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Comparative Analysis of CODAS, TOPSIS, and COCOSO Methods Using Objective Weighting in Multi-Criteria Decision Support Systems

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Abstract

In a multi-criteria decision support system, differences in the calculation mechanisms and sensitivity of the CODAS, TOPSIS, and COCOSO methods often result in inconsistent rankings of alternatives, even when using the same data and criteria. This situation creates the need for a structured comparative analysis with objective weighting so that the influence of each method's characteristics on the decision outcomes can be better understood and justified. This study aims to objectively assess teachers' pedagogical performance through the application and comparison of three multi-criteria decision-making methods, namely CODAS, TOPSIS, and COCOSO, with the criteria weights determined using the ITARA method. The ranking results show differences in evaluation patterns among the methods, where the CODAS method places Teacher RD in the first rank, followed by Teacher GH and Teacher DG, while Teacher AN is ranked last. In contrast, the TOPSIS and COCOSO methods produced relatively consistent rankings, with Teacher TY ranking first, followed by Teacher AN and Teacher NH in TOPSIS, and Teacher NH and Teacher DG in COCOSO. These differences in results indicate that each method has a different evaluative perspective on the performance of alternatives, depending on the preference calculation approach used. The results of the rank correlation analysis using Spearman's correlation show that the CODAS method obtained a correlation value of 0.5595, TOPSIS 0.7362, and COCOSO 0.7481. These values indicate that TOPSIS and COCOSO have a higher level of ranking consistency compared to CODAS in representing the order of alternatives. This finding confirms that differences in calculation mechanisms in each method affect the stability of decision results in a multicriteria decision support system.

1.INTRODUCING

Multi-criteria decision making (MCDM) plays a very important role in the development of modern decision support systems (DSS) because it is able to handle decision-making problems that involve multiple criteria with different and often conflicting characteristics[1]–[3]. In the context of an increasingly complex, data-driven environment, MCDM helps decision-makers organize, evaluate, and compare various alternatives systematically and rationally, using both subjective and objective approaches. MCDM methods allow the integration of quantitative and qualitative data so that decisions are based not only on intuition but also on measurable and transparent analysis. In addition, MCDM supports the determination of criteria weights, evaluation of alternative performance, and sensitivity analysis to test the stability of decision results against changes in parameters[4]–[7]. This role becomes

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increasingly relevant in modern decision support systems that utilize computational technology and artificial intelligence, as MCDM can enhance consistency, accuracy, and fairness in the decision-making process across various fields, such as education, industry, healthcare, and resource management, making the resulting decisions more accountable and aligned with the intended objectives.

The need for accurate and stable ranking methods has become a crucial issue in DSS, especially when decisions must be made based on multiple criteria with varying levels of importance[8]–[10]. Accurate ranking methods are necessary to ensure that evaluation results truly reflect the relative performance of each alternative objectively and consistently, thereby minimizing bias and assessment errors. Meanwhile, the stability of the method is important to ensure that small changes in data or criteria weights do not lead to significant and unreasonable shifts in rankings. Without stability, ranking results have the potential to cause doubt and reduce decision-makers' confidence in the system being used[11], [12]. Therefore, the development and implementation of ranking methods that can maintain a balance between accuracy and stability are greatly needed so that the decisions produced are reliable, transparent, and accountable in various modern decision-making contexts.

Conventional DSS still have several fundamental limitations that affect the quality of decision outcomes, particularly regarding the dominance of subjective weighting and the high sensitivity of ranking results to changes in criteria weights. In many cases, criteria weights are determined based on expert or decision-maker assessments, which, although experienced, are still vulnerable to personal bias, certain preferences, and inconsistencies in judgment. This dominance of subjective weighting can lead to evaluation results that do not fully reflect the objective conditions of the alternatives being assessed. Furthermore, conventional DSS systems often exhibit high sensitivity to small changes in criteria weights, where minor adjustments can result in significant changes in rankings. This condition leads to instability in outcomes and reduces confidence in the system, especially when the decisions made have strategic implications. These limitations indicate that conventional DSS still requires a more robust and adaptive approach to be able to produce rankings that are more consistent, fair, and reliable in dealing with the complexities of modern decision-making.

