units and value ranges between criteria are still clearly visible.

$$X = [x_{ij}]_{mxn} \tag{1}$$

The second stage is normalization using a logarithmic approach. Logarithmic normalization aims to reduce distortion caused by extreme scale differences and suppress the influence of excessively large values. Each element in the decision matrix is normalized using the logarithmic function relative to the maximum value of the relevant criterion. This approach makes the data distribution more stable and proportional, allowing variations between alternatives to be compared more fairly, especially when the data is non-homogeneous.

$$n_{ij} = \left| \frac{\ln x_{ij}}{\ln(\prod_{i=1}^{m} x_{ij})} \right| ; benefit\ criteria \tag{2}$$

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$$n_{ij} = \left| \frac{1 - \frac{\ln x_{ij}}{\ln\left(\prod_{i=1}^{m} x_{ij}\right)}}{n-1} \right|; cost\ criteria \tag{3}$$

The third stage is the calculation of the standard deviation for each criterion based on the logarithmic normalization results. Standard deviation is used to measure the degree of spread or variation of a criterion's values among all alternatives. The larger the standard deviation, the higher the criterion's ability to differentiate the performance of alternatives. Thus, criteria with high variation are considered more informative in the decision-making process.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n} \left(n_{ij} - \bar{n}_j\right)^2}{n}} \tag{4}$$

$$g_j = \sigma_j * \left(\left| \sum_{i=1}^{m} \left(\ln(n_{ij}) \right) \right| \right)^{-1} \tag{5}$$

The fourth stage is the determination of criteria weights. The criteria weights are obtained by normalizing the standard deviation values of each criterion against the total standard deviation of all criteria. This process produces objective weights that reflect the relative contribution of each criterion based on its level of variation.

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{6}$$

The LOGSTA method can be seen as a robust and rational approach to criteria weighting in supporting data-driven multi-criteria decision making. By combining logarithmic normalization and standard deviation, this method can address differences in data scales while objectively capturing the level of variation of information across criteria. Therefore, LOGSTA is suitable for use as a basis for criteria weighting in various decision-making problems involving heterogeneous data and requiring scientifically accountable results.

2.2. Comprehensive Distance-based Ranking (COBRA) Method

COBRA method is a ranking method in multi-criteria decision making MCDM that is based on the concept of comprehensive distance between each alternative and the ideal solution (best solution) and the anti-ideal solution (worst solution). The main principle of COBRA is that an alternative is assessed to be better if its position is closer to the ideal condition and further away from the worst condition[18], [20]. With this approach, COBRA not only looks at the performance of an alternative from one side (e.g., proximity to the ideal), but also considers its distance from the negative side, resulting in a more balanced, objective, and comprehensive ranking.

The first step is to compile a decision matrix that contains the values of each alternative against the established criteria. This matrix illustrates the initial assessment conditions, where the rows represent the alternatives, and the columns represent the assessment criteria. The

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decision matrix serves as the foundational basis for all calculations made using equation (1).

Because each criterion usually has different measurement scales, a normalization process is needed to align all values to the same scale, generally 0-1. With normalization, the comparison between criteria becomes fairer, so that no single criterion dominates simply because of differences in measurement units.

$$r_{ij} = \frac{x_{ij}}{max_{ij}^{i}} \tag{7}$$

The next step is to calculate the weighted normalization matrix, which reflects the actual contribution of each criterion to the evaluation of alternatives. In this way, more important criteria will have a greater influence in the subsequent calculations, which are computed using the following equation.

$$\Delta_{ij} = w_j * r_{ij} \tag{8}$$

The next step is to determine three types of reference solutions, namely the positive ideal solution (the best value for each criterion), the negative ideal solution (the worst value for each criterion), and the average solution (the middle value of each criterion). These three solutions serve as comparison points that will be used to measure the closeness and distance of each alternative calculated using the following equation.

$$PIS_j \begin{cases} = \max \Delta_{ij}^{j} \,; for\ benefit\ criteria \\ = \min \Delta_{ij}^{j} \,; for\ cost\ criteria \end{cases} \tag{9}$$

$$NIS_j \begin{cases} = \min \Delta_{ij}^{j} \,; for\ benefit\ criteria \\ = \max \Delta_{ij}^{j} \,; for\ cost\ criteria \end{cases} \tag{10}$$

$$AS_j = \frac{\sum_{j=1}^{n} \Delta_{ij}}{n} \tag{11}$$

The next step is to calculate its distance to the positive ideal solution, the negative ideal solution, and the average solution. This calculation uses the concept of distance, which shows how close or far an alternative is from the best, worst, and average conditions. The closer it is to the positive ideal solution and the farther it is from the negative ideal solution, the better the alternative is considered, calculated using the following equation.

$$d(S_i) = dE(S_i) + \beta * dE(S_i) * dT(S_i) \tag{12}$$

where Sj is any solution (PISj, NISj, or ASj), and β is the correction coefficient calculated using the following equation.

$$\beta = max_{dE(S_i)_i}^{i} - min_{dE(S_i)_i}^{i} \tag{13}$$

where dE represents the Euclidean distance and dT represents the Taxi distance for the positive ideal solution, obtained using the following equation.

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$$dE(PIS_i)^+ = \sqrt{\sum_{i=1}^{m}(PIS_j - \Delta_{ij})^2} \tag{14}$$

$$dT(PIS_i)^+ = \sum_{i=1}^{m}\left|PIS_j - \Delta_{ij}\right| \tag{15}$$

where dE is the Euclidean distance and dT is the Taxicab distance for the negative ideal solution, obtained using the following equation.

$$dE(NIS_i)^- = \sqrt{\sum_{i=1}^{m}(NIS_j - \Delta_{ij})^2} \tag{16}$$

$$dT(NIS_i)^- = \sum_{i=1}^{m}\left|NIS_j - \Delta_{ij}\right| \tag{17}$$

where dE represents the Euclidean distance and dT represents the taxicab distance for the average positive ideal solution, obtained using the following equation.

$$dE(AS_i)_i^+ = \sqrt{\sum_{i=1}^{m}\tau^+ * (AS_j - \Delta_{ij})^2} \tag{18}$$

$$dT(AS_i)_i^+ = \sum_{i=1}^{m}\tau^+ * \left|AS_j - \Delta_{ij}\right| \tag{19}$$

$$\tau^+ = \begin{cases} 1 \text{ } if \text{ } AS_j < \Delta_{ij} \\ 0 \text{ } if \text{ } AS_j > \Delta_{ij} \end{cases} \tag{20}$$

where dE represents the Euclidean distance and dT represents the Taxi distance for the average negative ideal solution, obtained using the following equation.

$$dE(AS_i)_i^- = \sqrt{\sum_{i=1}^{m}\tau^- * (AS_j - \Delta_{ij})^2} \tag{21}$$

$$dT(AS_i)_i^- = \sum_{i=1}^{m}\tau^- * \left|AS_j - \Delta_{ij}\right| \tag{22}$$

$$\tau^- = \begin{cases} 1 \text{ } if \text{ } AS_j > \Delta_{ij} \\ 0 \text{ } if \text{ } AS_j < \Delta_{ij} \end{cases} \tag{23}$$

The last step is to calculate the final value for each alternative based on the distance obtained. This value reflects the relative position of the alternatives against the three reference solutions. The alternatives are then ranked based on this final value to generate a ranking, so that it can be determined which alternative is the most feasible and closest to the ideal condition calculated using the following equation.

$$dC_i = \frac{d(PIS_i)_i - d(NIS_i)_i - d(AS_i)_i^+ + d(AS_i)_i^-}{4} \tag{24}$$

The COBRA method as a ranking approach evaluates alternatives based on their proximity to the positive ideal solution and their distance from the negative ideal solution and the average solution. With stages starting from the formation of the decision matrix, normalization, weighting, to the calculation of distance and determination of final values, COBRA is capable of providing more objective, comprehensive, and consistent ranking results. The main advantage of this method is its ability to produce balanced and transparent decisions, making it highly relevant to apply in microcredit feasibility assessment and other multi-criteria decision-making contexts.

