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Evaluation of Recruitment Candidates Based on Data Objectivity Using LOGSTA and CORASO Integration

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ABSTRACT *– The employee selection process often faces problems such as evaluator subjectivity, inconsistency between criteria, and decision biases, which affect the stability of candidate ranking results. This research originates from the existence of a gap in the study of recruitment candidate evaluation, which is still dominated by subjective weighting and has not widely integrated objective weighting approaches with ranking methods that can maintain result stability. This research contributes through the development of the integrative LOGSTA–CORASO model, which combines data-driven weighting mechanisms with comprehensive compromise techniques within a systematic evaluation framework. The proposed approach integrates the LOGSTA method as an objective-criteria weighting technique based on logarithmic transformation and CORASO as an alternative ranking method based on ideal–compromise solutions. LOGSTA is used to determine criteria weights objectively based on data dispersion and information content, while CORASO is utilized to comprehensively evaluate and rank candidates. The research results show that the proposed method is capable of producing a stable and transparent ranking of candidates, as well as reducing subjective bias in the selection process. Based on the final CORASO scores, candidate Gina ranked first with a score of 0.5055, followed by Nugroho in second place with a score of 0.4039, and Saputra in third place with a score of 0.3024. Scenario analysis of changes in criteria weights also indicates that the rankings of the top candidates are relatively consistent, reaffirming the reliability of the proposed approach in supporting fair and data-driven recruitment decision-making. The novelty of this research lies in the combination of these two methods, which has not been widely applied in the context of candidate selection, as well as in its ability to produce decisions that are more consistent and based on objectivity compared to conventional MCDM methods, which generally operate independently or still rely on subjective assessments in determining criteria weights.*

Keywords *– CORASO; Decision Support System; LOGSTA; Multi-Criteria Decision Making; Recruitment Candidate Selection.*

1. INTRODUCTION

Objective and consistent evaluation of recruitment candidates plays an important role in ensuring that hiring decisions are truly aligned with the organization's needs[1], [2]. Without an objective approach, the selection process is susceptible to personal preferences, subjective assumptions, or fleeting impressions that do not always reflect the candidate's actual competence. Consistency in assessment is also necessary so that each applicant is judged by the same standards, creating a sense of fairness and transparency in the recruitment process. A structured evaluation helps organizations compare candidates based on relevant criteria, such as technical abilities, work attitude, and long-term development potential. In addition to improving the accuracy of decisions, this approach can reduce the risk of hiring mistakes that affect team performance and organizational costs. An objective and consistent process also facilitates documentation and the re-evaluation of decisions if needed in the future.

Common problems in employee selection often stem from the high subjectivity of evaluators in assessing the abilities and character of candidates[3], [4]. Assessments that rely too heavily on personal perception, intuition, or individual experience can lead to decisions that do not fully reflect the applicant's actual competence. In addition, inconsistencies between assessment criteria also pose a challenge, especially when each criterion does not have clear weighting or definition. This situation leads evaluators to tend to emphasize certain aspects while neglecting others that are equally important. Decision biases, whether conscious or unconscious, such as biases related to educational background, age, or personal similarities, further worsen the quality of selection outcomes. As a result, the candidate who best fits the organization's needs may not necessarily be selected, while another candidate might pass due to non-technical factors. If this issue is not addressed with a systematic approach, the employee selection process has the potential to produce inconsistent decisions and harm the organization in the long term.

A decision support system (DSS) based on multi-criteria decision making (MCDM) plays a strategic role in the recruitment process by providing a more structured, objective, and transparent assessment[5]–[7]. This system allows organizations to evaluate candidates based on various relevant criteria, such as technical competence, experience, communication skills, and development potential, while assigning proportional weights according to organizational priorities. With DSS-MCDM, assessments no longer rely solely on the intuition or subjective preferences of evaluators, thereby reducing the risk of bias and inconsistencies among criteria[8]–[10]. Additionally, this system can process candidate data quickly and present rankings or scores that make it easier for decision-makers to select the best candidates. MCDM-based DSS also supports documentation and auditing of the recruitment process, making it easier to re-evaluate and account for decisions.

Conventional and single-method approaches in employee selection often face limitations in producing stable and accurate candidate rankings. Traditional methods usually rely on subjective assessments from HR or managers, which are prone to personal bias, preferences, and temporary perceptions, so the results can vary even when the same candidates are reassessed[11], [12]. Furthermore, using a single method to evaluate all criteria often fails to capture the complexity of candidate competencies, especially when the criteria have different levels of importance or characteristics. This can lead to inconsistencies in rankings, where candidates who actually excel in several important aspects may not appear as top choices. Single-method approaches are also less flexible in accommodating changes in organizational weights or priorities, meaning that even minor adjustments can significantly alter ranking results. These limitations become even more apparent when organizations face many candidates and diverse criteria, as simple methods are unable to provide a comprehensive comparison. As a result, recruitment decisions may be less than optimal, increasing the risk of selecting the wrong candidates and reducing the efficiency of the selection process.

The research gap in the field of employee selection based on MCDM lies in the dominant use of subjective weighting that depends on the decision-maker's preferences, which can potentially lead to bias and inconsistency in ranking results. Many previous studies have focused on applying a single ranking method without integrating it with an objective weighting mechanism based on actual data. In addition, the aspects of stability and reliability of decision outcomes are often not thoroughly tested, especially in the context of candidate selection involving multiple criteria with diverse data characteristics. This situation indicates the need to develop an evaluation model that can combine objective weighting and robust ranking methods within a unified framework to produce more transparent, consistent, and accountable decisions.

