



E-ARIE: A Novel Hybrid Entropy and ARIE Method for Best Employee Selection in the Banking Sector

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ABSTRACT

Keywords:

E-ARIE;
Entropy
Weighting;
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Employee
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Multi-Criteria
Decision-
Making;

Employee selection is a critical decision-making process in the banking sector because employee performance directly influences service quality, operational efficiency, and organizational competitiveness. However, conventional selection approaches often rely on subjective criterion weighting and may produce rankings that are sensitive to changes in criterion importance. This study proposes E-ARIE (Entropy-based Adaptive Ranking with Ideal Evaluation), a Multi-Criteria Decision-Making (MCDM) approach that integrates entropy-based objective weighting with the Adaptive Ranking with Ideal Evaluation (ARIE) method. The proposed approach determines criterion weights based on the discriminatory information contained in the assessment data and ranks employee candidates according to their relative closeness to ideal and anti-ideal conditions. The method was evaluated using data from 15 employee candidates across eight criteria: performance score, sales achievement, customer service, attendance, work experience, disciplinary record, teamwork, and competency. The results show that work experience (CBE-5) obtained the highest weight of 0.2605, followed by competency (CBE-8) with 0.1728 and performance score (CBE-1) with 0.1418. Employee 7 achieved the highest relative closeness score of 0.5513, followed by Employee 11 (0.5433) and Employee 3 (0.5363). Sensitivity analysis demonstrated that the ranking remained unchanged under criterion-weight perturbations of ± 0.05 and ± 0.10 , indicating high ranking stability and robustness. Overall, E-ARIE provides an objective, adaptive, and robust framework for supporting transparent and data-driven employee selection in the banking sector.

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I. Introduction

Employee selection plays a critical role in improving the performance of banking organizations because employees directly influence service quality, operational efficiency, customer satisfaction, and the achievement of organizational targets[1], [2]. The banking sector requires employees who possess not only appropriate technical competencies but also accuracy, discipline, integrity, communication skills, and the ability to adapt to dynamic financial and technological environments. An inappropriate selection process can result in mismatches between employee capabilities and job requirements, leading to reduced productivity, increased operational risks, and higher employee turnover[3], [4]. Therefore, a systematic and objective employee selection process is essential for identifying candidates who best meet the organization's needs, enabling banks to optimize human resources, strengthen service performance, minimize risks, and ultimately achieve sustainable organizational performance.

The banking sector has distinctive characteristics that require high-quality human resources because its activities are closely related to financial management, customer service, transaction security, and the achievement of business objectives. In this context, employees are expected to possess appropriate competence, demonstrate high productivity in performing their tasks effectively and efficiently, and maintain strong integrity to preserve customer trust and minimize operational risks. In addition, the ability to provide fast, accurate, and professional service is essential for maintaining customer satisfaction, while the ability to achieve established performance targets is necessary to support the bank's overall business objectives. These characteristics highlight the importance of an objective and comprehensive employee selection process that considers multiple performance-related criteria, enabling banking organizations to recruit employees who are well aligned with organizational requirements and capable of making an optimal contribution to organizational performance[5], [6].

Employee selection can be formulated as a Multi-Criteria Decision Making (MCDM) problem because the process involves evaluating multiple candidates based on several criteria that may have different characteristics and levels of importance. These criteria can include competence, productivity, integrity, service quality, and target achievement, where each criterion may represent either a benefit or cost attribute. Benefit criteria indicate that higher values reflect better candidate performance, whereas cost criteria indicate that lower values are preferred[7], [8]. The presence of heterogeneous criteria makes employee evaluation more complex, as decision-makers must simultaneously consider different performance dimensions and trade-offs among candidates. Therefore, an appropriate MCDM approach is required to systematically aggregate these criteria and produce an objective and reliable ranking of employee candidates[9], [10].

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Conventional approaches to employee selection often rely on subjective criteria weighting, in which the importance of each criterion is determined based on the decision-maker's judgment, experience, or personal preferences[11]-[13]. Although this approach is relatively simple and easy to implement, it may introduce bias and inconsistency into the decision-making process, particularly when different decision-makers assign different levels of importance to the same criteria. Subjective weighting may also fail to adequately reflect the actual variation and information contained in the evaluation data[14], [15]. Consequently, the resulting employee rankings may be sensitive to individual judgments and may not fully represent the objective performance of the candidates. These limitations highlight the need for a more objective and data-driven weighting approach to improve the reliability and fairness of employee selection.

MCDM ranking methods may face limitations when they rely on a static ranking mechanism that does not sufficiently adapt to the characteristics and distribution of the decision data[16], [17]. A fixed ranking procedure may produce similar evaluation patterns even when the underlying data exhibit substantial differences in scale, variation, or relative performance among alternatives. This limitation can reduce the sensitivity of the ranking process to changes in criterion values and may affect the ability of the method to accurately distinguish between competing alternatives. Consequently, a more adaptive ranking mechanism is needed to accommodate the characteristics of the data and provide rankings that are more responsive, consistent, and representative of the actual performance of the alternatives.

The integration of Entropy weighting with an adaptive ranking mechanism is important for developing a more objective and responsive MCDM framework. Entropy weighting determines criterion importance based on the amount of information and variation contained in the decision data, thereby reducing dependence on subjective judgments[18]-[20]. However, objective weighting alone does not guarantee that the ranking process will fully reflect the characteristics of the evaluated alternatives[21], [22]. Therefore, combining Entropy weighting with an adaptive ranking mechanism can enable the ranking process to respond more effectively to differences in data distribution, criterion importance, and alternative performance. Such integration is expected to produce rankings that are more objective, data-sensitive, consistent, and robust, particularly in complex employee selection problems involving heterogeneous evaluation criteria.

The Adaptive Ranking with Ideal Evaluation (ARIE) Method is needed to provide an evaluation approach that ranks alternatives according to their closeness to an ideal condition while adapting the ranking process to the characteristics of the decision data[23]. In employee selection, ARIE can evaluate candidates by considering their overall performance across multiple criteria, such as competence, productivity, integrity, service quality, and target achievement. By incorporating an ideal-based evaluation mechanism, ARIE enables alternatives that exhibit performance closer to the ideal condition to receive higher rankings. This approach

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can provide a more adaptive, objective, and discriminative ranking process, making it suitable for complex employee selection problems involving heterogeneous criteria and varying levels of candidate performance.