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III. Result and Discussion

This research results section presents a comprehensive analysis of the application of the LOGSTA method integrated with COBRA in determining microcredit eligibility. The results obtained reflect how the criterion weights determined objectively through LOGSTA influence the evaluation and ranking process of prospective borrowers based on the comprehensive distance to the ideal eligibility condition. The presentation of results focuses on the ability of the proposed method to consistently and rationally differentiate eligibility levels among alternatives, as well as to demonstrate its effectiveness in processing heterogeneous microcredit data. Thus, this section provides an empirical basis for assessing the reliability of the approach used in supporting more accurate and accountable microcredit decision-making.

3.1. Data Collection of Loan Applicants

The initial step in determining microcredit eligibility is to identify relevant and significant criteria as a basis for consideration. These criteria serve as the main parameters that reflect the ability and willingness of potential borrowers to meet their credit obligations. In practice, financial institutions generally use a combination of quantitative and qualitative criteria, such as monthly income, credit history, number of dependents, owned assets, and the reputation or character of the potential borrower. Accurate identification of these criteria is an important foundation for making accurate decisions and reducing the risk of problematic credit. In addition, the selection of criteria must consider the micro context, namely the scale of small businesses, limited sources of income, and the financial literacy level of borrowers. This distinguishes microcredit from large-scale commercial credit that typically has a more complex assessment structure. By adjusting the criteria to the needs and conditions of potential borrowers, the evaluation process can become more inclusive and fair. Therefore, the stage of identifying criteria is not just a technical administrative matter, but also a strategy to ensure that credit distribution is truly targeted and supports the goals of empowering small communities. The criteria data in determining microloan eligibility is displayed in table 1.

Table 1. Criteria Data in Determining Microcredit Eligibility.

Code	Name	Type	Description
CC-A	Monthly Income	Benefit	Describing the ability of prospective borrowers to pay installments according to the amount of credit applied.
CC-B	Credit History	Benefit	Includes the payment history of previous loans, both from formal and non-formal institutions.
CC-C	Guarantees or Owned Assets	Benefit	Demonstrating the ability of the prospective borrower to provide collateral as a form of security.

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CC-D	Job or Business Stability	Benefit	Assessing the sustainability of the prospective borrower's income, both from permanent employment and self-employment.
CC-E	Number of Dependents	Cost	The more dependents there are, the higher the risk of financial limitations in repaying loans.

The five evaluation criteria used in this study were selected based on their frequent adoption in creditworthiness assessment literature and their practical relevance to microcredit risk evaluation. Monthly Income reflects the applicant's repayment capacity and financial strength, while Credit History provides information regarding past repayment behavior and credit discipline. Guarantees or Owned Assets serve as indicators of financial security and collateral support in the event of default. Job or Business Stability represents the consistency and sustainability of the applicant's income source, which is essential for long-term repayment capability. Meanwhile, the Number of Dependents is included to capture the applicant's financial burden, as a higher number of dependents may reduce disposable income available for loan repayment. Collectively, these criteria encompass key financial, behavioral, and socio-economic factors commonly considered in credit evaluation, thereby providing a comprehensive basis for assessing the eligibility of microcredit applicants.

In the context of microcredit, field approaches often become the primary choice because many potential borrowers are not yet fully connected to the formal financial system. Therefore, the data collection process is not just an administrative activity but also a step in building trust relationships between financial institutions and potential borrowers. Evaluation data from Loan Applicants is presented in Table 2.

Table 2. Micro Credit Eligibility Assessment Data

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	4500000	4	15	2	5
Candidate A2	3200000	3	10	3	4
Candidate A3	2800000	2	8	4	3
Candidate A4	5100000	5	20	2	5
Candidate A5	3500000	3	12	3	4
Candidate A6	2500000	2	7	5	3
Candidate A7	4400000	4	14	2	5
Candidate A8	3800000	3	9	3	4

The evaluation data consists of eight microcredit applicants who were assessed using five main criteria. The Monthly Income value (CC-A) ranges from 2500000 to 5100000, indicating a variation in applicants' financial ability to meet loan repayment obligations. In the Credit History criterion (CC-B), scores range from 2 to 5, reflecting differences in payment behavior quality and credit discipline among applicants. The Collateral or Owned Assets criterion (CC-C) has values

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between 7 and 20, illustrating variations in the level of asset ownership or collateral capacity that can be used as a form of credit security. Meanwhile, Job or Business Stability (CC-D) shows a score range of 2 to 5, representing the level of sustainability of the applicant's income from permanent employment or business activities. Meanwhile, Number of Dependents (CC-E), treated as a cost criterion, ranges from 3 to 5, where lower values indicate a smaller financial burden.

The dataset used in this study consists of eight microcredit applicant alternatives selected to represent a variety of borrower characteristics commonly encountered in microcredit evaluation. This dataset serves as a representative case study for demonstrating the implementation process of the proposed LOGSTA-COBRA framework, including objective weighting calculation, ranking generation, comparative analysis, and sensitivity testing. Although the number of alternatives is relatively limited, the dataset was intentionally designed to include variations in performance across all evaluation criteria, allowing the proposed method to effectively distinguish the relative suitability of each applicant. Therefore, the primary objective of this study is to illustrate the applicability and analytical capabilities of the proposed approach rather than to provide a large-scale empirical validation, which remains an important direction for future research.

3.2. Determination of Criteria Weights Using the LOGSTA Method

In the process of multi-criteria decision making, determining the weight of criteria is a very important stage because the weight reflects the relative importance of each criterion used. In the context of assessing the feasibility of microcredit, the weight of the criteria serves to ensure that the most relevant aspects are considered. The LOGSTA method was chosen in this study as an approach to determine the criteria weights more objectively and adaptively. This approach also provides advantages in terms of transparency and consistency compared to conventional weighting methods, making the results more accountable.

The first stage is the formation of a decision matrix, which represents the relationship between alternatives and criteria in the form of a decision matrix. Each row represents an alternative, while each column represents an evaluation criterion. The values in this matrix come from initial data, which can be quantitative data or the performance measurement results of alternatives against each criterion, created using (1).

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} \end{bmatrix}$$

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The decision matrix for microcredit feasibility assessment data from each alternative based on the data in Table 1 is as follows.

$$X = \begin{bmatrix} 4500000 & 4 & 15 & 2 & 5 \\ 3200000 & 3 & 10 & 3 & 4 \\ 2800000 & 2 & 8 & 4 & 3 \\ 5100000 & 5 & 20 & 2 & 5 \\ 3500000 & 3 & 12 & 3 & 4 \\ 2500000 & 2 & 7 & 5 & 3 \\ 4400000 & 4 & 14 & 2 & 5 \\ 3800000 & 3 & 9 & 3 & 4 \end{bmatrix}$$

The second stage is normalization using a logarithmic approach. Logarithmic normalization aims to reduce distortion due to extreme scale differences and suppress the influence of overly large values. Each element in the decision matrix is normalized using a logarithmic function relative to the maximum value of the related criterion, calculated using (2) and (3).

$$n_{11} = \left| \frac{\ln x_{11}}{\ln(x_{11} * x_{12} * x_{13} * x_{14} * x_{15} * x_{16} * x_{17} * x_{18})} \right|$$
$$= \left| \frac{\ln(4500000)}{\ln(4500000 * 3200000 * 2800000 * 5100000 * 3500000 * 2500000 * 4400000 * 3800000)} \right|$$
$$= \left| \frac{15.3196}{120.8358} \right| = 0.1268$$

The overall results of the normalization value calculations in the LOGSTA method are presented in Table 3.

