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Employee Performance Evaluation of the Purchasing Division Based on Data Objectivity Using the LODECI and MUNRA Methods

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Abstract: The main problem in evaluating the performance of employees in the Purchasing Division often lies in the high subjectivity of the assessor, bias in assigning criteria weights, and inconsistency in ranking results due to differences in data scale and characteristics. This situation has the potential to produce decisions that are less fair and do not fully reflect the actual performance of employees. This study aims to develop a data-driven performance evaluation model by integrating the LODECI method for criteria weighting and the MUNRA method for ranking alternatives. The weighting results using LODECI show that Negotiation Skills have the highest weight at 0.2236, followed by Cost Efficiency at 0.2081, Timeliness at 0.2037, Procedure Compliance at 0.1892, and Supplier Quality at 0.1754. Subsequently, MUNRA was applied through a multi-normalization approach to enhance the stability and consistency of the ranking results. The study involved nine employees with five main criteria as the basis for constructing the decision matrix. The calculation results show that Kurniawan obtained a final score of 0.2974, ranking first, followed by Maharani with a score of 0.2961 in second place, and Santoso with a score of 0.276 in third place. Overall, the integration of LODECI and MUNRA is able to produce a more objective, transparent, and accountable evaluation system in supporting managerial decision-making.
Keywords: Employee Performance Evaluation; Purchasing Division; LODECI Weighting; MUNRA Method; Decision Support System;

1. INTRODUCING

Employee performance evaluation in the Purchasing Division plays an important role in ensuring the smooth procurement of goods and services, which directly impacts the company's operational efficiency[1], [2]. This division is not only responsible for purchasing but also for supplier selection, price negotiation, quality control, and timely delivery. Therefore, performance assessments need to consider various criteria such as accuracy in planning requirements, negotiation skills, cost control, compliance with procedures, and the quality of communication with both suppliers and internal divisions.[3] Systematic evaluations help the company identify the strengths and weaknesses of each employee objectively. Additionally, the evaluation results can serve as a basis for decisions related to promotions, training, or the provision of incentives. This process also promotes

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transparency and accountability because each performance indicator is measured against clear targets and standards. With a structured and data-driven approach, performance evaluation in the Purchasing Division can improve procurement efficiency while supporting the overall achievement of the company's strategic objectives.

A common issue in performance evaluation is often related to subjectivity that arises from assessments that rely too heavily on the evaluator's personal perception[4], [5]. When indicators are not formulated in a measurable and clear manner, evaluations tend to be influenced by personal opinion, emotional closeness, or the recency effect regarding the employee. Evaluator bias also poses a serious challenge, such as the halo effect, where one particular strength overshadows other weaknesses, or contrast bias, which disproportionately compares employees with their colleagues. Additionally, inconsistencies in weighting criteria frequently occur due to the lack of a systematic and data-driven weighting method. As a result, criteria that should be more important are given lower weight, or vice versa, making the final results less representative. Instability in evaluation results can also arise when there are small changes in weights or assessments without a rational basis[6], [7]. If this situation continues, decisions related to promotions, rewards, or employee development risk being unfair and can lower work motivation. Therefore, a more objective, structured, and consistent evaluation approach is needed so that the assessment results truly reflect actual performance.

A data-driven objectivity approach in Decision Support Systems (DSS) is becoming increasingly important because organizational decisions today face complex criteria and large volumes of information[8], [9]. Without a measurable data foundation, decision support systems risk producing recommendations influenced by subjective assumptions or the preferences of certain individuals. Data objectivity allows each alternative to be assessed based on clear, standardized, and verifiable indicators, making the decision-making process more transparent[10], [11]. Additionally, the use of quantitative data helps minimize bias and improve consistency of results, especially when decisions involve multiple interacting criteria. In the context of performance evaluation, supplier selection, or determining strategic priorities, this approach ensures that weights and scores are assigned rationally and can be accounted for. A system built on data is also more adaptable to changes, as updates to information can directly influence analysis results without relying solely on intuition. Thus, a data-driven DSS not only improves decision accuracy but also strengthens stakeholders' trust in the process and outcomes produced[12], [13].

The logarithmic decomposition of criteria importance (LODECI) method, as an objective weighting approach, is designed to generate criterion weights rationally based on data characteristics, rather than on subjective assessments by decision-makers[14], [15]. This method works by analyzing the variation, distribution, and contribution levels of each criterion to the overall alternatives being evaluated. By utilizing the numerical information available in the decision matrix, LODECI can identify which criteria have the most significant distinguishing power. The greater a criterion's ability to differentiate the performance of alternatives, the greater the weight assigned proportionally. This approach helps reduce weighting inconsistencies that often arise when weights are determined based on individual preferences. Furthermore, the use of objective weighting such as LODECI enhances the stability of ranking results because the weights are derived directly from the actual data structure. In a DSS, LODECI can strengthen the transparency and accountability of the evaluation process, especially in cases involving many criteria and complex alternatives.

The Multi-Normalized Ranking Approach (MUNRA) is a ranking method within the framework of multi-criteria decision making that emphasizes the use of more than one normalization technique to produce more stable and representative evaluation results[16]. This approach stems from the understanding that each normalization technique has

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different characteristics and sensitivity to data scales, so using only one method could potentially introduce bias into the final results. In MUNRA, alternative values are first normalized using several relevant normalization schemes, and then the results are integrated to obtain a more comprehensive aggregate score. This strategy aims to reduce distortions caused by differences in units, value ranges, or data distribution across criteria. By combining various normalization perspectives, MUNRA is able to enhance the consistency and robustness of rankings against small changes in the data. This method is particularly suitable for implementation in Decision Support Systems that handle many heterogeneous criteria, as it can provide a more balanced evaluation overview. Overall, MUNRA offers a ranking approach that is more robust, transparent, and adaptive compared to methods that rely on a single normalization technique.