Several gaps can be identified in existing MCDM approaches for employee selection. First, the subjective weighting problem arises because criterion weights based on expert judgment may introduce bias and inconsistency into the decision-making process. Second, the weight imbalance problem occurs when certain criteria receive excessively high or low weights, which may cause some performance dimensions to dominate the overall evaluation. Third, the ranking rigidity problem reflects the limitation of conventional ranking mechanisms, which may not be sufficiently adaptive to changes in the distribution and relative performance of alternatives. Fourth, the ideal evaluation limitation concerns ideal-solution approaches that often rely on relatively fixed formulations and may therefore have limited flexibility in responding to variations in decision data[24]-[26]. Finally, these limitations reveal an employee selection gap, indicating the need for a method that simultaneously integrates objective weighting, adaptive ranking, and ideal evaluation to provide a more objective, flexible, and data-responsive framework for employee selection.

Conceptually, E-ARIE (Entropy-based Adaptive Ranking with Ideal Evaluation) consists of two main integrated components. The first component, Entropy-based objective weighting, determines the importance of each criterion objectively based on the amount of information and variation contained in the decision data, thereby reducing reliance on subjective judgments from decision-makers. The second component, the ARIE Method, evaluates and ranks alternatives by considering the characteristics of the decision data and their relative closeness to an ideal condition. The adaptive ranking mechanism enables the evaluation process to respond to differences in alternative performance and data distribution, while the ideal evaluation provides a basis for identifying alternatives that most closely represent the desired performance. By integrating these two components, E-ARIE provides an approach that combines objective criterion weighting with adaptive and ideal-based ranking, making it suitable for addressing complex employee selection problems involving multiple evaluation criteria.

This study aims to develop E-ARIE by integrating entropy-based objective weighting with the ARIE Method to address the limitations of conventional MCDM approaches in employee selection. The proposed method is designed to reduce subjectivity in criterion weighting by determining criterion importance from the information and variation contained in the decision data, while its adaptive ranking mechanism enables the evaluation process to respond to differences in alternative performance and data distribution. In addition, the ideal evaluation component provides a systematic basis for identifying employee candidates whose overall performance is closest to the desired ideal condition. The main contribution of this research is therefore the development of an integrated MCDM approach that combines objective weighting, adaptive

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ranking, and ideal-based evaluation, together with an empirical assessment of its effectiveness and robustness in producing objective, discriminative, and reliable employee rankings.

II. Methodology

2.1. Research Framework

A research framework is a systematic structure that describes the logical flow of a research study, from problem identification and theoretical foundation to method development, implementation, evaluation, and conclusion. In this study, the Research Framework illustrates the sequence of activities undertaken to develop and evaluate E-ARIE for employee selection. The framework provides a clear overview of how the research problem is addressed through entropy-based objective weighting and the ARIE method, followed by comparative and ranking stability analyses to assess the effectiveness and robustness of the proposed approach, as illustrated in Figure 1.

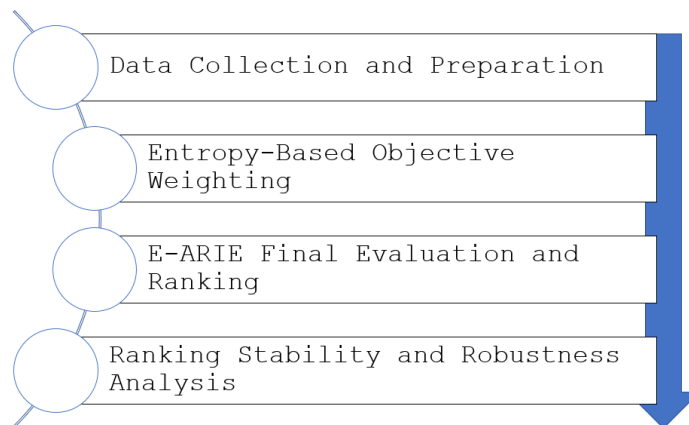


Figure 1. Research Framework

The research process begins with Data Collection and Preparation, in which the employee selection data are collected, organized, and structured into a decision matrix according to the relevant evaluation criteria and alternatives. The next stage, Entropy-Based Objective Weighting, determines the objective importance of each criterion based on the information and variation contained in the decision data, thereby minimizing the influence of subjective judgment. The resulting criterion weights are then incorporated into the E-ARIE Final Evaluation and Ranking stage, where the proposed E-ARIE method evaluates each employee candidate based on the adaptive ranking mechanism and ideal-based evaluation to generate a comprehensive evaluation score and final ranking. Finally, Ranking Stability and Robustness Analysis is conducted to examine the consistency of the resulting rankings under changes in criterion weights or decision conditions, thereby assessing the reliability and robustness of E-ARIE for employee selection.



2.2. Data Collection

Data collection focuses on obtaining comprehensive and relevant employee performance data for Best Employee Selection in the Banking Sector. The data are gathered from employee performance records and evaluation results based on predetermined criteria that represent important dimensions of banking employee performance, including competence, productivity, integrity, service quality, and target achievement. Each employee candidate is evaluated using the same set of criteria to ensure comparability among alternatives. The collected data may consist of quantitative performance scores or structured assessment results that reflect the actual capabilities and achievements of employees during the evaluation period. To maintain the quality of the dataset, the collected information is organized systematically and examined for completeness, consistency, and relevance to the employee selection objectives. The resulting dataset provides a comprehensive representation of the performance characteristics of each employee candidate and serves as the basis for objectively comparing the candidates within the selection process.

The candidate assessment data for Best Employee Selection consist of evaluation scores assigned to each employee candidate based on the established assessment framework. The assessment data represent the observed performance of each candidate during the specified evaluation period and are recorded using a consistent scoring scale to ensure comparability among alternatives. Each candidate is assessed using the same evaluation procedure, allowing differences in individual performance to be systematically captured. The resulting assessment data are organized into a structured decision matrix, where each row represents an employee candidate and each column represents an assessment dimension. The complete assessment data for the Best Employee candidates are presented in Table 1, providing a clear representation of the performance of all candidates and supporting a systematic and objective selection process.