Table 3. Normalization Results Using the LOGSTA Method

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	0.1268	0.1529	0.1399	0.0828	0.1223
Candidate A2	0.1240	0.1212	0.1190	0.1312	0.1252
Candidate A3	0.1229	0.0765	0.1074	0.1656	0.1288
Candidate A4	0.1278	0.1776	0.1548	0.0828	0.1223
Candidate A5	0.1247	0.1212	0.1284	0.1312	0.1252
Candidate A6	0.1219	0.0765	0.1005	0.1923	0.1288
Candidate A7	0.1266	0.1529	0.1364	0.0828	0.1223
Candidate A8	0.1254	0.1212	0.1135	0.1312	0.1252

The third stage is the calculation of the standard deviation for each criterion based on the results of logarithmic normalization. Standard deviation is used to measure the degree of dispersion or variation of a criterion's values among all alternatives, calculated using (4) and (5).

$$\sigma_1 = \sqrt{\frac{(n_{11} - \bar{n}_1)^2 * (n_{12} - \bar{n}_1)^2 * (n_{13} - \bar{n}_1)^2 * (n_{14} - \bar{n}_1)^2 * (n_{15} - \bar{n}_1)^2 * (n_{26} - \bar{n}_1)^2 * (n_{17} - \bar{n}_1)^2 * (n_{18} - \bar{n}_1)^2}{8}}$$

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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$$= \sqrt{\frac{\begin{array}{c}(0.1268-0.1250)^2*(0.1240-0.1250)^2*(0.1229-0.1250)^2*(0.1278-0.12501)^2*\\(0.1247-0.1250)^2*(0.1219-0.1250)^2*(0.1266-0.1250)^2*(0.1254-0.1250)^2\end{array}}{8}}$$
$$= 0.0019$$
$$g_1 = \sigma_1 * (|\ln(n_{11}) + \ln(n_{12}) + \ln(n_{13}) + \ln(n_{14}) + \ln(n_{15}) + \ln(n_{16}) + \ln(n_{17}) + \ln(n_{18}) +|)^{-1}$$
$$= 0.0019 * (|\ln(0.1268) + \ln(0.1240) + \ln(0.1229) + \ln(0.1278) + \ln(0.1247) + \ln(0.1219) + \ln(0.1266) + \ln(0.1254) +|)^{-1}$$
$$= 0.0019 * (16.6365)^{-1}$$
$$= 0.00011$$

The overall results of the standard deviation value calculations in the LOGSTA method are presented in Table 4.

Table 4. Standard Deviation Results Using the LOGSTA Method

CC-A	CC-B	CC-C	CC-D	CC-E
0.0019	0.0337	0.0170	0.0381	0.0177

The overall results of the standard deviation for each criterion based on the logarithmic normalization results value calculations in the LOGSTA method are presented in Table 5.

Table 5. Standard Deviation for each Criterion Results Using the LOGSTA Method

CC-A	CC-B	CC-C	CC-D	CC-E
0.00011	0.00199	0.00102	0.00224	0.00106

The fourth stage is the determination of criterion weights. Criterion weights are obtained by normalizing the standard deviation values of each criterion against the total standard deviation of all criteria, calculated using (6).

$$w_1 = \frac{g_1}{g_1 + g_2 + g_3 + g_4 + g_5}$$
$$= \frac{0.00011}{0.00011 + 0.00199 + 0.00102 + 0.00224 + 0.00015} = 0.0178$$

The overall results of the criterion weights value calculations in the LOGSTA method are presented in Table 6.

Table 6. Criterion Weights Results Using the LOGSTA Method

CC-A	CC-B	CC-C	CC-D	CC-E
0.0178	0.3094	0.1589	0.3490	0.1649

The results of the criteria weighting using the LOGSTA method show a fairly clear difference in the level of importance among the five criteria used in the assessment of microcredit eligibility. The CC-D criterion has the highest weight, at 0.3490, indicating that this criterion plays the most dominant role in distinguishing the eligibility level of prospective debtors. Next, CC-B ranks second with a weight of

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0.3094, showing a significant contribution to the decision evaluation process. The CC-E and CC-C criteria have relatively moderate weights, at 0.1649 and 0.1589 respectively, indicating that both still have an impact but are not as strong as CC-D and CC-B. Meanwhile, CC-A has the lowest weight, at 0.0178, showing that the data variation for this criterion is very small, so its contribution in differentiating the feasibility among alternatives is relatively limited. Overall, this weight distribution reflects the weighting method's ability to identify the most informative criteria based on the characteristics of the data used.

3.3. Alternative Assessment Using the COBRA Method

The alternative assessment stage using the COBRA Method is an important part of the multi-criteria decision-making process for determining the feasibility of microcredit comprehensively. At this stage, each prospective debtor alternative is evaluated using the COBRA approach, which considers the distance of the alternatives from the ideal condition based on all previously weighted criteria. This evaluation allows for a more thorough analysis of the performance of each alternative, as it not only considers proximity to the best values but also takes into account the relative differences between alternatives simultaneously. The use of the COBRA method in the alternative assessment stage aims to produce rankings that are more accurate, consistent, and capable of reflecting the feasibility of microcredit objectively and based on data.

The first step is to create a decision matrix that contains the value of each alternative against the criteria that have been set. The decision matrix serves as the basis for all calculations carried out using equation (1), and the result is the same as the decision matrix in the LOGSTA method.

The second step in the COBRA method is calculating the normalization value, which is necessary to align all values to the same scale. With normalization, comparisons between criteria become fairer, so that no single criterion dominates simply due to differences in measurement units, calculated using (7).

$$r_{11} = \frac{x_{11}}{max_{ij}^{1}} = \frac{4500000}{5100000} = 0.8824$$

The overall results of the normalization value calculations in the COBRA method are presented in Table 7.

Table 7. Normalization Results Using the COBRA Method

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	0.8824	0.8000	0.7500	0.4000	1.0000
Candidate A2	0.6275	0.6000	0.5000	0.6000	0.8000
Candidate A3	0.5490	0.4000	0.4000	0.8000	0.6000
Candidate A4	1.0000	1.0000	1.0000	0.4000	1.0000

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Candidate A5	0.6863	0.6000	0.6000	0.6000	0.8000
Candidate A6	0.4902	0.4000	0.3500	1.0000	0.6000
Candidate A7	0.8627	0.8000	0.7000	0.4000	1.0000
Candidate A8	0.7451	0.6000	0.4500	0.6000	0.8000

The next step is to calculate the weighted normalization matrix, which reflects the actual contribution of each criterion to the evaluation of alternatives calculated using (8).

$$\Delta_{11} = w_1 * r_{11} = 0.0178 * 0.8824 = 0.0157$$

The overall results of the weighted normalization matrix value calculations in the COBRA method are presented in Table 8.

