Employee Performance Evaluation Using RECA-based Weighting and RAWEC: Evidence from Textile Manufacturing

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Abstract. *Employee performance evaluation in the textile industry production division still faces issues of subjectivity, limited indicators, and inconsistency in ranking that do not yet reflect the real contribution of employees. This study aims to assess employee performance using a multi-criteria decision-making approach by integrating the RECA method for determining objective criterion weights and the RAWEC method for generating performance rankings. Performance data is collected based on several key criteria, namely work productivity, production quality, timeliness, work discipline, and production error rates, which reflect the operational conditions in the textile manufacturing environment. The analysis results indicate that the applied approach clearly distinguishes employee performance and produces a stable ranking, with Gina taking first place with a final score of 0.483 and Citra with a score of 0.2933. These findings indicate that RECA and RAWEC support more reliable and data-driven managerial decisions in the textile industry.*
Keywords: *Employee Performance, Textile Industry, Multi-Criteria Decision, Objective Evaluation, Performance Ranking*

Abstrak. *Evaluasi kinerja karyawan di divisi produksi industri tekstil masih menghadapi masalah subjektivitas, keterbatasan indikator, dan ketidakkonsistenan pemeringkatan yang belum mencerminkan kontribusi nyata karyawan. Penelitian ini bertujuan untuk menilai kinerja karyawan menggunakan pendekatan pengambilan keputusan multi-kriteria dengan mengintegrasikan metode RECA untuk menentukan bobot kriteria objektif dan metode RAWEC untuk menghasilkan peringkat kinerja. Data kinerja dikumpulkan berdasarkan beberapa kriteria utama, yaitu produktivitas kerja, kualitas produksi, ketepatan waktu, disiplin kerja, dan tingkat kesalahan produksi, yang mencerminkan kondisi operasional pada lingkungan manufaktur tekstil. Hasil analisis menunjukkan bahwa pendekatan yang diterapkan mampu membedakan kinerja karyawan secara jelas dan menghasilkan pemeringkatan yang stabil, di mana Gina menempati peringkat pertama dengan nilai akhir 0.483 Citra dengan nilai 0,2933. Temuan ini menunjukkan RECA dan RAWEC mendukung keputusan manajerial yang lebih andal dan berbasis data di industri tekstil.*
Kata Kunci: *Kinerja Karyawan, Industri Tekstil, Pengambilan Keputusan Multikriteria, Evaluasi Objektif, Peringkat Kinerja*

1. Introduction

Employee performance evaluation in the production division of the textile industry is an important process for ensuring the achievement of production targets, product quality, and operational efficiency on a continuous basis [1], [2]. Employee performance evaluation in the textile industry production division still faces various fundamental problems that directly impact operational effectiveness and the quality of production output [3]–[5]. The main issue lies in the use of performance indicators that are not yet comprehensively structured, where assessments often focus solely on the quantity of work results without considering quality aspects, time efficiency, production error rates, compliance with operational standards, and the ability to adapt to continuously evolving machinery and technology. In addition, the evaluation process tends to be subjective because it heavily relies on the direct supervisor's assessment, which can lead to bias, inconsistencies among evaluators, and unfairness in determining performance. As a result, performance evaluation outcomes are less able to reflect employees' actual contributions, making it difficult for management to make accurate decisions.

Multi-Attribute Decision Making (MADM) is a decision-making approach used to select or rank the best alternative based on a number of attributes or criteria that are fixed and well-defined [6]–[9]. The main challenge in MADM lies in determining representative criteria weights as well as selecting normalization and aggregation methods that can handle scale differences and conflicts between criteria objectively [6], [10], [11]. Therefore, various MADM methods, such as Simple Additive Weighting (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Combinative Distance-based Assessment (CODAS), Multi-Objective Optimization based on Ratio Analysis (MOORA), and their developments, are designed to improve ranking accuracy by balancing the contribution of each criterion, so that decision outcomes can reflect real conditions and support a rational and systematic decision-making process.

Challenges in determining criteria weights and the ranking process objectively in multi-criteria evaluation mainly arise due to the complexity of the relationships between criteria, differences in measurement scales, and the heterogeneity of data used in the assessment process [12], [13]. The determination of criteria weights is often still influenced by the subjective preferences of decision-makers, which can potentially lead to bias and inconsistency, especially when the number of criteria increases and they have overlapping levels of importance. As a result, multi-criteria evaluation outcomes are often unstable with small changes in data, making it difficult for decision-makers to obtain rankings that truly reflect the relative performance of alternatives objectively and reliably.

The Respond to Criteria (RECA) method is a weighting approach in Multi-Attribute Decision Making aimed at producing objective criteria weights by considering the characteristics and data responses for each evaluated criterion [14], [15]. The basic principle of RECA emphasizes that the importance level of a criterion is determined by how well the criterion can distinguish performance among alternatives, so the weights are not set based on the subjective judgment of decision-makers, but are systematically calculated from the available data patterns. This approach is effectively used in heterogeneous multicriteria data conditions because it can maintain weight consistency, reduce assessor bias, and improve the reliability of evaluation results as a basis for rational and data-driven decision making.

The Ranking of Alternatives with Weights of Criterion (RAWEC) method is a ranking approach in Multi-Attribute Decision Making that focuses on consistently combining the performance of alternatives and the weights of criteria to produce a representative order of alternatives [16]–[18]. In this method, each alternative is evaluated based on the normalized performance scores across all criteria, and then combined with the criterion weights reflecting the relative importance of each attribute. The RAWEC method's advantage lies in its ability to maintain a balance between the influence of criteria and the performance of alternatives, making it more sensitive in distinguishing alternatives with similar evaluation scores [19], [20]. With these characteristics, RAWEC is capable of producing rankings that are stable, logical, and easy to interpret, making it effective as a basis for objective and systematic multi-criteria decision-making.

The combination of the RECA and RAWEC methods offers a complementary solution in multi-criteria decision-making that requires objectivity and consistency of results. RECA plays a role in the weighting stage by producing data-driven criterion weights, thereby reducing the dominance of subjectivity and reflecting the actual contribution of each criterion in differentiating alternatives. The weights produced are then used by RAWEC in the ranking stage to aggregate the performance values of alternatives proportionally according to the importance levels of the criteria. The integration of these two methods allows the evaluation process to be conducted systematically, starting from the determination of rational weights to the compilation of stable and easily interpretable alternative rankings.

This study aims to develop a well-defined methodological contribution within the Multi-Attribute Decision Making framework by integrating RECA for deriving objective criterion weights based on data characteristics and RAWEC for generating robust. Overall, this work contributes by introducing a coherent model that strengthens analytical rigor while offering a transparent, fair, and data-driven basis to support managerial decision-making in human resource evaluation within complex industrial environments such as textile production.

2. Literature Review

Recent research shows that the use of Decision Support Systems (DSS) is becoming increasingly important in enhancing the objectivity of employee performance evaluations. Research from [21] emphasizes that DSS can integrate various criteria such as job performance, discipline, communication, and responsibility into a more structured assessment system. The results of this systematic literature review also indicate that methods such as SAW, AHP, and TOPSIS are the most frequently used approaches in DSS to produce more accurate and consistent decisions. In addition, this research highlights the importance of flexible weighting mechanisms so that the system can adapt to the needs of a dynamic organization. However, most research still uses static weighting approaches that are not yet able to capture changes in performance data distribution in real-time.