Table 1. Alternative Assessment Data

Alternatives	CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
Employee 1	85	82	88	94	72	88	86	84
Employee 2	78	85	82	91	68	91	88	81
Employee 3	92	90	94	97	81	83	93	95
Employee 4	81	76	85	89	75	94	82	80
Employee 5	88	87	91	95	79	85	90	89
Employee 6	79	80	84	92	65	96	85	78
Employee 7	95	94	96	98	86	80	95	97
Employee 8	84	79	87	93	70	89	84	83
Employee 9	87	86	90	96	77	86	89	88
Employee 10	75	81	79	88	63	88	80	76
Employee 11	91	93	95	97	84	81	94	96
Employee 12	80	78	83	90	69	92	83	79
Employee 13	89	88	92	94	80	84	91	90
Employee 14	77	83	81	91	67	95	86	82
Employee 15	86	91	89	95	78	87	92	87

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The eight criteria provide a comprehensive basis for evaluating employee performance in the banking sector. Performance Score (CBE-1) measures the overall level of employee performance based on periodic evaluations, while Sales Achievement (CBE-2) reflects the employee's ability to meet or exceed assigned sales targets. Customer Service (CBE-3) assesses the quality of service provided to customers, including responsiveness, communication, and the ability to address customer needs. Attendance (CBE-4) represents the employee's consistency and compliance with established working schedules, whereas Work Experience (CBE-5) reflects the length and relevance of experience supporting the employee's responsibilities. Disciplinary Record (CBE-6) measures the number or severity of disciplinary violations, where a lower value indicates better performance. Teamwork (CBE-7) evaluates the employee's ability to collaborate and contribute effectively within a team, while Competency (CBE-8) represents the knowledge, skills, abilities, and qualifications required to perform assigned duties effectively. Together, these criteria capture multiple dimensions of employee performance and provide a comprehensive basis for selecting the best employee.

The data used in this study were obtained from employee performance assessments conducted within a banking organization. The dataset comprises assessment records for 15 employee candidates who were evaluated using eight predefined criteria relevant to best employee selection. The assessment data reflect the actual performance of the candidates during the specified evaluation period and were collected through the organization's employee evaluation process. The collected data were subsequently structured into a decision matrix while maintaining the original assessment values to ensure consistency and comparability among candidates. This dataset provides a practical basis for evaluating the applicability of the proposed E-ARIE method to the best employee selection problem in the banking sector.

2.3. Entropy Weighting Method

The Entropy Weighting Method is an objective weighting technique used to determine the relative importance of evaluation criteria based on the degree of information and variation contained in the decision matrix. Unlike subjective weighting approaches that rely on expert preferences, the entropy method derives criterion weights directly from the observed data. A criterion with greater variation among alternatives provides more useful information and therefore receives a higher weight, whereas a criterion with relatively uniform values contributes less discriminatory information and receives a lower weight. The procedure of the entropy weighting method consists of several computational stages.

The Entropy Weighting Method consists of several sequential stages, beginning with the construction of the decision matrix, which represents the performance values of alternatives across the evaluation criteria, as expressed in (1). The decision matrix is then normalized to transform the values into a comparable scale, with separate normalization procedures as presented in (2). The normalized values are

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subsequently used to calculate the entropy value of each criterion as given in (3). The degree of diversification is then calculated in (4) to measure the amount of useful information and variation provided by each criterion. Finally, the objective weight of each criterion is obtained through the normalization of the diversification values, as presented in (5). These resulting weights represent the objective importance of the criteria based on the information and variation contained in the decision data.

$$X = [x_{ij}]_{m \times n} \quad (1)$$

$$k_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (2)$$

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m k_{ij} * \ln(k_{ij}) \quad (3)$$

$$D_j = 1 - E_j \quad (4)$$

$$w_j = \frac{D_j}{\sum_{j=1}^n D_j} \quad (5)$$

Symbol $X = [x_{ij}]_{m \times n}$ denote the decision matrix, where x_{ij} is the value of alternative i for criterion j , m is the number of alternatives, and n is the number of criteria. The normalized proportion k_{ij} represents the proportion of x_{ij} to the total value of criterion j , E_j represents the entropy value of criterion j , D_j represents the degree of diversification or information utility of criterion j , and w_j represents the final objective weight of criterion j . The indices i and j denote the alternative and criterion, respectively.

The entropy weighting process produces a set of objective criterion weights that reflect the relative information content and variation of each criterion. A higher weight indicates that the corresponding criterion provides greater discriminatory information, while a lower weight indicates relatively less variation among the evaluated values. The resulting weights are normalized so that their total value equals one, providing a consistent representation of the relative importance of all criteria.

2.4. ARIE Method

The ARIE method is a multi-criteria decision-making approach designed to evaluate and rank alternatives by considering their relative performance and closeness to an ideal condition. The method combines an adaptive ranking mechanism with ideal-based evaluation, allowing the assessment process to respond to differences in the performance distribution of alternatives rather than relying solely on a fixed ranking structure. Through this approach, each alternative is evaluated according to its position relative to the ideal performance, while the contribution of each criterion is incorporated into the overall evaluation. Alternatives that demonstrate performance closer to the ideal condition are assigned higher evaluation values and consequently receive better rankings. This mechanism provides a flexible and discriminative framework for comparing alternatives across multiple criteria.