Table 8. Weighted Normalization Matrix Results Using the COBRA Method

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	0.0157	0.2475	0.1192	0.1396	0.1649
Candidate A2	0.0112	0.1856	0.0794	0.2094	0.1319
Candidate A3	0.0098	0.1237	0.0635	0.2792	0.0989
Candidate A4	0.0178	0.3094	0.1589	0.1396	0.1649
Candidate A5	0.0122	0.1856	0.0953	0.2094	0.1319
Candidate A6	0.0087	0.1237	0.0556	0.3490	0.0989
Candidate A7	0.0154	0.2475	0.1112	0.1396	0.1649
Candidate A8	0.0133	0.1856	0.0715	0.2094	0.1319

The next step is to determine three types of reference solutions, namely the positive ideal solution (the best value for each criterion), the negative ideal solution (the worst value for each criterion), and the average solution (the middle value of each criterion) which are calculated using (9), (10), and (11).

$$PIS_1 = \max(\Delta_{11}; \Delta_{12}; \Delta_{13}; \Delta_{14}; \Delta_{15}; \Delta_{16}; \Delta_{17}; \Delta_{18}) = 0.0178$$
$$NIS_1 = \min(\Delta_{11}; \Delta_{12}; \Delta_{13}; \Delta_{14}; \Delta_{15}; \Delta_{16}; \Delta_{17}; \Delta_{18}) = 0.0087$$
$$AS_1 = \frac{\Delta_{11} + \Delta_{12} + \Delta_{13} + \Delta_{14} + \Delta_{15} + \Delta_{16} + \Delta_{17} + \Delta_{18}}{8} = 0.0130$$

The overall results of the three types of reference solutions value calculations in the COBRA method are presented in Table 9.

Table 9. Three Types of Reference Solutions Results Using the COBRA Method

Type	CC-A	CC-B	CC-C	CC-D	CC-E
PIS	0.0178	0.3094	0.1589	0.3490	0.0989
NIS	0.0087	0.1237	0.0556	0.1396	0.1649
AS	0.0130	0.2011	0.0943	0.2094	0.1361

The next step is to calculate the distances to the positive ideal solution, the negative ideal solution, and the average solution. This calculation uses the concept of distance, which indicates how close or far an alternative is from the best, worst, and average conditions. The

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positive ideal solution calculations for the Euclidean distance and Taxicab distance are calculated using (14) and (15).

$$
\begin{aligned}
dE(PIS_1)^+ &= \sqrt{(PIS_1-\Delta_{11})^2+(PIS_2-\Delta_{21})^2+(PIS_3-\Delta_{31})^2+(PIS_4-\Delta_{41})^2+(PIS_5-\Delta_{51})^2} \\
&= \sqrt{\begin{matrix}(0.0178-0.0157)^2+(0.3094-0.2475)^2+(0.1589-0.1192)^2 \\ +(0.3490-0.1396)^2+(0.0989-0.1649)^2\end{matrix}} \\
&= 0.2315 \\
dT(PIS_1)^+ &= |PIS_1-\Delta_{11}|+|PIS_2-\Delta_{21}|+|PIS_3-\Delta_{31}|+|PIS_4-\Delta_{41}|+|PIS_5-\Delta_{51}| \\
&= |0.0178-0.0157|+|0.3094-0.2475|+|0.1589-0.1192|+|0.3490-0.1396| \\
&\quad +|0.0989-0.1649| \\
&= 0.3791
\end{aligned}
$$

The results of the positive ideal solution calculations for Euclidean distance and Taxicab distance are shown in Table 10.

Table 10. Positive Ideal Solution Results Using the COBRA Method

Candidate Name	Euclidean Distance	Taxicab Distance
Candidate A1	0.2315	0.3791
Candidate A2	0.2055	0.3824
Candidate A3	0.2202	0.3588
Candidate A4	0.2196	0.2754
Candidate A5	0.1999	0.3655
Candidate A6	0.2126	0.2980
Candidate A7	0.2330	0.3874
Candidate A8	0.2087	0.3883

Calculation of the negative ideal solution for Euclidean distance and Taxicab distance calculated using (16) and (17).

$$
\begin{aligned}
dE(NIS_1)^- &= \sqrt{(NIS_1-\Delta_{11})^2+(NIS_2-\Delta_{21})^2+(NIS_3-\Delta_{31})^2+(NIS_4-\Delta_{41})^2+(NIS_5-\Delta_{51})^2} \\
&= \sqrt{\begin{matrix}(0.0087-0.0157)^2+(0.1237-0.2475)^2+(0.0556-0.1192)^2 \\ +(0.1396-0.1396)^2+(0.0989-0.1649)^2\end{matrix}} \\
&= 0.1393 \\
dT(NIS_1)^- &= |NIS_1-\Delta_{11}|+|NIS_2-\Delta_{21}|+|NIS_3-\Delta_{31}|+|NIS_4-\Delta_{41}|+|NIS_5-\Delta_{51}| \\
&= |0.0087-0.0157|+|0.1237-0.2475|+|0.0556-0.1192|+|0.1396-0.1396| \\
&\quad +|0.0989-0.1649| \\
&= 0.1943
\end{aligned}
$$

The results of the negative ideal solution calculations for Euclidean distance and Taxicab distance are shown in Table 11.

Table 11. Negative Ideal Solution Results Using the COBRA Method

Candidate Name	Euclidean Distance	Taxicab Distance
Candidate A1	0.1393	0.1943
Candidate A2	0.1018	0.1909
Candidate A3	0.1546	0.2146
Candidate A4	0.2126	0.2980
Candidate A5	0.1067	0.2079

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Candidate A6	0.2196	0.2754
Candidate A7	0.1358	0.1860
Candidate A8	0.1003	0.1851

Calculation of the average positive ideal solution for Euclidean distance and Taxicab distance calculated using (18), (19), and (20).

$$\tau_{11}{}^{+} = AS_1 < \Delta_{11} = 0.0130 < 0.0157 = 1$$

The overall results of the threshold positive value calculations in the COBRA method are presented in Table 12.

Table 12. Threshold Positive Results Using the COBRA Method

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	1	1	1	0	1
Candidate A2	0	0	0	0	0
Candidate A3	0	0	0	1	0
Candidate A4	1	1	1	0	1
Candidate A5	0	0	1	0	0
Candidate A6	0	0	0	1	0
Candidate A7	1	1	1	0	1
Candidate A8	1	0	0	0	0

The calculation of the average positive ideal solution for Euclidean distance and Taxicab distance is as follows.

$$dE(AS_i)_1^{+} = \sqrt{\begin{gathered}(\tau_{11}{}^{+} * (AS_1 - \Delta_{11})^2) + (\tau_{21}{}^{+} * (AS_2 - \Delta_{21})^2) + (\tau_{31}{}^{+} * (AS_3 - \Delta_{31})^2) \\ +(\tau_{41}{}^{+} * (AS_4 - \Delta_{41})^2) + (\tau_{51}{}^{+} * (AS_5 - \Delta_{51})^2)\end{gathered}}$$

$$= \sqrt{\begin{gathered}(1 * (0.0130 - 0.0157)^2) + (1 * (0.2011 - 0.2475)^2) + (1 * (0.0943 - 0.1192)^2) \\ +(0 * (0.2094 - 0.1396)^2) + (1 * (0.1361 - 0.1649)^2)\end{gathered}}$$

$$= 0.0601$$

$$dT(AS_i)_1^{+} = (\tau_{11}{}^{+} * |AS_1 - \Delta_{11}|) + (\tau_{21}{}^{+} * |AS_2 - \Delta_{21}|) + (\tau_{31}{}^{+} * |AS_3 - \Delta_{31}|) + (\tau_{41}{}^{+} * |AS_4 - \Delta_{41}|) + (\tau_{51}{}^{+} * |AS_5 - \Delta_{51}|)$$

$$= (1 * |0.0130 - 0.0157|) + (1 * |0.2011 - 0.2475|) + (1 * |0.0943 - 0.1192|) + (0 * |0.2094 - 0.1396|) + (1 * |0.1361 - 0.1649|)$$

$$= 0.1028$$

The results of the average positive ideal solution calculations for Euclidean distance and Taxicab distance are shown in Table 13.