Furthermore, research by [22] developed a DSS based on the Analytical Hierarchy Process (AHP) for employee performance evaluation and bonus allocation. This study shows that the application of AHP in DSS can improve transparency and fairness in decision-making compared to manual methods. The system also provides a clear hierarchical structure in determining the priority of criteria, making multi-criteria decision-making easier. Nevertheless, the AHP method has limitations in terms of assessment consistency and sensitivity to expert subjectivity, especially when the number of criteria and alternatives increases. In addition, most of the systems developed still stand alone and have not integrated a hybrid approach that can improve the accuracy of ranking results.

Furthermore, recent research is beginning to lead towards the development of DSS based on hybrid methods and web-based to improve system accuracy and efficiency. Research from [23] combines AHP and SAW to produce a more comprehensive evaluation system, while research from [24] Group decision support system for employee performance evaluation using combined simple additive weighting and Borda implements the SMART method in a web-based DSS, which has been proven capable of reducing subjective bias. Therefore, the novelty of this research lies in the development of an employee performance evaluation DSS that integrates objective weighting methods with more stable ranking methods, and is equipped with sensitivity tests to ensure the consistency of decision results. This approach is expected to produce an evaluation system that is more objective, adaptive, and accurate compared to previous studies.

3. Methodology

3.1. Research Stage

The research stages were carried out through structured and sequential steps, starting with determining relevant evaluation aspects in accordance with the evaluation objectives, followed by the collection and processing of performance data to form the basis for analysis [25]. The determination of evaluation aspects is carried out by considering their suitability to the assessment objectives, so that each criterion can represent performance conditions relevantly. The performance data used is collected from valid sources and reflects actual operational activities, then processed consistently to form a strong basis for analysis. This approach is designed so that the evaluation results are not only descriptive but also capable of providing a clear picture of performance differences between alternatives. The research stages conducted are shown in Figure 1.

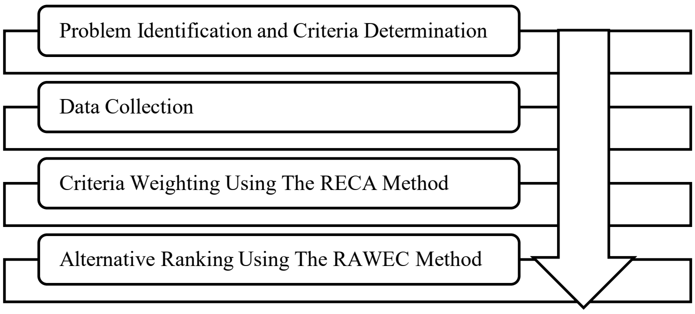

Figure 1. Research Stage

The research flow begins with problem identification and the determination of criteria aimed at establishing relevant assessment aspects according to the evaluation objectives. The next stage is data collection to obtain accurate and representative performance information as the basis for analysis. The collected data is then used in the criteria weighting stage using the RECA method to determine the level of importance of each criterion objectively based on data characteristics. The final stage is the process of ranking alternatives using the RAWEC method, where the weighted performance values are processed to produce a consistent order of alternatives that can be used as a basis for decision-making.

The application of the RECA and RAWEC methods in performance evaluation provides important implications both methodologically and practically. From a methodological perspective, the use of RECA allows for the determination of criteria weights objectively based on data, thereby reducing dependence on the subjectivity of evaluators and increasing consistency in the evaluation process. Its integration with RAWEC produces more stable rankings and can distinguish individual performance more clearly, even under varying data conditions. From a practical perspective, this approach encourages the creation of a more transparent and fair assessment system, thereby boosting employee confidence in the evaluation results. In addition, accurate ranking results can be used as a basis for strategic decision-making, such as providing incentives, promotions, or training planning, thereby contributing to increased productivity and effectiveness in human resource management, especially in a production industry environment.

3.2. RECA Method

The RECA method is a weighting approach in multi-criteria decision-making that emphasizes the use of data characteristics to determine the importance level of each criterion objectively. RECA works by analyzing the variation and response of criterion values to the evaluated alternatives, so that the resulting weights reflect the criteria's ability to distinguish performance effectively. This approach reduces reliance on subjective judgments of decision-makers and maintains consistency of weights, especially when the data is heterogeneous. With these characteristics, RECA is effective for producing rational, data-based criterion weights as a foundation for more accurate evaluation and ranking.

A decision matrix is an initial representation of data that presents the performance values of each alternative against all the criteria used in the evaluation. This matrix serves as the basis for analysis because it depicts the actual condition of the alternatives in a structured manner and allows for comparison between alternatives on each criterion, as shown in Equation 1.

$$X = [x_{ij}]_{mxn} \qquad (1)$$

In equation (1), the symbol X represents the entire matrix containing performance data, while x_{ij} is the element that represents the value of the i^{th} alternative with respect to the j^{th} criterion.

The notation m indicates the number of alternatives evaluated, and n represents the number of criteria used in the assessment. The purpose of this representation is to organize the data systematically so that each alternative can be directly compared based on all relevant criteria.

Preference values describe the degree of inclination or relative advantage of an alternative based on its performance values on certain criteria. These values reflect how well an alternative meets the established criteria and are an important component in the assessment aggregation process, as shown in Equation 2.

$$PV_{ij} = \frac{x_{ij}}{\sqrt[n]{\prod_{i=1}^{m} x_{ij}}} \tag{2}$$

In equation (2), the symbol PV_{ij} indicates the preference value of the i-th alternative for the j-th criterion, while x_{ij} is the initial performance value at that position. The parameter m is the number of alternatives, while n refers to the number of elements in the root calculation process (usually the number of alternatives for that criterion). The purpose of this equation is to measure the relative tendency of each value to the overall distribution of data for the same criterion, thereby producing values that are more proportional and can be compared objectively in the next stage of analysis.

Normalization values are the result of transforming values in the decision matrix into a comparable scale so that differences in units and data ranges between criteria do not affect the evaluation results. Normalization ensures that each criterion has a fair contribution in the subsequent calculation process, as shown in Equation 3.

$$R_{ij} = \frac{PV_{ij}}{PV_{ij}^{max}} \tag{3}$$

In equation (3), the symbol R_{ij} j represents the normalized value for the ith alternative on the jth criterion. The purpose of this equation is to convert the preference values into a uniform range, generally between 0 and 1, so that differences in scale between criteria do not affect the evaluation results.

The standard value of a criterion is a reference value obtained from processing the criterion data to describe general characteristics, such as the average value or other measures of central tendency. This value is used as a comparison to assess deviations or performance differences between alternatives for each criterion, as shown in Equation 4.

$$N_j = \frac{1}{n} * \sum_{i=1}^{m} R_{ij} \tag{4}$$

In equation (4), the symbol N_j represents the average value of the jth criterion. The purpose of this equation is to obtain a representative value that describes the general characteristics of each criterion, so that it can be used as a reference in measuring the level of dispersion or variation of values in the next stage of analysis.

The variation value of a criterion indicates the level of dispersion or diversity of values for each criterion across all alternatives. The greater the variation a criterion has, the greater its ability to differentiate the performance of alternatives, making that criterion more significant in the evaluation, as shown in Equation 5.

$$\emptyset_j = \sum_{i=1}^{m} \left(R_{ij} - N_j\right)^2 \tag{5}$$

In equation (5), the symbol $\emptyset_j$ represents the level of dispersion or diversity of values in the jth criterion. The purpose of this equation is to measure the extent to which the values in a criterion are spread from their central value, so that the ability of the criterion to differentiate performance among alternatives can be known. The greater the variation value, the higher the role of the criterion in contributing to the evaluation process.