The ARIE method consists of several sequential computational stages. First, the performance values of the alternatives are normalized to obtain comparable values across all criteria, as calculated in (6). The normalized values are then combined with the corresponding criterion weights to produce the weighted normalized values, as determined in (7). Subsequently, the ideal similarity is calculated in (8) to measure the degree of similarity between each alternative and the ideal condition, while the anti-ideal similarity is calculated in (9) to measure its similarity to the anti-ideal condition. Finally, the relative closeness of each alternative to the ideal condition is determined in (10) by considering both ideal and anti-ideal similarity values.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}}; \text{benefit} \\ \frac{\min_j x_{ij}}{x_{ij}}; \text{cost} \\ 1 - \frac{|x_{ij} - x_j^T|}{\max(|x_j^{\max} - x_j^T|, |x_j^{\min} - x_j^T|)} \end{cases} \quad (6)$$

$$v_{ij} = w_j * r_{ij} \quad (7)$$

$$sim_i^{best} = \sum_{j=1}^n \left(\frac{v_{ij}}{\max_j v_{ij}} \right)^{\gamma} \quad (8)$$

$$sim_i^{worst} = \sum_{j=1}^n \left(\frac{\min_j v_{ij}}{v_{ij}} \right)^{\gamma} \quad (9)$$

$$RC_i = \frac{\kappa * sim_i^{best}}{\kappa * sim_i^{best} + (1 - \kappa) * sim_i^{worst}} \quad (10)$$

The ARIE evaluation process produces a relative closeness value for each alternative, representing its position between the ideal and anti-ideal conditions. A higher relative closeness value indicates that the alternative has greater similarity to the ideal condition and lower similarity to the anti-ideal condition, resulting in a more favorable evaluation. Conversely, alternatives with lower relative closeness values are positioned farther from the ideal condition and closer to the anti-ideal condition. These values provide the basis for establishing the final ranking of alternatives, where the alternative with the highest relative closeness value receives the highest rank.

III. Result and Discussion

The E-ARIE framework is proposed as a hybrid multi-criteria decision-making approach to address the complexity of best employee selection in the banking sector. The method integrates Entropy-based objective weighting, which determines criterion importance from the information and variation contained in the assessment data, with the ARIE method, which evaluates alternatives according to their relative closeness to ideal and anti-ideal conditions. This integration is intended to reduce subjectivity in criterion weighting while providing a more flexible and data-responsive ranking mechanism. By combining objective weighting with adaptive ideal-based evaluation, E-ARIE provides a systematic framework for distinguishing employee candidates

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across multiple performance dimensions and generating a comprehensive final ranking.

3.1. Determining Criteria Weights using the Entropy Method

The entropy method is employed to determine the objective weights of the evaluation criteria based on the information and variability contained in the assessment data. The method assigns greater importance to criteria that exhibit higher variation among alternatives because they provide stronger discriminatory information, while criteria with lower variation receive relatively smaller weights. Through this approach, the criterion weights are derived directly from the data without relying on subjective judgments, providing an objective basis for subsequent evaluation and ranking.

The first stage of the entropy weighting Method is the construction of the decision matrix, which organizes the performance values of each alternative according to the corresponding evaluation criteria. The decision matrix contains the assessment values of all alternatives across the selected criteria, where each row represents an alternative and each column represents a criterion, as formulated in (1). The decision matrix is constructed using the candidate assessment data presented in Table 1, which provides the performance values of all alternatives across the evaluated criteria.

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & \dots & x_{71} & x_{81} \\ x_{12} & x_{22} & x_{32} & \dots & x_{72} & x_{82} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{115} & x_{215} & x_{315} & \dots & x_{715} & x_{815} \end{bmatrix} \quad X = \begin{bmatrix} 85 & 82 & 88 & \dots & 86 & 84 \\ 78 & 85 & 82 & \dots & 88 & 81 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 86 & 91 & 89 & \dots & 92 & 87 \end{bmatrix}$$

The second stage of the Entropy Weighting Method is the normalization of the decision matrix to transform the assessment values into a comparable scale. The normalization process is performed using (2) according to the characteristics of each criterion, ensuring that the values can be appropriately compared across alternatives. The results of the normalization process are presented in Table 2.

Table 2. Normalization Results in the Entropy Method

Alternatives	CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
Employee 1	0.0671	0.0644	0.0669	0.0671	0.0646	0.0667	0.0653	0.0654
Employee 2	0.0616	0.0668	0.0623	0.0650	0.0610	0.0690	0.0668	0.0630
Employee 3	0.0726	0.0707	0.0714	0.0693	0.0727	0.0629	0.0706	0.0739
Employee 4	0.0639	0.0597	0.0646	0.0636	0.0673	0.0713	0.0622	0.0623
Employee 5	0.0695	0.0683	0.0691	0.0679	0.0709	0.0644	0.0683	0.0693
Employee 6	0.0624	0.0628	0.0638	0.0657	0.0583	0.0728	0.0645	0.0607
Employee 7	0.0750	0.0738	0.0729	0.0700	0.0772	0.0607	0.0721	0.0755
Employee 8	0.0663	0.0621	0.0661	0.0664	0.0628	0.0675	0.0637	0.0646
Employee 9	0.0687	0.0676	0.0684	0.0686	0.0691	0.0652	0.0675	0.0685
Employee 10	0.0592	0.0636	0.0600	0.0629	0.0566	0.0667	0.0607	0.0591
Employee 11	0.0718	0.0731	0.0722	0.0693	0.0754	0.0614	0.0713	0.0747
Employee 12	0.0631	0.0613	0.0631	0.0643	0.0619	0.0697	0.0630	0.0615
Employee 13	0.0702	0.0691	0.0699	0.0671	0.0718	0.0637	0.0690	0.0700
Employee 14	0.0608	0.0652	0.0616	0.0650	0.0601	0.0720	0.0653	0.0638
Employee 15	0.0679	0.0715	0.0676	0.0679	0.0700	0.0660	0.0698	0.0677



The third stage of the Entropy Weighting Method is the calculation of the entropy value for each criterion based on the normalized decision matrix. The entropy values are calculated using (3) to measure the degree of information and variation contained in each criterion. The results of the entropy value calculation for all criteria are presented in Table 3.

Table 3. Entropy Value Results in the Entropy Method

CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
0.9991	0.9992	0.9994	0.9998	0.9984	0.9995	0.9995	0.9989

The fourth stage of the Entropy Weighting Method is the calculation of the degree of diversification for each criterion. This value is determined using (4) to measure the degree of variation and information differentiation provided by each criterion based on its entropy value. A higher degree of diversification indicates that the criterion contains greater discriminatory information among the alternatives. The results of the degree of diversification calculation for all criteria are presented in Table 4.