Table 13. Average Positive Ideal Solution Results Using the COBRA Method

Candidate Name	Euclidean Distance	Taxicab Distance
Candidate A1	0.0601	0.1028
Candidate A2	0.0000	0.0000
Candidate A3	0.0698	0.0698
Candidate A4	0.1294	0.2065
Candidate A5	0.0010	0.0010
Candidate A6	0.1396	0.1396

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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Candidate A7	0.0572	0.0945
Candidate A8	0.0003	0.0003

Calculation of the average negative ideal solution for Euclidean distance and Taxicab distance calculated using (21), (22), and (23).

$$\tau_{11}{}^{-} = AS_1 > \Delta_{11} = 0.0130 > 0.0157 = 0$$

The overall results of the threshold negative value calculations in the COBRA method are presented in Table 14.

Table 14. Threshold Negative Results Using the COBRA Method

Candidate Name	CC-A	CC-B	CC-C	CC-D	CC-E
Candidate A1	0	0	0	1	0
Candidate A2	1	1	1	0	1
Candidate A3	1	1	1	0	1
Candidate A4	0	0	0	1	0
Candidate A5	1	1	0	0	1
Candidate A6	1	1	1	0	1
Candidate A7	0	0	0	1	0
Candidate A8	0	1	1	0	1

The calculation of the average negative ideal solution for Euclidean distance and Taxicab distance is as follows.

$$dE(AS_i)_1^- = \sqrt{\begin{matrix}(\tau_{11}{}^{-} * (AS_1 - \Delta_{11})^2) + (\tau_{21}{}^{-} * (AS_2 - \Delta_{21})^2) + (\tau_{31}{}^{-} * (AS_3 - \Delta_{31})^2) \\ +(\tau_{41}{}^{-} * (AS_4 - \Delta_{41})^2) + (\tau_{51}{}^{-} * (AS_5 - \Delta_{51})^2)\end{matrix}}$$

$$= \sqrt{\begin{matrix}(0 * (0.0130 - 0.0157)^2) + (0 * (0.2011 - 0.2475)^2) + (0 * (0.0943 - 0.1192)^2) \\ +(1 * (0.2094 - 0.1396)^2) + (0 * (0.1361 - 0.1649)^2)\end{matrix}}$$

$$= 0.0698$$

$$dT(AS_i)_1^- = (\tau_{11}{}^{-} * |AS_1 - \Delta_{11}|) + (\tau_{21}{}^{-} * |AS_2 - \Delta_{21}|) + (\tau_{31}{}^{-} * |AS_3 - \Delta_{31}|) + (\tau_{41}{}^{-} * |AS_4 - \Delta_{41}|) + (\tau_{51}{}^{-} * |AS_5 - \Delta_{51}|)$$

$$= (0 * |0.0130 - 0.0157|) + (0 * |0.2011 - 0.2475|) + (0 * |0.0943 - 0.1192|) + (1 * |0.2094 - 0.1396|) + (0 * |0.1361 - 0.1649|)$$

$$= 0.0698$$

The results of the average positive ideal solution calculations for Euclidean distance and Taxicab distance are shown in Table 15.

Table 15. Average Negative Ideal Solution Results Using the COBRA Method

Candidate Name	Euclidean Distance	Taxicab Distance
Candidate A1	0.0698	0.0698
Candidate A2	0.0219	0.0363
Candidate A3	0.0912	0.1485
Candidate A4	0.0698	0.0698
Candidate A5	0.0160	0.0204
Candidate A6	0.0942	0.1575
Candidate A7	0.0698	0.0698

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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Candidate A8	0.0279	0.0424

The calculation of the correction coefficient value is calculated using (13).

$$\beta = max^{i}_{dE(S_i)_1} - min^{i}_{dE(S_i)_1} = 0.2330 - 0.1999 = 0.0331$$

The calculation of the distance to the positive ideal solution, the negative ideal solution, and the average solution is carried out using (12).

$$d(PIS\ S_1) = dE(PIS\ S_1) + \beta * dE(PIS\ S_1) * dT(PIS\ S_1)$$
$$= 0.2315 + 0.0331 * 0.2315 * 0.3791$$
$$= 0.2345$$
$$d(NIS\ S_1) = dE(NIS\ S_1) + \beta * dE(NIS\ S_1) * dT(NIS\ S_1)$$
$$= 0.1393 + 0.0331 * 0.1393 * 0.1943$$
$$= 0.1402$$
$$d(AS\ S_1)^{+} = dE\left(AS\ {S_1}^{+}\right) + \beta * dE\left(AS\ {S_1}^{+}\right) * dT\left(AS\ {S_1}^{+}\right)$$
$$= 0.0601 + 0.0331 * 0.0601 * 0.1028$$
$$= 0.0603$$
$$d(AS\ S_1)^{-} = dE(AS\ {S_1}^{-}) + \beta * dE(AS\ {S_1}^{-}) * dT(AS\ {S_1}^{-})$$
$$= 0.0698 + 0.0331 * 0.0698 * 0.0698$$
$$= 0.0700$$

The results of the distance to the positive ideal solution, the negative ideal solution, and the average solution calculations are shown in Table 16.

Table 16. Positive Ideal Solution, Negative Ideal Solution, and Average Solution Results Using the COBRA Method

Candidate Name	Distance to Positive Ideal Solution	Distance to Negative Ideal Solution	Distance to Average Positive Ideal Solution	Distance to Average Negative Ideal Solution
Candidate A1	0.2345	0.1402	0.0603	0.0700
Candidate A2	0.2081	0.1024	0.0000	0.0220
Candidate A3	0.2228	0.1557	0.0700	0.0916
Candidate A4	0.2216	0.2147	0.1303	0.0700
Candidate A5	0.2023	0.1074	0.0010	0.0160
Candidate A6	0.2147	0.2216	0.1403	0.0947
Candidate A7	0.2360	0.1367	0.0574	0.0700
Candidate A8	0.2114	0.1009	0.0003	0.0279

The final step is to calculate the final value for each alternative based on the distance obtained from each alternative calculated using (24).

$$dC_1 = \frac{d(PIS_i)_1 - d(NIS_i)_1 - d(AS_i)^{+}_1 + d(AS_i)^{-}_1}{4} = \frac{0.2345 - 0.1402 - 0.0603 + 0.0700}{4} = 0.0260$$

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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The results of the final value for each alternative calculation are shown in Table 17.

