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An Entropy-Assisted COBRA Framework to Support Complex Bounded Rationality in Employee Recruitment

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Abstract−In the employee recruitment process, decision-making often involves many criteria and relies on the subjective judgment of the decision-maker. The main problem lies in how to develop a decision support system that can overcome this complexity while maintaining rationality and objectivity. This study aims to apply a hybrid framework based on the entropy and COBRA methods to support objective decision-making in the employee recruitment process, and to overcome the limitations of subjectivity and bounded rationality in candidate selection with a structured data-driven approach. The entropy method is used to objectively determine the weight of criteria based on data variations, thereby helping to reduce subjectivity in decision-making and increase the rationality of COBRA analysis results. The results of the final calculation using the Entropy-COBRA method, were ranked nine candidates based on their final scores which reflected relative proximity to the ideal solution in the recruitment process. The candidate with the lowest score is considered to be the closest to the ideal solution and has the best overall performance. Raka employees ranked first with a final score of -0.0618, followed by Andra in second place with a score of -0.0597, and Fajar in third place with -0.0357. The results of the final score in the COBRA method with a lower score indicate that an alternative shows superior performance over the other. This framework makes a real contribution to data-driven decision-making for human resource management, particularly in the context of recruitment involving multiple criteria and alternatives.

Keywords: COBRA Method; Decision Making; Employee Recruitment; Entropy Weighting; Hybrid Framework

1. INTRODUCTION

Employee recruitment is a strategic process undertaken by organizations to attract, screen, and select the most suitable individuals to fill a specific position within the company[1]–[3]. This process aims to ensure that the human resources recruited have the competencies, qualifications, and potential needed to support the achievement of organizational goals. Success in the recruitment process has a profound effect on a company's long-term performance, as the right employees can make a significant contribution to efficiency, innovation, and a positive work culture. The complexity of the employee recruitment process is a real challenge faced by many organizations, especially when it comes to selecting the best candidates from a diverse pool of applicants with diverse backgrounds, skills, and characteristics. This process involves not only evaluating objective aspects such as education, work experience, and technical ability, but also subjective aspects such as personality, organizational cultural suitability, and potential adaptation and collaboration. Each of these criteria has different weights and importance depending on the position being applied for, so an assessment approach that is able to handle a wide range of data with varying levels of importance is needed. In addition, decision-making in recruitment is often influenced by time constraints, pressure from management, cognitive bias, and incomplete or ambiguous information, all of which can interfere with the objectivity of the selection process[4], [5]. Therefore, a decision support system is needed that is able to simplify and optimize this process by considering the complexity and limitations of human rationality in making strategic decisions related to human resources.

Bounded rationality in human resource decision-making refers to conditions in which decision-makers, such as HR managers or recruitment teams, are not always able to make completely rational decisions due to various limitations. In this context, decisions are often influenced by factors such as limited information, limited time, individual cognitive capacity, as well as situational pressures or personal biases. For example, in the recruitment process, a manager may not have enough complete data about all candidates, or there is too much information that it is difficult to process optimally[6]–[8]. In addition, judgments are often based on intuition or subjective experience, which risks creating bias and inaccuracies. The concept of bounded rationality emphasizes that even if decision-makers are rational in their intentions, they tend to look for "satisfactory" solutions, not optimal solutions. Therefore, in HR management, it is important to develop a decision support system capable of helping to overcome these limitations by providing structured data, objective analysis methods, and technology-based approaches to improve the quality of decisions taken.

This study aims to apply a hybrid framework based on the entropy and COBRA methods to support objective decision-making in the employee recruitment process, and to overcome the limitations of subjectivity and bounded rationality in candidate selection with a structured data-driven approach. Applying a framework based on the Comprehensive Distance Based Ranking Method (COBRA Method) in supporting recruitment decisions is an innovative approach designed to address the complexity and limitations of rationality in the employee selection process. COBRA is

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a comprehensive distance-based method that evaluates alternatives (in this case candidates) based on their proximity to positive and negative ideal solutions, taking into account all dimensions of the assessment as a whole[9]–[11]. In the context of recruitment, COBRA is able to integrate various important criteria such as technical competence, work experience, communication skills, personality, and organizational cultural suitability. Each candidate is evaluated based on a distance score against the ideal solution, which reflects the best candidate theoretically. This approach not only considers how well a candidate performs on each of the criteria, but also looks at the overall suitability of the candidate's profile relative to other candidates.

The implementation of COBRA in the recruitment process becomes more objective and structured because all assessments are carried out based on consistent mathematical calculations[12], [13]. This method is particularly effective for use in multi-criteria decision-making situations, especially when many variables must be considered simultaneously. The integration of COBRA into the HR decision support system allows decision-makers to reduce cognitive bias, increase the transparency of the selection process, and provide a logical justification for each recruitment decision taken. When combined with objective weighting approaches such as entropy weighting, the effectiveness of this framework will be further enhanced as it is able to generate a weighting of criteria that represents a variation of real information from candidate assessment data. Thus, the implementation of COBRA in recruitment not only helps organizations select the best candidates, but also strengthens accountability and fairness in HR decision-making.