The integration of LODECI as an objective weighting method with MUNRA as a multi-normalized ranking approach is driven by the need for a decision support system that is not only objective in weighting but also stable in the ranking process. LODECI ensures that the weight of each criterion is determined based on the characteristics and discriminative power of the data, thereby reducing reliance on subjective judgment. On the other hand, MUNRA addresses potential biases that arise from using a single normalization technique by combining multiple normalization schemes to produce more balanced scores. The combination of the two creates a complementary evaluation framework, where rational weighting is paired with a more robust ranking process. This approach is particularly important in decision-making cases involving multiple criteria with varied scales and data distributions. In addition to improving the accuracy and consistency of results, this integration also enhances transparency because each stage, from weighting to final ranking, is based on measurable data analysis. Thus, the integration of LODECI and MUNRA offers a comprehensive solution for producing decisions that are fairer, more stable, and accountable in complex environments.

The aim of this study is to develop a performance evaluation model for employees of the Purchasing Division that can produce assessments that are objective, consistent, and stable through a data-based approach. Specifically, this study aims to apply LODECI as a weighting method that emphasizes variation and the differentiating power of data so that each criterion receives a weight rationally according to its characteristics. Furthermore, this study also implements MUNRA as a multi-normalization-based ranking method to minimize distortions caused by differences in scale and value distribution across criteria. The combination of these two approaches is expected to improve the accuracy of evaluation results compared to conventional methods, which tend to be subjective. The main contribution of this study lies in the integration of objective weighting and a more robust ranking technique within a DSS framework. In addition, this study offers a performance evaluation model for purchasing that is more transparent and accountable because the entire process is calculated based on actual data structures. Thus, the research results are expected to serve as a methodological reference in the development of a fair and stable performance evaluation system within organizations.

2. RESEARCH METHODOLOGY

Research methods are a series of systematic steps designed to address research questions and achieve research objectives in a structured manner. These methods include the approach used, the type of data collected, data collection techniques, and the analysis procedures applied. In the context of quantitative research, research methods serve as a framework that ensures each stage is carried out logically, measurably, and can be tested again[17], [18]. Clarity in the method is crucial so that the research results have high validity and reliability. Furthermore, research methods also serve as guidelines in controlling variables and minimizing potential bias during data collection and analysis. With

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properly designed methods, objective findings that align with empirical conditions can be produced.

2.1. Research Framework

The research framework is a conceptual overview that explains the researcher's thought process in connecting the problem, variables, methods, and expected results[19], [20]. This framework functions as a map that shows the logical relationships between research components, ensuring that the analysis process is directed and systematic. Through the research framework, the researcher can clarify the position of the variables being studied, the approach used, and the stages that will be carried out to answer the research questions. In addition, the research framework helps ensure that every step taken remains consistent with the research objectives. Having a clear framework also makes it easier for readers to understand the structure and flow of the research as a whole. Figure 1 illustrates the research framework developed and applied in this study.

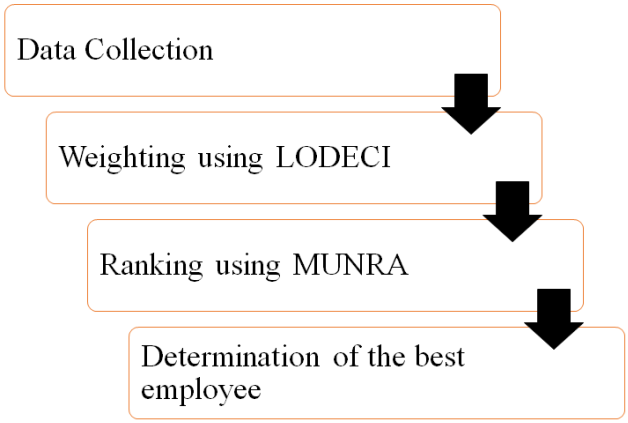

Figure 1. Research Framework

This research framework describes a systematic flow that begins with the data collection stage as the main foundation in the evaluation process. The obtained data is then organized into a decision matrix for further analysis according to the established criteria. In the next stage, weighting is carried out using the LODECI method to determine the importance level of each criterion objectively based on data variation and characteristics. Once the weights are obtained, the process continues with ranking alternatives using the MUNRA method, which integrates several normalization techniques to produce more stable and consistent results. The final stage of this framework is the determination of the best employee based on the highest aggregate score, reflecting the most optimal performance. These stages are interconnected and form a structured, transparent evaluation process based on quantitative analysis. With this process, the decisions made are expected to be more rational and accountable.

2.2. LODECI Weighting

LODECI weighting is a method for determining the weights of criteria objectively by utilizing the level of variation and discriminative power of data in the decision matrix. This method works by analyzing the extent to which each criterion can differentiate the performance of alternatives so that the resulting weights truly reflect the real contribution of each indicator. Unlike subjective approaches that rely on the evaluator's preferences, LODECI derives weights mathematically based on the structure and distribution of existing values. One of its advantages is its ability to reduce individual bias and increase consistency in the evaluation process. In addition, LODECI produces weights that are more adaptive to changes in data because the calculation is done directly from the actual conditions of the

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evaluated alternatives. This method also helps enhance transparency because each weight value can be traced through a clear calculation process. With these characteristics, LODECI weighting is highly relevant to be applied in decision support systems that require objectivity and stability of results.

The stages in the LODECI method begin with the preparation of a decision matrix that represents the alternatives and performance values for each criterion based on the available data, created using (1). This decision matrix is then processed through a normalization stage to equalize the data scale across criteria, so that differences in units and value ranges do not affect the calculation results, calculated using (2). After that, the deviation value is calculated to measure the level of dispersion or variation of values in each criterion as an indicator of the criterion's ability to distinguish between alternatives, calculated using (3). The deviation values are subsequently transformed into logarithmic deviation values using a logarithmic function to stabilize extreme differences and enhance the sensitivity of the analysis to relevant data variations, calculated using (4). The final stage is the determination of criteria weights, where the weights are obtained from the normalization of the logarithmic deviation values so that the total weight equals one and reflects the objective level of importance of the criteria, calculated using (5).

