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Objective Approach in Supplier Selection: Integration of RECA Weighting and Combinative Distance-based Assessment Method

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Abstract: Selecting suppliers constitutes a strategic process that has a significant influence on operational effectiveness and overall supply chain performance. This research seeks to develop a multi-criteria decision-making framework for assessing and prioritizing suppliers objectively by considering various performance criteria. The evaluation is conducted using five main criteria, namely price, quality, delivery, responsiveness, and capacity and flexibility. A total of nine supplier alternatives were assessed, and a quantitative decision model was applied to aggregate the performance of each alternative into a final score and ranking. The findings demonstrate that the proposed method can effectively differentiate supplier performance, which is evidenced by the noticeable variation in the final scores obtained by each alternative. The evaluation results reveal that PT Cipta Solusi Persada secured the highest rank with a final value of 0.5171, followed by PT Karya Nusantara in second place with a score of 0.4626, while PT Prima Logistik Indonesia occupied the third position with a score of 0.3922. These outcomes suggest that suppliers exhibiting consistent and balanced performance across all evaluation criteria are more likely to obtain superior rankings. The study also highlights that suppliers with lower rankings generally exhibit structural weaknesses in key criteria, suggesting the need for performance improvement or strategic reconsideration. In general, this study contributes to the development of decision support system literature by presenting a systematic and objective framework for supplier evaluation and selection. In addition, the proposed approach provides practical benefits for organizations in improving supplier management processes and enhancing the quality of supply chain decision-making.
Keywords: Decision Support System; Multi-Criteria Decision Making; Objective Evaluation; Supplier Selection; Supply Chain Management.

1. INTRODUCING

Supplier selection plays a strategic role in improving supply chain efficiency and strengthening organizational competitiveness because suppliers directly affect costs, quality, and supply continuity[1]–[3]. The right supplier can ensure the consistent availability of raw materials so that the production process can run without disruption. In addition, timely delivery and stable quality from suppliers contribute to lower operational costs and reduced risk of distribution delays. In the context of increasingly intense competition, organizations are required to build long-term collaborations with suppliers

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who have superior performance and are adaptive to changes in market demand. However, the process of selecting suppliers is not a simple decision because it involves many interrelated criteria, such as price, quality, delivery reliability, production capacity, flexibility, and commitment to sustainability. Each criterion has a different level of importance depending on the organization's strategy and goals[4], [5]. The complexity of the decision increases when the organization must evaluate many supplier alternatives with diverse characteristics and strengths. Differences in performance among suppliers are often not linear, making it difficult to determine based on a single indicator alone. Furthermore, the trade-offs between criteria, for example between lower costs and higher quality, require decision-makers to make a more comprehensive assessment. This situation has the potential to introduce subjectivity if not supported by a systematic and structured approach. Supplier selection requires an evaluation framework that can accommodate multiple criteria and alternatives objectively. An appropriate decision-making approach will help organizations choose the best suppliers, improve supply chain efficiency, and ultimately strengthen their competitive position in the market.

In the practice of multi-criteria decision-making, criterion weighting is still largely influenced by subjective approaches that depend significantly on the judgments and experience of decision-makers [6]–[8]. Subjective approaches are often used because they are easy to apply and can directly reflect managerial preferences. However, the dominance of this method poses serious challenges regarding the consistency and objectivity of the evaluation results. The weights of criteria determined based on the perceptions of individuals or vulnerable groups are influenced by personal interests, organizational pressures, and limitations of information. Differences in the background and experience among decision-makers can also result in non-uniform weights for the same issue. This condition has the potential to affect the overall process of evaluating alternatives. The risk of bias increases as the number of criteria and alternatives being assessed grows. Cognitive biases, such as preferences for certain suppliers or the tendency to stick to previous decisions, can unconsciously influence judgment. As a result, the ranking outcomes produced do not fully reflect the actual performance of the alternatives. Reliance on subjective methods also complicates the process of validating and replicating decisions in the future[9], [10]. In addition, the decisions produced tend to be less transparent because it is difficult to trace the rationale behind the determination of weights. In organizations that demand high accountability, this condition can reduce the level of trust in the decision outcomes. The dominance of subjective methods in weighting criteria needs to be critically examined to minimize the risk of bias and improve the quality of ranking results.

Data-based or objective weighting is becoming increasingly important in multi-criteria decision-making because it can reduce reliance on the subjective judgments of decision-makers[11]–[13]. This approach places empirical data as the main basis for determining the importance level of each criterion. By utilizing the information contained in the data, criterion weights can more accurately reflect real conditions and performance differences among alternatives. Objective weighting also enhances the consistency of decision outcomes because its calculation process follows clear and replicable mathematical rules. This is highly relevant when the number of criteria and alternatives becomes larger and more complex. One important aspect of objective weighting is the method's ability to capture data variations between criteria. Criteria with high levels of variation generally provide more information in distinguishing alternatives. In this context, the respond to criteria weighting (RECA) method serves as an objective weighting approach that considers the actual contribution of each criterion to the evaluation process[14], [15]. RECA evaluates how strongly variations in a criterion’s value influence the results of alternative assessments. Therefore, criteria that exhibit a greater impact on data changes are assigned higher weights. This method enables the identification of criteria that have a substantial role in the decision-making process. In addition, RECA helps to avoid giving excessive weight to criteria with relatively low information. The implementation of RECA supports

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transparency and accountability because the basis for determining weights can be explained logically and data-driven. Data-based weighting with RECA provides an important contribution to producing more objective and accountable ranking results.

The single-distance-based multicriteria decision-making method has limitations in comprehensively representing the closeness of alternatives to the ideal solution[16], [17]. This approach generally relies on only one type of distance measure, such as Euclidean or Manhattan distance, to assess the differences between alternatives and the ideal point. Using a single distance often fails to capture the diverse data distribution characteristics for each criterion. As a result, important information related to variation, direction, and scale of differences between alternatives may be diminished. In certain conditions, two alternatives with different criterion values can produce the same single distance, making it difficult to distinguish them accurately. This has the potential to cause distortions in the ranking process. Additionally, single-distance-based methods tend to be sensitive to extreme values and assumptions of homogeneity among criteria. These limitations become increasingly significant when the criteria used have conflicting characteristics or unequal levels of importance. Therefore, an approach capable of integrating more than one distance perspective in the evaluation process is needed. Combinative distance-based approaches offer a solution by combining several distance measures to represent the closeness of alternatives to the ideal solution more comprehensively. The combination of distances allows for an assessment that considers various aspects of differences, both in absolute and relative terms. Thus, the evaluation results become more stable and sensitive to relevant data variations. This approach also enhances the method's ability to differentiate between alternatives with similar performance. Overall, the application of combinative distance supports a decision-making process that is more accurate and representative of real conditions.