Table 4. Degree of Diversification Results in the Entropy Method

CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
0.0009	0.0008	0.0006	0.0002	0.0016	0.0005	0.0005	0.0011

The final stage of the Entropy Weighting Method is the determination of the objective weight for each criterion. The criterion weights are calculated using (5) based on the degree of diversification obtained in the previous stage. The resulting weights indicate the relative importance of each criterion according to the information and variation contained in the assessment data. The calculated criterion weights are normalized so that their total value equals one. The results of the criterion weight calculation are presented in Table 5.

Table 5. Criteria Weight Results Using the Entropy Method

CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
0.1418	0.1230	0.1036	0.0309	0.2605	0.0894	0.0779	0.1728

The results criterion weights obtained using the Entropy Method in table 5 show that CBE-5 has the highest weight of 0.2605, indicating that it provides the greatest relative information and discriminatory capability among the evaluated criteria. CBE-8 follows with a weight of 0.1728, while CBE-1 and CBE-2 obtain weights of 0.1418 and 0.1230, respectively. The remaining criteria, namely CBE-3, CBE-6, CBE-7, and CBE-4, receive weights of 0.1036, 0.0894, 0.0779, and 0.0309, respectively. CBE-4 has the lowest weight, indicating that it contributes the least amount of discriminative information to the overall evaluation compared with the other criteria. Overall, the resulting weights reflect the relative information content and variation of each criterion within the assessment data.

The criterion weights derived from the Entropy Method provide the weighting basis for the subsequent ARIE evaluation. These weights are



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incorporated into the ARIE calculation to account for the relative contribution of each criterion in evaluating the performance of the alternatives. By using the entropy-derived weights, the ARIE process considers the objective information contained in the assessment data when determining the relative position of each alternative toward the ideal and anti-ideal conditions. The resulting weighted values are then used in the subsequent ARIE stages to obtain the final evaluation scores and rankings.

3.2. Alternative Assessment using the ARIE Method

The alternative evaluation using the ARIE method is performed to determine the relative performance and ranking of each candidate based on the established assessment criteria. At this stage, the assessment values are processed by considering the criterion weights obtained from the Entropy Method, allowing each criterion to contribute according to its objective importance. The ARIE process evaluates the alternatives based on their relationship with the ideal and anti-ideal conditions, producing a relative closeness value that represents the overall performance of each candidate. The resulting values are subsequently used to establish the final ranking, where alternatives with higher evaluation scores indicate more favorable performance.

The first stage of the ARIE Method is the normalization of the decision matrix, which aims to transform the original performance values of the alternatives into comparable values across all criteria. This process considers the characteristics of each criterion to ensure that the normalized values appropriately represent the relative performance of the alternatives. The normalization is performed using (6), resulting in standardized values that can be further processed in the subsequent ARIE stages. The results of the normalization process for all alternatives and criteria are presented in Table 6.

Table 6. Normalization Results in the ARIE Method

Alternatives	CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
Employee 1	0.8947	0.8723	0.9167	0.9592	0.8372	0.9091	0.9053	0.8660
Employee 2	0.8211	0.9043	0.8542	0.9286	0.7907	0.8791	0.9263	0.8351
Employee 3	0.9684	0.9574	0.9792	0.9898	0.9419	0.9639	0.9789	0.9794
Employee 4	0.8526	0.8085	0.8854	0.9082	0.8721	0.8511	0.8632	0.8247
Employee 5	0.9263	0.9255	0.9479	0.9694	0.9186	0.9412	0.9474	0.9175
Employee 6	0.8316	0.8511	0.8750	0.9388	0.7558	0.8333	0.8947	0.8041
Employee 7	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Employee 8	0.8842	0.8404	0.9063	0.9490	0.8140	0.8989	0.8842	0.8557
Employee 9	0.9158	0.9149	0.9375	0.9796	0.8953	0.9302	0.9368	0.9072
Employee 10	0.7895	0.8617	0.8229	0.8980	0.7326	0.9091	0.8421	0.7835
Employee 11	0.9579	0.9894	0.9896	0.9898	0.9767	0.9877	0.9895	0.9897
Employee 12	0.8421	0.8298	0.8646	0.9184	0.8023	0.8696	0.8737	0.8144
Employee 13	0.9368	0.9362	0.9583	0.9592	0.9302	0.9524	0.9579	0.9278
Employee 14	0.8105	0.8830	0.8438	0.9286	0.7791	0.8421	0.9053	0.8454
Employee 15	0.9053	0.9681	0.9271	0.9694	0.9070	0.9195	0.9684	0.8969

The second stage of the ARIE Method is weighted normalization, which incorporates the objective criterion weights obtained from the

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Entropy Method into the normalized performance values. At this stage, each normalized value is weighted according to the relative importance of its corresponding criterion, ensuring that criteria with greater information contribution have a proportionally greater influence on the evaluation. The weighted normalization is performed using (7), and the resulting values are subsequently used in the ideal and anti-ideal similarity calculations. The results of the weighted normalization process are presented in Table 7.

Table 7. Weighted Normalization Results in the ARIE Method

Alternatives	CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
Employee 1	0.1269	0.1073	0.0950	0.0297	0.2181	0.0813	0.0705	0.1496
Employee 2	0.1165	0.1112	0.0885	0.0287	0.2060	0.0786	0.0722	0.1443
Employee 3	0.1374	0.1178	0.1015	0.0306	0.2453	0.0862	0.0763	0.1692
Employee 4	0.1209	0.0994	0.0918	0.0281	0.2272	0.0761	0.0672	0.1425
Employee 5	0.1314	0.1138	0.0982	0.0300	0.2393	0.0841	0.0738	0.1585
Employee 6	0.1180	0.1047	0.0907	0.0290	0.1969	0.0745	0.0697	0.1389
Employee 7	0.1418	0.1230	0.1036	0.0309	0.2605	0.0894	0.0779	0.1728
Employee 8	0.1254	0.1034	0.0939	0.0294	0.2120	0.0804	0.0689	0.1479
Employee 9	0.1299	0.1125	0.0971	0.0303	0.2332	0.0832	0.0730	0.1568
Employee 10	0.1120	0.1060	0.0853	0.0278	0.1908	0.0813	0.0656	0.1354
Employee 11	0.1359	0.1217	0.1025	0.0306	0.2544	0.0883	0.0771	0.1710
Employee 12	0.1194	0.1021	0.0896	0.0284	0.2090	0.0777	0.0681	0.1407
Employee 13	0.1329	0.1152	0.0993	0.0297	0.2423	0.0851	0.0746	0.1603
Employee 14	0.1150	0.1086	0.0874	0.0287	0.2029	0.0753	0.0705	0.1461
Employee 15	0.1284	0.1191	0.0961	0.0300	0.2363	0.0822	0.0754	0.1550