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

$$d_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}}; benefit\ criteria \\ 1 - \frac{x_{ij}}{\max_j x_{ij}}; cost\ criteria \end{cases} \tag{2}$$

$$SD_{ij} = \max\{|d_{ij} - d_r|\} r \neq i \tag{3}$$

$$LSD_j = \ln\left(1 + \frac{\sum_{i=1}^{m} SD_{ij}}{m}\right) \tag{4}$$

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

The symbol X is a decision matrix, x_{ij} represents the value of the i-th alternative for the j-th criterion, d_{ij} is the normalization value, SD_{ij} represents the degree of separation, d_{rj} is the normalization value of the r-th alternative, LSD_j is the logarithmic separation degree, w_j represents the weight of the j-th criterion, m is the number of alternatives, n is the number of criteria, and $\ln$ represents the natural logarithm.

As an objective weighting method, LODECI offers a robust approach in determining the importance level of criteria based on actual data characteristics. By focusing on the variation and discriminative power of each indicator, this method can produce more rational and proportional weights. This approach helps reduce the dominance of subjective preferences that often influence conventional evaluation processes. Moreover, LODECI enhances the consistency of results since weights are calculated through clear and structured mathematical procedures. When there are changes in the alternative data, weight adjustments can be made adaptively without compromising the calculation logic. This makes LODECI relevant for application in decision support systems that require high transparency and accountability.

2.3. MUNRA Method

The MUNRA method is a ranking approach in multi-criteria decision-making that integrates several normalization techniques to produce more stable and representative evaluation scores. Its basic principle is that each normalization method has different sensitivities to the scale and distribution of data, so using just one technique could potentially distort the results. By applying multi-normalization, MUNRA combines multiple

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calculation perspectives before aggregating the final alternative values. One of its main advantages is its ability to enhance the ranking's robustness against small changes in data or criterion weights. Additionally, this method helps minimize bias caused by differences in measurement units across heterogeneous criteria. MUNRA also provides more consistent results because the final score is obtained from the integration of several normalization schemes, rather than from a single approach. With these characteristics, MUNRA is highly suitable for use in decision support systems that require accuracy, stability, and reliability in the process of ranking alternatives.

The stages of the MUNRA method begin with the preparation of a decision matrix that includes all alternatives and criteria to be evaluated in the form of structured numerical values using (1). Next, a normalization stage is carried out using more than one normalization technique to harmonize differences in scale and units between criteria, so that the data can be compared fairly. The results of these various normalization schemes are then integrated to obtain a more balanced value representation using (6) to (9). The next stage is weighted arithmetic operations, which is the process of multiplying normalized values by predetermined criteria weights, followed by arithmetic operations such as summation or aggregation according to the method's framework using (10) to (12). The final stage is the calculation of the final score used to determine the ranking of alternatives using (13), where the alternative with the highest score is declared the best choice based on the multi-normalization approach that has been applied.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\max(x_{ij})}; if\ j \epsilon B \\ \frac{\min(x_{ij})}{x_{ij}}; if\ j \epsilon C \end{cases} \quad (6)$$

$$y_{ij} = \begin{cases} \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}; if\ j \epsilon B \\ 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}; if\ j \epsilon \end{cases} \quad (7)$$

$$p_{ij} = \begin{cases} \left(\frac{x_{ij}}{\max(x_{ij})}\right)^2; if\ j \epsilon B \\ \left(\frac{\min(x_{ij})}{x_{ij}}\right)^3; if\ j \epsilon C \end{cases} \quad (8)$$

$$r_i' = \sum_{j \epsilon B} w_j * r_{ij} + \sum_{j \epsilon C} w_j * r_{ij} \quad (9)$$

$$y_i' = \sum_{j \epsilon B} w_j * y_{ij} + \sum_{j \epsilon C} w_j * y_{ij} \quad (11)$$

$$p_i' = \sum_{j \epsilon B} w_j * p_{ij} + \sum_{j \epsilon C} w_j * p_{ij} \quad (12)$$

$$v_i = \propto r_i' + \beta y_i' + \gamma p_i' \quad (13)$$

The symbol r_{ij} is the normalization value based on the ratio, y_{ij} is the normalization value based on the vector, p_{ij} is the normalization value based on rank, r_i', y_i', and p_i' each express the value of the i-th alternative preference based on the three normalization approaches, v_i is the value of the last alternative preference i-th, (w_j) is the weight of the j-th criterion, x_{ij} is the second alternative value i-th in the j-th criterion, (B) expresses the benefit criterion set, (C) expresses the cost criterion set, (m) is the alternative amount, (n) is the criterion sum, i-th is the alternative index, j-th is the criterion index, while (alpha), (beta), and (gamma) are the coefficient parameters used to combine the three preference values in the calculation of the alternative final value.

The MUNRA method provides a more comprehensive approach in generating accurate and stable alternative rankings. By combining several normalization techniques, this method is able to reduce potential distortions that often arise due to differences in scale or data characteristics. The final results obtained not only reflect the performance of alternatives

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quantitatively, but also demonstrate consistency when there are small changes in the data or criteria weights.

3. RESULT AND DISCUSSIONS

Employee Performance Evaluation in the Purchasing Division based on data objectivity using the LODECI and MUNRA methods is a structured approach that emphasizes quantitative analysis in the performance assessment process. The LODECI method is applied to determine the weight of criteria objectively by analyzing the level of variation and discriminative power of each indicator, so that the resulting weights truly reflect the actual contribution of each criterion. This approach helps reduce subjectivity and evaluator bias in the weighting stage. Furthermore, the MUNRA method is used in the ranking process by integrating several normalization techniques so that the evaluation results are more stable and not sensitive to differences in data scales. The combination of these two methods results in a more consistent, transparent, and rational evaluation system. The final outcome, in the form of employee rankings, reflects performance that is measured and accountable. Overall, the integration of LODECI and MUNRA forms a decision support system framework that enhances fairness and stability in evaluating the performance of the Purchasing Division.