Table 17. Final Value for each Alternative Results Using the COBRA Method

Candidate Name	Final Value
Candidate A1	0.0260
Candidate A2	0.0319
Candidate A3	0.0222
Candidate A4	-0.0134
Candidate A5	0.0275
Candidate A6	-0.0131
Candidate A7	0.0280
Candidate A8	0.0345

The final scores of each alternative using the COBRA Method indicate that the COBRA method is capable of producing clear and consistent rankings of alternatives based on the final scores obtained from the comprehensive distance calculations to the ideal condition. These final scores represent the relative feasibility level of each alternative by considering all criteria and weights that have been previously established objectively. The differences in scores between alternatives reflect the COBRA method's ability to distinguish performance levels rationally, even when the differences between alternatives are relatively small. Thus, these final scores provide a strong and reliable basis for decision-makers in determining the most feasible alternative, while also demonstrating the effectiveness of the COBRA method in supporting a systematic and data-driven multi-criteria decision-making process.

The ranking results are presented to show the order of feasibility levels for each alternative based on the final scores obtained from the application of the method used. This ranking is the result of a synthesis of the process of weighting criteria and evaluating alternatives comprehensively, thereby reflecting the differences in performance levels among alternatives objectively. The resulting order provides a clear picture of the alternatives with the highest to lowest feasibility levels, while also demonstrating the method's ability to consistently differentiate between alternatives. Thus, these ranking results serve as an important basis for decision-makers in determining the most feasible alternative rationally and data-driven. Table 18 shows the results of the alternative rankings in determining the feasibility of micro credit.

Table 18. Alternative Ranking Results

Candidate Name	Final Value	Rank
Candidate A4	-0.0134	1
Candidate A6	-0.0131	2
Candidate A3	0.0222	3

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Candidate A1	0.026	4
Candidate A5	0.0275	5
Candidate A7	0.028	6
Candidate A2	0.0319	7
Candidate A8	0.0345	8

The ranking results obtained from the integration of the LOGSTA and COBRA methods show a clear difference in feasibility levels among the eight candidates evaluated. Candidate A4 ranks first with the lowest final score of -0.0134, indicating that this candidate has the most optimal feasibility level based on the objective criteria weights and comprehensive distance calculation. The second and third positions are occupied by Candidate A6 and Candidate A3 with final scores of -0.0131 and 0.0222, respectively, indicating relatively close performance but still below the top candidate. Candidate A1 and Candidate A5 are in the middle ranking with positive scores that still reflect a fairly good level of suitability. Meanwhile, Candidate A7 ranks sixth with a lower score, indicating a decrease in alignment with the ideal conditions. The last two candidates, Candidate A2 and Candidate A8, received negative final scores, showing that both are farther from the ideal solution compared to the other alternatives. Overall, these results confirm that the integration of LOGSTA and COBRA is capable of producing consistent and rational rankings, as well as providing a solid basis for objectively differentiating the candidates' levels of suitability.

The COBRA method determines the best alternative based on the smallest ranking value obtained from the compromise assessment process. In this approach, each alternative is evaluated according to its relative proximity to the ideal solution while considering the weighted influence of all criteria. Consequently, alternatives with lower COBRA scores indicate better overall performance because they exhibit smaller deviations from the desired reference conditions and achieve a more favorable balance among all evaluation criteria. Therefore, the alternative ranked first in the COBRA method is the one with the lowest final score, reflecting the highest level of suitability and preference among the evaluated alternatives.

3.4. Sensitivity Analysis

Sensitivity analysis is conducted to evaluate the level of stability and reliability of ranking results against changes in criteria weights in a decision support system[21]-[23]. Through this analysis, it is possible to observe the extent to which variations in weights, whether increases or decreases in certain criteria, affect the final values and the ranking order of alternatives. Sensitivity analysis is important because criteria weights play a dominant role in determining the final outcome, so even small changes can potentially shift the position of alternatives with close values. By conducting controlled simulations of weight changes, the study can identify the criteria that have the most influence on decision outcomes and assess the consistency

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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of the method used. The stable sensitivity analysis results indicate that the method is capable of producing robust decisions that are not easily distorted by changes in parameters, while significant ranking shifts suggest the need to reevaluate the weighting structure or criteria used. Therefore, sensitivity analysis serves as an important validation tool to ensure that the generated ranking results are reliable and relevant in supporting rational and data-driven decision making.

Changes in the weight of criteria in determining microcredit eligibility provide an important insight into the system's sensitivity to the dynamics of each criterion's significance[24]–[26], particularly for criteria CC-A, CC-B, CC-C, CC-D, and CC-E. Scenarios for changing the weight of criteria in determining microcredit eligibility can be designed by considering increases and decreases in weight by 0.05 and 0.1 for each of the criteria CC-A, CC-B, CC-C, CC-D, and CC-E as a form of testing the model's flexibility. In the weight increase scenario, each criterion is assumed to increase alternately by 0.05 to reflect a moderate adjustment in importance, and by 0.1 to represent conditions when a criterion is considered significantly more important compared to the initial condition. Conversely, in the weight reduction scenario, each criterion is assumed to decrease by 0.05 as a minor adjustment and by 0.1 as a more significant adjustment to reflect reduced importance. In each scenario, the weights of the other criteria are assumed to be adjusted proportionally to ensure that the total weight remains one. The development of these scenarios aims to illustrate variations in weighting policies that may be applied in microcredit evaluations, as well as to provide a systematic framework for analyzing the dynamics of changes in criterion weights without directly linking them to ranking outcomes. Table 19 presents the scenarios for changes in criterion weights.

Table 19. Criterion Weights Results Using the LOGSTA Method

Scenario Test	CC-A	CC-B	CC-C	CC-D	CC-E
Initial Weight	0.0178	0.3094	0.1589	0.3490	0.1649
Scenario 1 CC-A Weight Increases by 0.1	0.1071	0.2813	0.1445	0.3173	0.1499
Scenario 2 CC-B Weight Increases by 0.1	0.0162	0.3722	0.1445	0.3173	0.1499
Scenario 3 CC-C Weight Increases by 0.1	0.0162	0.2813	0.2354	0.3173	0.1499
Scenario 4 CC-D Weight Increases by 0.1	0.0162	0.2813	0.1445	0.4082	0.1499
Scenario 5 CC-E Weight Increases by 0.1	0.0162	0.2813	0.1445	0.3173	0.2408
Scenario 6 CC-A Weight Decreases by 0.1	0.0000	0.3438	0.1766	0.3878	0.1832
Scenario 7 CC-B Weight Decreases by 0.1	0.0198	0.2327	0.1766	0.3878	0.1832
Scenario 8 CC-C Weight Decreases by 0.1	0.0198	0.3438	0.0654	0.3878	0.1832
Scenario 9 CC-D Weight Decreases by 0.1	0.0198	0.3438	0.1766	0.2767	0.1832
Scenario 10 CC-E Weight Decreases by 0.1	0.0198	0.3438	0.1766	0.3878	0.0721
Scenario 11 CC-A Weight Increases by 0.05	0.0646	0.2947	0.1513	0.3324	0.1570
Scenario 12 CC-B Weight Increases by 0.05	0.0170	0.3423	0.1513	0.3324	0.1570
Scenario 13 CC-C Weight Increases by 0.05	0.0170	0.2947	0.1990	0.3324	0.1570
Scenario 14 CC-D Weight Increases by 0.05	0.0170	0.2947	0.1513	0.3800	0.1570
Scenario 15 CC-E Weight Increases by 0.05	0.0170	0.2947	0.1513	0.3324	0.2047
Scenario 16 CC-A Weight Decreases by 0.05	0.0000	0.3257	0.1673	0.3674	0.1736
Scenario 17 CC-B Weight Decreases by 0.05	0.0187	0.2731	0.1673	0.3674	0.1736
Scenario 18 CC-C Weight Decreases by 0.05	0.0187	0.3257	0.1146	0.3674	0.1736

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Scenario 19 CC-D Weight Decreases by 0.05	0.0187	0.3257	0.1673	0.3147	0.1736

The scenario of changes in criteria weights that has been developed illustrates a systematic evaluation framework to understand the dynamics of adjusting the level of importance of criteria CC-A, CC-B, CC-C, CC-D, and CC-E in determining microcredit eligibility. Variations in scenarios with weight increases and decreases of 0.05 and 0.1 provide a comprehensive picture of possible weight configurations that can be applied according to policy needs or specific assessment focus. Weight adjustments are conducted in a controlled manner while maintaining the total weight balance, so that each scenario represents a realistic and consistent evaluation condition. The development of these scenarios serves as an analytical basis for testing the flexibility of the weighting model, while also enhancing understanding of the relative roles of each criterion without directly linking them to the ranking outcome of alternatives.