Combinative distance-based assessment (CODAS) is a multi-criteria decision-making method that assesses alternatives by measuring their relative distances from the ideal and anti-ideal solutions through a combined distance evaluation approach[18]–[20]. This method was introduced to overcome the shortcomings of single-distance-based approaches, which frequently encounter difficulties in differentiating alternatives with nearly identical performance levels. CODAS using two principal distance measurements, namely the Euclidean distance as the main indicator and the Taxicab distance as a supplementary indicator during the evaluation process. The integration of these distance measures enables a more thorough representation of the disparities among alternatives, both in terms of overall magnitude and cumulative deviations across criteria. Within the CODAS framework, alternatives located farther from the negative ideal solution are regarded as having superior performance. Consequently, this method offers a distinct evaluation perspective compared to approaches that only emphasize proximity to the positive ideal solution. The advantage of CODAS lies in its ability to enhance the ranking sensitivity to small yet significant data variations[21]–[23]. This is particularly important when alternatives have almost uniform criterion values. This method is also flexible to be combined with various criterion weighting techniques, both subjective and objective. In the context of complex decision-making, CODAS help generate alternative rankings that are more rational and logically traceable. The transparency of the calculation process is an added value, as each evaluation stage can be explained mathematically. Therefore, CODAS is widely used as a reliable approach to support strategic decisions in various fields.

The combination of RECA weighting and the CODAS method provides a more objective and representative framework for multi-criteria decision-making. RECA is utilized to determine criterion weights objectively by considering data variation and the actual contribution of each criterion to differences among alternatives. On the other hand, CODAS evaluates alternative performance through a combination of distances from the ideal and anti-ideal solutions, thereby offering a more comprehensive assessment compared to single-distance-based approaches. The primary purpose of this study is to develop and

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validate a decision-making model that can improve the accuracy and reliability of ranking outcomes in complex multi-criteria problems. In addition, this research seeks to demonstrate that data-driven weighting approaches and combinative distance-based evaluations can complement each other effectively from a methodological perspective. From a theoretical standpoint, the integration of RECA and CODAS contributes to the advancement of multi-criteria decision-making literature, particularly in the area of combining objective weighting techniques with distance-based evaluation models. The proposed framework broadens the understanding of how criterion variation relates to the measurement of closeness to ideal solutions. Practically, this approach can be implemented in various decision-making applications, including supplier selection, performance assessment, and strategic priority determination. The findings of this study are expected to support decision-makers in generating recommendations that are more rational, transparent, and accountable.

2. RESEARCH METHODOLOGY

In this section, each researcher expected to be able to make the most recent contribution related to the solution to the existing problems. Researchers can also use images, diagrams, and flowcharts to explain the solutions to these problems.

Research Stage

The research stages provide an overview of the flow and scope of each step carried out in the research process. Each stage is designed to have a clear purpose and role, making them logically interconnected. Figure 1 shows the research stages conducted

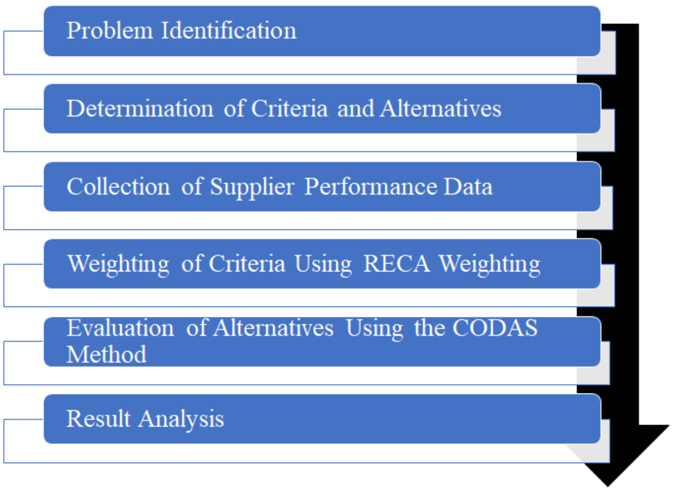

Figure 1. Research Stage

The research stages in Figure 1 begin with problem identification and goal setting, carried out to formulate the main issue in supplier selection, which is how to determine the best supplier objectively amidst the many available criteria and alternatives. The stage of determining criteria and alternatives aims to identify relevant evaluation factors and to establish the list of suppliers to be evaluated, so that the decision scope is well defined. Then, the collection of supplier performance data is conducted by gathering quantitative data that represents the performance of each supplier on each of the established criteria. This data serves as the main basis in the analysis process because it reflects the actual performance conditions. The criteria weighting stage using the RECA method is carried out to determine the level of importance of each criterion objectively based on the variation and contribution of its information. The resulting weights are then used in the alternative evaluation stage using the CODAS method, where each supplier is assessed based on their

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combined distance to the negative solution to obtain a preference value. The final stage is the result analysis, which focuses on interpreting the scores and ranking of suppliers produced, as well as evaluating their implications for supplier selection decision-making.

Respond to Criteria (RECA) Weighting

Respond to Criteria (RECA) Weighting is a data-based-criteria weighting method designed to determine the importance level of each criterion objectively in multi-criteria decision making[24], [25]. This method works by evaluating the extent of response or the effect of changes in a criterion's value on the variation in the performance of alternatives. RECA assumes that criteria with greater informational contribution will show more significant variation in distinguishing alternatives. With these characteristics, RECA supports a weighting process that is transparent, rational, and replicable in different decision-making contexts.

The first stage in RECA weighting is the formation of a decision matrix as an initial representation that contains the performance values of each alternative against all criteria. This matrix serves as the main basis for all subsequent calculation processes. Each row represents an alternative, while each column represents a criterion.

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

The second stage in RECA weighting is the preference value, which reflects the relative performance tendency of each alternative for each criterion. This value is used to see the position of the alternatives before scale normalization is carried out. This stage helps identify the initial pattern of differences between alternatives.