The preference variation value is a measure that describes the degree of tendency for changes or the spread of performance values in a criterion across all alternatives. This value reflects how significant the preference differences generated by a criterion are, indicating the criterion's ability to effectively distinguish between alternatives. The higher the preference variation value, the greater the criterion's contribution to influencing the evaluation results, as the criterion has a stronger distinguishing power compared to a criterion with a low preference variation value, as shown in Equation 6.

$$\varphi_j = \left|1 - \emptyset_j\right| \tag{6}$$

In equation (6), the symbol φ_j on the left side represents the preference value of the jth criterion variation, and the notation $|\cdot|$ denotes the absolute value, which ensures that the calculation result is always positive. The purpose of this equation is to convert the variation values into preference measures that reflect the relative importance of a criterion, where higher values indicate a more significant contribution in distinguishing alternatives.

The weight of a criterion represents the value that reflects the relative importance of each criterion in the decision-making process. This weight is determined based on the data characteristics and the variation value of the criteria, thus reflecting the actual contribution of each criterion in objectively differentiating the alternatives, as shown in Equation 7.

$$w_j = \frac{\varphi_j}{\sum_{j=1}^{n} \varphi_j} \tag{7}$$

In equation (7), the symbol w_j represents the weight of the jth criterion. The purpose of this equation is to perform normalization so that all criterion weights have a total value of 1, while also reflecting the relative importance level of each criterion proportionally.

The RECA method provides a framework for weighting criteria that is rational and data-driven, emphasizing the ability of each criterion to differentiate the performance of alternatives. Through analysis of data characteristics and variations, RECA can produce more objective and consistent criterion weights, thereby reducing reliance on subjective judgment. With weights that represent the actual contribution of each criterion, this method serves as a strong foundation for subsequent evaluation and ranking processes, as well as supporting more accurate and accountable multi-criteria decision-making.

3.3. RAWEC Method

The RAWEC method is a ranking approach in multi-criteria decision making that integrates the performance values of alternatives and the weights of criteria to produce a comprehensive order of alternatives. This method works by combining normalized values with the criteria weights, so that each criterion contributes according to its level of importance in the calculation of the final score. RAWEC is designed to maintain a balance between the performance of alternatives and the influence of criteria, making it capable of distinguishing alternatives with closely valued evaluations more clearly. With stable and easily interpretable ranking results, RAWEC is effectively used as a basis for objective and data-driven decision-making. The stages in the RAWEC method are as follows.

The decision matrix is the initial stage that presents the performance values of each alternative against all criteria in a structured table. This matrix serves as the basis for calculations because it represents the actual conditions of the alternatives and allows direct comparison on each criterion using Equation 1.

Normalization is carried out to convert the values in the decision matrix into a comparable scale, so that differences in units and value ranges between criteria do not affect the evaluation results. This stage ensures that all criteria have a fair calculation basis before being combined as shown in Equations 8 and 9.

$$n_{ij} = \frac{x_{ij}}{\max x_{ij}}; and\ n_{ij}' = \frac{\min x_{ij}}{x_{ij}}; benefit\ criteria \tag{8}$$

$$n_{ij} = \frac{\min x_{ij}}{x_{ij}}; and\ n_{ij}' = \frac{x_{ij}}{\max x_{ij}}; cost\ criteria \tag{9}$$

In equations (8) and (9), the symbol n_{ij} represents the main normalization value of the i^{th} alternative for the j^{th} criterion, while n_{ij}' is the comparative normalization value used as a pair in the analysis. For benefit criteria, n_{ij} is calculated with reference to the maximum value because a higher value is preferred, whereas n_{ij}' uses the minimum value as a comparison. Conversely, for cost criteria, n_{ij} refers to the minimum value because a lower value is better, and n_{ij}' uses the maximum value as a comparison. The purpose of this approach is to standardize the data scale while maintaining the preference direction of each criterion, so that all alternatives can be compared fairly and consistently in subsequent evaluation processes.

Deviation from the criterion weight describes the degree of deviation of an alternative's performance value from the predetermined criterion weight. This process aims to assess the extent to which an alternative's performance aligns with or deviates from the importance level of the criteria, so that the contribution of each criterion to the alternative can be proportionally reflected as shown in Equations 10 and 11.

$$v_i = \sum_{i=1}^{m} w_j * (1 - n_{ij}) \tag{10}$$

$$v_i' = \sum_{i=1}^{m} w_j * (1 - n_{ij}') \tag{11}$$

In equations (10) and (11), the symbol v_i represents the total deviation of the third alternative from the ideal value using the main normalization value n_{ij}, whereas v_i' is the comparative deviation calculated using the normalization value of the alternative n_{ij}'. The purpose of this calculation is to measure the degree of closeness or deviation of the alternative from the ideal value, which then becomes the basis for determining the final value and the ranking process.

The final value of an alternative is the result of aggregating all performance scores of each alternative. This value is used as the basis for ranking, where the alternative with the highest final value indicates performance closest to the desired condition in the decision-making process, as shown in Equation 12.

$$Q_i = \frac{v_i' - v_i}{v_i' + v_i} \tag{12}$$

In equation (12), the symbol Q_i represents the final score of the i^{th} alternative, which is obtained from the comparison between two deviation values, namely v_i' as the comparative deviation, and v_i as the main deviation. The purpose of this equation is to produce an aggregate value that can clearly and consistently distinguish the performance of alternatives, so that it can be used directly in determining the ranking order from the best to the lowest.

The RAWEC method provides a logical and consistent ranking approach by proportionally integrating alternative performance and criterion weights. Through the process of normalization and evaluation of deviations from criterion weights, this method is able to produce final alternative values that more accurately reflect relative performance. With stable and easily interpretable ranking results, RAWEC becomes an effective tool for supporting objective and accountable multi-criteria decision-making.

4. Result and Discussion

This study discusses an approach to employee performance evaluation that focuses on the objectivity and consistency of assessments in a textile production environment characterized by complex work and diverse performance data. The integration of data-based criteria weighting and alternative ranking that considers the level of criteria importance allows evaluation results to reflect more realistic performance conditions, especially when there are differences in abilities, workloads, and achievements among employees. This study reinforces the role of performance evaluation as a strategic instrument that not only assesses achievements but also promotes continuous performance improvement and the competitiveness of the textile industry. In addition, this study provides practical contributions to management by offering a strong analytical basis for decision-making related to human resource management, so that performance evaluation is not only administrative in nature but also serves as a strategic tool for improving productivity and production quality.

4.1. Problem Identification and Criteria Determination

Problem Identification and Criteria Determination begin with identifying the main issues that arise in the performance evaluation system, particularly related to inaccurate assessments, potential biases, and discrepancies between evaluation results and individuals' actual contributions to achieving organizational targets. Therefore, problem identification is conducted in depth to understand the root causes of evaluation challenges, from the perspectives of processes, data, and decision-making needs, so that the objectives of the evaluation can be clearly and effectively formulated.

The stage of determining criteria is then carried out by establishing assessment aspects that are relevant, measurable, and directly related to the objectives of performance evaluation. Each criterion is selected based on its ability to objectively represent performance dimensions and distinguish the level of contribution among individuals. This process ensures that the criteria used are not overlapping and are able to accurately capture performance variations, thereby forming a consistent, logical, and accountable basis for the next stage of analysis. Table 1 shows the criteria used in the assessment.