The integration of LOGSTA and CORASO in the employee selection process emerges as a solution to address the limitations of conventional methods, which often result in subjective assessments and unstable candidate rankings. LOGSTA serves as an objective weighting mechanism based on logarithmic transformation, enabling fair and proportional calculation of criteria weights without being influenced by evaluator preferences, ensuring that every criterion important to the organization contributes appropriately to the evaluation[13]. Meanwhile, CORASO functions as a ranking method based on an ideal-compromise solution, capable of placing candidates in rankings that best reflect a balance between absolute excellence and compromise across other criteria[14], [15]. By combining these two approaches, the selection process becomes more systematic because the objective criteria weights from LOGSTA can be directly utilized by CORASO to produce stable and transparent rankings. This integration also allows for more accurate sensitivity analysis, so that changes in weights or criteria priorities do not drastically alter the candidate ranking. In addition, this combination helps reduce bias and inconsistency, as assessments are no longer solely dependent on the assessor's intuition. Another motivation is the system's ability to handle multiple criteria with different characteristics, both quantitative and qualitative, making the ranking results more comprehensive and accountable. With LOGSTA–CORASO, organizations can make recruitment decisions that are more precise, efficient, and fair, while enhancing the credibility of the selection process in the eyes of prospective employees.

This research stems from the explicit problem of high subjectivity in the weighting of criteria and the instability of candidate ranking results in conventional employee selection methods, resulting in decisions that do not fully reflect data objectivity. Based on this condition, the research conducted in the selection system is able to produce criteria weights objectively, ensure that candidate rankings are consistent and stable, and examine the extent to which the integration of LOGSTA and CORASO can improve decision quality compared to the MCDM approach used separately. The contribution of this research lies in the development of a data-based integrative model, the provision of a transparent and accountable evaluation mechanism, the improvement of stability and accuracy of ranking results, as well as the formulation of a methodological framework that is applicable for organizations. The novelty of this research lies in the integration of LOGSTA as an objective weighting method and CORASO as a compromise method within a single integrated system for employee selection, which has not been extensively studied in previous MCDM literature.

2. RELATED WORK

In recent years, research on employee selection has increasingly emphasized the importance of a system-based approach to support decision-making[16]–[18]. Traditional selection processes that rely on the evaluator's intuition are often prone to subjectivity, bias, and inconsistencies between criteria, so the ranking of candidates does not always reflect their actual competence. Previous studies have shown that DSS not only improves the accuracy of candidate selection but also speeds up the selection process, minimizes bias, and provides accountable documentation.

Research on the use of AHP in DSS allows for the systematic determination of criteria weights. The selection results become more transparent and consistent compared to conventional methods. Candidates chosen based on DSS have work performance that better aligns with the organization's needs. This underscores the importance of a multi-criteria approach in supporting fair recruitment decisions[19]. The WASPAS method has proven capable of processing multiple assessment criteria simultaneously, including competence, experience, and work attitude. This system produces stable and easily accountable candidate rankings. Evaluators can reduce personal bias because decisions are based on multi-criteria scores. This DSS supports a fast and efficient selection process in a hospital setting[20].

The implementation of the VIKOR method is able to provide an optimal compromise between conflicting criteria. The system supports managers in objectively selecting the best candidate. The selection process becomes faster because the DSS reduces the need for manual evaluation. In addition, the DSS helps record decisions for future audit evaluation[21]. The combination of profile matching and PROMETHEE increases objectivity in the selection of new candidates. Candidates are evaluated against the ideal profile based on organizational criteria. DSS makes it easier for decision-makers to see the trade-offs between criteria. The selection results are more stable and accountable[22]. Various case studies from previous research confirm the effectiveness of DSS in producing candidate rankings that are stable and relevant to organizational needs by using the AHP, WASPAS, VIKOR, PROMETHEE, and profile matching methods. The literature shows that the use of multi-criteria-based DSS has become an increasingly important approach in modernizing employee recruitment and selection processes.

The comparison of previous studies used in this research is presented in Table 1.

Table 1. Previous Research

Weighting Type	Ranking Type	Weaknesses
Subjective	AHP	Highly dependent on the decision maker's perception, prone to bias and inconsistency in pairwise comparisons, and becomes complex as the number of criteria increases.
Subjective	WASPAS	Sensitive to subjective weights, so small changes in preferences can affect the ranking results, and it does not fully ensure decision stability.
Subjective	AHP	The evaluation process requires a lot of comparative assessments, can potentially cause assessor fatigue, and results may differ if the evaluator is different.

Subjective	Profile Matching and PROMETHEE	The determination of the ideal profile and preference function parameters is subjective, so it carries the risk of producing ranking variations depending on the assumptions and preferences used.

Based on this comparison, it is clear that previous research has still been dominated by subjective weighting approaches that heavily rely on the perceptions and preferences of decision-makers, which can potentially lead to bias, inconsistency, and instability in ranking outcomes. Although methods such as AHP, WASPAS, or combinations of Profile Matching and PROMETHEE have been widely used, most have not fully been able to meet the need for a candidate evaluation system that is truly data-driven and objectively measurable. This gap underscores the urgency of developing a model that integrates objective weighting with a more robust ranking mechanism, in order to produce recruitment decisions that are more transparent, consistent, and accountable both scientifically and practically.

3. METHODOLOGY

Research methodology is a systematic framework used to plan, carry out, and evaluate all stages of research in a structured manner. This methodology includes determining the research approach, data collection techniques, establishing the criteria and variables studied, as well as the analysis methods used to answer the research objectives. Through a clear methodology, the research process can be conducted in a directed, logical, and accountable manner. In addition, research methodology plays an important role in ensuring the accuracy of results, consistency of analysis, and validity of the conclusions drawn. With the right methodology, research not only produces relevant findings but can also be replicated and used as a reference for future research.

Research Stage

The research stages are a series of systematic steps arranged to ensure the research process runs in a structured and directed manner. These stages generally start with problem identification and formulation of research objectives, followed by a literature review to strengthen the theoretical foundation and determine research gaps. Next, data is collected and processed according to the established methods, followed by data analysis using relevant approaches or models. The analysis results are then interpreted to address the research objectives and draw logical conclusions. Through clear research stages, each process can be accounted for and produce findings that are valid and consistent. Figure 1 shows the research stages carried out in this study.