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

The third step in RECA weighting, namely matrix normalization, is carried out to equalize the assessment scale among criteria that have different units and value ranges. This process ensures that no criterion dominates just because its value scale is larger. The results of normalization allow for a fair comparison between criteria.

$$R_{ij} = \frac{PV_{ij}}{\max_{j} PV} \quad (3)$$

The fourth stage in RECA weighting, the standard matrix values, is the result of the normalization process that has been carried out. These values reflect the performance of alternatives in a uniform and measurable form. The standard matrix becomes the main input for criteria variation analysis.

$$N_j = \frac{1}{n} \sum_{i=1}^{m} R_{ij} \quad (4)$$

The fifth stage in RECA weighting is calculating the preference variation value to measure the spread of alternative values for each criterion. Greater variation indicates a higher ability of the criterion to differentiate the alternatives. This stage emphasizes the informative role of each criterion.

$$\emptyset_j = \sum_{j=1}^{n} [R_{ij} - N_j]^2 \quad (5)$$

The sixth stage in RECA weighting is the preference deviation value, which indicates the relative contribution of each criterion to the overall data variation. This value reflects how

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significant a criterion is in influencing differences between alternatives. Preference deviation serves as the basis for determining the objective weight of the criteria.

$$\varphi_j = \left|1 - \emptyset_j\right| \quad (6)$$

The final stage in RECA weighting is that the weighted criterion values are obtained by normalizing the preference deviation so that the total weight equals one. These weights represent the level of importance of each criterion proportionally and based on data. The weighted values are used in the alternative evaluation stage to produce an objective ranking.

$$w_j = \frac{\varphi_j}{\sum_{j=1}^{n} \varphi_j} \quad (7)$$

The RECA method provides an objective, data-driven criterion weighting approach in multi-criteria decision making. By utilizing variations and deviations in preferences as the basis for determining weights, RECA can identify criteria that truly contribute to distinguishing alternatives. This approach reduces reliance on subjective assessment and improves the consistency of weighting results. In addition, its calculation steps are systematic and transparent, making them easy to trace and replicate. Therefore, RECA is suitable to be used as a reliable weighting method, especially when decisions involve many criteria and alternatives with complex characteristics.

Combinative Distance-Based Assessment (CODAS)

Combinative Distance-based Assessment (CODAS) is a multi-criteria decision-making method developed to evaluate and rank alternatives based on their closeness to the ideal solution more representatively[26]. This method uses a combinative distance approach by combining more than one distance measure to capture the differences in alternative performance comprehensively. CODAS assessment alternatives based on their distance to the negative solution, so the alternative that is farthest away is considered to have better performance. This approach is designed to enhance discrimination capability when alternatives have relatively close criterion values. Additionally, CODAS can reduce the weaknesses of single-distance-based methods, which are often less sensitive to certain data variations[27]. With a clear and logical calculation structure, CODAS is widely used to support complex decision-making that requires a high level of objectivity.

The first step in the CODAS method involves constructing a decision matrix in which alternatives are represented in rows and criteria are arranged in columns. This matrix stores the performance values of each alternative with respect to every criterion and serves as the foundation for all subsequent calculation procedures, as expressed in (1).

The subsequent stage in the CODAS method is the normalization process, which is performed to standardize the data scale since each criterion generally possesses different units and value ranges. Through normalization, all values in the decision matrix are transformed into a comparable scale, enabling fair and consistent comparisons among criteria.

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_j x_{ij}}; if\ j\ \in benefit \\ \dfrac{\min_j x_{ij}}{x_{ij}}; if\ j\ \in cost \end{cases} \quad (8)$$

The next step in the CODAS method involves multiplying the normalized values by the corresponding criterion weights to incorporate the relative importance of each criterion. This procedure ensures that criteria with higher significance exert a stronger influence on

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the overall evaluation of the alternatives.

$$r_{ij} = w_j * n_{ij} \tag{9}$$

The following stage in the CODAS method involves identifying the negative ideal solution, which represents the worst reference point for each criterion derived from the weighted normalized decision matrix. This solution is used as a benchmark to evaluate the distance of each alternative from the least favorable condition.

$$ns_j = \min_j r_{ij} \tag{10}$$

The next stage in the CODAS method involves computing the distance of each alternative from the negative ideal solution using two different measures, namely the Euclidean distance and the Manhattan (taxicab) distance. Employing these two-distance metrics provides a more comprehensive assessment of how close each alternative is to the worst possible condition.

$$E_i = \sqrt{\sum_{j=1}^{n} (r_{ij} - ns_j)^2} \tag{11}$$

$$T_i = \sum_{j=1}^{n} \left| r_{ij} - ns_j \right| \tag{12}$$

The next stage in the CODAS method involves computing the relative assessment values by comparing the distances of each alternative against those of the other alternatives. This step is used to determine the degree of superiority of each alternative within the overall set of candidates being evaluated.

$$h_{ik} = (E_i - E_k) + (\varphi * (E_i - E_k)) * (T_i - T_k) \tag{13}$$

The final stage of the CODAS method involves computing the final score based on the previously obtained relative ranking values. The alternative with the highest final score is selected as the best option, as it indicates the greatest separation from the negative ideal solution compared to the other alternatives.

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{14}$$

The CODAS method is able to produce objective and comprehensive alternative rankings by integrating Euclidean distance and Manhattan distance with respect to the negative ideal solution. This approach enables more precise evaluation of alternatives by considering both the squared deviation magnitude and the absolute differences in weighted preference values. The resulting total dominance index reflects the relative superiority of each alternative, making CODAS an effective, transparent, and consistent method for supporting multi-criteria decision-making in various evaluation and selection problems.

3. RESULT AND DISCUSSIONS

Supplier selection is a strategic decision that directly affects operational performance, supply chain stability, and the organization's competitiveness in the long term. In practice, this process is faced with many interrelated criteria, requiring a systematic and data-driven evaluation approach. However, much research and managerial practice is still dominated by subjective weighting that heavily relies on decision-makers' preferences, which can potentially lead to bias and inconsistent results. Therefore, an objective approach is becoming increasingly relevant to ensure that criteria weights and alternative assessments

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are derived directly from the characteristics of the available data. The integration of the RECA weighting method as an objective approach allows for determining the importance level of criteria based on the variation and contribution of their information, thereby reflecting the actual conditions of supplier performance. Meanwhile, the CODAS method provides an evaluation framework capable of comprehensively comparing supplier alternatives through measurements of distance from ideal and anti-ideal solutions. The combination of these two methods offers a more rational, consistent, and transparent supplier selection mechanism by reducing reliance solely on intuition in decision-making.

Problem Identification

Problem identification is a very crucial initial stage in research because it determines the direction of analysis, the choice of methods, and the validity of the results to be obtained. In the context of complex decision-making, such as evaluating and selecting suppliers, problems often do not arise in isolation but rather as a series of interrelated conditions influenced by many factors. Limitations in information, data inconsistencies, and the dominance of subjective considerations in evaluating criteria are the main sources of decision inaccuracies. In addition, the increasing number of supplier alternatives and the variation in evaluation criteria increase the level of complexity, making it difficult for decision-makers to determine the most rational choice. This condition is exacerbated when the methods used are unable to represent the characteristics of the data objectively and systematically. As a result, the decisions produced may be suboptimal and fail to accurately reflect the actual performance of suppliers. Therefore, a comprehensive problem identification process is necessary to clearly and systematically formulate the root cause of the problem. Proper problem formulation will serve as the foundation for determining the appropriate analytical approach, ensuring that the solutions generated are not only theoretically relevant but also practical in supporting more accurate and accountable decision-making.