3.1. Data Collection

The Data Collection stage is a crucial initial step in the research process as it forms the foundation for all subsequent analysis stages. In this stage, employee performance data from the Purchasing Division is systematically collected according to predefined criteria. The data collection process can be carried out through documentation of work reports, internal evaluation notes, observations, or assessments based on measurable indicators. The data obtained must be relevant, accurate, and reflect actual performance conditions so that the analysis results do not deviate from reality. Additionally, consistency in format and data completeness must also be considered to facilitate the preparation of decision matrices. This stage ensures that each alternative has values that can be compared objectively across all criteria. With structured and valid data collection, the weighting and ranking processes in the following stages can be carried out more accurately and reliably.

Criteria data is a key component in the evaluation process because it serves as the basis for assessing each alternative analyzed. The criteria used must be relevant to the evaluation objectives and be able to represent important aspects of the performance being measured. Each criterion needs to be clearly defined to avoid differing interpretations during the evaluation process. In addition, the data collected must be measurable so that it can be processed quantitatively in a decision matrix. Accuracy in determining and organizing criteria data will greatly affect the accuracy of weighting and ranking results. Therefore, the preparation of criteria data must be carried out systematically to support an objective and consistent evaluation process.

Alternative assessment data is a quantitative representation of the performance of each employee evaluated based on established criteria. This data shows the extent to which each alternative meets the performance indicators that serve as the basis for evaluation. The process of compiling assessment data must be carried out consistently so that each employee is evaluated on the same scale and standards. The scores given can be sourced from performance reports, measurement results of target achievements, or periodic evaluation summaries. The accuracy of the data is crucial as it will affect the weighting and ranking results in the subsequent stages. Additionally, alternative assessment data should be organized in the form of a decision matrix so that it can be systematically processed using quantitative methods. With complete and structured data, the evaluation process can produce rankings that reflect performance conditions objectively and are accountable.

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Table 1 is the data of the assessment for each alternative based on the criteria used in the evaluation.

Table 1. Alternative Assessment Data

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	85	90	88	92	87
Employee SO	88	85	90	89	91
Employee CA	82	88	85	90	86
Employee KN	90	92	91	94	93
Employee EA	87	86	89	88	90
Employee HY	84	87	86	91	85
Employee MR	89	91	92	93	94
Employee SP	83	84	87	86	88
Employee PR	86	89	88	90	89

The assessment data that has been compiled provides a comprehensive overview of each employee's performance based on criteria relevant to their duties and responsibilities in the Purchasing Division. This data not only serves as descriptive information but also as a quantitative basis for further analysis. With a structured format and consistent scale, each alternative can be evaluated fairly and consistently. The clarity of scores for each criterion supports a systematic process of weighting and ranking.

3.2. Weighting Using LODECI Method

The implementation of weighting using LODECI is an important stage in the performance evaluation process because it aims to determine the level of importance of each criterion objectively based on the characteristics of the available data. The main principle of LODECI is that criteria with higher levels of variation have a greater ability to differentiate employee performance, thus deserving more significant weights. The calculation process is carried out mathematically and systematically so that the resulting weights are not influenced by the subjective preferences of the evaluators. With this approach, each performance indicator obtains a proportion of importance that corresponds to its contribution to the evaluation results. The implementation of LODECI also helps to improve consistency because the weights are derived directly from the actual data structure. This stage becomes an important foundation before the ranking process is carried out, as the quality of the final results greatly depends on the accuracy of the applied weighting.

The stages in the LODECI method are systematically arranged to produce objective criteria weights. The first stage is to prepare a decision matrix containing all alternatives along with their performance values for each criterion based on the available data, formulated using equation (1). The resulting decision matrix is as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{12} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} \end{bmatrix} \rightarrow X = \begin{bmatrix} 85 & 90 & 88 & 92 & 87 \\ 88 & 85 & 90 & 88 & 91 \\ 82 & 88 & 85 & 90 & 86 \\ 90 & 92 & 91 & 94 & 93 \\ 87 & 86 & 89 & 88 & 90 \\ 84 & 87 & 86 & 91 & 85 \\ 89 & 91 & 92 & 93 & 94 \\ 83 & 84 & 87 & 86 & 88 \\ 86 & 89 & 88 & 90 & 89 \end{bmatrix}$$

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The second stage is to normalize the decision matrix to equalize the scale among criteria so that differences in units and value ranges do not affect the analysis results, calculated using equation (2). The normalization results are presented in Table 2.

Table 2. Normalization

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.9444	0.9783	0.9565	0.9787	0.9255
Employee SO	0.9778	0.9239	0.9783	0.9468	0.9681
Employee CA	0.9111	0.9565	0.9239	0.9574	0.9149
Employee KN	1.0000	1.0000	0.9891	1.0000	0.9894
Employee EA	0.9667	0.9348	0.9674	0.9362	0.9574
Employee HY	0.9333	0.9457	0.9348	0.9681	0.9043
Employee MR	0.9889	0.9891	1.0000	0.9894	1.0000
Employee SP	0.9222	0.9130	0.9457	0.9149	0.9362
Employee PR	0.9556	0.9674	0.9565	0.9574	0.9468

The third stage is to calculate the deviation value for each criterion as a measure of the level of variation or data dispersion, which indicates the criterion's ability to differentiate performance among alternatives, as calculated using equation (3). The deviation values for each criterion are presented in Table 3.

Table 3. Deviation Value

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.0556	0.0652	0.0435	0.0638	0.0745
Employee SO	0.0667	0.0761	0.0543	0.0532	0.0638
Employee CA	0.0889	0.0435	0.0761	0.0426	0.0851
Employee KN	0.0889	0.0870	0.0652	0.0851	0.0851
Employee EA	0.0556	0.0652	0.0435	0.0638	0.0532
Employee HY	0.0667	0.0543	0.0652	0.0532	0.0957
Employee MR	0.0778	0.0761	0.0761	0.0745	0.0957
Employee SP	0.0778	0.0870	0.0543	0.0851	0.0638
Employee PR	0.0444	0.0543	0.0435	0.0426	0.0532

The fourth stage is to transform the deviation values into a logarithmic deviation using a logarithmic function to stabilize extreme differences and enhance sensitivity to relevant variations, as calculated using equation (4). The results of the logarithmic deviation values are shown in Table 4.