Table 1. Assessment Criteria

Criteria Code	Criteria Name	Type of Criteria	Criteria Description
K1	Work Productivity	Benefit	Measuring employees' ability to produce output according to targets within a certain period. The higher the level of productivity, the better the employee's performance.
K2	Production Quality	Benefit	Shows the level of conformity of work results with the quality standards set by the company, including minimal product defects.
K3	Punctuality	Benefit	Describes the employee's ability to complete work according to the schedule and the specified production time targets.
K4	Work Discipline	Benefit	Reflecting employees' compliance with work rules, working hours, and operational procedures in the production environment.
K5	Production Error Rate	Cost	Indicates the frequency of errors or defects produced during the work process. Lower values indicate better performance.

The criteria data form the foundation for objective and consistent performance evaluation. Clear selection of benefit and cost criteria ensures proportional assessment and supports fair, transparent, and accountable decision-making. The validation of criteria in this study was carried out through expert assessment, specifically involving managers in the production field as parties who have a direct understanding of work processes, operational standards, and relevant performance indicators in the industrial environment. The involvement of production managers ensures that each criterion used truly reflects real conditions in the field and is able to accurately represent employee contributions.

4.2. Data Collection

Data collection in performance evaluation is conducted to obtain accurate, relevant information that reflects actual performance conditions. The data collection process is carried out systematically to ensure that the data aligns with established criteria, so that each value used truly represents performance achievements. Additionally, the timing of data collection is also considered to allow for fair performance comparisons and to avoid being affected by temporary fluctuations.

Alternative assessment data is a collection of performance values that represent the achievements of each alternative against all established criteria. This data is obtained from relevant performance measurements and is organized in a structured manner to allow objective comparisons between alternatives. Each value reflects the level of achievement of an alternative in a specific aspect, so the overall data can comprehensively depict performance variations. With accurate and consistent alternative assessment data, the evaluation process can produce rankings that more accurately and reliably reflect relative performance. The assessment data for the alternatives are presented in Table 2.

Table 2. Alternative Assessment Data

Alternative	K1	K2	K3	K4	K5
Andi	85	88	90	87	5
Budi	80	82	85	83	7
Citra	90	91	88	89	4
Dedi	78	80	82	81	8
Eko	88	86	92	90	6
Fajar	83	84	87	85	6
Gina	92	93	91	92	3
Hadi	76	78	80	79	9
Indra	87	89	86	88	5

Table 2 shows the performance evaluation data of nine employees based on five main criteria. The first four criteria are benefit criteria, while the Production Error Rate is a cost criterion, meaning that lower values indicate better performance. This data is used as the basis for performance evaluation analysis and objective employee ranking.

4.3. Criteria Weighting Using the RECA Method

Criteria weighting using the RECA method focuses on determining the weights of criteria objectively by utilizing the characteristics of the available assessment data. This approach evaluates the importance level of each criterion based on its ability to differentiate performance among alternatives, so that the resulting weights reflect the actual contribution of each criterion in the evaluation process. By considering the variation and distribution patterns of criterion scores, RECA produces a weighting that is more consistent and not dependent on the subjective preferences of the assessors. Therefore, criteria weighting using the RECA method provides a strong, data-driven basis to support a more accurate and accountable evaluation and ranking process.

The first step in determining weights using the RECA method is to create a decision matrix, which is the initial representation of data showing the performance values of each alternative against all the criteria used in the evaluation, using equation (1). The resulting RECA decision matrix is as follows.

$$X=\begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} \end{bmatrix} \qquad X=\begin{bmatrix} 85 & 88 & 90 & 87 & 5 \\ 80 & 82 & 85 & 83 & 7 \\ 90 & 91 & 88 & 89 & 4 \\ 78 & 80 & 82 & 81 & 8 \\ 88 & 86 & 92 & 90 & 6 \\ 83 & 84 & 87 & 85 & 6 \\ 92 & 93 & 91 & 92 & 3 \\ 76 & 78 & 80 & 79 & 9 \\ 87 & 89 & 86 & 88 & 5 \end{bmatrix}$$

The second stage in determining weights using the RECA method is calculating the preference values, which represent the degree of tendency or relative superiority of an alternative based on its performance values on certain criteria using equation (2). The results of the RECA method preference values are as follows.

$$PV_{11}=\frac{x_{11}}{\sqrt[9]{\prod_{i=1}^{m} x_{i1}}}=\frac{85}{\sqrt[9]{85*80*90*78*88*83*92*76*87}}=\frac{85}{84.172401}=1.0098$$

The overall calculation results of preference values calculated using equation (2) from the RECA method are presented in Table 3.

Table 3. Preference Value

Alternative	K1	K2	K3	K4	K5
Andi	1.0098	1.0289	1.0381	1.0128	0.8924
Budi	0.9504	0.9587	0.9805	0.9662	1.2493
Citra	1.0692	1.0639	1.0151	1.0361	0.7139
Dedi	0.9267	0.9353	0.9459	0.9429	1.4278
Eko	1.0455	1.0055	1.0612	1.0477	1.0708
Fajar	0.9861	0.9821	1.0035	0.9895	1.0708
Gina	1.0930	1.0873	1.0497	1.0710	0.5354
Hadi	0.9029	0.9119	0.9228	0.9197	1.6063
Indra	1.0336	1.0405	0.9920	1.0244	0.8924

The third step in determining weights using the RECA method is calculating the normalization value, which is the result of transforming the values in the decision matrix into a comparable scale so that differences in units and data ranges among the criteria do not affect the evaluation results using equation (3). The normalization values for the RECA method are as follows.

$$R_{11}=\frac{PV_{11}}{PV_1^{max}}=\frac{1.0098}{1.0930}=0.9239$$

The overall calculation results of normalization values calculated using equation (3) from the RECA method are presented in Table 4.

Table 4. Normalization Value

Alternative	K1	K2	K3	K4	K5
Andi	0.9239	0.9462	0.9783	0.9457	0.5556
Budi	0.8696	0.8817	0.9239	0.9022	0.7778
Citra	0.9783	0.9785	0.9565	0.9674	0.4444
Dedi	0.8478	0.8602	0.8913	0.8804	0.8889
Eko	0.9565	0.9247	1.0000	0.9783	0.6667
Fajar	0.9022	0.9032	0.9457	0.9239	0.6667
Gina	1.0000	1.0000	0.9891	1.0000	0.3333
Hadi	0.8261	0.8387	0.8696	0.8587	1.0000
Indra	0.9457	0.9570	0.9348	0.9565	0.5556

The fourth stage in determining weights using the RECA method is calculating the standard value of the criteria, which is a reference value obtained from processing the criteria data to describe general characteristics, such as the average value or other measures of central tendency. Using equation (4), the standard criterion values for the RECA method are as follows.

$$N_1 = \frac{1}{9} * (0.9239 + 0.8696 + 0.9783 + 0.8478 + 0.9565 + 0.9022 + 1.0000 + 0.8261 + 0.9457)$$

$$N_1 = \frac{1}{9} * (8.2500) = 0.9167$$

The result of the overall standard value calculation calculated using equation (4) from the RECA method, where K1 has a value of 0.9167, K2 is 0.9211, K3 reaches 0.9432, K4 is 0.9348, and K5 has the lowest value of 0.6543.