Determining of Criteria and Alternatives

Determining criteria is a key stage in the multi-criteria decision-making process because it directly plays a role in shaping the evaluation framework used to assess each alternative objectively and consistently. The criteria set must be able to represent the decision objectives comprehensively, covering important aspects such as performance, efficiency, risk, and sustainability according to the context of the problem being studied. Inaccuracies in determining the criteria, both in terms of relevance and clarity of definition, can lead to assessment bias and reduce the accuracy of decision outcomes. Furthermore, criteria need to be formulated in a measurable form so that they can be quantitatively processed and systematically analyzed using appropriate methods. This process requires an in-depth literature review, understanding of organizational needs, and adaptation to the available data conditions. Consistency between criteria is also an important factor to avoid overlap and redundancy in the evaluation. With the right and structured determination of criteria, the subsequent analysis process can proceed more effectively and produce decisions that are rational, transparent, and accountable both academically and practically. Table 1 presents the criteria data used in this study.

Table 1. Criteria Data

ID Criteria Data	Criteria Name	Criteria Type	Criteria Description
IDC-01	Price	Cost	Covers price levels, price stability, as well as flexibility in offering discounts or payment schemes. Competitive pricing is important, but it must still be balanced with the quality received.

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IDC-02	Quality	Benefit	Assessing the extent to which a supplier can provide products or services that meet the established quality standards. Consistent quality will reduce the risk of returns, defective products, and operational disruptions.
IDC-03	Delivery	Benefit	Assessing the timeliness of delivery, the reliability of distribution schedules, and the ability to meet urgent demands. Suppliers with good logistics performance help maintain the smooth flow of the supply chain.
IDC-04	Responsiveness	Benefit	Assessing the quality of communication, the speed of response to complaints, and after-sales support. Good service enhances long-term relationships between the company and suppliers.
IDC-05	Capacity and Flexibility	Benefit	Describes the supplier's ability to meet order volumes and adjust production when demand changes. This flexibility is especially important in a dynamic business environment.

Determining alternatives is an important stage in multi-criteria decision making because it identifies the objects that will be systematically evaluated and compared. The selected alternatives must represent real available options and be relevant to the decision objectives, so that the evaluation results have practical value for the organization. This process requires a thorough identification of alternatives based on actual data, performance records, and alignment with operational and strategic needs. Incompleteness or the selection of inappropriate alternatives can limit the scope of analysis and potentially lead to biased decisions. Additionally, each alternative needs to have consistent data that can be compared across all established criteria. Challenges often arise when the number of alternatives is quite large or when data quality varies, thus requiring an initial selection that is rational and information-based. By determining alternatives in an objective and structured manner, the subsequent evaluation process can reflect real conditions and result in decisions that are more accurate, transparent, and accountable. Table 2 presents the alternative data used in this study.

Table 2. Alternative Data

ID Criteria Data	Criteria Name
SP0001	PT Sumber Makmur Abadi
SP0002	CV Mitra Sejahtera
SP0003	PT Karya Nusantara
SP0004	CV Sentosa Jaya
SP0005	PT Prima Logistik Indonesia
SP0006	PT Anugerah Teknik Mandiri
SP0007	CV Berkah Utama
SP0008	PT Cipta Solusi Persada
SP0009	PT Global Mitra Supply

The determination of criteria and alternatives is the main foundation that dictates the success of the entire multi-criteria decision-making process. Precisely formulated criteria ensure that important aspects relevant to the decision objectives can be evaluated objectively and consistently, while comprehensively chosen alternatives provide a realistic

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view of the available options. The balance between clear criteria and complete alternatives becomes a determining factor in producing accurate and reliable analysis. This process demands a systematic, data-driven approach aligned with organizational needs to ensure that the evaluation results are not partial or biased. With structured determination of criteria and alternatives, the subsequent analysis stages can be carried out more effectively and yield rational decision recommendations.

Collection of Supplier Performance Data

Collecting supplier performance data is a critical step in an objective-based decision-making process, as the quality of the gathered data strongly influences the accuracy of the evaluation outcomes. Supplier performance information represents the actual condition of each alternative being assessed, including aspects such as price, quality, delivery, responsiveness, as well as capacity and flexibility. For this reason, data collection should be conducted in a structured manner using reliable sources, such as internal reports, transaction records, audit findings, and operational documents.

Moreover, standardization of data formats and measurement scales is necessary to ensure that all suppliers can be compared fairly across the defined criteria. However, challenges often emerge due to inconsistencies in recording practices and differences in observation periods, making data verification and validation essential prior to analysis. With systematic and evidence-based data collection, the evaluation process can better reflect real-world conditions and support decision-making that is rational, transparent, and accountable. Table 3 presents the results of the supplier performance assessment.

Table 3. Supplier Performance Evaluation Data

Alternative ID	ID Data Criteria				
	C1	C2	C3	C4	C5
SP0001	195000	8	7	7	8
SP0002	210000	7	6	8	7
SP0003	165000	9	8	7	9
SP0004	230000	6	7	6	6
SP0005	245000	8	9	9	8
SP0006	205000	7	7	6	7
SP0007	240000	6	6	7	6
SP0008	150000	9	8	8	8
SP0009	190000	8	7	8	7

Collecting supplier performance data is a determining factor in ensuring that the evaluation and decision-making processes are conducted objectively and reliably. Accurate, consistent, and verified data allow each supplier to be assessed based on actual conditions, rather than mere assumptions or subjective perceptions. The success of this stage greatly depends on the accuracy of the data sources, the uniformity of recording methods, and the validity of the information used. With systematically organized data, subsequent analysis stages can be carried out more effectively and result in fair comparisons between suppliers. Therefore, collecting supplier performance data not only serves as analytical input but also as the basis for making rational and transparent decisions. This stage ensures that the final recommendations produced have a strong empirical foundation and are relevant to the organization's operational needs.