Table 4. Logarithmic Deviation

Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
0.0669	0.0654	0.0564	0.0608	0.0718

The fifth and final stage is to determine the criteria weights through the process of normalizin g the logarithmic deviation values so that the total weight equals one and reflects the objective importance level of each criterion, calculated using equation (5). The results of the criteria weight values are shown in Table 5.

Table 5. Criteria Weight

Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
0.2081	0.2037	0.1754	0.1892	0.2236

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Based on the weighting results using the LODECI method, the Negotiation Skills criterion received the highest weight at 0.2236, indicating that negotiation ability has the greatest contribution in differentiating the performance of Purchasing Division employees. Next, Cost Efficiency has a weight of 0.2081, followed by Timeliness at 0.2037, indicating that aspects of cost control and timeliness also have a significant impact on the evaluation. Procedure Compliance holds a weight of 0.1892, reflecting the importance of adhering to procedures in maintaining good procurement governance. Meanwhile, Supplier Quality has a weight of 0.1754, which, although the lowest compared to the other criteria, still provides a relevant contribution to the overall assessment. This distribution of weights shows that all criteria play a relatively balanced role, but with a stronger emphasis on negotiation and cost efficiency aspects. These results reflect that strategic capability in interacting with suppliers is a key factor in determining optimal performance in the Purchasing Division.

3.3. Ranking using MUNRA Method

The Ranking stage using MUNRA is a subsequent process after the criterion weights have been determined objectively, aimed at arranging the performance order of alternatives comprehensively and stably. In this stage, the value of each alternative is analyzed through a multi-normalization approach so that differences in scale and data characteristics among criteria do not lead to bias in the final results. Using more than one normalization technique allows the evaluation to be conducted from multiple calculation perspectives, resulting in more balanced outcomes. The normalized values are then combined with the criterion weights through an arithmetic aggregation process to obtain an integrated score. This approach helps improve ranking consistency and reduces sensitivity to small changes in the data. Thus, this stage ensures that the resulting employee ranking truly reflects performance objectively. Ranking using MUNRA is an important step in producing final decisions that are rational and accountable.

The stages of the MUNRA method are carried out sequentially to produce a systematic and stable ranking process. The first stage is to compile a decision matrix that contains all alternatives and criteria in the form of structured numerical values, as formulated using equation (1). The decision matrix results of the MUNRA method are the same as the decision matrix results of the LODECI method.

The second stage is the normalization process, applying more than one normalization technique to align differences in scale and units among the criteria so that the data can be compared fairly. The third stage is to integrate the results from these various normalization schemes to obtain a more balanced and comprehensive representation of values, calculated using equations (6) to (9). The results of the first normalization are presented in Table 6.

Table 6. First Normalization

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.9444	0.9783	0.9565	0.9787	0.9255
Employee SO	0.9778	0.9239	0.9783	0.9468	0.9681
Employee CA	0.9111	0.9565	0.9239	0.9574	0.9149
Employee KN	1.0000	1.0000	0.9891	1.0000	0.9894
Employee EA	0.9667	0.9348	0.9674	0.9362	0.9574
Employee HY	0.9333	0.9457	0.9348	0.9681	0.9043
Employee MR	0.9889	0.9891	1.0000	0.9894	1.0000
Employee SP	0.9222	0.9130	0.9457	0.9149	0.9362
Employee PR	0.9556	0.9674	0.9565	0.9574	0.9468

The results of the second normalization are presented in Table 7.

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Table 7. Second Normalization

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.3293	0.3408	0.3316	0.3394	0.3249
Employee SO	0.3409	0.3218	0.3391	0.3283	0.3398
Employee CA	0.3177	0.3332	0.3203	0.3320	0.3211
Employee KN	0.3487	0.3483	0.3429	0.3467	0.3473
Employee EA	0.3371	0.3256	0.3353	0.3246	0.3361
Employee HY	0.3254	0.3294	0.3240	0.3357	0.3174
Employee MR	0.3448	0.3445	0.3466	0.3431	0.3510
Employee SP	0.3216	0.3180	0.3278	0.3172	0.3286
Employee PR	0.3332	0.3370	0.3316	0.3320	0.3323

The results of the third normalization are presented in Table 8.

Table 8. Third Normalization

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.8920	0.9570	0.9149	0.9579	0.8566
Employee SO	0.9560	0.8536	0.9570	0.8964	0.9372
Employee CA	0.8301	0.9149	0.8536	0.9167	0.8370
Employee KN	1.0000	1.0000	0.9784	1.0000	0.9788
Employee EA	0.9344	0.8738	0.9358	0.8764	0.9167
Employee HY	0.8711	0.8943	0.8738	0.9372	0.8177
Employee MR	0.9779	0.9784	1.0000	0.9788	1.0000
Employee SP	0.8505	0.8336	0.8943	0.8370	0.8764
Employee PR	0.9131	0.9358	0.9149	0.9167	0.8964

The fourth stage is performing weighted arithmetic operations, which involves multiplying the normalized values by the previously determined criteria weights, followed by an aggregation or summation process according to the framework of the method, as calculated using equations (10) to (12). The results of the first arithmetic calculation are shown in Table 9.

Table 9. First Arithmetic

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.1965	0.1993	0.1678	0.1851	0.2069
Employee SO	0.2035	0.1882	0.1716	0.1791	0.2165
Employee CA	0.1896	0.1949	0.1621	0.1811	0.2046
Employee KN	0.2081	0.2037	0.1735	0.1892	0.2212
Employee EA	0.2012	0.1904	0.1697	0.1771	0.2141
Employee HY	0.1942	0.1927	0.1640	0.1831	0.2022
Employee MR	0.2058	0.2015	0.1754	0.1871	0.2236
Employee SP	0.1919	0.1860	0.1659	0.1731	0.2093
Employee PR	0.1989	0.1971	0.1678	0.1811	0.2117

The results of the second arithmetic calculation are shown in Table 10.