The third stage of the ARIE Method is the calculation of the ideal and anti-ideal similarity values based on the weighted normalized values obtained in the previous stage. The ideal similarity measures the degree of similarity between each alternative and the ideal condition, while the anti-ideal similarity measures the similarity between each alternative and the anti-ideal condition. These calculations are performed using (8) and (9), respectively, to determine the relative position of each alternative with respect to both reference conditions. The results of the ideal and anti-ideal similarity calculations are presented in Table 8.

Table 8. Similarity Ideal and Anti-Ideal Results in the ARIE Method

Alternatives	Similarity Ideal	Similarity Anti-Ideal
Employee 1	7.1605	7.2697
Employee 2	6.9392	7.5079
Employee 3	7.7589	6.7099
Employee 4	6.8658	7.5889
Employee 5	7.4938	6.9460
Employee 6	6.7844	7.6811
Employee 7	8.0000	6.5104
Employee 8	7.0326	7.4043
Employee 9	7.4174	7.0168
Employee 10	6.6393	7.8549
Employee 11	7.8702	6.6167
Employee 12	6.8149	7.6387

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Employee 13	7.5589	6.8873
Employee 14	6.8376	7.6190
Employee 15	7.4617	6.9783

The final stage of the ARIE Method is the calculation of the relative closeness value, which determines the overall position of each alternative between the ideal and anti-ideal conditions. The relative closeness is calculated using (10) by considering the ideal and anti-ideal similarity values obtained in the previous stage. A higher relative closeness value indicates that an alternative is closer to the ideal condition and therefore has better overall performance. The results of the relative closeness calculation for all alternatives are presented in Table 9, which provides the basis for determining the final ranking of the alternatives.

Table 9. Relative Closeness Value Results in the ARIE Method

Alternatives	Relative Closeness Value
Employee 1	0.4962
Employee 2	0.4803
Employee 3	0.5363
Employee 4	0.4750
Employee 5	0.5190
Employee 6	0.4690
Employee 7	0.5513
Employee 8	0.4871
Employee 9	0.5139
Employee 10	0.4581
Employee 11	0.5433
Employee 12	0.4715
Employee 13	0.5232
Employee 14	0.4730
Employee 15	0.5167

Based on the relative closeness values obtained from the ARIE Method, the alternatives are subsequently ranked from the highest to the lowest value. An alternative with a higher relative closeness value indicates better overall performance and is therefore assigned a higher rank. The resulting ranking provides a clear comparison of the performance of all evaluated candidates and identifies the most favorable alternative based on the established criteria and objective criterion weights. The final ranking results are presented in Figure 2.

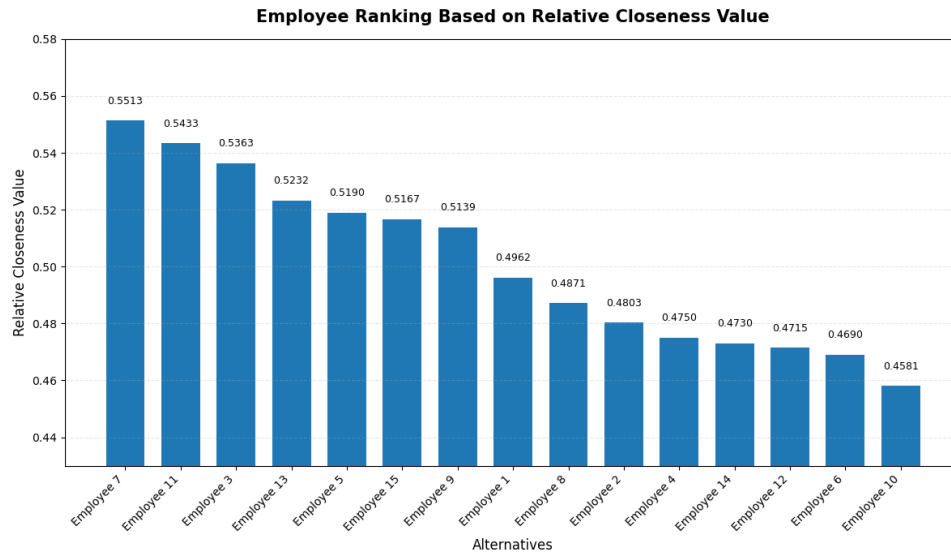


Figure 2. Ranking Alternatives using the ARIE Method

The ARIE Method produces different relative closeness values for the 15 employee candidates, as presented in Figure 2. Employee 7 achieves the highest relative closeness value of 0.5513, followed by Employee 11 with 0.5433 and Employee 3 with 0.5363, indicating the most favorable overall performance among the evaluated candidates. Employee 13, Employee 5, and Employee 15 obtain relative closeness values of 0.5232, 0.5190, and 0.5167, respectively, while Employee 9 records a value of 0.5139. The remaining candidates obtain values below 0.50, with Employee 1 at 0.4962, Employee 8 at 0.4871, Employee 2 at 0.4803, and Employee 4 at 0.4750. Employee 14, Employee 12, and Employee 6 obtain values of 0.4730, 0.4715, and 0.4690, respectively, while Employee 10 records the lowest relative closeness value of 0.4581. These results indicate that Employee 7 has the most favorable overall position and is therefore ranked as the best-performing candidate based on the ARIE evaluation.