Weighting of Criteria Using RECA Weighting

Weighting the criteria using the RECA method is a crucial step in multi-criteria decision-making, as it defines the relative importance of each criterion within the evaluation process. The RECA weighting approach is developed as an objective technique that

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determines criterion weights based on the inherent characteristics of the available performance data, thereby minimizing the influence of subjective judgment from decision-makers. Through analysis of variation and the information contribution of each criterion, this method provides a more realistic picture of each criterion's role in differentiating the performance of alternatives. A common challenge in weighting criteria is the inconsistency and bias often found in expert-based assessment methods, which can affect the accuracy of the final results. By using RECA, the weighting process becomes more transparent and replicable as it is entirely based on empirical data. In addition, the weights produced reflect the actual conditions of the system being analyzed, not just theoretical assumptions. The application of RECA Weighting is expected to improve the reliability of the evaluation process and provide a strong foundation for the subsequent analysis stages in producing rational and accountable decisions.

The initial stage in the RECA weighting method involves constructing a decision matrix, which serves as a structured representation of the performance values of each alternative across all criteria. This matrix becomes the fundamental basis for subsequent calculations, as expressed in (1).

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} \\ x_{19} & x_{29} & x_{39} & x_{49} & x_{59} \end{bmatrix} \rightarrow X = \begin{bmatrix} 195000 & 8 & 7 & 7 & 8 \\ 210000 & 7 & 6 & 8 & 7 \\ 165000 & 9 & 8 & 7 & 9 \\ 230000 & 6 & 7 & 6 & 6 \\ 245000 & 8 & 9 & 9 & 8 \\ 205000 & 7 & 7 & 6 & 7 \\ 240000 & 6 & 6 & 7 & 6 \\ 150000 & 9 & 8 & 8 & 8 \\ 190000 & 8 & 7 & 8 & 7 \end{bmatrix}$$

The second stage in the RECA weighting method involves determining the preference values, which represent the relative performance tendencies of each alternative for each criterion. These values are used to identify the position of alternatives prior to scale normalization and are calculated using (2).

$$PV_{11} = \frac{x_{11}}{\sqrt[9]{x_{11} * x_{12} * x_{13} * x_{14} * x_{15} * x_{16} * x_{17} * x_{18} * x_{19}}}$$
$$= \frac{195000}{\sqrt[9]{195000 * 210000 * 165000 * 230000 * 245000 * 205000 * 240000 * 150000 * 190000}}$$
$$= \frac{195000}{200931.99} = 0.9705$$

Table 4 presents the overall results of the preference value calculations for each alternative across all considered criteria.

Table 4. Preference Value of the RECA Weighting

Alternative ID	ID Data Criteria				
	C1	C2	C3	C4	C5
SP0001	0.9705	1.0698	0.9769	0.9625	1.1000
SP0002	1.0451	0.9360	0.8374	1.1000	0.9625
SP0003	0.8212	1.2035	1.1165	0.9625	1.2376
SP0004	1.1447	0.8023	0.9769	0.8250	0.8250
SP0005	1.2193	1.0698	1.2561	1.2376	1.1000
SP0006	1.0202	0.9360	0.9769	0.8250	0.9625
SP0007	1.1944	0.8023	0.8374	0.9625	0.8250

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SP0008	0.7465	1.2035	1.1165	1.1000	1.1000
SP0009	0.9456	1.0698	0.9769	1.1000	0.9625

The third stage in the RECA weighting method is matrix normalization, which is performed to standardize the scales of assessment across criteria that have different units and value ranges. This step ensures that no criterion dominates the evaluation solely due to having larger numerical values, and it is calculated using (3).

$$R_{11} = \frac{PV_{11}}{\max_1 PV} = \frac{0.9705}{1.2193} = 0.7959$$

Table 5 presents the overall results of the matrix normalization calculations for each alternative across all evaluated criteria.

Table 5. Matrix Normalization of the RECA Weighting

Alternative ID	ID Data Criteria				
	C1	**C2**	**C3**	**C4**	**C5**
SP0001	0.7959	0.8889	0.7778	0.7778	0.8889
SP0002	0.8571	0.7778	0.6667	0.8889	0.7778
SP0003	0.6735	1.0000	0.8889	0.7778	1.0000
SP0004	0.9388	0.6667	0.7778	0.6667	0.6667
SP0005	1.0000	0.8889	1.0000	1.0000	0.8889
SP0006	0.8367	0.7778	0.7778	0.6667	0.7778
SP0007	0.9796	0.6667	0.6667	0.7778	0.6667
SP0008	0.6122	1.0000	0.8889	0.8889	0.8889
SP0009	0.7755	0.8889	0.7778	0.8889	0.7778

The fourth stage in the RECA weighting method is the standard matrix value, which is obtained as the output of the normalization process. This value represents the performance of each alternative in a standardized and comparable form, and it is calculated using (4).

$$N_1 = \frac{1}{9} * (R_{11} + R_{12} + R_{13} + R_{14} + R_{15} + R_{16} + R_{17} + R_{18} + R_{19})$$
$$= \frac{1}{9} * (0.7959 + 0.8571 + 0.6735 + 0.9388 + 1.0000 + 0.8367 + 0.9796 + 0.6122 + 0.7755)$$
$$= \frac{1}{9} * (7.4694) = 0.8299$$

Table 6 presents the overall results of the standard matrix value calculations for each alternative across all considered criteria.

Table 6. Standard Matrix of the RECA Weighting

ID Data Criteria				
C1	**C2**	**C3**	**C4**	**C5**
0.8299	0.8395	0.8025	0.8148	0.8148

The fifth stage in the RECA weighting method involves calculating the preference variation value, which is used to quantify the degree of dispersion of alternative values for each criterion. A higher level of variation indicates that the criterion has a stronger ability to differentiate between alternatives, and it is calculated using (5).

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$$\begin{aligned}\emptyset_1 =&([R_{11}-N_1]^2+[R_{12}-N_1]^2+[R_{13}-N_1]^2+[R_{14}-N_1]^2+[R_{15}-N_1]^2+[R_{16}-N_1]^2\\&+[R_{17}-N_1]^2+[R_{18}-N_1]^2+[R_{18}-N_1]^2)\\=&([0.7959-0.8299]^2+[0.8571-0.8299]^2+[0.6735-0.8299]^2+[0.9388-0.8299]^2\\&+[1.0000-0.8299]^2+[0.8367-0.8299]^2+[0.9796-0.8299]^2\\&+[0.6122-0.8299]^2+[0.7755-0.8299]^2)\\=&\,0.0012+0.0007+0.0245+0.0118+0.0289+0.0000+0.0224+0.0474+0.0030\\=&\,0.1399\end{aligned}$$

Table 7 presents the overall results of the preference variation value calculations across all considered criteria.