The fifth stage in determining weights using the RECA method is calculating the criterion variation value, which shows the level of dispersion or diversity of values for each criterion across all alternatives using equation (5). The results of the criterion variation values using the RECA method are as follows.

$$\emptyset_1 = \sum_{i=1}^{m} (R_{i1} - N_1)^2$$

$$\emptyset_1 = (0.0001 + 0.0022 + 0.0038 + 0.0047 + 0.0016 + 0.0002 + 0.0069 + 0.0082 + 0.0008)$$

$$\emptyset_1 = 0.0286$$

The overall calculation results of the criterion variation values calculated using equation (5) from the RECA method, where K1 is 0.0286, K2 is 0.0238, K3 is 0.0153, K4 is 0.0177, and K5 has a significantly higher value of 0.3567.

The eighth stage in determining weights using the RECA method is calculating the preference variation value, which is a measure that describes the degree of tendency for changes or the spread of performance values in a criterion across all alternatives using (6). The results of the preference variation value using the RECA method are as follows.

$$\varphi_1 = |1 - \emptyset_1| = |1 - 0.0286| = 0.9714$$

The overall calculation results of preference variation value calculated using equation (6) from the RECA method, where K1 is 0.9714, K2 is 0.9762, K3 reaches 0.9847, K4 is 0.9823, and K5 is 0.6433.

The final stage in determining the weights using the RECA method is calculating the criterion weight values, which are values that represent the relative importance of each criterion in the decision-making process using equation (7). The results of the criteria weight values in the RECA method are as follows.

$$w_1 = \frac{0.9714}{0.9714 + 0.9762 + 0.9847 + 0.9823 + 0.6433} = \frac{0.9714}{4.5579} = 0.2131$$

The overall calculation results of the criteria weight values calculated using equation (7) from the RECA method, where K1 is 0.2131, K2 is 0.2142, K3 has the highest weight at 0.2160, K4 is 0.2155, and K5 has the lowest weight at 0.1411.

The weighting results show that Punctuality (K3) has the highest weight at 0.2160, indicating that punctuality is the most influential aspect in performance evaluation. Next, Work Discipline (K4) receives a weight of 0.2155, followed by Production Quality (K2) at 0.2142 and Work Productivity (K1) at 0.2131, indicating that these four criteria have relatively balanced importance and all play a crucial role in assessing overall performance. Meanwhile, the Production Error Rate (K5) has the lowest weight at 0.1411, indicating that the production error rate contributes less compared to the other criteria, although it still serves as a supporting factor in differentiating employee performance. This weight distribution reflects a proportional and data-driven assessment, thus supporting an objective and consistent performance evaluation process.

4.4. Alternative Ranking Using the RAWEC Method

Alternative ranking using the RAWEC method focuses on arranging alternative rankings based on the combination of performance scores that have been normalized with criterion weights reflecting the relative importance of each assessment aspect. This approach produces final alternative values that represent overall performance proportionally, enabling fair comparisons between alternatives. Through a consistent ranking mechanism, this method can differentiate alternatives with close performance values and generate a stable ranking order. The resulting rankings provide a clear and easily understandable analytical basis to support objective, data-driven decision-making.

The first stage in ranking alternatives using the RAWEC method is creating a decision matrix, which is an initial representation of data that presents the performance values of each alternative against all the criteria used in the evaluation using equation (1). The results of the RAWEC decision matrix are as follows.

$$X = \begin{bmatrix} 85 & 88 & 90 & 87 & 5 \\ 80 & 82 & 85 & 83 & 7 \\ 90 & 91 & 88 & 89 & 4 \\ 78 & 80 & 82 & 81 & 8 \\ 88 & 86 & 92 & 90 & 6 \\ 83 & 84 & 87 & 85 & 6 \\ 92 & 93 & 91 & 92 & 3 \\ 76 & 78 & 80 & 79 & 9 \\ 87 & 89 & 86 & 88 & 5 \end{bmatrix}$$

The second stage in ranking alternatives using the RAWEC method is calculating the normalization value, which is done to convert the values in the decision matrix into a comparable scale, so that differences in units and value ranges between criteria do not affect the evaluation results using equations (8) and (9). The normalization values of the RAWEC method are as follows.

$$n_{11} = \frac{x_{ij}}{\max x_{ij}} = \frac{85}{92} = 0.9239\,;\, n_{11}{}' = \frac{\min x_{ij}}{x_{ij}} = \frac{76}{85} = 0.9239$$

The overall calculation results of normalization values calculated using equations (8) and (9) from the RAWEC method are presented in Table 5.

Table 5. Normalization Value

			Score Results n_{ij}		
Alternative	**K1**	**K2**	**K3**	**K4**	**K5**
Andi	0.9239	0.9462	0.9783	0.9080	0.5556
Budi	0.8696	0.8817	0.9239	0.9518	0.7778
Citra	0.9783	0.9785	0.9565	0.8876	0.4444
Dedi	0.8478	0.8602	0.8913	0.9753	0.8889
Eko	0.9565	0.9247	1.0000	0.8778	0.6667
Fajar	0.9022	0.9032	0.9457	0.9294	0.6667
Gina	1.0000	1.0000	0.9891	0.8587	0.3333
Hadi	0.8261	0.8387	0.8696	1.0000	1.0000
Indra	0.9457	0.9570	0.9348	0.8977	0.5556
			Score Results $n_{ij}{}'$		
Alternative	**K1**	**K2**	**K3**	**K4**	**K5**
Andi	0.8941	0.8864	0.8889	0.9080	0.5556
Budi	0.9500	0.9512	0.9412	0.9518	0.7778
Citra	0.8444	0.8571	0.9091	0.8876	0.4444
Dedi	0.9744	0.9750	0.9756	0.9753	0.8889
Eko	0.8636	0.9070	0.8696	0.8778	0.6667
Fajar	0.9157	0.9286	0.9195	0.9294	0.6667

Gina	0.8261	0.8387	0.8791	0.8587	0.3333
Hadi	1.0000	1.0000	1.0000	1.0000	1.0000
Indra	0.8736	0.8764	0.9302	0.8977	0.5556

The second stage in ranking alternatives using the RAWEC method is calculating the deviation from the criterion weight, which illustrates the degree of deviation of the alternative performance values from the established criterion weights using equations (10) and (11). The results of the Deviation from the criterion weight using the RAWEC method are as follows.

$$v_1 = \sum_{i=1}^{m} w_j * (1 - n_{ij})$$
$$v_1 = (w_1 * (1 - n_{11})) + (w_2 * (1 - n_{21})) + (w_3 * (1 - n_{31})) + (w_4 * (1 - n_{41}) + (w_5 * (1 - n_{51})))$$
$$v_1 = (0.2131 * (1 - 0.9239)) + (0.2142 * (1 - 0.9462)) + (0.2160 * (1 - 0.9783)) + (0.2155 * (1 - 0.9080)) + (0.1411 * (1 - 0.5556))$$
$$v_1 = 0.0162 + 0.0115 + 0.0047 + 0.0117 + 0.0565$$
$$v_1 = 0.1006$$

The overall calculation results of normalization values calculated using equations (10) and (11) from the RAWEC method are presented in Table 6.