Table 10. Second Arithmetic

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.0685	0.0694	0.0582	0.0642	0.0726
Employee SO	0.0709	0.0656	0.0595	0.0621	0.0760
Employee CA	0.0661	0.0679	0.0562	0.0628	0.0718

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Employee KN	0.0726	0.0710	0.0601	0.0656	0.0776
Employee EA	0.0701	0.0663	0.0588	0.0614	0.0751
Employee HY	0.0677	0.0671	0.0568	0.0635	0.0710
Employee MR	0.0718	0.0702	0.0608	0.0649	0.0785
Employee SP	0.0669	0.0648	0.0575	0.0600	0.0735
Employee PR	0.0693	0.0687	0.0582	0.0628	0.0743

The results of the third arithmetic calculation are shown in Table 11.

Table 11. Third Arithmetic

Employee Name	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Employee PM	0.1856	0.1950	0.1605	0.1812	0.1915
Employee SO	0.1990	0.1739	0.1679	0.1696	0.2095
Employee CA	0.1728	0.1864	0.1497	0.1734	0.1872
Employee KN	0.2081	0.2037	0.1716	0.1892	0.2189
Employee EA	0.1945	0.1780	0.1642	0.1658	0.2050
Employee HY	0.1813	0.1822	0.1533	0.1773	0.1828
Employee MR	0.2035	0.1993	0.1754	0.1852	0.2236
Employee SP	0.1770	0.1698	0.1569	0.1583	0.1960
Employee PR	0.1900	0.1907	0.1605	0.1734	0.2004

The fifth and final stage is to calculate the final score for each alternative using equation (13); the results of the final value calculation are displayed in Table 12.

Table 12. Final Value

Employee Name	Final Value
Employee PM	0.2741
Employee SO	0.2760
Employee CA	0.2608
Employee KN	0.2974
Employee EA	0.2722
Employee HY	0.2631
Employee MR	0.2961
Employee SP	0.2574
Employee PR	0.2745

The final scores obtained by each employee reflect the aggregated performance results after going through a weighting process and multi-normalization-based calculations. Employee KN scored 0.2974, followed by Employee MR with 0.2961, reflecting a very strong performance contribution based on the overall evaluation criteria. Employee SO recorded a score of 0.2760, while Employee PR and Employee PM scored 0.2745 and 0.2741 respectively, indicating relatively close performance. Employee EA obtained a score of 0.2722, while Employee HY and Employee CA recorded 0.2631 and 0.2608 respectively. Employee SP scored 0.2574, which still represents a performance contribution based on the measured indicators. The relatively small differences in scores among employees indicate that the evaluation was conducted fairly, taking all criteria into account proportionally. This final score reflects the comprehensive results of the quantitative analysis process that has been applied systematically.

3.4. Determination of the Best Employee

The Determination of the Best Employee stage is the final step in the performance evaluation process, aimed at identifying the employee with the most optimal performance based on quantitative calculations. At this stage, all final scores obtained from the weighting and ranking process are analyzed comprehensively to ensure that the decisions

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made truly reflect each individual's performance contribution. The determination is carried out objectively by referring to the highest aggregate scores, which represent a balanced performance across all evaluation criteria. This process not only highlights individual achievements but also ensures that the decisions made are transparent and accountable. With a data-driven approach, selecting the best employee becomes more rational and avoids subjective bias. This stage also serves as a basis for management to provide recognition, promotions, or career development. The complete ranking results are shown in Figure 2.

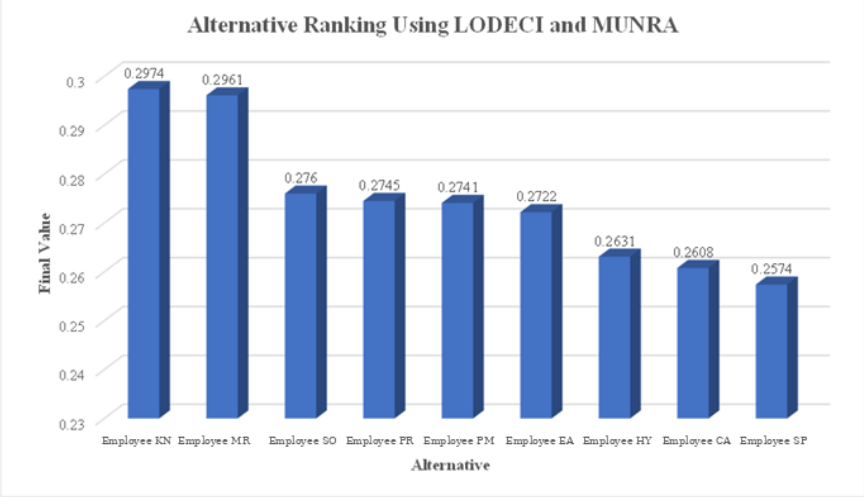

Figure 2. Alternative Ranking

The evaluation results showed that Employee KN achieved the highest final score of 0.2974, ranking first, followed very closely by Employee MR with a score of 0.2961 in second place. Employee SO ranked third with a score of 0.276, while Employee PR and Employee PM occupied the fourth and fifth positions with scores of 0.2745 and 0.2741, a relatively small difference. Employee EA was in sixth place with a score of 0.2722, followed by Employee HY in seventh with 0.2631. Employee CA held the eighth position with a score of 0.2608, and Employee SP was ninth with a score of 0.2574. The fairly small gaps in scores among employees indicate that the performance competition was quite tight and that each individual made a competitive contribution based on the assessed criteria. This ranking reflects the comprehensive evaluation results calculated objectively through a data-based weighting and aggregation process.