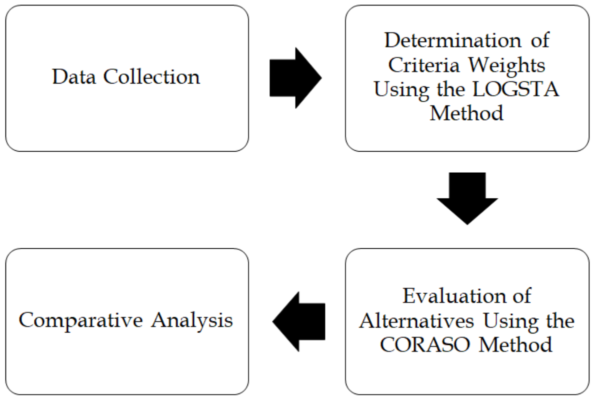

Figure 1. Research Stage

The research stages begin with data collection, which includes candidate data as decision alternatives as well as evaluation criteria data relevant to the organization's needs, both quantitative and qualitative. The collected data is then used in the stage of determining the criteria weights using the LOGSTA method, where weighting is carried out objectively through logarithmic transformation to reflect the importance level of each criterion proportionally without involving the subjective preferences of the assessors. After the criterion weights are obtained, the next stage is the evaluation of alternatives using the CORASO method, which aims to rank candidates based on their closeness to the ideal solution and the compromise solution, thereby producing a sequence of candidates that best meet the set criteria. The final stage is a comparative analysis, which involves comparing the CORASO ranking results with other methods or actual conditions to assess the consistency, stability, and advantages of the results obtained. Through this series of stages, the selection process can be carried out systematically, objectively, and in an accountable manner.

LOGSTA Method

The LOGSTA method is a criterion weighting approach designed to generate weights objectively by utilizing a logarithmic transformation of evaluation data. This method aims to reduce the influence of evaluator subjectivity by emphasizing differences in the importance levels of criteria based on the distribution and variation of existing data. Through logarithmic transformation, LOGSTA is able to stabilize data scales and prevent the dominance of certain criteria with extreme values. The resulting weights reflect the relative contribution of each criterion proportionally and rationally. With these characteristics, LOGSTA is highly suitable for multi-criteria decision-making problems that demand fairness, consistency, and transparency, particularly in the context of selection and performance evaluation.

The LOGSTA method begins with the preparation of a decision matrix that contains the performance values of each alternative against all established criteria using (1). This matrix is then normalized to equalize the data scale across criteria so that they can be compared fairly using (2). After normalization, the standard deviation is calculated to measure the level of variation or data dispersion in each criterion, reflecting the extent to which the criterion contributes differently in distinguishing alternatives using (3). The standard deviation values are then combined with an inverse logarithmic transformation to produce logarithmic dispersion information values, which represent the objective information content of each criterion using (4). The final stage is the determination of criteria weights, where the obtained information values are renormalized to produce final weights that are proportional, objective, and ready to be used in the alternative ranking stage using (5).

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

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

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n} (n_{ij} - \overline{n}_j)^2}{n}} \tag{3}$$

$$g_j = \sigma_j * \left(\left| \sum_{i=1}^{n} (\ln(n_{ij})) \right| \right)^{-1} \tag{4}$$

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{5}$$

The LOGSTA method begins with the construction of a decision matrix $X = [x_{ij}]_{mxn}$, where m represents the number of alternatives, n denotes the number of criteria, and x_{ij} is the performance value of alternative i with respect to criterion j. These values are then transformed into normalized scores n_{ij} using a natural logarithmic function, with different treatments for benefit and cost criteria to maintain preference direction consistency, while incorporating the product of all alternative values under the same criterion as a scaling reference. After obtaining the normalized matrix, the standard deviation σ_j is calculated for each criterion based on the mean value $\overline{n}_j$, reflecting the dispersion level and discriminatory power of the data. Next, the information measure g_j is determined by multiplying the standard deviation by the inverse of the sum of the logarithmic normalized values, thereby integrating both variability and logarithmic distribution characteristics. Finally, the criterion weights w_j are derived by normalizing the g_j values, dividing each by the total sum of all information measures, resulting in objective weights that proportionally represent the underlying data structure.

The LOGSTA method offers an objective and systematic approach to criteria weighting by utilizing data dispersion characteristics and logarithmic transformation. This method can reduce dependence on subjective judgment by producing criteria weights that reflect the actual information content of the data. The resulting weights are proportional and stable, thereby enhancing the consistency of decision-making outcomes. With these advantages, LOGSTA is suitable for use as a basis for weighting in multi-criteria decision-making problems, especially when a high level of objectivity and transparency is required.

CORASO Method

The CORASO method is a multi-criteria decision-making method that focuses on the process of ranking alternatives based on ideal solution and compromise solution approaches[23], [24]. This method evaluates each alternative by considering its closeness to the best ideal condition as well as its distance from the worst condition, so that the evaluation results do not only emphasize maximum or minimum values alone. CORASO is designed to handle conflicts between criteria by producing balanced and rational solutions, especially when no alternative excels in all criteria. Through a systematic aggregation mechanism, CORASO is capable of producing stable alternative rankings that are easy for decision-makers to understand.