Table 7. Preference Variation Value of the RECA Weighting

ID Data Criteria				
C1	**C2**	**C3**	**C4**	**C5**
0.1399	0.1262	0.0933	0.0988	0.0988

The sixth stage in the RECA weighting method is the preference deviation value, which represents the relative contribution of each criterion to the overall data variation. This value reflects the extent to which a criterion influences differences among alternatives, and it is calculated using (6).

$$\varphi_1 = |1-\emptyset_1| = |1-0.1399| = 0.8601$$

Table 8 presents the overall results of the preference deviation value calculations for all considered criteria.

Table 8. Preference Deviation Value of the RECA Weighting

ID Data Criteria				
C1	**C2**	**C3**	**C4**	**C5**
0.8601	0.8738	0.9067	0.9012	0.9012

The final stage in the RECA weighting method is the determination of the weighted criteria values, which are obtained by normalizing the preference deviation values so that their total sum equals one. These weights represent the proportional importance of each criterion in a data-driven manner, and they are calculated using (7).

$$w_1 = \frac{\varphi_1}{\varphi_1+\varphi_2+\varphi_3+\varphi_4+\varphi_5} = \frac{0.8738}{0.8601+0.8738+0.9067+0.9012+0.9012} = \frac{0.8738}{4.4430} = 0.1936$$

Table 9 presents the overall results of the weighted criteria value calculations for all considered criteria.

Table 9. Criteria Weight Value of the RECA Weighting

ID Data Criteria				
C1	**C2**	**C3**	**C4**	**C5**
0.1936	0.1967	0.2041	0.2028	0.2028

The resulting criterion weights show that all criteria possess a relatively balanced level of importance within the evaluation process. Criterion IDC-03 has the highest weight of 0.2041, indicating that it contributes the most in distinguishing the performance of alternatives compared to the other criteria. Meanwhile, IDC-04 and IDC-05 share an almost identical weight of 0.2028, reflecting their equally significant roles in the decision-making

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process. IDC-02 obtains a weight of 0.1967, while IDC-01 has the lowest weight at 0.1936, although the difference among them is minimal.

These small variations in weight indicate that no single criterion is overly dominant, allowing the assessment process to remain balanced and proportional. This condition demonstrates an objective and stable weighting outcome, where each criterion still contributes meaningfully to the final evaluation results.

Evaluation of Alternatives Using the CODAS Method

Alternative evaluation using the CODAS method is an analytical stage designed to determine the ranking of alternatives objectively based on their proximity to the ideal solution. This method evaluates each alternative by calculating both the Euclidean distance and the Taxicab distance from the ideal and anti-ideal conditions, resulting in a more sensitive comparison of performance differences among alternatives.

One of the main advantages of CODAS is its ability to integrate two distance measures, thereby improving evaluation accuracy, particularly when alternatives exhibit only slight differences in performance. In multi-criteria decision-making contexts, this distance-based approach supports a more rational assessment by considering the relative position of each alternative within the decision space. Furthermore, the incorporation of predefined criterion weights ensures that each criterion contributes proportionally to the final results.

This procedure helps reduce potential subjective bias while increasing the consistency of the ranking outcomes. Overall, the application of the CODAS method provides a robust and transparent evaluation framework for producing decisions that are both accurate and scientifically as well as practically justifiable.

The initial stage in the CODAS method involves constructing a decision matrix in which alternatives are arranged in rows and criteria are placed in columns. This matrix contains the performance values of each alternative for each criterion and serves as the fundamental basis for all subsequent calculations, as shown in (1).

$$X=\begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} \\ x_{19} & x_{29} & x_{39} & x_{49} & x_{59} \end{bmatrix} \rightarrow X=\begin{bmatrix} 195000 & 8 & 7 & 7 & 8 \\ 210000 & 7 & 6 & 8 & 7 \\ 165000 & 9 & 8 & 7 & 9 \\ 230000 & 6 & 7 & 6 & 6 \\ 245000 & 8 & 9 & 9 & 8 \\ 205000 & 7 & 7 & 6 & 7 \\ 240000 & 6 & 6 & 7 & 6 \\ 150000 & 9 & 8 & 8 & 8 \\ 190000 & 8 & 7 & 8 & 7 \end{bmatrix}$$

The next stage in the CODAS method is normalization, which is performed to standardize the data scale since each criterion generally has different units and value ranges. This step ensures that all values become comparable across criteria and is calculated using (8).

$$n_{11}=\frac{\min_{1} x_{1j}}{x_{11}}=\frac{150000}{195000}=0.7692$$

Table 10 presents the overall results of the matrix normalization calculations for each alternative across all considered criteria.

Table 10. Matrix Normalization of the CODAS Method

Alternative ID	ID Data Criteria				
	C1	C2	C3	C4	C5
SP0001	0.7692	0.8889	0.7778	0.7778	0.8889

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SP0002	0.7143	0.7778	0.6667	0.8889	0.7778
SP0003	0.9091	1.0000	0.8889	0.7778	1.0000
SP0004	0.6522	0.6667	0.7778	0.6667	0.6667
SP0005	0.6122	0.8889	1.0000	1.0000	0.8889
SP0006	0.7317	0.7778	0.7778	0.6667	0.7778
SP0007	0.6250	0.6667	0.6667	0.7778	0.6667
SP0008	1.0000	1.0000	0.8889	0.8889	0.8889
SP0009	0.7895	0.8889	0.7778	0.8889	0.7778

The next stage in the CODAS method involves multiplying the normalized values by the corresponding criterion weights to reflect their relative importance. This step ensures that each criterion contributes proportionally to the overall evaluation process and is calculated using (9).

$$r_{11} = w_1 * n_{11} = 0.1936 * 0.7692 = 0.1489$$

Table 11 presents the overall results of the weighted normalization calculations for each alternative across all considered criteria.

Table 11. Weighted Normalization of the CODAS Method

Alternative ID	ID Data Criteria				
	C1	**C2**	**C3**	**C4**	**C5**
SP0001	0.1489	0.1748	0.1587	0.1578	0.1803
SP0002	0.1383	0.1530	0.1361	0.1803	0.1578
SP0003	0.1760	0.1967	0.1814	0.1578	0.2028
SP0004	0.1262	0.1311	0.1587	0.1352	0.1352
SP0005	0.1185	0.1748	0.2041	0.2028	0.1803
SP0006	0.1416	0.1530	0.1587	0.1352	0.1578
SP0007	0.1210	0.1311	0.1361	0.1578	0.1352
SP0008	0.1936	0.1967	0.1814	0.1803	0.1803
SP0009	0.1528	0.1748	0.1587	0.1803	0.1578

The next stage in the CODAS method involves determining the negative ideal solution, which represents the worst reference point for each criterion derived from the weighted normalized matrix. This solution is used as a benchmark to evaluate how far each alternative is from the least desirable condition and is calculated using (10).

$$ns_1 = \min_{1} r_{1j} = \min(0.1489; 0.1383; 0.1760; 0.1262; 0.1185; 0.1416; 0.1210; 0.1936; 0.1528) = 0.1185$$

Table 12 presents the overall results of the negative ideal solution values calculated across all considered criteria.