Integrating entropy-based objective weighting methods in the decision-making framework, especially in the employee recruitment process, provides significant added value to the objectivity and validity of selection results[14]–[16]. The entropy method works with the principle of measuring the uncertainty of information in data, where criteria that have a higher diversity of values are considered to provide greater information, and thus are given a higher weight. With the entropy approach, the weight of the criteria is not determined subjectively by the assessor, but based on the actual variation of the available assessment data. By using entropy weighting, organizations can ensure that criteria that truly differentiate the qualities of candidates will receive greater attention in the selection process[17]–[19]. This directly improves the accuracy in selecting the best candidates and ensures that the recruitment process is more equitable, measurable, and based on the power of data.

Offering a hybrid framework that supports data-driven decisions in the recruitment process is a strategic step to improve the quality and accountability of employee selection. This framework combines the advantages of the entropy method as an objective weighting approach with the COBRA method as a comprehensive alternative ranking mechanism[20]. This integration allows organizations to manage the complexity of multi-criteria recruitment systematically and transparently, while still taking into account bounded rationality. This hybrid framework supports robust data-driven decision-making, as the entire process is carried out quantitatively, structured, and replicated. The use of this model not only reduces subjective bias, but also increases the efficiency of the selection process and provides a clear justification for the decisions taken. Thus, the organization can guarantee that the selected candidate is truly the best choice based on a comprehensive and objective analysis. This hybrid approach is also flexible to be adapted in various recruitment contexts, both for technical, managerial, and strategic positions. This work is also to overcome the limitations of subjectivity in candidate selection is a crucial step to ensure that the recruitment process runs fairly, transparently, and based on real competencies. Subjectivity in selection often arises as a result of judgments that rely too much on the intuition, personal experience, or individual preferences of the recruitment team, which can lead to bias, inconsistencies, and inaccuracies in candidate selection. This can be detrimental to the organization because potential candidates may be missed, while those selected may not necessarily be objectively suited to the needs of the available position.

The contribution of this research is the implementation of a hybrid framework that integrates the entropy and COBRA methods in the recruitment process, which allows for more objective, transparent, and data-driven decision-making. In addition, this research also provides solutions to overcome subjective bias and limitations of rationality in candidate selection, thereby increasing efficiency and accuracy in selecting employees who best suit the needs of the organization.

2. RESEARCH METHODOLOGY

2.1 Research Framework

A research framework is a conceptual design that systematically describes the flow and direction of a research. The main function of the research framework is as a map or work guide that helps researchers to stay focused on the goals and scope of the research that have been set. In addition, this framework plays an important role in ensuring that each step of the research is done logically and systematically, as well as making it easier for the reader to understand the entire research process. The research framework in the research conducted is shown in figure 1.

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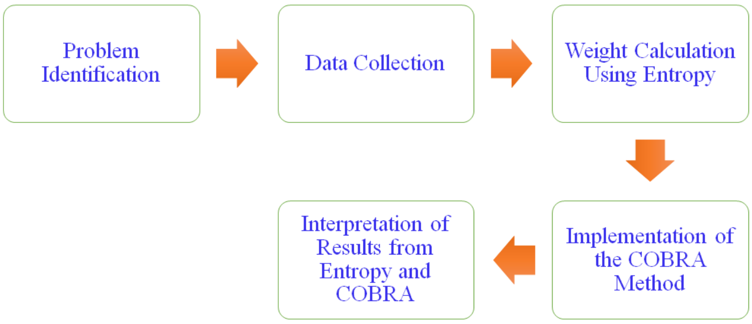

Figure 1. Research Framework

In the employee recruitment process, decision-making often involves many criteria and relies on the subjective judgment of the decision-maker. This becomes even more complex when there is limited information, limited time, and limited cognitive abilities on the part of HR or managers, known as bounded rationality. The main problem lies in how to develop a decision support system that can overcome this complexity while maintaining rationality and objectivity. The data collected consists of an assessment of a number of employee candidates based on several predetermined recruitment criteria. Assessment of candidates is carried out by the HR team or experts. Once the candidate data has been collected, the next step is to calculate the objective weight of each criterion using the Entropy method. This method analyzes the degree of irregularity (entropy) of each criterion. The higher the variation in the value of a criterion, the greater the contribution of the information provided, and the higher the weight. Thus, the Entropy method can help avoid subjectivity in weighting and generate weights based on actual information from the data. Once the weight of each criterion is determined, the COBRA method is applied to evaluate and rank the alternatives (candidates). COBRA takes into account limitations in real decision-making, such as the limited attention of decision-makers to all criteria at once, allowing for a process of simplification or adjustment of preferences based on complex conditions. This method mimics how humans make decisions in the real world with limitations of rationality, yet still directional and logical. The final result of this process is the ranking of candidates based on the combined score between the objective weight of Entropy and the complex evaluation of the COBRA method. Interpretation is carried out by comparing candidates with each other based on final scores, as well as evaluating the consistency of the results with expert opinions or actual company decisions. These results were also analyzed to see how the weight of Entropy affects the decision structure in the COBRA approach, as well as how much this system helps in more effective and measurable decision-making.