The stages of the CORASO method begin with the formation of a decision matrix that contains the values of each alternative against all established criteria using (1). The matrix is then normalized to eliminate differences in scale between criteria so that all values are on the same basis of comparison using (6). Next, weighting is applied, where the normalized results are multiplied by the criteria weights to reflect the relative importance of each criterion in the decision-making process using (7). Based on the weighted matrix, ideal and anti-ideal values are determined, representing the best and worst conditions of each criterion as reference points for evaluation using (8) and (9). The final stage is the calculation of the final CORASO value, which integrates the closeness of alternatives to the ideal solution and compromise to the anti-ideal solution, resulting in a score using (10).

$$t_{ij} = \begin{cases} \frac{x_{ij}}{\max(x_{ij})} ; benefit\ criteria \\ \frac{\min(x_{ij})}{x_{ij}} ; cost\ criteria \end{cases} \tag{6}$$

$$y_i = \sum_{i=1}^{m} (w_j * t_{ij}) \tag{7}$$

$$R_i = \frac{y_i}{\max y_i} \tag{8}$$

$$R_i' = \frac{\min y_i}{y_i} \quad (9)$$

$$Q_i = \frac{R_i - R_i'}{R_i + R_i'} \quad (10)$$

In the CORASO method, the process begins by calculating the normalized value t_{ij}, which represents the performance of alternative i with respect to criterion j, adjusted according to the criterion type. For benefit criteria, normalization is performed by dividing x_{ij} by the maximum value within the same criterion, whereas for cost criteria, the minimum value is divided by x_{ij}, ensuring that all normalized values follow a consistent preference direction. Next, the weighted aggregated score y_i is computed as the sum of the products between each criterion weight w and its corresponding normalized value t_{ij}, representing the overall performance score of each alternative. This score is then used to determine R_i, defined as the ratio of y_i to the maximum y_i, and R_i', defined as the ratio of the minimum y_i to y_i. These two measures indicate the relative position of each alternative with respect to the best and lowest performance levels. Finally, the compromise index Q_i is calculated as the difference between R_i and R_i' divided by their sum, producing the final evaluation value that reflects the relative preference level of each alternative in the decision-making process.

The CORASO method provides a comprehensive alternative ranking approach by considering proximity to the ideal solution as well as a balance of compromises among criteria. This method is capable of handling conflicts of interest between criteria rationally, ensuring that the ranking results are not extreme and are more stable. Its structured calculation process also facilitates result interpretation by decision-makers. With these characteristics, CORASO becomes an effective and relevant method to support multi-criteria decision-making, particularly in the context of candidate selection that demands objectivity and consistency.

4. RESULT AND DISCUSSION

Candidate recruitment evaluation is a crucial stage in determining the quality of human resources that will join an organization. However, selection practices that are still dominated by subjective assessments and single-method approaches often result in decisions that are inconsistent and difficult to justify. Therefore, a data-driven approach that ensures objectivity and stability in evaluation results is needed. The integration of LOGSTA as an objective weighting method based on logarithmic transformation and CORASO as a ranking method based on ideal and compromise solutions offers a more systematic and rational evaluation framework. This approach allows each candidate to be fairly assessed based on the proportional contribution of criteria and produces rankings that reflect a balance between criteria. The integration of LOGSTA and CORASO is expected to improve the quality and credibility of the candidate recruitment evaluation process based on data objectivity.

Data Collection

Data collection is a very important initial stage in this research because the quality of the evaluation results heavily depends on the completeness and accuracy of the data used. Data is collected by identifying candidates as decision alternatives and establishing assessment criteria relevant to the organization's recruitment needs. The information collected includes quantitative data, such as test results and work experience, as well as qualitative data, such as communication skills and work attitude, which are then converted into a specific rating scale. The data collection process is carried out systematically through recruitment documents, selection evaluation results, and valid internal data sources. All obtained data is selected and verified to ensure consistency and to avoid incomplete or biased values.

Assessment criteria are an important component in the candidate recruitment evaluation process because they serve as the basis for objectively comparing the abilities and potential of each candidate. The establishment of criteria is carried out by considering the organization's needs as well as the competency aspects relevant to the position applied for, so that the evaluation results can reflect the overall suitability of the candidate. Each criterion is designed to represent the key dimensions that influence the candidate's performance and contribution, both technically and behaviorally. With clear and defined criteria, the evaluation process can be conducted consistently and in a structured manner. The complete description of each assessment criterion used in this study is presented in Table 2.

Table 2. Criteria Data

Code	Name	Description
RE-1	Technical Competence	The candidate's ability to master knowledge and technical skills relevant to the position being applied for.
RE-2	Work Experience	The length and relevance of the candidate's work experience support their readiness to perform job duties and responsibilities.
RE-3	Communication Skills	The candidate's ability to convey ideas, interact, and

		collaborate effectively with others.
RE-4	Work Attitude	The candidate's work behavior that reflects discipline, responsibility, ethics, and commitment to the job.
RE-5	Development Potential	The candidate's ability to grow, adapt, and improve competencies in the future according to the organization's needs.

The assessment data were obtained from the evaluation results of candidates against all criteria established in the employee selection process. Each candidate was evaluated using a uniform numerical scale to ensure consistency and ease in comparing alternatives. These assessments reflect the level of achievement of each candidate on the respective criteria based on selection results, tests, and relevant evaluations. All data obtained have gone through a verification process to ensure accuracy and completeness before being used in the analysis. The candidate assessment data used in this study are presented in Table 3.

Table 3. Assessment Data

Name	RE-1	RE-2	RE-3	RE-4	RE-5
Andi	85	2	78	82	75
Budi	78	3	80	79	82
Citra	90	4	85	88	80
Dewi	82	5	76	80	77
Saputra	88	6	83	85	84
Nugroho	75	7	72	74	71
Gina	80	8	79	81	78
Hadi	92	5	90	91	89
Permata	70	4	75	72	74

The compiled assessment data provides an objective overview of each candidate's relative performance based on the established criteria. Presenting scores in a quantitative form allows the evaluation process to be conducted consistently and reduces the potential for subjectivity in the assessment. With a systematic and standardized data structure, this assessment data is ready to be used as input in a decision support system to produce more accurate and accountable candidate rankings.

Determination of Criteria Weights Using the LOGSTA Method

Determining the weight of criteria is a crucial stage in decision support systems because the weight reflects the relative importance of each criterion in the evaluation process. In this study, the LOGSTA method is used to determine the criteria weights objectively by considering data variability and the information contained in each criterion. This approach is designed to reduce reliance on the subjective judgment of decision-makers and improve the consistency of weighting results. The use of the LOGSTA method is expected to produce more representative criteria weights and serve as a strong foundation for the subsequent candidate assessment and ranking process.