Table 12. The Negative Ideal Solution Value of the CODAS Method

ID Data Criteria				
C1	**C2**	**C3**	**C4**	**C5**
0.1185	0.1311	0.1361	0.1352	0.1352

The next stage in the CODAS method involves calculating the distance of each alternative from the negative ideal solution using two measures, namely the Euclidean distance and the Taxicab distance. The application of these two distance metrics aims to provide a more comprehensive assessment of how close each alternative is to the worst-case condition,

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and these calculations are expressed in (11) and (12).

$$E_1 = \sqrt{(r_{11} - ns_1)^2 + (r_{21} - ns_2)^2 + (r_{31} - ns_3)^2 + (r_{41} - ns_4)^2 + (r_{51} - ns_5)^2}$$
$$= \sqrt{\begin{matrix}(0.1489 - 0.1185)^2 + (0.1748 - 0.1311)^2 + (0.1587 - 0.1361)^2 \\ +(0.1578 - 0.1352)^2 + (0.18030.1352)^2\end{matrix}}$$
$$= \sqrt{0.0009 + 0.0019 + 0.0005 + 0.0005 + 0.0020}$$
$$= \sqrt{0.0059} = 0.0767$$
$$T_i = |r_{11} - ns_1| + |r_{21} - ns_2| + |r_{31} - ns_3| + |r_{41} - ns_4| + |r_{51} - ns_5|$$
$$= |0.1489 - 0.1185| + |0.1748 - 0.1311| + |0.1587 - 0.1361| + |0.1578 - 0.1352| + |0.1803 - 0.1352|$$
$$= |0.0304| + |0.0437| + |0.0227| + |0.0225| + |0.0451| = 0.1644$$

Table 13 presents the overall results of the calculated distances of each alternative from the negative ideal solution across all considered criteria.

Table 13. Distance of each Alternative from Negative Ideal Solution of the CODAS Method

Alternative ID	Euclidean Distance	Taxicab Distance
SP0001	0.0767	0.1644
SP0002	0.0584	0.1092
SP0003	0.1214	0.2585
SP0004	0.0240	0.0304
SP0005	0.1146	0.2244
SP0006	0.0451	0.0902
SP0007	0.0227	0.0250
SP0008	0.1267	0.2761
SP0009	0.0784	0.1683

The next stage in the CODAS method involves determining the relative ranking values by comparing the distances of each alternative with those of the other alternatives. This step is used to measure the relative superiority of each alternative and is calculated using (13).

$$h_{11} = (E_1 - E_1) + (0.5 * (E_1 - E_1)) * (T_1 - T_1)$$
$$= (0.0767 - 0.0767) + (0.5 * (0.0767 - 0.0767)) * (0.1644 - 0.1644)$$

Table 14 presents the overall results of the relative ranking value calculations for all alternatives in comparison with each other.

Table 14. Relative Ranking Values of the CODAS Method

	SP0001	SP0002	SP0003	SP0004	SP0005	SP0006	SP0007	SP0008	SP0009
SP0001	0.0000	0.0189	-0.0426	0.0563	-0.0368	0.0328	0.0578	-0.0472	-0.0016
SP0002	-0.0178	0.0000	-0.0583	0.0358	-0.0530	0.0134	0.0372	-0.0626	-0.0194
SP0003	0.0468	0.0677	0.0000	0.1085	0.0069	0.0827	0.1102	-0.0053	0.0450
SP0004	-0.0492	-0.0331	-0.0863	0.0000	-0.0819	-0.0205	0.0013	-0.0901	-0.0507
SP0005	0.0390	0.0595	-0.0066	0.0995	0.0000	0.0742	0.1011	-0.0117	0.0373
SP0006	-0.0305	-0.0131	-0.0699	0.0218	-0.0649	0.0000	0.0232	-0.0740	-0.0320
SP0007	-0.0503	-0.0342	-0.0872	-0.0013	-0.0828	-0.0217	0.0000	-0.0910	-0.0517
SP0008	0.0528	0.0740	0.0054	0.1154	0.0124	0.0892	0.1171	0.0000	0.0509
SP0009	0.0016	0.0206	-0.0411	0.0582	-0.0353	0.0346	0.0597	-0.0457	0.0000

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The final stage in the CODAS method involves calculating the final score based on the previously obtained relative ranking values. This final score is derived from equation (14) and is used to determine the overall ranking of the alternatives.

$$H_i = h_{11} + h_{12} + h_{13} + h_{14} + h_{15} + h_{16} + h_{17} + h_{18} + h_{19}$$
$$= 0.0000 + 0.0189 + (-0.0426) + 0.0563 + (-0.0368) + 0.0328 + 0.0578 + (-0.0472) + (-0.0016)$$
$$= 0.0377$$

Table 15 presents the overall results of the final score calculations for each alternative obtained using the CODAS method.

Table 15. Final Score of the CODAS Method

Alternative ID	Final Score
SP0001	0.0377
SP0002	-0.1248
SP0003	0.4626
SP0004	-0.4105
SP0005	0.3922
SP0006	-0.2393
SP0007	-0.4201
SP0008	0.5171
SP0009	0.0526

Evaluating alternatives using the CODAS method offers a structured and data-driven framework for objectively determining rankings. By measuring the distance from both ideal and anti-ideal solutions, this method is able to differentiate alternative performance more precisely, even when the differences are relatively small. The resulting evaluation reflects the comprehensive relative position of each alternative by incorporating all defined criteria and their respective weights.

This approach reduces dependence on subjective judgment and improves the consistency of the analytical results. Moreover, the transparency of the calculation process facilitates easier tracking and validation of the final decisions. Overall, the CODAS method functions not only as a ranking tool but also as a solid foundation for generating decision recommendations that are rational, reliable, and applicable to real-world decision-making contexts.

Result Analysis

Result analysis is a crucial stage for interpreting the outcomes obtained from the entire decision-making process. At this stage, the computational results and alternative rankings are not only presented in numerical form but are also examined to gain a deeper understanding of their meaning and implications. The ranking results of all alternatives are presented in Table 16.