Table 6. Deviation from the Criterion Weight Value

Alternative	v_i	v_i'
Andi	0.1006	0.1535
Budi	0.1713	0.0756
Citra	0.0609	0.1860
Dedi	0.1998	0.0371
Eko	0.1006	0.1506
Fajar	0.1403	0.1129
Gina	0.0023	0.2223
Hadi	0.2243	0.0000
Indra	0.1007	0.1533

The final stage in ranking alternatives using the RAWEC method is to calculate the final value of the alternatives, which is the result of the aggregation of all performance values of each alternative using (12). The final value of the alternatives using the RAWEC method is as follows.

$$Q_1 = \frac{v_1' - v_1}{v_1' + v_1} = \frac{0.1535 - 0.1006}{0.1535 + 0.1006} = \frac{0.0529}{0.2541} = 0.2081$$

The overall calculation results of the final value of the alternatives calculated using equation (12) from the RAWEC method are presented in Table 7.

Table 7. Final Value of the Alternatives

Alternative	Q_i
Andi	0.2081
Budi	-0.3878
Citra	0.5064
Dedi	-0.6869
Eko	0.1987
Fajar	-0.1081
Gina	0.9791
Hadi	-1.0000
Indra	0.2069

Alternative ranking is carried out to determine the performance order based on the final scores that comprehensively reflect the contribution of each criterion. Each alternative obtains an aggregate score resulting from the combination of performance values and the importance level of the criteria, so performance differences between alternatives can be clearly identified. Alternatives with the highest scores are placed at the top rank because they show performance closest to the desired conditions, while alternatives with lower scores indicate the need for improvement in certain aspects. The results of this ranking provide a comprehensive overview of the relative position of each alternative and serve as an objective basis for rational and accountable decision-making. The ranking of alternatives using the RAWEC method is shown in Figure 2.

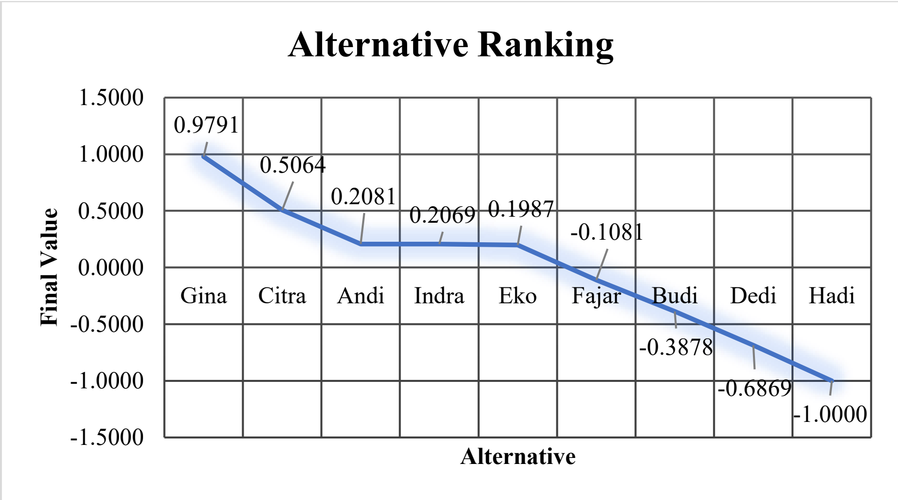

Figure 2. Alternative Ranking using the RAWEC Method

The ranking results of employee performance are based on the final scores generated by the method used. Gina occupies the highest position with a score of around 0.9791, followed by Citra with 0.5064, which shows a significant difference compared to the other alternatives. The middle group consists of Andi (0.2081), Indra (0.2069), and Eko (0.1987) with relatively close scores, reflecting an almost balanced performance level. Meanwhile, Fajar starts to show a negative score (-0.1081), followed by Budi (-0.3878), Dedi (-0.6869), and up to Hadi, who is in the last position with the lowest score (-1.0000). This pattern illustrates the ability of the RAWEC method to gradually and consistently differentiate the performance of alternatives based on overall evaluation scores.

4.5. Sensitivity Analysis

Sensitivity analysis in this study was conducted to examine the extent to which changes in the criteria weights affect the final ranking results of alternatives, so that the robustness and reliability of the model used can be determined. This approach is important because, in the context of multi-criteria decision-making, criterion weights are often the most influential factor on evaluation results, and even small changes can potentially shift the ranking order. Therefore, a series of test scenarios was conducted with systematic variations in increasing and decreasing weights to observe the model's response to these changes. Through this analysis, it is possible not only to identify alternatives that are sensitive to changes but also to evaluate whether the model can maintain ranking consistency under various conditions.

The testing scenario was carried out by increasing the weight of each criterion by 0.05 to analyze the model's sensitivity to changes in the importance level of the criteria. This adjustment aims to observe the extent to which a uniform increase in weight can affect the evaluation results and the stability of the ranking of alternatives. After re-normalization to ensure the total weight remains proportional, the recalculation process produces preference values and alternative rankings, which are then compared with the initial condition. The results of this scenario show that weight changes have a certain impact on the final values of each alternative, but in general, the ranking pattern remains relatively stable, especially for the top-performing and lowestperforming alternatives. Detailed results of the calculations from the scenario of a 0.05 weight increase for each criterion are presented in Table 8.

Table 8. Scenario of Increased Criteria Weight by 0.05

Test	K1	K2	K3	K4	K5
Initial Weight Using the RECA Method	0.2131	0.2142	0.2160	0.2155	0.1411
The weight of Criterion K1 is increased by 0.05 (Test 1)	0.2506	0.2040	0.2057	0.2053	0.1344
The weight of Criterion K2 is increased by 0.05 (Test 2)	0.2030	0.2516	0.2057	0.2053	0.1344
The weight of Criterion K3 is increased by 0.05 (Test 3)	0.2030	0.2040	0.2534	0.2053	0.1344
The weight of Criterion K4 is increased by 0.05 (Test 4)	0.2030	0.2040	0.2057	0.2529	0.1344
The weight of Criterion K5 is increased by 0.05 (Test 5)	0.2030	0.2040	0.2057	0.2053	0.1820

The ranking results from the scenario of increasing the weight by 0.05 based on the weight changes in Table 8 for each criterion are shown in Figure 3.

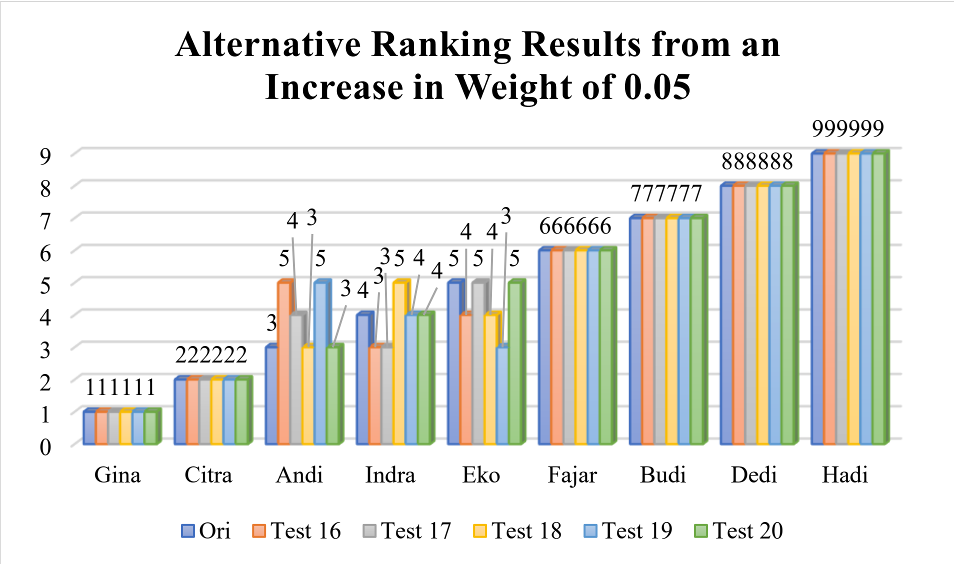

Figure 3. Ranking Results from the Scenario of Increasing the weight by 0.05

The ranking results of the alternatives after increasing the weight by 0.05 for each criterion, where the resulting ranking pattern still shows consistency with the initial condition. The alternative with the best performance still occupies the top position with a clear score difference compared to other alternatives, while the group of alternatives at the middle level shows relatively slight score differences, causing small shifts in the ranking order. On the other hand, the alternative with the lowest performance remains at the bottom position, reflecting that the weight change does not have a significant impact on the overall ranking structure.