The stages of the LOGSTA method begin with the preparation of a decision matrix using (1) based on the assessment data in Table 3, the general form of the decision matrix is as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} \end{bmatrix}$$

The results of the decision matrix for the evaluation data are as follows.

$$X = \begin{bmatrix} 85 & 2 & 78 & 82 & 75 \\ 78 & 3 & 80 & 79 & 82 \\ 90 & 4 & 85 & 88 & 80 \\ 82 & 5 & 76 & 80 & 77 \\ 88 & 6 & 83 & 85 & 84 \\ 75 & 7 & 72 & 74 & 71 \\ 80 & 8 & 79 & 81 & 78 \\ 92 & 5 & 90 & 91 & 89 \\ 70 & 4 & 75 & 72 & 74 \end{bmatrix}$$

The second stage of the LOGSTA method is to calculate the normalization values to equalize the data scale across criteria so they can be fairly compared using (2). The results of the normalization value calculations are as follows.

$$n_{11} = \left| \frac{\ln x_{11}}{\ln(\prod_{i=1}^{9} x_{i1})} \right| = \left| \frac{4.4427}{13.3448} \right| = 0.3329$$

Table 4 shows the results of the normalization value calculations using the LOGSTA method.

Table 4. Normalization Results Using the LOGSTA Method

Name	RE-1	RE-2	RE-3	RE-4	RE-5
Andi	0.333	0.209	0.328	0.331	0.326
Budi	0.326	0.332	0.330	0.328	0.332
Citra	0.337	0.418	0.334	0.336	0.330
Dewi	0.330	0.486	0.326	0.329	0.328
Saputra	0.336	0.541	0.333	0.333	0.334
Nugroho	0.324	0.587	0.322	0.323	0.321
Gina	0.328	0.628	0.329	0.330	0.328
Hadi	0.339	0.486	0.339	0.339	0.338
Permata	0.318	0.418	0.325	0.321	0.325

The third stage of the LOGSTA method is

calculating the standard deviation to measure the level of variation or dispersion of data for each criterion using (3), with the results of the standard deviation calculation as follows.

$$\sigma_1 = \sqrt{\frac{\sum_{i=1}^{9}(n_{i1} - \overline{n_1})^2}{9}} = \sqrt{\frac{0.00036099}{9}} = 0.0063$$

Table 5 shows the results of calculating the standard deviation values using the LOGSTA method.

Table 5. Standard Deviation Results Using the LOGSTA Method

RE-1	RE-2	RE-3	RE-4	RE-5
0.0063	0.1224	0.0049	0.0053	0.0049

The fourth step of the LOGSTA method is calculating the logarithmic inverse to produce the logarithmic dispersion information value using (4), the calculation results of the logarithmic inverse value are as follows.

$$g_1 = \sigma_1 * \left(\left|\sum_{i=1}^{9}(\ln(n_{i1}))\right|\right)^{-1}$$

$$g_1 = 0.0063 * (9.9753)^{-1} = 0.0063 * 0.1002 = 0.00063$$

Table 6 shows the results of calculating the logarithmic inverse values using the LOGSTA method.

Table 6. Logarithmic Inverse Results Using the LOGSTA Method

RE-1	RE-2	RE-3	RE-4	RE-5
0.00063	0.01639	0.00049	0.00054	0.00049

The final stage of the LOGSTA method is calculating the criterion weights using (5), with the results of the criterion weight calculations as follows.

$$w_1 = \frac{g_1}{\sum_{j=1}^{5} g_j} = \frac{g_1}{\sum_{j=1}^{5} g_j} = \frac{0.00063}{0.01854} = 0.0342$$

Table 7 shows the results of calculating the criterion weights values using the LOGSTA method.

Table 7. Criterion Weights Results Using the LOGSTA Method

RE-1	RE-2	RE-3	RE-4	RE-5
0.0342	0.8840	0.0262	0.0289	0.0266

The results of the criteria weight calculation using the LOGSTA method show a clear difference in the level of importance for each candidate assessment criterion. Work Experience (RE-2) received the highest weight of 0.8840, indicating that work experience is the most dominant factor in the evaluation process and has the greatest influence on the ranking results. Next, Technical Competence (RE-1) has a weight of 0.0342, which indicates a supporting role in assessing the candidate's technical abilities. Communication Skills (RE-3) received a weight of 0.0262, Work Attitude (RE-4) 0.0289, and Development Potential (RE-5) 0.0266, reflecting a relatively smaller but still relevant contribution to the overall assessment. This weight distribution demonstrates that LOGSTA is capable of capturing variations and information content in the data objectively, so criteria with the highest dispersion receive greater emphasis in accordance with the characteristics of the evaluation data.

Evaluation of Alternatives Using the CORASO Method

Alternative evaluation is a key stage in a recruitment decision support system because, at this phase, all candidates are systematically compared to determine the best ranking. The CORASO method is used in this study as a ranking approach capable of accommodating differences in candidate performance across various interrelated criteria. CORASO works by considering the proximity of each alternative to the ideal solution and its distance from the anti-ideal solution, so the evaluation results focus not only on the highest scores but also on the balance between criteria. This approach is relevant in the recruitment context because the selection process often involves criteria that are complementary and potentially conflicting. By integrating the pre-determined criteria weights, CORASO is able to produce a more objective and consistent ranking of candidates. In addition, this method makes it easier for decision-makers to understand the relative position of each candidate comprehensively. The implementation of CORASO is expected to improve the quality of recruitment decisions and support a more transparent and accountable selection process.

The first step of the CORASO method is the formation of a decision matrix that contains the values of each alternative against all the established criteria using (1); the result of the CORASO decision matrix is the same as the LOGSTA decision matrix. The second step of the CORASO method is to calculate the normalization values using (6); the results of the CORASO normalization value calculations are as follows.

$$t_{11} = \frac{x_{11}}{\max(x_{i1})} = \frac{85}{92} = 0.924$$

Table 8 shows the results of the normalization value calculations using the LOGSTA method.