2.2 Data Collection

The data collection in this study is focused on the selection and recruitment process of new employees. The data collected is primary data, which is obtained through direct assessment from the HRD team and related division managers of a number of candidates. The assessment is carried out based on several selection criteria that have been set. With this approach, the data collected not only reflects the subjective perception of the assessor's side, but is also processed through a quantitative approach to support rational and data-driven decisions. In addition to using direct assessments, data is also collected through administrative documents such as curriculum vitae (CV), interview results, as well as the results of technical ability tests and psychological tests. The information from this document is used to verify the data provided by the candidate and complete a quantitative assessment of the predetermined criteria.

2.3 Entropy Weighting Method

The Entropy method is one of the objective weighting techniques used in multicriteria decision-making. This method comes from the concept of information theory, which states that entropy measures the degree of uncertainty or diversity of information from a data. Entropy is used to determine the importance of each criterion based on the distribution of alternative values on each criterion. The Entropy method produces objective weight because it relies entirely on actual data, not on the decision-maker's subjective preferences or intuition. This is especially useful in decision support systems, especially when manual weighting risks creating bias.
The first step is to build a decision matrix based on the assessment data, where each row represents one alternative, and each column represents one criterion. The result matrix is created using the following equations.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

The next step is to normalize the values in the matrix so that each value is on the same scale. This normalization aims to convert the raw value into a proportion or comparison that can be further processed. This is important because each criterion can have a different unit or scale calculated using the following equation.

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

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The next step is to calculate the entropy for each criterion. Entropy here indicates how much variation or irregularity of values in a criterion is. If all the values in the criteria are almost the same, then the entropy is high, which means that the criteria provide little information in distinguishing the alternatives are calculated using the following equation.

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

The next step is to determine the degree of diversification, which is a measure that shows how much information from each criterion contributes. The greater the value of diversification, the more important the criterion is in the decision-making process because having a high variation of data is calculated using the following equation.

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

The final step is to calculate the weights for each criterion based on its diversification value. This weight reflects the relative importance of each criterion objectively, without the intervention of subjective preferences calculated using the following equation.

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

The Entropy method is very useful in decision support systems (DSS) because it provides objective weight based on existing data, without the influence of subjective preferences of decision makers. As a result, the decisions taken are more measurable and accountable.

2.4 COBRA Method

The comprehensive distance-based ranking method (COBRA) is a method in multicriteria decision-making that aims to rank or rank alternatives based on several criteria considered. This method was developed to help address complex decision-making problems, especially when there is a limitation of information or a limitation in decision-making abilities, known as bounded rationality. COBRA uses a distance-based approach to compare alternatives based on relevant criteria. The goal is to evaluate how far or close each alternative is to the desired ideal solution based on distance measurements in multicriteria spaces.
The first stage in the COBRA method is to collect data to form a decision-making matrix. This matrix consists of alternatives that are evaluated based on predetermined criteria. Each row in the matrix represents the alternatives to be evaluated, while each column represents the relevant criteria in decision-making made using equation (1).
The next stage in the COBRA method is data normalization, this process converts the values in the matrix into proportional or standard values, to avoid comparisons between data that have different scales or units. Normalization ensures that all data can be objectively compared calculated using the following equation.

$$r_{ij} = \frac{x_{ij}}{max_{ij}^{i}} \quad (6)$$

The next stage in the COBRA method is weighted normalization, this process describes the multiplication of the weight with the normalization results of each alternative which is calculated using the following equation.

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

The next stage in the COBRA method is to determine the Positive Ideal Solution (PIS), Negative Ideal Solution (NIS), and Mean Solution (AS). The Ideal Positive solution is the alternative that has the best value for each criterion, i.e. the solution that provides the highest results for each criterion evaluated. Negative Ideal Solutions are alternatives that have the worst value for each criterion, i.e. solutions that provide the lowest results for each criterion. Average Solution is This solution represents the average value of all alternatives for each criterion. This solution is used as an additional reference in the calculation of distances. The values of PIS, NIS, and AS are determined using the following equations.

$$PIS_i \begin{cases} = \max \Delta_{ij}^{i} \text{ ; } for\ benefit\ criteria \\ = \min \Delta_{ij}^{i} \text{ ; } for\ cost\ criteria \end{cases} \quad (8)$$

$$NIS_i \begin{cases} = \min \Delta_{ij}^{i} \text{ ; } for\ benefit\ criteria \\ = \max \Delta_{ij}^{i} \text{ ; } for\ cost\ criteria \end{cases} \quad (9)$$

$$AS_i = \frac{\sum_{i=1}^{n} \Delta_{ij}}{n} \quad (10)$$

The next stage in the COBRA method is to calculate the distance between each alternative and a positive ideal solution, the negative ideal solution, and the average solution are calculated using the following equation.

$$d(S_i) = dE(S_i) + \beta * dE(S_i) * dT(S_i) \quad (11)$$

where S_j is any solution (PIS_j, NIS_j or AS_j), and β is the correction coefficient calculated using the following equation.