3.3. Sensitivity Analysis

Sensitivity analysis is conducted to examine the robustness and stability of the E-ARIE method under variations in criterion weights[27]–[29]. This analysis evaluates whether changes in the relative importance of individual criteria can substantially influence the final ranking of employee candidates. The procedure is performed by systematically modifying the criterion weights while maintaining the overall weight structure, allowing the sensitivity of the ranking results to changes in criterion importance to be observed. Several scenarios are generated by increasing or decreasing the weight of each criterion at different levels, while the weights of the remaining criteria are adjusted accordingly to preserve the total weight of one. For each scenario, the E-ARIE method is recalculated to obtain the corresponding relative closeness values and ranking positions of all alternatives. The resulting rankings are then compared with the original ranking to identify changes



in alternative positions and determine the degree of ranking stability exhibited by the proposed method. Particular attention is given to the frequency and magnitude of rank changes across the tested scenarios, as limited changes indicate that the method is less sensitive to variations in criterion importance and therefore provides more robust decision results. Conversely, substantial changes in ranking positions indicate a higher sensitivity of the evaluation process to criterion-weight variations[30], [31]. Through this systematic analysis, the robustness of E-ARIE can be assessed by determining its ability to maintain consistent ranking results despite moderate or substantial changes in criterion importance, thereby providing additional evidence regarding the reliability and stability of the proposed decision-making approach.

Sensitivity analysis is conducted to evaluate the robustness and stability of the E-ARIE method under variations in criterion weights. The analysis is performed by systematically increasing and decreasing the weight of each criterion by 0.05 and 0.10 from its original weight to observe the resulting changes in the ranking of employee candidates. For each variation scenario, the E-ARIE method is recalculated to obtain the corresponding relative closeness values and ranking positions. The adjusted criterion weights are maintained within the decision framework to ensure that the total weight remains equal to one. The resulting rankings from each scenario are subsequently compared with the original ranking to identify changes in alternative positions and determine the degree of ranking stability exhibited by E-ARIE. The sensitivity analysis therefore provides an assessment of how consistently the method produces rankings when the importance of individual criteria is moderately or substantially changed. A ranking that remains relatively stable across the tested weight variations indicates that E-ARIE is robust and less sensitive to changes in criterion importance, whereas considerable changes in ranking positions indicate greater sensitivity to weight variations. The results of the sensitivity analysis using weight changes of ± 0.05 and ± 0.10 are presented in Table 1.

Table 10. Criteria Weight Results Using the Entropy Method

Scenario	CBE-1	CBE-2	CBE-3	CBE-4	CBE-5	CBE-6	CBE-7	Cbe-8
Initial Weight	0.1418	0.1230	0.1036	0.0309	0.2605	0.0894	0.0779	0.1728
CBE-1+0.05	0.1918	0.1158	0.0976	0.0291	0.2453	0.0842	0.0734	0.1627
CBE-1-0.05	0.0918	0.1302	0.1096	0.0327	0.2757	0.0946	0.0824	0.1829
CBE-2+0.05	0.1337	0.1730	0.0977	0.0291	0.2457	0.0843	0.0735	0.1630
CBE-2-0.05	0.1499	0.0730	0.1095	0.0327	0.2754	0.0945	0.0823	0.1827
CBE-3+0.05	0.1339	0.1162	0.1536	0.0292	0.2460	0.0844	0.0736	0.1632
CBE-3-0.05	0.1497	0.1299	0.0536	0.0326	0.2751	0.0944	0.0823	0.1825
CBE-4+0.05	0.1345	0.1167	0.0983	0.0809	0.2471	0.0848	0.0739	0.1639
CBE-5+0.05	0.1322	0.1147	0.0966	0.0288	0.3105	0.0834	0.0726	0.1611
CBE-5-0.05	0.1514	0.1313	0.1106	0.0330	0.2105	0.0955	0.0832	0.1845
CBE-6+0.05	0.1340	0.1163	0.0979	0.0292	0.2462	0.1394	0.0736	0.1633
CBE-6-0.05	0.1496	0.1298	0.1093	0.0326	0.2748	0.0394	0.0822	0.1823
CBE-7+0.05	0.1341	0.1163	0.0980	0.0292	0.2464	0.0846	0.1279	0.1634
CBE-7-0.05	0.1495	0.1297	0.1092	0.0326	0.2747	0.0943	0.0279	0.1822
CBE-8+0.05	0.1332	0.1156	0.0973	0.0290	0.2448	0.0840	0.0732	0.2228

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CBE-8-0.05	0.1504	0.1304	0.1099	0.0328	0.2763	0.0948	0.0826	0.1228
CBE-1+0.1	0.2418	0.1087	0.0915	0.0273	0.2302	0.0790	0.0688	0.1527
CBE-1-0.1	0.0418	0.1373	0.1157	0.0345	0.2909	0.0998	0.0870	0.1930
CBE-2+0.1	0.1256	0.2230	0.0918	0.0274	0.2308	0.0792	0.0690	0.1531
CBE-2-0.1	0.1580	0.0230	0.1154	0.0344	0.2902	0.0996	0.0868	0.1925
CBE-3+0.1	0.1260	0.1093	0.2036	0.0275	0.2315	0.0794	0.0692	0.1535
CBE-3-0.1	0.1576	0.1367	0.0036	0.0344	0.2896	0.0994	0.0866	0.1921
CBE-4+0.1	0.1272	0.1103	0.0929	0.1309	0.2336	0.0802	0.0699	0.1550
CBE-5+0.1	0.1226	0.1064	0.0896	0.0267	0.3605	0.0773	0.0674	0.1494
CBE-5-0.1	0.1610	0.1396	0.1176	0.0351	0.1605	0.1015	0.0884	0.1962
CBE-6+0.1	0.1262	0.1095	0.0922	0.0275	0.2319	0.1894	0.0694	0.1538
CBE-7+0.1	0.1264	0.1097	0.0924	0.0276	0.2323	0.0797	0.1779	0.1541
CBE-8+0.1	0.1247	0.1081	0.0911	0.0272	0.2290	0.0786	0.0685	0.2728
CBE-8-0.1	0.1590	0.1379	0.1161	0.0346	0.2920	0.1002	0.0873	0.0728

The sensitivity analysis was further conducted by increasing and decreasing the criterion weights by 0.05 to examine the changes in the ranking of the 15 employee candidates. For each scenario, the adjusted criterion weights were applied to the ARIE evaluation while maintaining the total weight at one. The resulting relative closeness values were recalculated and used to determine the ranking of each candidate under the corresponding weight variation. The rankings obtained from the increased and decreased weight scenarios were then compared with the original ranking to identify changes in the positions of the alternatives and assess the stability of the E-ARIE evaluation. The comparative ranking results under the ± 0.05 weight variation scenarios are presented in Figure 3, providing an overview of the ranking behavior of the alternatives under changes in criterion importance.