Table 8. Normalization Results Using the CORASO Method

Name	RE-1	RE-2	RE-3	RE-4	RE-5
Andi	0.924	0.250	0.867	0.901	0.843
Budi	0.848	0.375	0.889	0.868	0.921
Citra	0.978	0.500	0.944	0.967	0.899
Dewi	0.891	0.625	0.844	0.879	0.865

Saputra	0.957	0.750	0.922	0.934	0.944
Nugroho	0.815	0.875	0.800	0.813	0.798
Gina	0.870	1.000	0.878	0.890	0.876
Hadi	1.000	0.625	1.000	1.000	1.000
Permata	0.761	0.500	0.833	0.791	0.831

The third step of the CORASO method is to calculate the weighted multiplication values using (7), the results of the CORASO method weighted multiplication calculation are as follows.

$$y_1 = (w_1 * t_{11}) + (w_2 * t_{12}) + (w_3 * t_{13}) + (w_4 * t_{14}) + (w_5 * t_{15})$$

$$y_1 = (0.0342 * 0.924) + (0.8840 * 0.250) + (0.0262 * 0.867) + (0.0289 * 0.901) + (0.0266 * 0.843)$$

$$y_1 = 0.3238$$

Table 9 shows the results of the normalization value calculations using the LOGSTA method.

Table 9. Weighted Multiplication Results Using the CORASO Method

Name	Weight Multiplication
Andi	0.3238
Budi	0.4334
Citra	0.5521
Dewi	0.6536
Saputra	0.7721
Nugroho	0.8671
Gina	0.9859
Hadi	0.6685
Permata	0.5349

The fourth stage of the CORASO method is calculating the ideal and anti-ideal values using (8) and (9). The results of the calculation of the ideal and anti-ideal values of the CORASO method are as follows.

$$R_1 = \frac{y_1}{\max y_i} = \frac{0.3238}{0.9859} = 0.3285$$

$$R_1' = \frac{min\, y_1}{y_1} = \frac{0.3238}{0.3238} = 1.0000$$

Table 10 shows the results of the ideal and anti-ideal value calculations using the LOGSTA method.

Table 10. Ideal and Anti-ideal Results Using the CORASO Method

Name	Ideal	Anti-Ideal
Andi	0.3285	1.0000
Budi	0.4397	0.7471
Citra	0.5600	0.5865
Dewi	0.6630	0.4954
Saputra	0.7831	0.4194
Nugroho	0.8796	0.3734
Gina	1.0000	0.3285
Hadi	0.6781	0.4844
Permata	0.5426	0.6054

The final step of the CORASO method is to calculate the final value of each alternative against the ideal solution and the compromise against the anti-ideal solution using (10). The results of the final value calculations of the CORASO method are as follows.

$$Q_1 = \frac{R_1 - R_1'}{R_1 + R_1'} = \frac{0.3285 - 1.0000}{0.3285 + 1.0000} = -0.5055$$

Table 11 shows the results of the ideal and anti-ideal value calculations using the LOGSTA method.

Table 11. Final Value Results Using the CORASO Method

Name	Final Value
Andi	-0.5055
Budi	-0.2591
Citra	-0.0231
Dewi	0.1446
Saputra	0.3024
Nugroho	0.4039
Gina	0.5055
Hadi	0.1666
Permata	-0.0547

The final result of applying the CORASO method is obtained through the calculation of the final value of each alternative, which represents the proximity of the candidate to the ideal solution and its distance from the anti-ideal solution. This value is then used as a basis for objectively and consistently ranking candidates according to the weighting of criteria previously established. Candidates with the highest CORASO values occupy the top ranks because they are considered to have the most balanced performance across all assessment criteria. This ranking process provides a clear picture of the relative position of each candidate in the selection process and facilitates decision-makers in determining the best candidate. The complete results of the candidate ranking based on the final CORASO values are presented in Table 12.

Table 12. Alternative Ranking Results

Name	Final Value	Rank
Gina	0.5055	1
Nugroho	0.4039	2
Saputra	0.3024	3
Hadi	0.1666	4
Dewi	0.1446	5
Citra	-0.0231	6
Permata	-0.0547	7
Budi	-0.2591	8
Andi	-0.5055	9

The ranking results of candidates based on the final scores using the CORASO method show a fairly clear performance difference among the alternatives. Gina ranked first with a final score of 0.5055, indicating the closest proximity to the ideal solution and the overall best performance. Second and third places were held by Nugroho with a score of 0.4039 and Saputra with a score of 0.3024, demonstrating competitive performance even though still below the best candidate. Hadi and Dewi ranked fourth and fifth with scores of 0.1666 and 0.1446, reflecting fairly good performance but not yet optimal across all criteria. Meanwhile, Citra, Permata, Budi, and Andi received negative final scores, indicating a closer distance to the anti-ideal solution compared to the ideal solution. These results confirm that the CORASO method is capable of objectively distinguishing the quality of candidates and providing a clear ranking basis to support recruitment decision-making.

Comparative Analysis

Comparative analysis is conducted to evaluate the consistency and reliability of ranking results obtained from the integration of the LOGSTA and CORASO methods by comparing them with other relevant approaches. This analysis aims to see the extent to which differences in criterion weights and aggregation mechanisms affect the final position of candidates in the selection process. Through the comparison of ranking results, the level of rank stability and the method's sensitivity to variations in evaluation data can be identified. Additionally, comparative analysis helps assess whether the proposed method is able to reduce bias and inconsistencies that often arise in conventional or single-method approaches. The results of this analysis provide a more comprehensive picture of the strengths and limitations of each method, enabling decision-makers to choose the approach that best fits recruitment needs.