3.5. Sensitivity Analysis

Sensitivity analysis is conducted to evaluate the robustness, stability, and consistency of the ranking results generated by the Multi-Normalized Ranking Approach (MUNRA) under variations in criterion weights. This analysis aims to examine the extent to which changes in the relative importance of individual criteria influence the preference values and ranking positions of the evaluated alternatives. In multi-criteria decision-making problems, the assignment of criterion weights plays an important role in determining the final ranking outcomes. Therefore, it is necessary to investigate whether the ranking results remain consistent when the initial weights are modified or whether relatively small changes in criterion importance lead to significant shifts in alternative rankings. Through this evaluation, the reliability of the MUNRA method can be assessed, particularly in terms of its ability to maintain stable ranking results under different weighting conditions.

The sensitivity analysis is performed using five evaluation criteria: Cost Efficiency, Timeliness, Supplier Quality, Procedure Compliance, and Negotiation Skills. Each criterion

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is independently subjected to four weight variation scenarios, consisting of increases and decreases of 0.05 and 0.10 from its initial weight. During each scenario, the weight of the selected criterion is modified, while the weights of the remaining criteria are proportionally adjusted to maintain the total weight equal to 1. This procedure produces 20 weight variation scenarios, in addition to the initial weighting scenario, which serves as the baseline for comparison. The resulting scenarios provide a systematic basis for examining the effects of individual criterion weight variations on the final preference values and ranking positions of the alternatives. The complete set of weight variation scenarios employed in the sensitivity analysis is presented in Table 13.

Table 13. Scenario for Testing Changes in Criteria Weights

Scenario	Cost Efficiency	Timeliness	Supplier Quality	Procedure Compliance	Negotiation Skills
Initial Weight	0.2081	0.2037	0.1754	0.1892	0.2236
CE - 0.10	0.1081	0.2294	0.1975	0.2131	0.2518
CE - 0.05	0.1581	0.2166	0.1865	0.2011	0.2377
CE + 0.05	0.2581	0.1908	0.1643	0.1773	0.2095
CE + 0.10	0.3081	0.178	0.1533	0.1653	0.1954
T - 0.10	0.2342	0.1037	0.1974	0.213	0.2517
T - 0.05	0.2212	0.1537	0.1864	0.2011	0.2376
T + 0.05	0.195	0.2537	0.1644	0.1773	0.2096
T + 0.10	0.182	0.3037	0.1534	0.1654	0.1955
SQ - 0.10	0.2333	0.2284	0.0754	0.2121	0.2507
SQ - 0.05	0.2207	0.2161	0.1254	0.2007	0.2372
SQ + 0.05	0.1955	0.1913	0.2254	0.1777	0.21
SQ + 0.10	0.1829	0.179	0.2754	0.1663	0.1965
PC - 0.10	0.2338	0.2288	0.197	0.0892	0.2512
PC - 0.05	0.2209	0.2163	0.1862	0.1392	0.2374
PC + 0.05	0.1953	0.1911	0.1646	0.2392	0.2098
PC + 0.10	0.1824	0.1786	0.1538	0.2892	0.196
NS - 0.10	0.2349	0.2299	0.198	0.2136	0.1236
NS - 0.05	0.2215	0.2168	0.1867	0.2014	0.1736
NS + 0.05	0.1947	0.1906	0.1641	0.177	0.2736
NS + 0.10	0.1813	0.1775	0.1528	0.1648	0.3236
W0 (Awal)	0.2081	0.2037	0.1754	0.1892	0.2236
CE - 0.10	0.1081	0.2294	0.1975	0.2131	0.2518

The ranking results obtained from each weight variation scenario were further analyzed to evaluate the stability and consistency of the MUNRA method in determining the priority of employee alternatives. Each scenario involved ranking the nine employees based on the resulting preference values after applying the corresponding weight adjustments. The ranking positions were then compared with the initial ranking to identify changes in alternative positions resulting from increases and decreases in criterion weights. This comparison provides an overview of the sensitivity of the ranking results to variations in the relative importance of each criterion and helps identify alternatives that maintain consistent ranking positions across different scenarios. The ranking results for all weight variation scenarios are presented graphically in Figure 3.

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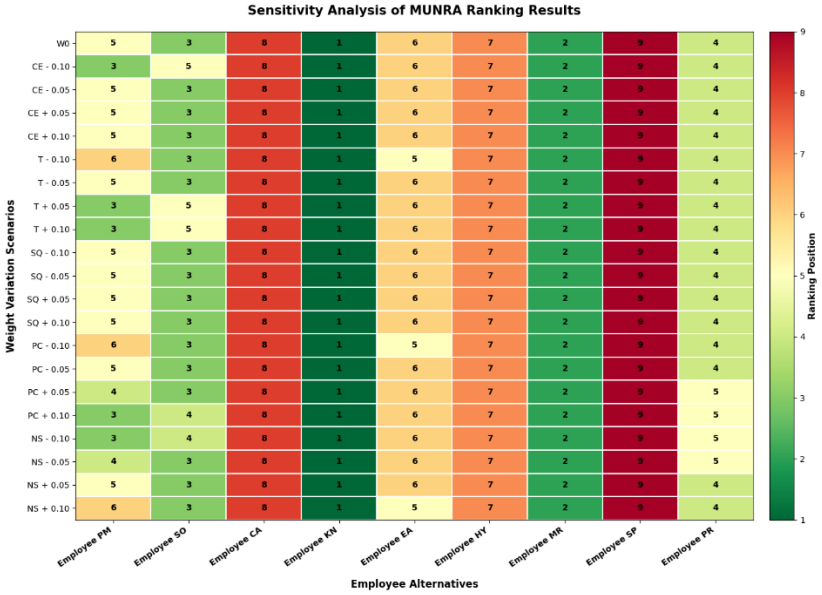

Figure 3. Alternative Ranking

Based on the sensitivity analysis presented in Figure 3, the ranking results indicate that the MUNRA method demonstrates a relatively high degree of stability across the 21 weight variation scenarios. Employee KN consistently maintains the first position, followed by Employee MR in second place, while Employee CA and Employee SP remain in eighth and ninth positions, respectively, under all scenarios. Meanwhile, Employee PM, Employee SO, Employee EA, and Employee PR experience minor ranking changes when the weights of Cost Efficiency, Timeliness, Procedure Compliance, and Negotiation Skills are adjusted. These changes indicate that variations in criterion weights can influence the relative positions of certain alternatives; however, they do not affect the highest-ranked alternative. Overall, the consistent ranking of Employee KN across all scenarios suggests that the MUNRA method provides robust and reliable ranking results, particularly in identifying the best-performing employee despite variations in criterion importance.