Distance and compromise-based methods are groups of methods in MCDM designed to evaluate alternatives based on their closeness to the ideal solution or through a compromise approach among conflicting criteria. Technique for order preference by similarity to ideal solution (TOPSIS) is known as a classic distance-based method that assesses alternatives by measuring the shortest distance to the positive ideal solution and the farthest distance from the negative ideal solution, thereby providing an intuitive and easy-to-understand evaluation framework[13]–[15]. However, in practice, this approach is highly dependent on the weighting of criteria and can be sensitive to small changes in those parameters. Combinative distance-based assessment (CODAS) is the development of distance-based methods by emphasizing relative comparisons to the anti-ideal solution, using a combination of Euclidean and Taxicab distances to distinguish alternatives more clearly, especially when the performance differences between alternatives are relatively small[16]–[18]. Meanwhile, combined compromise solution (COCOSO) adopts a compromise approach based on aggregated scores by combining several normalization and aggregation strategies to produce more balanced preference values, thus better representing trade-offs among criteria fairly[19]–[21]. These three methods demonstrate how distance-based and compromise approaches play an important role in producing more rational and informative rankings in the context of multi-criteria decision-making.

The necessity of objective weighting arises as an important need in multi-criteria decision making because subjective approaches often cannot guarantee the consistency and objectivity of the results[22]–[25]. The weaknesses of subjective judgment are evident from its reliance on the perceptions, experiences, and preferences of decision-makers, which can potentially lead to bias, inconsistency, and differences in assessment even for the same problem[26], [27]. This condition can significantly affect the criteria weights and directly impact the ranking results of alternatives. In this context, objective weighting serves as a solution to reduce the dominance of subjectivity by utilizing information contained in the data, such as the level of variation, distribution, or the contribution of each criterion to distinguishing alternatives. The role of objective weighting not only enhances the fairness and transparency of the decision-making process but also helps produce more stable and accountable outcomes, especially when decision support systems are used for complex and data-driven problems.

Setiawansyah: *Corresponding Author

The indifference threshold-based attribute ratio analysis (ITARA) method is one of the objective weighting methods in MCDM, aimed at determining the importance level of criteria based on the information contained in the data without involving the subjective judgment of decision-makers[28]–[30]. ITARA works by utilizing the concept of an indifference threshold to identify differences that are truly significant between criterion values, allowing relevant data variations to be separated from changes considered insignificant. This approach makes the resulting weights more stable and representative of the actual data conditions, particularly in decision-making problems involving many alternatives with diverse characteristics. The ITARA method plays an important role in enhancing the objectivity, consistency, and reliability of data-driven decision support systems.

The research contribution of this study lies in presenting a systematic comparative study between the CODAS, TOPSIS, and COCOSO methods using an objective weighting scheme as the basis for evaluation. This approach allows for a fairer comparison of the performance of distance- and compromise-based methods by reducing the influence of subjective preferences in determining criteria weights. In addition, this study emphasizes the evaluation of the stability and consistency of ranking results through sensitivity analysis of weight changes, allowing us to understand the extent to which each method can reliably maintain the order of alternatives. The results of this evaluation provide a deeper understanding of the characteristics of each method in dealing with variations in decision parameters. Thus, the contribution of this research not only enriches methodological studies in MCDM, but also provides practical value for the development of data-based DSS that require accuracy, consistency, and transparency in the decision-making process.

2.RESEARCH METHOD

The research stages in this study were systematically arranged to ensure that the analytical process runs in a structured, objective, and replicable manner. The research began with problem identification and goal formulation, followed by a literature review as a conceptual foundation for selecting the CODAS, TOPSIS, and COCOSO methods, as well as the objective weighting approach. Next, criteria and alternatives were determined based on relevant data, after which data collection and processing were carried out before calculating the criteria weights and applying each multicriteria decision-making method. The results obtained were analyzed comparatively to assess the consistency, stability, and ranking characteristics of each method. The entire series of research stages is presented concisely and visually in Figure 1.