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$$\beta = max^{i}_{dE(S_i)_i} - min^{i}_{dE(S_i)_i} \tag{12}$$

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

$$dE(PIS_i) = \sqrt{\sum_{i=1}^{m}(PIS_i - \Delta_{ij})^2} \tag{13}$$

$$dT(PIS_i) = \sum_{i=1}^{m}\left|PIS_i - \Delta_{ij}\right| \tag{14}$$

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

$$dE(NIS_i) = \sqrt{\sum_{i=1}^{m}(NIS_i - \Delta_{ij})^2} \tag{15}$$

$$dT(NIS_i) = \sum_{i=1}^{m}\left|NIS_i - \Delta_{ij}\right| \tag{16}$$

where dE represents Euclidean distance and dT represents the Taxicab distance for a positive average solution, is obtained using the following equation.

$$dE(AS_i)_i^+ = \sqrt{\sum_{i=1}^{m}\tau^+ * (AS_i - \Delta_{ij})^2} \tag{17}$$

$$dT(AS_i)_i^+ = \sum_{i=1}^{m}\tau^+ * \left|AS_i - \Delta_{ij}\right| \tag{18}$$

$$\tau^+ = \begin{cases} 1 \; if \; AS_i < \Delta_{ij} \\ 0 \; if \; AS_i > \Delta_{ij} \end{cases} \tag{19}$$

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

$$dE(AS_i)_i^- = \sqrt{\sum_{i=1}^{m}\tau^- * (AS_i - \Delta_{ij})^2} \tag{20}$$

$$dT(AS_i)_i^- = \sum_{i=1}^{m}\tau^- * \left|AS_i - \Delta_{ij}\right| \tag{21}$$

$$\tau^- = \begin{cases} 1 \; if \; AS_i > \Delta_{ij} \\ 0 \; if \; AS_i < \Delta_{ij} \end{cases} \tag{22}$$

The final stage in the COBRA method is to calculate the alternative end value by increasing the comprehensive distance value calculated using the following equation.

$$dC_i = \frac{d(PIS_i)_i - d(NIS_i)_i - d(AS_i)_i^+ + d(AS_i)_i^-}{4} \tag{23}$$

The COBRA method is a distance-based decision-making method used to rank alternatives by considering the proximity to the ideal solution and the distance from the anti-ideal solution. COBRA combines the strengths of a distance-based approach, but in a more comprehensive and flexible way.

3. RESULT AND DISCUSSION

The employee recruitment process is a strategic activity that requires multidimensional considerations, where decision-makers are faced with a variety of complex criteria and data. However, in practice, recruitment decisions are often influenced by cognitive limitations, imperfect information, and time and resource pressures, a condition theoretically known as bounded rationality. To respond to these challenges, adaptive and data-driven decision support methods are essential. One promising approach is COBRA method, a framework designed to model decision-making in the context of limited rationality by considering the comprehensive distances between alternatives based on a variety of criteria. In this study, an Entropy-Assisted COBRA framework was developed that integrates the Entropy method as an objective approach to determine the weight of criteria with a distance-based ranking model from COBRA. The Entropy method allows the evaluation of the relative significance of each criterion based on the degree of variation in the information in the data, thereby reducing subjective bias in weighting. This integration aims to improve the accuracy and rationality of decisions in the employee selection process, especially when complex data and decision-makers' preferences cannot be fully defined explicitly. As such, this framework is not only theoretically relevant, but also practical in supporting a fairer, more transparent, and efficient recruitment process.

3.1 Problem Identification

The employee recruitment process often involves a lot of complex criteria and information, making it difficult to make objective and rational decisions. In conditions of limited information and cognitive ability of decision-makers, the

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bounded rationality approach becomes very relevant. The following are the results of the identification of problems in employee recruitment carried out in this study.

a. Complexity in recruitment decision-making: The employee selection process involves many criteria such as technical competence, soft skills, work experience, and organizational culture suitability. This complexity often makes it difficult for decision-makers to evaluate objectively and consistently.
b. Bounded rationality: In practice, decision-makers do not always have the complete information or cognitive ability to evaluate all alternatives thoroughly. This causes the recruitment process to tend to be subjective and prone to bias.
c. Inobjectivity in determining the weight of criteria: Many traditional recruitment methods rely on intuition or expert opinion in determining the weight of criteria, which can result in bias and inconsistencies in evaluation results.
d. The need for a ranking method that is able to handle multi-criteria data: The selection system requires a calculation model that is able to comprehensively measure the proximity of alternatives (candidates) to the ideal solution, so that the resulting rankings can be more accurate and reflect actual conditions.
e. Lack of integration between objective methods and bounded rationality-based models in recruitment systems: Although many decision-making methods have been developed, there are still few that combine objective approaches such as Entropy with distance-based models such as COBRA to support decision-making under the constraints of rationality.

3.2 Data Collection

Data collection in this study was carried out to obtain information about employee selection criteria and assessment of each candidate. Primary data was collected through questionnaires provided to the HR team and managers of the relevant divisions, with the aim of identifying criteria that were considered important in the recruitment process. The assessment of candidates is carried out using criteria, namely age (SE-1) with the type of cost criteria, Technical Competency (SE-2) with the type of benefit criteria, Work Experience (SE-3) with the type of benefit criteria, Communication Ability (SE-4) with the type of benefit criteria, Integrity (SE-5) with the type of benefit criteria, Teamwork (SE-6) with the type of benefit criteria. In addition, secondary data is obtained from internal company documents, such as CVs, test results, and preliminary evaluation reports, which are used to support the validity and accuracy of the assessment. The results of the assessment of employees are shown in table 1.