The selection of weight change scenarios of ±0.05 and ±0.1 was carried out to represent moderate and significant levels of decision preference changes in the criteria evaluation process. A change of ±0.05 is used to illustrate small adjustments that generally occur due to changes in internal policy or adjustments in evaluation priorities, while a change of ±0.1 represents a stronger change in the importance level of a criterion. Both scenarios were chosen to gradually test the sensitivity and stability of the model, so that it can be analyzed how weight changes affect the consistency of alternative rankings. In addition, the use of relatively simple and proportional change intervals allows the interpretation of sensitivity results to be more easily understood and provides a more realistic picture of possible changes in preferences in the assessment of microcredit feasibility.

The ranking of alternatives from scenarios of weight changes is presented to illustrate how variations in the importance levels of criteria affect the evaluation process in determining microcredit eligibility. Each weighting scenario, whether an increase or decrease in criteria weights, is used as the basis for recalculating the alternative values using the same method, allowing comparisons between scenarios to be made consistently. The presentation of these ranking results aims to provide a systematic overview of the model's response to changes in weight configuration, while also demonstrating the flexibility of the approach used in accommodating various possible adjustments in assessment policies. Thus, this section serves as an analytical bridge between weighting scenarios and the comprehensive interpretation of alternative evaluation results. Figure 2 shows the alternative rankings from the criteria weight change scenarios.

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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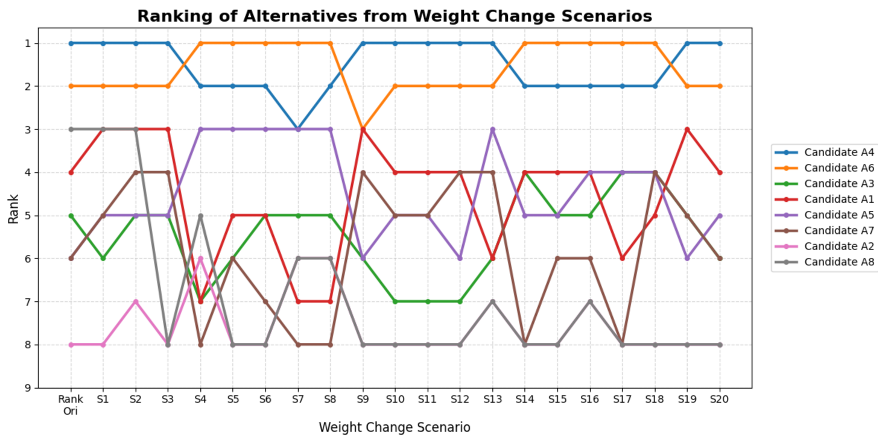

Figure 2. Ranking of Alternatives for the Scenario of Weight Changes

The alternative ranking chart from the weight change scenarios shows the dynamics of each candidate's position across various criteria weight configurations, from the initial condition to scenarios S1 through S20. Each line represents a candidate and illustrates the shifts in ranking that occur when the criteria weights increase or decrease. Visually, it can be seen that some candidates tend to maintain their positions within certain ranking ranges despite changes in weights, while other candidates show more noticeable ranking fluctuations between scenarios. This pattern illustrates that changes in the criteria weights affect the preference levels of alternatives differently, depending on each candidate's sensitivity to the adjusted criteria. Presenting this graph provides a comprehensive view of the stability and variation in alternative rankings, as well as helps understand how scenarios of weight changes interact with the characteristics of each candidate in the microcredit feasibility evaluation process.

The graph also shows tendencies of convergence and divergence in rankings under certain scenarios, indicating that some alternatives have relatively balanced assessment profiles in response to changes in criteria weights, while other alternatives are highly influenced by adjustments to specific weights. Repeated ranking fluctuations in some candidates reflect relative sensitivity to scenarios of increasing or decreasing weights, even without directly linking it to the final decision outcome. Thus, this graph serves as an exploratory tool to assess the consistency of alternative positions under various weight assumptions, as well as to provide a deeper understanding of the behavior of the decision support system when faced with variations in criteria preferences in determining microcredit eligibility.

3.5. Comparison with MCDM Method

A comparison with MCDM methods is conducted to provide an objective evaluation framework for the performance and characteristics of the proposed method by comparing it with several established MCDM

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approaches[27]-[29]. This comparison is important because each MCDM method has different underlying assumptions, weighting mechanisms, and ways of aggregating values, which can result in different rankings of alternatives even when using identical data and criteria. Through comparative analysis, it is possible to identify the consistency of results, the sensitivity to changes in weights, and the method's ability to represent the decision maker’s preferences. In addition, this subchapter serves to systematically assess the strengths and limitations of the proposed method, in terms of ranking stability, calculation transparency, and ease of implementation. Thus, the comparison with other MCDM methods aims not only to show differences in results but also to provide a strong empirical basis for evaluating the relevance and contribution of the method to multicriteria decision-making in a more comprehensive manner.

A comparison with the SAW, TOPSIS, MOORA, GRA, and MAUT methods was conducted to obtain a comprehensive overview of the position and characteristics of the proposed method within the spectrum of commonly used MCDM approaches[30]-[34]. Each of these methods represents a different decision-making logic, ranging from simple linear aggregation in SAW and SMART, the concept of closeness to the ideal solution in TOPSIS, optimization ratios in MOORA, analysis of the degree of relational closeness in GRA, to the utility approach in MAUT and a combination of addition and multiplication in WASPAS. By comparing the ranking results produced by each method on the same data and criteria, this analysis allows for evaluating the consistency of the alternative order and identifying differences in sensitivity to weights and data scales. Furthermore, this comparison provides a basis for assessing the relative advantages of each method in handling the complexities of microcredit decision-making, particularly in terms of result stability, interpretability, and the ability to reflect decision-makers' preferences. Through this comparative approach, it is expected that a stronger methodological justification can be obtained regarding the relevance and reliability of the proposed method compared to conventional MCDM methods that have been widely applied.

Comparison with MCDM methods using fixed weights determined by the LOGSTA method was conducted to ensure that all MCDM methods are evaluated under consistent and objective weighting conditions. The use of LOGSTA weights as a common reference aims to eliminate the influence of subjectivity in determining the importance levels of criteria, so that differences in ranking results truly reflect the characteristics of each method's calculation mechanism, rather than variations in weights. With this approach, each method is tested on identical data and weight structures, allowing for a fairer analysis of rank stability, sensitivity to alternative performance values, as well as the method's ability to capture performance differences among microcredit candidates. In addition, the LOGSTA-based weighted comparison provides an empirical basis for assessing the consistency of results between classical and modern MCDM methods, while also reinforcing the argument that integrating

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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objective weighting with different ranking techniques can result in a more transparent, measurable, and methodologically accountable creditworthiness evaluation. Figure 3 shows the results of the comparison of alternative rankings using the MCDM method.