3.6. Discussion

The integration of the Logarithmic Decomposition of Criteria Importance (LODECI) and Multi-Normalized Ranking Approach (MUNRA) provides a quantitative framework for evaluating employee performance in the Purchasing Division by combining objective criteria weighting and multi-normalization-based ranking. The LODECI method determines criterion weights based on the degree of variation and separation among employee performance values, reducing dependence on subjective assessments during the weighting process. The results indicate that Negotiation Skills has the highest weight (0.2236), followed by Cost Efficiency (0.2081) and Timeliness (0.2037). Meanwhile, Procedure Compliance and Supplier Quality receive weights of 0.1892 and 0.1754, respectively. This distribution suggests that negotiation capabilities, cost management, and timeliness have relatively greater discriminatory contributions to the evaluation of employee performance. In the context of purchasing activities, these criteria are important because employees must communicate effectively with suppliers, manage procurement costs, and ensure that purchasing activities are completed according to established schedules. Nevertheless, the relatively balanced weight distribution indicates that employee performance cannot be determined by a single criterion but requires consideration of multiple performance dimensions.

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The application of MUNRA further extends the evaluation process by integrating three normalization approaches to represent employee performance from different computational perspectives. The use of ratio-based, vector-based, and power-based normalization allows the method to accommodate differences in data distribution and provide a more comprehensive assessment of each alternative. Based on the final preference values, Employee KN achieves the highest score of 0.2974, followed closely by Employee MR with 0.2961. The relatively small difference between these two alternatives indicates that both employees demonstrate strong overall performance across the five evaluation criteria. Employee KN obtains comparatively strong results in Cost Efficiency, Timeliness, and Procedure Compliance, whereas Employee MR achieves the highest assessment values in Supplier Quality and Negotiation Skills. This comparison demonstrates that the highest-ranked alternative is not necessarily the employee who achieves the maximum score in every individual criterion, but rather the alternative that provides the strongest overall performance after considering the weighted contributions of all criteria. Consequently, the MUNRA aggregation process provides a comprehensive basis for identifying the most suitable employee according to the established evaluation priorities.

The ranking results also reveal differences in the performance profiles of the remaining employees. Employee SO ranks third with a preference value of 0.2760, followed by Employee PR and Employee PM with scores of 0.2745 and 0.2741, respectively. The small differences among these alternatives indicate relatively competitive performance levels, particularly in relation to their overall assessment across the five criteria. Employee EA occupies the sixth position with a score of 0.2722, followed by Employee HY with 0.2631, Employee CA with 0.2608, and Employee SP with 0.2574. These results provide management with more detailed information than a simple identification of the highest-performing employee because the ranking also highlights employees whose performance is relatively close to the leading alternatives and those who may require further development. For example, employees with lower overall rankings can be evaluated more specifically by examining their individual criterion scores to identify areas requiring improvement. Therefore, the proposed evaluation framework can support not only employee recognition but also performance monitoring, professional development, and the formulation of improvement strategies within the Purchasing Division.

The sensitivity analysis provides additional evidence regarding the stability of the ranking results when the importance of individual criteria is modified. Twenty weight variation scenarios were established by increasing and decreasing each criterion's initial weight by 0.05 and 0.10, while proportionally adjusting the remaining weights to maintain a total weight of one. The results show that Employee KN consistently maintains the first position across all 21 scenarios, including the initial weighting condition. Employee MR also remains in second place, while Employee CA and Employee SP consistently occupy the eighth and ninth positions, respectively. Although minor ranking changes occur among Employee PM, Employee SO, Employee EA, and Employee PR, these variations do not affect the identification of the highest-performing employee. This finding indicates that the final selection is not dependent solely on the initial distribution of criterion weights and remains consistent under the tested variations. From a managerial perspective, such consistency is important because it provides greater confidence in using the evaluation results as a basis for employee recognition and performance-related decisions. Overall, the combined LODECI-MUNRA framework demonstrates its potential as an objective and systematic decision-support approach for Purchasing Division employee evaluation, although its application should still consider the quality of assessment data, the relevance of the selected criteria, and periodic evaluation of performance standards.

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4. CONCLUSION

The application of the LODECI and MUNRA methods in evaluating the performance of employees in the Purchasing Division is able to produce an assessment system that is objective, consistent, and stable. LODECI determines the weight of criteria rationally based on data variation, thereby minimizing subjectivity in the weighting process, while MUNRA produces rankings that are more resilient to differences in scale and value distribution through a multi-normalization approach. The integration of these two methods forms a quantitative evaluation framework that is transparent and accountable. The final results show that Kurniawan ranks first with a score of 0.2974, followed by Maharani in second place with a score of 0.2961, and Santoso in third place with a score of 0.276. These positions reflect the most optimal performance based on the overall criteria evaluated. Overall, the developed model is not only capable of accurately identifying the top three employees but also provides a comprehensive overview of the performance distribution of all alternatives. Therefore, this approach is worthy of being used as a reference in the development of decision support systems for performance evaluation that emphasize objectivity and result stability.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Auliya Rahman Isnain: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Conceptualization. **Heni Sulistiani**: Writing – original draft, Data curation, Conceptualization. **Fadila Shelly Amalia**: Writing – original draft, Software, Investigation. **Maya Septianah**: Formal Analysis, Investigation. **Rajeska Purba**: Validation, Visualization. **Sufi Annisa**: Software, Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

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

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