Table 1. Assessment data

Employee Name	Criteria					
	SE-1	SE-2	SE-3	SE-4	SE-5	SE-6
Dimas	26	8	3	9	8	9
Raka	30	7	5	8	9	7
Fajar	28	9	4	7	8	8
Iqbal	27	6	3	9	9	9
Bayu	25	7	2	8	7	7
Rizky	29	8	4	8	8	8
Rendi	26	7	3	7	9	8
Andra	31	9	5	6	8	7
Galih	24	6	2	9	7	8

3.3 Determination of Weights of Criteria Using the Entropy Method

The Entropy method is used to determine the weight of criteria in multi-criteria decision-making, such as in employee recruitment selection. This process begins by normalizing the assessment data so that the value of each criterion can be compared fairly, even though the original data has different scales. After that, the next step is to calculate the entropy for each criterion, which describes its degree of uncertainty or confusion. Criteria with lower entropy indicate that they have clearer information and can be used more effectively in the evaluation process. The weight of the criteria is then calculated based on the value of the entropy, where the criteria with low entropy get a higher weight. This method helps in giving more objective and fair weight to each criterion in order to support more rational and measurable decision-making.
The first step is to build a decision matrix based on the assessment data, where each row represents one alternative, and each column represents one criterion. The result matrix is created using (1).

$$X = \begin{bmatrix} 26 & 8 & 3 & 9 & 8 & 9 \\ 30 & 7 & 5 & 8 & 9 & 7 \\ 28 & 9 & 4 & 7 & 8 & 8 \\ 27 & 6 & 3 & 9 & 9 & 9 \\ 25 & 7 & 2 & 8 & 7 & 7 \\ 29 & 8 & 4 & 8 & 8 & 8 \\ 26 & 7 & 3 & 7 & 9 & 8 \\ 31 & 9 & 5 & 6 & 8 & 7 \\ 24 & 6 & 2 & 9 & 7 & 8 \end{bmatrix}$$

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The next step is to normalize the values in the matrix so that each value is on the same scale this is important because each criterion can have different units or scales, the normalization process is calculated using (2).

$$k_{11} = \frac{x_{11}}{\sum_{j=1}^{n} x_{11,19}} = \frac{26}{26+30+28+27+25+29+26+31+24} = \frac{26}{246} = 0.1057$$

Table 2 is the result of calculating the normalization value in the entropy method which has been calculated using each existing alternative.

Table 2. Normalization results

Employee Name	Criteria					
	SE-1	SE-2	SE-3	SE-4	SE-5	SE-6
Dimas	0.1057	0.1194	0.0968	0.1268	0.1096	0.1268
Raka	0.1220	0.1045	0.1613	0.1127	0.1233	0.0986
Fajar	0.1138	0.1343	0.1290	0.0986	0.1096	0.1127
Iqbal	0.1098	0.0896	0.0968	0.1268	0.1233	0.1268
Bayu	0.1016	0.1045	0.0645	0.1127	0.0959	0.0986
Rizky	0.1179	0.1194	0.1290	0.1127	0.1096	0.1127
Rendi	0.1057	0.1045	0.0968	0.0986	0.1233	0.1127
Andra	0.1260	0.1343	0.1613	0.0845	0.1096	0.0986
Galih	0.0976	0.0896	0.0645	0.1268	0.0959	0.1127

The next step is to calculate the entropy for each criterion that shows how much variation or irregularity of the value in a criterion is from the total value that exists, the process of calculating the entropy value is calculated using (3).

$$E_1 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{11,19} \ln(k_{11,19}) = -0.4551 * (-2.1940) = 0.9985$$

$$E_2 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{21,29} \ln(k_{21,29}) = -0.4551 * (-2.1870) = 0.9953$$

$$E_3 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{31,39} \ln(k_{31,39}) = -0.4551 * (-2.1487) = 0.9779$$

$$E_4 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{41,49} \ln(k_{41,49}) = -0.4551 * (-2.1891) = 0.9963$$

$$E_5 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{51,59} \ln(k_{51,59}) = -0.4551 * (-2.1931) = 0.9981$$

$$E_6 = -\frac{1}{\ln 9} \sum_{i=1}^{n} k_{61,69} \ln(k_{61,69}) = -0.4551 * (-2.1929) = 0.9980$$

The next step is to determine the level of diversity for each criterion which shows how much information from each criterion contributes, the process of calculating the value of diversity is calculated using (4).

$$D_1 = 1 - E_1 = 1 - 0.9985 = 0.0015$$

$$D_2 = 1 - E_2 = 1 - 0.9953 = 0.0047$$

$$D_3 = 1 - E_3 = 1 - 0.9779 = 0.0221$$

$$D_4 = 1 - E_4 = 1 - 0.9963 = 0.0037$$

$$D_5 = 1 - E_5 = 1 - 0.9981 = 0.0019$$

$$D_6 = 1 - E_6 = 1 - 0.9980 = 0.0020$$

The last step is to calculate the weights for each criterion based on its diversification value, the process of calculating the weight value is calculated using (5).