Figure 3. Ranking Alternatives using the ARIE Method

Figure 3 shows a Bump Chart of the E-ARIE ranking stability across various sensitivity analysis scenarios with a criteria weight

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perturbation of ± 0.05 using the CBE approach. The results show that all alternatives, namely Employee 7, Employee 11, Employee 3, Employee 13, Employee 5, Employee 15, Employee 9, Employee 1, Employee 8, Employee 2, Employee 4, Employee 14, Employee 12, Employee 6, and Employee 10, maintained the same ranking positions across all scenarios from the initial condition to CBE+0.05 and CBE-0.05. There were no lines that switched positions or crossed between ranks, so it can be concluded that the E-ARIE ranking results are very stable and robust against criteria weight changes of ± 0.05 . This stability shows that small changes in weights do not affect the order of alternatives, meaning the model has good resilience in the decision-making process.

The rankings obtained from the increased and decreased weight scenarios were then compared with the original ranking to identify changes in the positions of the alternatives and assess the stability of the E-ARIE evaluation. The comparative ranking results under the ± 0.1 weight variation scenarios are presented in Figure 4, providing an overview of the ranking behavior of the alternatives under changes in criterion importance.



Figure 4. Ranking Alternatives using the ARIE Method

Figure 4 shows a Bump Chart of the E-ARIE ranking stability across various sensitivity analysis scenarios with a criteria weight perturbation of ± 0.1 . The visualization results show that all alternatives, from Employee 7 in first place to Employee 10 in fifteenth place, consistently maintain their ranking positions across all CBE ± 0.1 scenarios. No position changes, rank shifts, or line crossings between alternatives were observed. This indicates that the E-ARIE ranking is very stable against relatively large weight changes, meaning the model is highly robust and the decision results are not easily affected by variations in criteria weights.



3.4. Discussion

The results demonstrate that the proposed E-ARIE framework provides a systematic and objective approach to best employee selection in the banking sector by integrating entropy-based weighting with the ARIE evaluation mechanism. The entropy method determines criterion importance directly from the variation and information content of the assessment data, thereby reducing dependence on subjective preferences. The results show that CBE-5 (Work Experience) obtains the highest weight of 0.2605, followed by CBE-8 (Competency) at 0.1728 and CBE-1 (Performance Score) at 0.1418. This indicates that work experience provides the greatest discriminatory information within the dataset, whereas CBE-4 (Attendance) receives the lowest weight of 0.0309. The distribution of weights demonstrates that the proposed framework is capable of differentiating the contribution of each criterion according to the characteristics of the observed data rather than assigning equal or subjectively determined importance.

The ARIE evaluation further demonstrates the effectiveness of combining the objective entropy weights with an ideal-based ranking mechanism. Employee 7 achieves the highest relative closeness value of 0.5513, followed by Employee 11 (0.5433) and Employee 3 (0.5363), indicating that these candidates have the strongest overall performance across the evaluated criteria. Employee 7 achieves the maximum normalized value across all eight criteria, resulting in the highest ideal similarity value of 8.0000 and the lowest anti-ideal similarity value of 6.5104. This provides a clear explanation for its first-place position and demonstrates the ability of ARIE to recognize alternatives that perform consistently well across multiple dimensions. In contrast, Employee 10 obtains the lowest relative closeness value of 0.4581, reflecting comparatively weaker performance across several important criteria, particularly those receiving relatively high entropy weights. These findings indicate that E-ARIE can provide a comprehensive ranking by simultaneously considering criterion importance and the relative position of each candidate with respect to ideal and anti-ideal conditions.

An important finding is the high stability of the E-ARIE ranking under criterion-weight perturbations. The sensitivity analysis shows that increasing and decreasing criterion weights by ± 0.05 does not change the ranking positions of any of the 15 employees. The same stability is observed under the larger ± 0.10 perturbation scenarios, where Employee 7 remains first, Employee 11 remains second, Employee 3 remains third, and the remaining alternatives retain their respective positions through Employee 10 in fifteenth place. The absence of rank shifts or line crossings in the Bump Charts indicates that the ranking is not highly dependent on a particular criterion weight configuration. This result is particularly important for practical employee selection because organizational preferences or managerial priorities may change over time; nevertheless, the proposed model maintains consistent decision



outcomes under moderate and relatively substantial changes in criterion importance.

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IV. Conclusion

This study developed the E-ARIE (Entropy-based Adaptive Ranking with Ideal Evaluation) method as an objective and adaptive MCDM approach for best employee selection in the banking sector. The results demonstrate that the integration of Entropy weighting and ARIE can effectively determine criterion importance based on the information contained in the assessment data and subsequently rank employee candidates according to their closeness to ideal and anti-ideal conditions. The Entropy method identified CBE-5 (Work Experience) as the most influential criterion with a weight of 0.2605, while Employee 7 achieved the highest relative closeness value of 0.5513, followed by Employee 11 and Employee 3, indicating the strongest overall performance among the evaluated candidates. Furthermore, the sensitivity analysis showed that the ranking remained unchanged under both ± 0.05 and ± 0.10 criterion-weight variations, demonstrating the high stability and robustness of the proposed method. Overall, E-ARIE provides a systematic, objective, discriminative, and robust decision-making framework that can support banking organizations in selecting the best employees while reducing subjectivity and maintaining consistent ranking outcomes under changes in criterion importance.

CRedit Authorship Contribution Statement

Mesran: Methodology, Validation, Writing - Original Draft Preparation, Writing - Review & Editing. **Desyanti:** Conceptualization, Data curation, Formal analysis, Writing - Original Draft Preparation. **T. Ardiansah:** Investigation, Software, Writing - Original Draft Preparation.



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.

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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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