Table 15. Final Score of the CODAS Method

Alternative ID	Alternative Name	Final Score	Ranking
SP0008	PT Cipta Solusi Persada	0.5171	1
SP0003	PT Karya Nusantara	0.4626	2
SP0005	PT Prima Logistik Indonesia	0.3922	3
SP0009	PT Global Mitra Supply	0.0526	4
SP0001	PT Sumber Makmur Abadi	0.0377	5

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SP0002	CV Mitra Sejahtera	-0.1248	6
SP0006	PT Anugerah Teknik Mandiri	-0.2393	7
SP0004	CV Sentosa Jaya	-0.4105	8
SP0007	CV Berkah Utama	-0.4201	9

The evaluation results of the alternatives show variations in performance as measured by the final scores and the rankings produced. PT Cipta Solusi Persada (SP0008) achieved the highest score of 0.5171 and ranked first, followed by PT Karya Nusantara (SP0003) with a score of 0.4626 in second place, and PT Prima Logistik Indonesia (SP0005) with a score of 0.3922 in third place. In the middle tier, PT Global Mitra Supply (SP0009) ranked fourth with a score of 0.0526, followed by PT Sumber Makmur Abadi (SP0001) with a score of 0.0377 in fifth place. Meanwhile, CV Mitra Sejahtera (SP0002) obtained a score of −0.1248 and ranked sixth, PT Anugerah Teknik Mandiri (SP0006) with a score of −0.2393 ranked seventh, CV Sentosa Jaya (SP0004) with a score of −0.4105 ranked eighth, and CV Berkah Utama (SP0007) ranked last with a score of −0.4201. This distribution of scores indicates a fairly significant performance difference among the alternatives and confirms the evaluation method's ability to produce a clear and objective ranking.

The significant score differences between the top, middle, and bottom-ranked groups also indicate that the supplier performance structure is not homogeneous, but rather clearly segmented based on the ability to meet the company's operational needs. The dominance of PT Cipta Solusi Persada and PT Karya Nusantara in the top two positions suggests that these two companies excel not only in a particular aspect but are also able to maintain balanced performance across criteria, making them more adaptable to demand dynamics and changing market conditions. This is important because in the context of selecting long-term suppliers, performance stability is often more valuable than temporary superiority on a single indicator, such as low prices that are not matched by on-time delivery or quick response. Meanwhile, the relatively large score gap between the third and fourth rankings indicates a significant difference in service quality, so strategically, the company can consider focusing main cooperation on the top three, while mid-ranked suppliers serve as supporting or backup alternatives in the event of a demand surge. On the other hand, the dominance of negative scores in the bottom four rankings underscores that the problems faced are not merely minor differences, but rather structural mismatches with the company's needs, whether in terms of capacity, flexibility, or operational responsiveness. Thus, these ranking results not only serve as a selection tool, but can also be used as a strategic evaluation instrument for designing supplier development policies, such as performance improvement programs or contract renegotiations, so that decisions made are not static, but adaptive and oriented towards continuous improvement in the supply chain.

Discussion

The supplier ranking results show that the decision-making model used is capable of clearly and systematically identifying performance differences among all evaluated alternatives. The dominance of PT Cipta Solusi Persada and PT Karya Nusantara at the top ranks indicates that integrating various criteria—including price, quality, on-time delivery, responsiveness, as well as capacity and flexibility—can provide a more comprehensive performance overview compared to evaluations based on only one or two indicators. These findings confirm that suppliers with balanced performance across criteria tend to achieve higher aggregate scores, making them more suitable for prioritization in strategic decision-making. Additionally, the presence of significant score differences between rankings indicates that this model has good discriminatory ability in distinguishing superior suppliers from less competitive ones.

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Compared to previous research in the field of multi-criteria supplier selection, the results of this study are consistent with findings that indicate a quantitative approach can enhance the objectivity and consistency of decisions. Several earlier studies emphasized that a combination of operational and service criteria is a key factor in shaping sustainable supplier performance, and this is also reflected in the ranking results. Suppliers who excel only in price but are weak in quality or responsiveness tend to be downgraded to middle or lower rankings. Therefore, this study reinforces the argument that an integrated evaluation approach is more relevant in the context of modern supply chains that demand reliability, flexibility, and speed of response.

Another interesting finding is the emergence of supplier groups with scores near zero and negative scores, indicating the existence of a minimum performance threshold that some alternatives have not been able to meet. This condition suggests that the performance issues experienced by lower-ranked suppliers are structural and systemic, rather than merely small fluctuations in a specific criterion. From a managerial perspective, these results signal that these suppliers require more serious interventions, such as contract re-evaluation, performance improvement programs, or even removal from the list of key suppliers. Thus, the proposed model not only serves as a selection tool but also as a diagnostic means to identify areas of improvement in supplier relationships.

Overall, the results of this study support the hypothesis that using a structured multi-criteria approach can lead to more accurate and accountable supplier selection decisions. The main contribution of this research lies in providing an evaluation framework capable of clearly distinguishing supplier performance while offering a quantitative basis for strategic decision-making. Nevertheless, the results are still influenced by the choice of criteria and the quality of assessment data, so future research can develop this model further by incorporating sensitivity analysis or integrating other methods to test the stability of rankings. Thus, this study not only enriches the decision support systems literature but also offers strong practical implications for organizations in managing and optimizing their supply chain performance.

4. CONCLUSION

This study concludes that the multi-criteria decision-making approach applied is capable of producing supplier rankings that are objective and easy to interpret. Based on the evaluation results, PT Cipta Solusi Persada managed to secure the first rank with a final score of 0.5171, followed by PT Karya Nusantara in second place with a score of 0.4626, and PT Prima Logistik Indonesia in third place with a score of 0.3922. The achievements of these three suppliers indicate that superior and relatively balanced performance across all main criteria, namely price, quality, delivery punctuality, responsiveness, as well as capacity and flexibility, which are the dominant factors, contribute to obtaining a high aggregate score and top-ranking position. In addition to determining the best suppliers, the ranking results also show a significant performance gap between the top-ranked group and the other alternatives. The score difference between the first to third ranks and the subsequent ranks indicates that the top three suppliers have a more consistent and stable competitive advantage. This confirms that the model used has good discriminatory ability to differentiate between high-performing suppliers and those that still require improvement. Thus, the company can prioritize strategic collaboration with suppliers ranked 1 to 3, while other suppliers can be positioned as supporting partners or potential candidates for development in the future. Overall, this study provides a theoretical contribution by reinforcing the evidence that a multi-criteria approach is effective in supporting supplier selection decision-making, as well as a practical contribution as a systematic and measurable evaluation tool. The ranking results, particularly for positions 1 to 3, can serve as a strong basis for management in determining key suppliers and

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developing a more reliable supply chain strategy. Nevertheless, this study is still limited to the criteria and assessment data used, so future research is recommended to include sensitivity analysis or integrate other methods to test the stability of the rankings and enhance the generalizability of the proposed model.

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