$$w_1 = \frac{D_1}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0015}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0015}{0.0361} = 0.0423$$

$$w_2 = \frac{D_2}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0047}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0047}{0.0361} = 0.1304$$

$$w_3 = \frac{D_3}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0221}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0221}{0.0361} = 0.6137$$

$$w_4 = \frac{D_4}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0037}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0037}{0.0361} = 0.1038$$

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$$w_5 = \frac{D_5}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0019}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0019}{0.0361} = 0.0537$$

$$w_6 = \frac{D_6}{\sum_{j=1}^{n} D_{1,6}} = \frac{0.0020}{0.0015+0.0047+0.0221+0.0037+0.0019+0.0020} = \frac{0.0020}{0.0361} = 0.0561$$

The weighted results obtained through the Entropy method reflect the importance of each criterion in decision-making, taking into account the level of consistency and information available on each criterion. The highest weight on the SE-3 (Work Experience) criterion indicates that in the hiring process, work experience is seen as the most crucial factor in determining the quality and readiness of candidates. This reflects that organizations prioritize candidates who already have a strong professional track record, because they are considered able to adapt faster, have better practical knowledge, and can make a real contribution from the beginning of their career. The Entropy method helps to give objective weight to each criterion based on how much information can be extracted from the existing data, so that the decisions taken become more rational and based on a more thorough analysis of the variability of the data on each criterion.

3.4 Determination of Weights of Criteria Using the Entropy Method

In the employee recruitment process, proper decision-making is essential to ensure the quality of the human resources recruited. The complexity of considering various criteria requires a systematic and objective approach. Implementation of the COBRA method combined with Entropy weighting to evaluate and rank nine candidates based on six key criteria. The implementation of this method allows companies to consider various aspects proportionately and identify the best candidates who best suit the needs of the organization.

The first stage in the COBRA method is to collect data to form a decision-making matrix. The decision matrix of the COBRA method is the same as the decision matrix in the entropy method that is made using (1).

The next stage in the COBRA method is the normalization of the data to ensure that all data can be objectively compared which is calculated using (6).

$$r_{11} = \frac{x_{11}}{max^{1}_{11,19}} = \frac{26}{31} = 0.8387$$

Table 3 is the result of calculating the normalization value in the COBRA method which has been calculated using each existing alternative.

Table 3. Normalization results

Employee Name	Criteria					
	SE-1	SE-2	SE-3	SE-4	SE-5	SE-6
Dimas	0.8387	0.8889	0.6000	1.0000	0.8889	1.0000
Raka	0.9677	0.7778	1.0000	0.8889	1.0000	0.7778
Fajar	0.9032	1.0000	0.8000	0.7778	0.8889	0.8889
Iqbal	0.8710	0.6667	0.6000	1.0000	1.0000	1.0000
Bayu	0.8065	0.7778	0.4000	0.8889	0.7778	0.7778
Rizky	0.9355	0.8889	0.8000	0.8889	0.8889	0.8889
Rendi	0.8387	0.7778	0.6000	0.7778	1.0000	0.8889
Andra	1.0000	1.0000	1.0000	0.6667	0.8889	0.7778
Galih	0.7742	0.6667	0.4000	1.0000	0.7778	0.8889

The next stage in the COBRA method is weighted normalization, this process describes the multiplication of the weight with the normalization results of each alternative which is calculated using (7)

$$\Delta_{11} = w_1 * r_{11} = 0.0423 * 0.8387 = 0.0355$$

Table 4 is the result of calculating the weighted normalization in the COBRA method which has been calculated using each existing alternative.

Table 4. Weighted normalization

Employee Name	Criteria					
	SE-1	SE-2	SE-3	SE-4	SE-5	SE-6
Dimas	0.0355	0.1159	0.3682	0.1038	0.0477	0.0561
Raka	0.0410	0.1014	0.6137	0.0923	0.0537	0.0436
Fajar	0.0382	0.1304	0.4910	0.0808	0.0477	0.0499
Iqbal	0.0369	0.0869	0.3682	0.1038	0.0537	0.0561
Bayu	0.0341	0.1014	0.2455	0.0923	0.0418	0.0436
Rizky	0.0396	0.1159	0.4910	0.0923	0.0477	0.0499
Rendi	0.0355	0.1014	0.3682	0.0808	0.0537	0.0499
Andra	0.0423	0.1304	0.6137	0.0692	0.0477	0.0436

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Galih	0.0328	0.0869	0.2455	0.1038	0.0418	0.0499

The next stage in the COBRA method is to determine the Positive Ideal Solution (PIS) using (8), the Negative Ideal Solution (NIS) using (9), and the Mean Solution (AS) using (10) shown in table 5.