A comparative analysis with changes in criterion weights was conducted to test the sensitivity and stability of candidate ranking results against variations in the importance levels of the criteria. In this analysis, the criterion weights were gradually adjusted to see whether these changes caused significant shifts in candidate rankings. The test results showed that candidates with consistent performance across most criteria tended to maintain their positions even when weights changed. Conversely, candidates who had extreme scores in certain criteria were more sensitive to weight adjustments and potentially experienced ranking changes. This analysis provides an overview of the method's robustness in dealing with uncertainties in determining criterion weights. Table 13 presents the scenario of criterion weight changes.

Table 13. Weight Change Scenario

Scenario	RE-1	RE-2	RE-3	RE-4	RE-5
S1 (RE-2 + 0.05)	0.034	0.884	0.026	0.029	0.027
S2 (RE-2 − 0.05)	0.027	0.934	0.021	0.023	0.021
S3 (RE-1 + 0.05)	0.042	0.834	0.032	0.035	0.032
S4 (RE-1 − 0.05)	0.084	0.841	0.025	0.028	0.023
S5 (RE-3 + 0.05)	0.000	0.926	0.029	0.032	0.013
S6 (RE-3 − 0.05)	0.032	0.825	0.076	0.027	0.040
S7 (RE-4 + 0.05)	0.037	0.945	0.000	0.031	0.000
S8 (RE-4 − 0.05)	0.032	0.819	0.024	0.079	0.046
S9 (RE-5 + 0.05)	0.037	0.947	0.028	0.000	0.000
S10 (RE-5 −0.05)	0.032	0.822	0.024	0.027	0.095

Each scenario of changes in criteria weights that has been designed is then used to generate the final scores and ranking of candidates using the CORASO method. This process aims to observe the direct impact of increasing and decreasing weights on the candidates' ranking positions in each scenario. By comparing the ranking results across scenarios, the stability of the rankings and candidates who are sensitive to changes in criteria weights can be identified. Candidates who consistently occupy top positions across various scenarios demonstrate robust performance, while shifts in ranking reflect the dominant influence of certain criteria. This analysis provides a deeper understanding of the reliability of the proposed method in dealing with variations in weights. The complete results of candidate rankings for all weight change scenarios are shown in Figure 2.

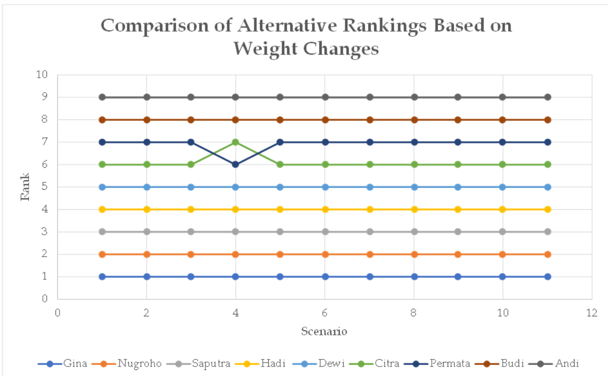

Figure 2. Ranking Results

Figure 2 shows a comparison of alternative rankings across ten scenarios of criteria weight changes, which is used to evaluate the stability of the CORASO method ranking results. In general, most candidates exhibit a relatively consistent ranking pattern across scenarios, indicated by horizontal or nearly flat lines. Gina consistently ranks first in all scenarios, indicating that her position is very stable and unaffected by variations in criteria weights. Nugroho and Saputra also maintain the second and third ranks without significant changes, indicating that their performance is resilient to weight changes. Hadi and Dewi are in the middle rankings and show similar stability, reflecting fairly balanced performance across the criteria. Meanwhile, Citra and Permata experience slight ranking fluctuations in some scenarios, indicating that their positions are more sensitive to certain weight adjustments. Budi and Andi consistently occupy the lower rankings, with changes in weights having little impact on their positions. Overall, this visualization shows that the CORASO method is capable of producing stable rankings under various weight-change scenarios, while also identifying candidates who are sensitive as well as robust in the evaluation process.

A comparative analysis with other Multi-Criteria Decision-Making methods is essential to evaluate the robustness, consistency, and discriminatory capability of the proposed approach. Since different MCDM techniques rely on distinct normalization schemes, aggregation structures, and ranking mechanisms, their results may vary even when applied to the same dataset. Conducting a structured comparison allows researchers to assess ranking stability, sensitivity to criteria weights, and the method's ability to reflect the actual performance patterns of alternatives. Through this comparison, it becomes possible to identify whether the proposed method offers improved objectivity, better compromise representation, or stronger differentiation among alternatives compared to established MCDM models, thereby strengthening its theoretical contribution and practical relevance in decision support systems.

A comparison with the Simple Additive Weighting (SAW), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Simple Multi-Attribute Rating Technique (SMART), and Grey Relational Analysis (GRA)methods was conducted to obtain a more comprehensive picture of the position and performance of the proposed method within the framework of multi-criteria decision-making. SAW emphasizes the concept of simple weighted summation that is easy to implement, MOORA relies on a ratio approach that directly considers the differences between benefit and cost attributes, SMART focuses on linear utility-based transformation to represent decision-makers' preferences, while GRA assesses the closeness of alternatives to reference patterns through relational analysis. By comparing the ranking results, the level of consistency, and sensitivity to changes in weights, this study can evaluate whether the developed method is capable of providing more stable, objective, and representative results compared to these approaches. The results of the ranking comparison using this method are shown in Figure 2.