The next testing scenario was conducted by reducing the weight of each criterion by 0.05 to evaluate the model's sensitivity to the reduction in the importance level of the criteria. The analysis results show that the reduction in weight affects changes in the final values for each alternative, although in general, the ranking structure does not experience significant changes, particularly for the alternatives with the highest and lowest performance. This indicates that the model used has a fairly good level of consistency against variations in weight. The detailed results of the scenario of reducing the weight by 0.05 for each criterion are presented in Table 9.

Table 9. Scenario of Decreasing Criteria Weight by 0.05

Test	K1	K2	K3	K4	K5
Initial Weight Using the RECA Method	0.2131	0.2142	0.2160	0.2155	0.1411
The weight of Criterion K1 is decreasing by 0.05 (Test 6)	0.1717	0.2255	0.2274	0.2269	0.1485

The weight of Criterion K2 is decreasing by 0.05 (Test 7)	0.2243	0.1729	0.2274	0.2269	0.1485
The weight of Criterion K3 is decreasing by 0.05 (Test 8)	0.2243	0.2255	0.1748	0.2269	0.1485
The weight of Criterion K4 is decreasing by 0.05 (Test 9)	0.2243	0.2255	0.2274	0.1742	0.1485
The weight of Criterion K5 is decreasing by 0.05 (Test 10)	0.2243	0.2255	0.2274	0.2269	0.0959

The ranking results obtained from the scenario of decreasing the weight by 0.05 for each criterion, referring to the data and weight adjustments in Table 9, are presented in Figure 4. This presentation aims to show the sensitivity of the ranking results to changes in the criteria weights used.

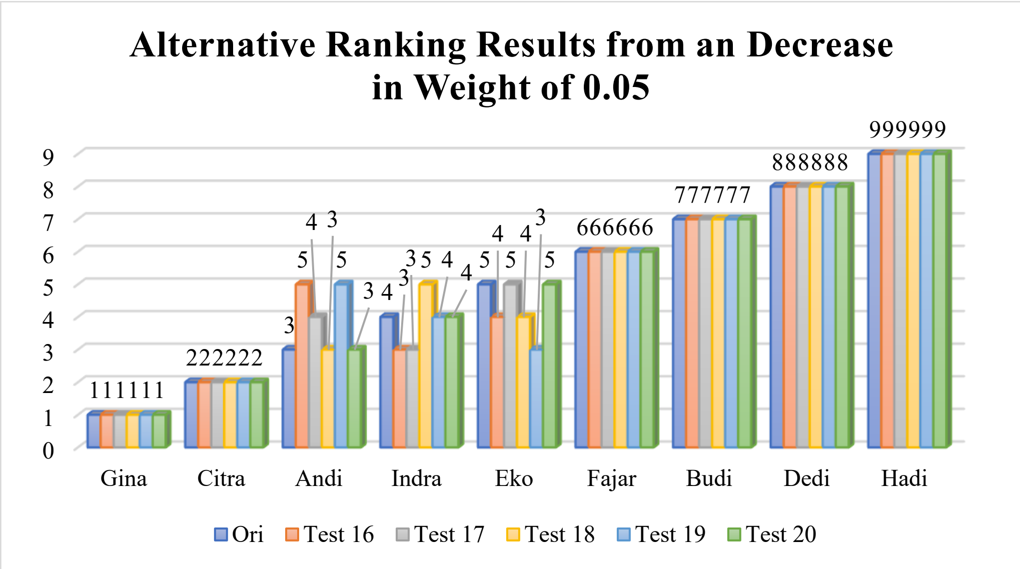

Figure 4. Ranking Results from the Scenario of Decreasing the Weight by 0.05

The ranking results of the alternatives after a decrease of 0.05 in weight for each criterion, where the resulting ranking pattern still shows consistency with the initial condition. Gina and Citra consistently occupy the first and second ranks without change, indicating the most dominant performance. In the middle group, there is slight dynamics among Andi, Indra, and Eko, where Andi occasionally shifts from third to fourth rank, while Indra and Eko exchange positions in some scenarios, reflecting limited sensitivity to weight changes. On the other hand, Fajar, Budi, Dedi, and Hadi show full stability by maintaining their respective positions throughout the testing.

The testing scenario was carried out by increasing the weight of each criterion by 0.1 to examine the model's sensitivity to more significant changes in the level of criterion importance. The results obtained show that an increase in weight by 0.1 has a more noticeable impact on the final value of the alternatives compared to the previous scenario, although generally the ranking order still tends to be stable, especially for alternatives with extreme performance. This indicates that the model has good resilience to weight changes on a larger scale. Details of the results from the scenario of increasing weights by 0.1 for each criterion are presented in Table 10.

Table 10. Scenario of Increased Criteria Weight by 0.1

Test	K1	K2	K3	K4	K5
Initial Weight Using the RECA Method	0.2131	0.2142	0.2160	0.2155	0.1411
The weight of Criterion K1 is increased by 0.1 (Test 11)	0.2847	0.1947	0.1964	0.1959	0.1283
The weight of Criterion K2 is increased by 0.1 (Test 12)	0.1937	0.2857	0.1964	0.1959	0.1283
The weight of Criterion K3 is increased by 0.1 (Test 13)	0.1937	0.1947	0.2873	0.1959	0.1283
The weight of Criterion K4 is increased by 0.1 (Test 14)	0.1937	0.1947	0.1964	0.2868	0.1283
The weight of Criterion K5 is increased by 0.1 (Test 15)	0.1937	0.1947	0.1964	0.1959	0.2192

The ranking results obtained from the scenario of increasing the weight by 0.1 for each criterion, referring to the data and weight adjustments in Table 10, are presented in Figure 5. This presentation aims to show the sensitivity of the ranking results to changes in the criteria weights used.