Table 5. Positive ideal solution, negative ideal solution, and mean solution results

	Criteria					
	SE-1	SE-2	SE-3	SE-4	SE-5	SE-6
PIS_i	0.0328	0.1304	0.6137	0.1038	0.0537	0.0561
NIS_i	0.0423	0.0869	0.2455	0.0692	0.0418	0.0436
AS_i	0.0373	0.1078	0.4228	0.0910	0.0484	0.0492

The next stage in the COBRA method is to calculate the euclidean and taxicab distance from the positive ideal solution, negative ideal solution, average solution using (13) to (22), the results of the calculation are shown in table 6.

Table 6. Euclidean, taxicab

Employee Name	Euclidean and taxicab							
	$dE(PIS_i)$	$dT(PIS_i)$	$dE(NIS_i)$	$dT(NIS_i)$	$dE(AS_i)_i^+$	$dT(AS_i)_i^+$	$dE(AS_i)_i^-$	$dT(AS_i)_i^-$
Dimas	0.2460	0.2687	0.1317	0.2116	0.0358	0.0255	0.1322	0.0570
Raka	0.0346	0.0612	0.3694	0.4191	0.0086	0.0133	0.1482	0.0120
Fajar	0.1253	0.1635	0.2497	0.3168	0.0690	0.0800	0.0717	0.0109
Iqbal	0.2493	0.2930	0.1288	0.1872	0.0588	0.0829	0.0549	0.0759
Bayu	0.3699	0.4345	0.0284	0.0458	0.0087	0.0134	0.1377	0.1991
Rizky	0.1246	0.1678	0.2484	0.3125	0.0013	0.0013	0.0438	0.0007
Rendi	0.2484	0.3065	0.1250	0.1738	0.0559	0.0738	0.0504	0.0731
Andra	0.0385	0.0626	0.3708	0.4176	0.0056	0.0062	0.1506	0.0280
Galih	0.3710	0.4298	0.0364	0.0504	0.1786	0.2028	0.1790	0.2094

Next calculating the value β is the correction coefficient calculated using (12), the results of the calculation are shown in table 7.

Table 7. Correction coefficient

	Correction coefficient			
	PIS	NIS	AS^-	AS^+
Max	0.371	0.3708	0.1786	0.179
Min	0.0346	0.0284	0.0013	0.0438
β	0.3364	0.3424	0.1773	0.1352

Next calculating the distance between each alternative and the positive ideal solution, the negative ideal solution, and the average solution are calculated using (11), the results are shown in table 8.

Table 8. Positive ideal solution, negative ideal solution, and average ideal solution

Employee Name	Euclidean and taxicab			
	$d(PIS_i)$	$d(NIS_i)$	$d(AS_i)_i^+$	$d(AS_i)_i^-$
Dimas	0.2682	0.1412	0.0360	0.1332
Raka	0.0353	0.4224	0.0086	0.1484
Fajar	0.1322	0.2768	0.0700	0.0718
Iqbal	0.2739	0.1371	0.0597	0.0555
Bayu	0.4240	0.0288	0.0087	0.1414
Rizky	0.1316	0.2750	0.0013	0.0438
Rendi	0.2740	0.1324	0.0566	0.0509
Andra	0.0393	0.4238	0.0056	0.1512
Galih	0.4246	0.0370	0.1850	0.1841

The final stage in the COBRA method is to calculate the alternative final value by increasing the comprehensive distance value calculated using (23), the results of which are shown in table 9.

Table 9. The final value of the alternative

Employee Name	Final Value
Dimas	0.0561

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Raka	-0.0618
Fajar	-0.0357
Iqbal	0.0332
Bayu	0.1320
Rizky	-0.0252
Rendi	0.0340
Andra	-0.0597
Galih	0.0967

Once all the stages in the COBRA method have been implemented, a final score is obtained for each candidate that reflects their relative proximity to the ideal solution. This score is calculated based on a combination of the distance of the ideal and anti-ideal solutions, which has been adjusted to the objective weight of each criterion through the Entropy method.

3.5 Interpretation of Results from Entropy and COBRA

The determination of the weight of the criteria using the Entropy method provides an objective foundation in the evaluation process, where the level of variation of data in each criterion is the main indicator in weighting. The results of the calculation showed that criteria with more diverse information, such as work experience, gained higher weight than other criteria. This reflects the importance of the role of data in determining the relative contribution of each criterion to the overall decision-making process. Thus, Entropy helps eliminate subjectivity in determining criteria priority, and makes the process more transparent and data-driven. Furthermore, the application of the COBRA method allows for a thorough evaluation of candidates based on their proximity to ideal solutions and anti-ideal solutions. By taking into account the weights of Entropy and calculating the distance between the alternatives to the best and worst scores, this method produces a final score that represents the relative performance of each candidate. The interpretation of these results provides a clear understanding of who is the best candidate objectively, and makes it easier for decision-makers to make the most rational choice and according to the needs of the organization. The results of the employee recruitment ranking are shown in table 10.