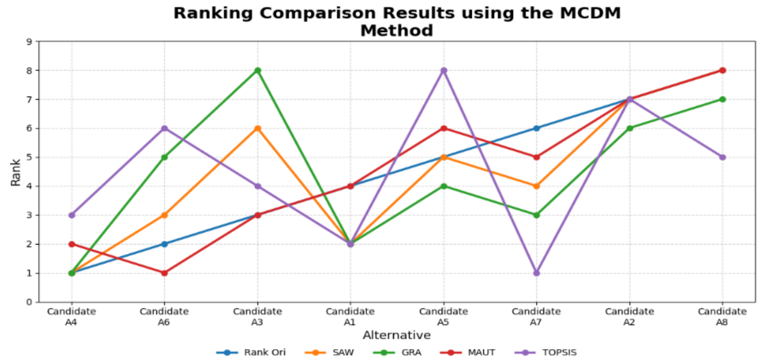

Figure 3. Comparison Results of Alternative Rankings using the MCDM Methods

The results of the comparison of alternative rankings using several MCDM methods show a clear variation in rank positions across methods, even though all methods use the same criteria weights. The graph shows that each candidate has a different ranking pattern when evaluated using Rank Ori, SAW, GRA, MAUT, and TOPSIS, reflecting differences in calculation principles and value aggregation mechanisms in each method. Some alternatives, such as Candidate A1 and Candidate A2, tend to show ranking consistency in the mid to upper range, indicating the stability of these alternatives' performance across different evaluation approaches. In contrast, candidates like A5 and A7 experience sharper ranking fluctuations, especially in the TOPSIS and MAUT methods, indicating sensitivity to the concepts of ideal solutions and utility. Candidate A8 generally ranks relatively high across most methods, indicating that this alternative has competitive performance and is fairly robust against differences in assessment techniques. These variations in ranking patterns emphasize that the choice of MCDM method directly affects the final recommendation results, and reinforce the importance of comparative method analysis to ensure that microcredit eligibility decisions are not solely dependent on a single approach, but are supported by a comprehensive and objective evaluation.

3.6. Discussion

The ranking results under various weight-change scenarios indicate that the proposed LOGSTA-COBRA approach has a relatively stable evaluation structure. Although changes in criterion weights caused several alternatives to shift positions, the overall ranking pattern remained consistent for most candidates. Alternatives with balanced performance across all criteria tended to maintain stable rankings, while alternatives that strongly depended on specific criteria experienced greater fluctuations. This finding demonstrates that the model is capable

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of capturing changes in decision-maker preferences logically without significantly distorting the overall evaluation structure. In the context of microcredit feasibility, these scenarios represent practical conditions in which financial institutions may prioritize certain aspects, such as repayment capacity, borrower character, or business stability, according to policy adjustments or economic conditions. Therefore, the sensitivity analysis confirms that the proposed method can support more adaptive and transparent decision-making processes.

The comparison with several MCDM approaches, including SAW, TOPSIS, GRA, and MAUT, shows that differences in normalization, aggregation, and evaluation mechanisms influence the ranking positions of alternatives. SAW tends to produce more linear and stable rankings, while TOPSIS is more sensitive to extreme criterion values because it considers the distance to ideal solutions. GRA emphasizes the similarity of alternative performance patterns, whereas MAUT evaluates alternatives through utility transformation. Despite these methodological differences, alternatives with consistently strong performance generally maintained high rankings across methods, indicating that the proposed LOGSTA–COBRA integration is competitive and reliable.

Compared with the benchmark methods, the LOGSTA–COBRA integration offers several advantages. LOGSTA provides objective criterion weighting by considering both variation and conflict among criteria, thereby reducing subjectivity in the decision-making process. Meanwhile, COBRA evaluates alternatives comprehensively through distance-based assessment, allowing clearer discrimination between feasible and less feasible candidates. This combination enables decision-makers to obtain more balanced and transparent ranking results. However, the proposed approach also has limitations. The computational process becomes more complex as the number of alternatives and criteria increases, and the results remain dependent on the quality and completeness of the input data. In addition, unlike some utility-based approaches, LOGSTA–COBRA does not explicitly model uncertainty or linguistic preferences.

From a practical perspective, the proposed method can assist microfinance institutions in improving the consistency and accountability of microcredit feasibility assessments. The ability of the model to evaluate alternatives under multiple weighting scenarios makes it useful for dynamic policy environments where evaluation priorities may change over time. Furthermore, the framework has the potential to handle larger datasets and additional criteria because both LOGSTA and COBRA are mathematically scalable and can be integrated into computerized decision support systems. This scalability provides opportunities for future implementation using real-time financial data, hybrid intelligent systems, or integration with Machine Learning techniques to enhance predictive performance and decision accuracy in large-scale microcredit evaluation applications.

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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IV. Conclusion

The integration of LOGSTA objective weighting with the COBRA comprehensive distance-based ranking method is capable of producing a systematic, objective, and transparent microcredit feasibility evaluation. The ranking results show that Candidate A8 occupies the first rank as the most feasible alternative, followed by Candidate A2 and Candidate A7 in the second and third ranks, while Candidate A5, A1, and A3 are at a moderate feasibility level. On the other hand, Candidate A6 and Candidate A4 occupy the lowest ranks, indicating relatively low feasibility. This ranking pattern reflects the ability of the LOGSTA-COBRA method to clearly differentiate alternatives based on the relative contribution of each criterion without relying on subjective assessments. In addition, the results of the sensitivity analysis through various scenarios of weight changes showed that the main ranking structure remained relatively stable, thus confirming the consistency and reliability of the proposed model in dealing with variations in criteria importance.

Comparison with several popular MCDM methods such as SAW, TOPSIS, GRA, and MAUT shows that although there are differences in ranking positions between methods, alternatives with dominant performance tend to demonstrate consistent results. These findings confirm that the proposed method is not only competitive but also capable of providing a more comprehensive evaluation perspective through objective weighting and distance-based assessment mechanisms. Thus, this study provides theoretical contributions to the development of MCDM methods as well as practical contributions for financial institutions as a basis for more accurate and accountable decision-making in determining the feasibility of microcredit.

Despite these contributions, this study still has several limitations, particularly regarding the limited number of criteria, alternatives, and the use of static evaluation data. In real-world applications, microcredit assessments are often influenced by dynamic financial conditions and uncertain risk factors that may not be fully represented in the current model. Therefore, future research is recommended to incorporate larger and more diverse datasets, integrate historical credit records and additional risk indicators such as probability of default and payment behavior, and develop real-time decision support mechanisms. In addition, further studies may explore hybrid approaches by combining the LOGSTA-COBRA framework with Machine Learning techniques, fuzzy systems, or intelligent decision support systems to improve predictive capability, adaptability, and robustness in practical microcredit evaluation environments.

CRediT Authorship Contribution Statement

Desyanti: Writing – original draft, Software, Methodology, Conceptualization. **I. Ahmad:** Writing – review & editing, Formal analysis,

*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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Data curation, Conceptualization. **Sanusi:** Writing – original draft, Validation, Investigation.

Declaration of Competing 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.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

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*Corresponding Author: desyanti@itbriaupesisir.ac.id (Desyanti)
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