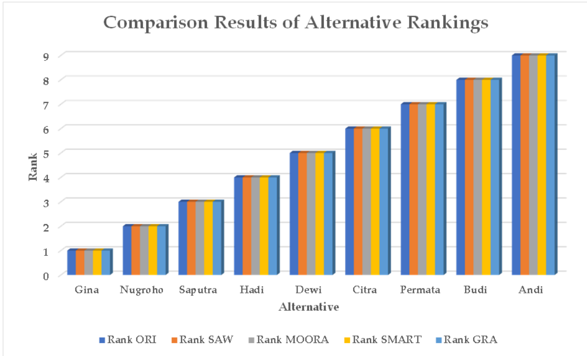

Figure 2. Ranking Comparison Results

The comparison results of alternative rankings show that all methods, namely ORI, SAW, MOORA, SMART, and GRA, produce a completely consistent ranking pattern without any changes in position among the alternatives. Gina ranks first, followed by Nugroho, Saputra, Hadi, Dewi, Citra, Permata, Budi, and Andi in the last position. Each method displays identical ranking values for each alternative, which is evident from the aligned height of the bars in each group. This indicates that the approaches compared have a very high level of compatibility and stability with the data structure used, resulting in no differences in interpretation during the evaluation process and the determination of the best alternative.

The results of the ranking comparison between methods were further analyzed using Spearman's correlation coefficient to measure the level of agreement and consistency in the relationships among the ranking orders of the alternatives. This approach was chosen because Spearman's method can evaluate the strength of monotonic relationships based on ranked data without being affected by differences in value scales. Through this testing, it can be determined to what extent the ranking results from each method follow a similar pattern, remain stable, and do not experience significant position swaps. Correlation values close to one indicate a very strong agreement, while lower values suggest differences in the ranking structures among the compared methods. Figure 3 shows the results of the comparison of correlation values of the alternative rankings.

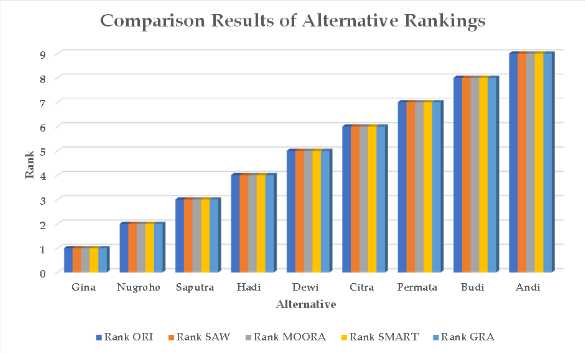

Figure 3. Comparison Results of Correlation Values

The comparison of correlation values shows that all methods, namely CORASO, SAW, MOORA, SMART, and GRA, have a correlation value of 1. This value indicates a perfect relationship and full consistency between the ranking results produced by each method and the reference ranking. There is no difference in the level of conformity among the compared methods, so it can be concluded that all approaches produce identical alternative rankings. This condition indicates a very high level of stability and alignment in the evaluation process, as well as reinforcing the validity of the obtained decision results.

Discussion

The results of this study indicate that the integration of the LOGSTA and CORASO methods is able to provide a more objective and consistent approach in the recruitment candidate evaluation process. LOGSTA plays an important role in generating criteria weights based on data characteristics, thereby minimizing reliance on subjective assessments. The resulting weights reflect the level of variation and information content of each criterion, which then serves as a strong foundation for the alternative evaluation stage. With an objective weighting foundation, the decision-making process becomes more transparent and accountable.

At the alternative evaluation stage, the application of the CORASO method has proven effective in comprehensively distinguishing candidate quality. This method not only considers the best values for each criterion but also takes into account the balance between the ideal and anti-ideal solutions. The ranking results show that candidates with consistent performance across various criteria tend to occupy top positions, while candidates with weaknesses in some criteria rank lower. This confirms CORASO's ability to capture candidates' relative performance comprehensively.

Comparative analysis through various weight change scenarios provides additional insights into the stability of the proposed method. The majority of candidates maintain relatively the same ranking positions despite adjustments in the criteria weights, indicating the robustness of the results against uncertainty in weight determination. Candidates experiencing ranking fluctuations are generally in the middle positions, which indicates sensitivity to certain criteria. These findings reinforce the argument that the integration of LOGSTA and CORASO can produce decisions that are both stable and adaptive to variations in preferences.

Overall, the results of this study make a significant contribution to the development of decision support systems in the field of recruitment. The proposed approach not only enhances the objectivity and consistency of selection outcomes but also provides a systematic and structured evaluation mechanism. Compared to conventional or single-method approaches, the integration of LOGSTA and CORASO offers advantages in reducing bias and improving the reliability of candidate rankings. Therefore, this method has great potential for broad application in various recruitment contexts that require fair and data-driven decisions.

5. CONCLUSION

This research integrates the LOGSTA and CORASO methods in a recruitment decision support system, enabling a more objective, consistent, and reliable candidate evaluation process. LOGSTA successfully determines the weight of criteria based on data characteristics objectively, thereby reducing the influence of subjectivity in assessing the importance level of criteria. Furthermore, CORASO can utilize these weights to produce candidate rankings that reflect a balanced closeness to the ideal solution. The results of the comparative analysis and weight change scenarios show that the resulting rankings are relatively stable, especially for candidates with consistent performance across various criteria. These findings confirm that the proposed method has good resilience to weight variations and is capable of minimizing decision bias. Overall, the integration of LOGSTA and CORASO provides a strong methodological contribution in supporting fair, transparent, and data-driven recruitment decision-making.

This study has several limitations, particularly in the scope of data, the number of candidates evaluated, and the dependence on structured quantitative criteria, which may not fully capture behavioral and contextual aspects of recruitment decisions. In addition, the integration of LOGSTA and CORASO was tested within a specific organizational setting, so its generalizability to different industries or larger recruitment datasets still requires further validation. Future research can expand the model by incorporating fuzzy or probabilistic approaches to accommodate uncertainty in candidate assessment, comparing its performance with other objective weighting and ranking methods, and applying it to multi-stage recruitment systems supported by real-time decision platforms. From a practical governance perspective, the integration of LOGSTA and CORASO offers a transparent and data-driven framework that reduces subjectivity, strengthens accountability in hiring decisions, and supports merit-based recruitment policies, thereby helping organizations build fairer, more consistent, and auditable talent selection processes.

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