Table 10. Employee recruitment ranking

Employee Name	Final Value	Rank
Raka	-0.0618	1
Andra	-0.0597	2
Fajar	-0.0357	3
Rizky	-0.0252	4
Iqbal	0.0332	5
Rendi	0.034	6
Dimas	0.0561	7
Galih	0.0967	8
Bayu	0.132	9

The results of the final calculation using the Entropy-COBRA method, were ranked nine candidates based on their final scores which reflected relative proximity to the ideal solution in the recruitment process. The candidate with the lowest score is considered to be the closest to the ideal solution and has the best overall performance. In this case, Raka ranks first with a final value of -0.0618, followed by Andra in second place with a value of -0.0597, and Fajar in third place with -0.0357. All three showed excellent performance compared to other candidates in five predetermined criteria. On the other hand, candidates such as Bayu, Galih, and Dimas had relatively high positive final values, 0.132, 0.0967, and 0.0561, respectively, indicating a greater distance from the ideal solution. This puts them at the bottom of the rankings (9, 8, and 7), so it needs to be further considered in the selection process. Overall, these results provide a systematic and objective picture of candidate performance based on a comprehensive multi-criteria approach.
The results of the analysis of the implementation of COBRA produced interesting findings, namely the emergence of candidates with a negative total score but actually ranked at the top. This may be surprisingly intuitive, but it reflects that in the context of the COBRA method, a lower (or even negative) final score indicates better performance. In addition, it is possible that candidates who were previously under-accounted for, turned out to have an advantage in priority criteria such as SE-3, which made them rank higher than previously championed candidates.

3.6 Discussion

The final ranking resulting from the COBRA method represents the level of suitability and feasibility of each candidate based on the objectively weighted recruitment criteria. Candidates with the lowest final score are considered the most qualified, as they show an optimal balance between excellence in the benefit criteria and the least disadvantage in the cost criteria. This ranking serves as a tool to facilitate decision-making by the HR team. The use of the Entropy method to objectively determine the weight of criteria reduces the dominance of subjective perceptions of decision-makers. Weights are determined based on the diversity of data from actual assessments, not individual preferences. Meanwhile, the

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COBRA method considers the proportion of candidate performance as a whole through a cost-benefit approach, thus aiding in more rational and data-driven decision-making. This combination effectively addresses two major issues in traditional recruitment: appraisal bias and rational inconsistency. Entropy weight has a direct influence on the calculation of the final COBRA score. Criteria that have high data variation between candidates get greater weight, because they are considered to provide more significant information in the process of discrimination between alternatives. This means that the candidate who excels in the high-weighted criteria will have a greater advantage in the final calculation. In contrast, good performance on the low-weight criteria had less impact. Therefore, accuracy and variety in the initial assessment are essential to produce a valid rating.

The results of this study provide important implications for HR management practices, namely that the use of quantitative and data-based approaches can strengthen objectivity in employee selection. HRD can use this method as a decision tool to avoid personal bias and focus more on the candidate profile that truly meets the organization's needs. Additionally, this approach can be used to build a digital recruitment system or automate the initial evaluation of candidates. The implementation of the Entropy–COBRA framework in the employee recruitment process has a number of limitations that need to be considered. One of the main limitations is the relatively small sample size, which can affect the stability of the weight calculation results using the Entropy method. The fewer candidates are assessed, the less varied the distribution of data, so the weight generated may not reflect the importance of each criterion optimally. The COBRA method is quite sensitive to small differences in input data, which can significantly affect the final rating. Therefore, the application of this method must be accompanied by careful data validation and interpretation of results so as not to lead to erroneous decisions.

A framework that combines the Entropy and COBRA methods can be claimed to be an effective approach in supporting the recruitment decision-making process because it is able to present an objective and measurable analysis. The Entropy method plays an important role in objectively determining the weight of criteria based on data variations, thereby reducing the influence of assessor subjectivity. Meanwhile, the COBRA method allows for a comprehensive evaluation of the benefits and costs aspects of each candidate through a performance ratio approach, which reflects the real conditions in the complex selection process. The combination of these two methods not only increases accuracy in ranking, but is also able to overcome the limitations of rationality that often occur in the human decision-making process, such as cognitive bias or emotional influence. By considering all alternatives systematically and data-driven, the framework has proven to be able to handle the multi-criteria complexity in employee selection, making it a powerful tool for modern human resource management practices.

4. CONCLUSION

This research successfully applied the Entropy-Assisted COBRA framework as an effective decision support system approach in the employee recruitment process. By combining the Entropy method for objectively weighting criteria and the COBRA method for ranking alternatives based on proximity to the ideal solution, this approach is able to address the complexity and limitations of rationality in decision-making. The final results show that this method is not only able to systematically identify the best candidates, but also provides transparency and accountability in the selection process. The results of the final calculation using the Entropy-COBRA method, were ranked nine candidates based on their final scores which reflected relative proximity to the ideal solution in the recruitment process. The candidate with the lowest score is considered to be the closest to the ideal solution and has the best overall performance. Raka employees ranked first with a final score of -0.0618, followed by Andra in second place with a score of -0.0597, and Fajar in third place with -0.0357. The results of the final score in the COBRA method with a lower score indicate that an alternative shows superior performance over the other. This framework makes a real contribution to data-driven decision-making for human resource management, particularly in the context of recruitment involving multiple criteria and alternatives. This approach can also be easily adapted for other similar decision-making cases, as well as further developed with the integration of artificial intelligence or web-based systems for increased efficiency.

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