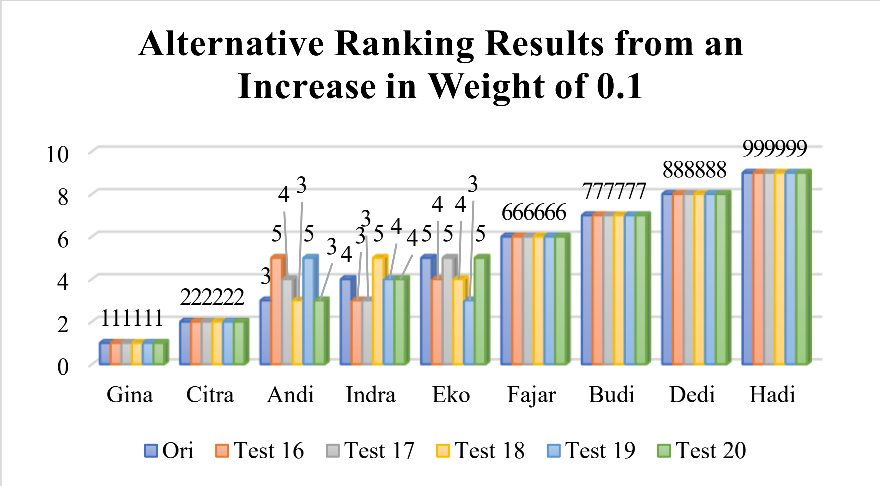

Figure 5. Ranking Results from the Scenario of Increasing the Weight by 0.1

The ranking results of alternatives in scenarios Test 11 to Test 15 still show a relatively stable pattern compared to the initial condition (Ori). Gina and Citra consistently maintain the first and second positions in the scenarios, confirming the dominance of their performance, which is not affected by changes in weights. In the middle group, there are more noticeable fluctuations among Andi, Indra, and Eko, where the three exchange positions between the third and fifth ranks, reflecting higher sensitivity to weight variations in the group with close values. Meanwhile, Fajar, Budi, Dedi, and Hadi remain consistent in their respective ranks without changes, indicating that alternatives with lower performance are not significantly affected by the test scenarios.

The next testing scenario was conducted by reducing each criterion's weight by 0.1 to test the model's sensitivity to a larger reduction in the importance level of the criteria. After the reduction was made, the weights were normalized again to ensure the total remained consistent, then the calculation process for preference values and alternative rankings was rerun. The analysis results showed that a 0.1 decrease in weight had a significant impact on the final values of each alternative, but in general, the ranking pattern remained relatively stable, particularly for the alternatives with the highest and lowest performance. This indicates that the model has a good level of stability even when facing more extreme weight changes. The detailed results of the 0.1 weight reduction scenario for each criterion are presented in Table 11.

Table 11. Scenario of Decreasing Criteria Weight by 0.1

Test	K1	K2	K3	K4	K5
Initial Weight Using the RECA Method	0.2131	0.2142	0.2160	0.2155	0.1411
The weight of Criterion K1 is decreasing by 0.1 (Test 16)	0.1257	0.2380	0.2400	0.2395	0.1568
The weight of Criterion K2 is decreasing by 0.1 (Test 17)	0.2368	0.1269	0.2400	0.2395	0.1568
The weight of Criterion K3 is decreasing by 0.1 (Test 18)	0.2368	0.2380	0.1289	0.2395	0.1568
The weight of Criterion K4 is decreasing by 0.1 (Test 19)	0.2368	0.2380	0.2400	0.1283	0.1568
The weight of Criterion K5 is decreasing by 0.1 (Test 20)	0.2368	0.2380	0.2400	0.2395	0.0457

The ranking results obtained from the scenario of a weight reduction of 0.1 on each criterion, referring to the data and weight adjustments in Table 11, are shown in Figure 6. This presentation aims to demonstrate the sensitivity of the ranking results to changes in the criterion weights used.

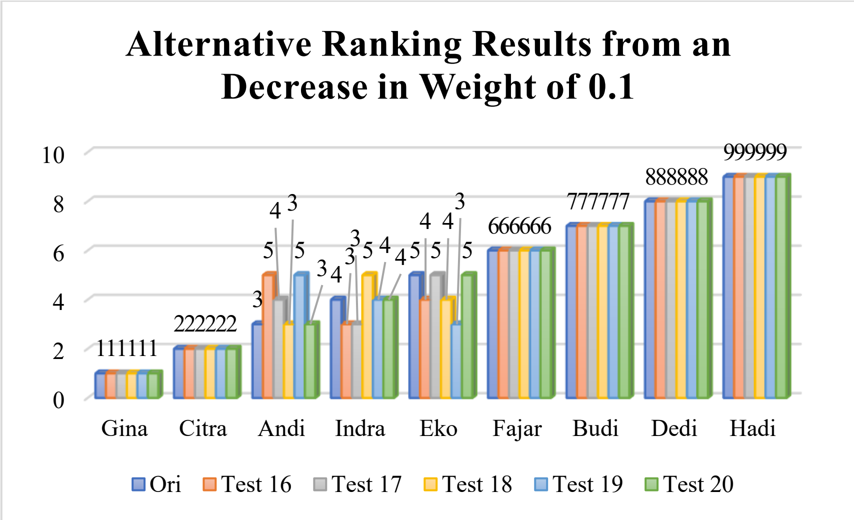

Figure 6. Ranking Results from the Scenario of Increasing the Weight by 0.1

The ranking results on Tests 16–20 remain very consistent compared to the initial condition. Gina and Citra are stable in the first and second positions, while only minor changes occur with Andi, Indra, and Eko in the middle positions. Fajar, Budi, Dedi, and Hadi remain completely stable with no changes in rank.

Overall, all scenarios of weight changes, whether increases or decreases at various levels, show that the model used has a high level of stability and consistency in generating alternative rankings. The positions of alternatives with the best and lowest performance tend not to change across all scenarios, while shifts only occur to a limited extent among groups of alternatives with close values, particularly in the middle rankings. This indicates that weight variations do not have a significant impact on the main ranking structure, so the results obtained remain reliable.

4.6. Discusion

The findings demonstrate that the proposed framework can translate complex production performance data into a structured and reliable evaluation outcome. By combining data-driven weighting through RECA with a ranking mechanism via RAWEC, the approach reduces reliance on subjective judgment and strengthens analytical transparency. The distribution of criterion weights, which appears relatively balanced except for the lower contribution of the error rate criterion, reflects how performance dimensions interact in a real production setting. This balance ensures that no single aspect disproportionately dominates the evaluation, allowing a more proportional representation of employee contributions. As a result, the ranking output is not only mathematically consistent but also aligned with practical expectations in industrial operations where multiple performance aspects must be considered simultaneously.

Another key insight is the method's ability to clearly distinguish performance levels while remaining sensitive to closely ranked individuals. The gap between top and lower performers is evident, while smaller differences in the middle group show responsiveness to subtle variations without causing unstable rankings. This supports fair comparisons and helps decision-makers identify both top performers and employees with similar potential for targeted development. Sensitivity analysis confirms the model's robustness, as rankings remain largely stable under various weight changes. Such stability is crucial in dynamic production environments and supports accurate evaluations for performance appraisal, rewards, and continuous improvement.

5. Conclusion

Research results show that the RECA and RAWEC methods are able to produce performance evaluations that are objective and consistent according to the characteristics of data in the textile production environment. The evaluation results show clear variations in final scores among employees, making the applied system effective in distinguishing overall performance contribution levels and providing a basis for more accurate managerial decision-making. The ranking results show that Gina ranks first with a final score of 0.483, followed by Citra in second place with a score of 0.2933, and Andi in third place with a score of 0.0912. These three employees demonstrate the best performance compared to other alternatives and can serve as a reference in determining awards, career development, and planning for continuous performance improvement in the textile manufacturing industry. These findings provide a strong basis for management in establishing human resource management policies, such as granting awards, planning competency development, and continuously improving performance in the textile manufacturing sector.

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