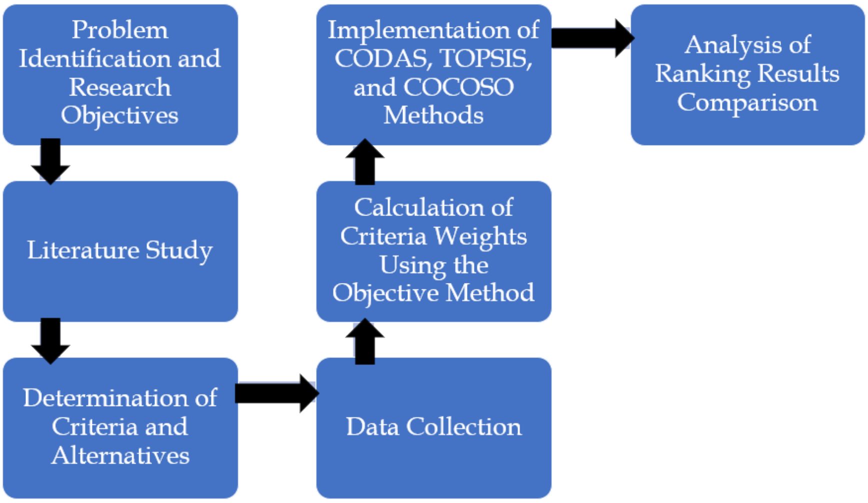

Figure 1. Research stage

The research began by identifying problems in the multi-criteria decision support system, particularly related to differences in ranking results that arise from the use of different methods and criteria weights. This stage also establishes the main objective of the study, which is to compare the performance of the CODAS, TOPSIS, and COCOSO methods based on objective weighting. This stage

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includes a review of theories and previous research on the CODAS, TOPSIS, and COCOSO methods, the concept of objective weighting, as well as its application in decision support systems. The literature study aims to strengthen the theoretical foundation and identify relevant research gaps. Criteria and alternatives are determined according to the context of the decision problem being studied. This determination is carried out objectively based on the available data so that the analysis results are not influenced by the subjective preferences of the decision-makers. Data is collected from relevant sources, then pre-processed such as initial normalization, data completeness checks, and scale adjustments to make the data ready for use in the MCDM calculation process. The criteria weights are calculated using the chosen objective weighting method. This stage ensures that the weights reflect the characteristics of the data without subjective assessment intervention. Each MCDM method is applied using the objective weights obtained. This process yields preference values and alternative rankings for each method. The ranking results from the three methods were compared to observe similarities, differences, and emerging patterns. This analysis aims to assess the consistency and sensitivity of the methods to objective weights. This stage evaluates the stability of alternative rankings against changes in criteria weights or certain scenarios. Sensitivity analysis is used to see the resilience of each method in facing data variations.

Objective Weighting

Objective weighting is an approach to criteria weighting that is entirely based on data characteristics, without involving the preferences or subjective judgments of decision-makers. This approach aims to reduce the bias that often arises in subjective weighting, especially in multi-criteria decision problems with a large number of criteria and alternatives. By utilizing variations, dispersion, and relationships among data, objective weighting can represent the importance level of criteria more consistently and transparently. Therefore, the use of objective weighting becomes important in data-driven decision support systems, particularly when stable and methodologically accountable ranking results are required.

One of the objective weighting methods used in this study is the ITARA method. The ITARA method determines the weights of criteria by considering the indifference threshold to identify significant differences between attribute values. Through this approach, criteria with data variation exceeding the indifference threshold will receive higher weights, as they are considered to have a more meaningful contribution to the decision-making process. ITARA allows for a weighting determination that is more adaptive to the data structure, thereby enhancing the accuracy and reliability of evaluation results in a multi-criteria decision support system.

The process of determining criterion weights using the ITARA method begins with the formation of a decision matrix that represents the performance values of each alternative against all criteria using (1). Next, the criterion values and the indifference threshold are normalized to equalize the data scale and ensure fair comparisons among attributes using (2) and (3). The normalized values are then arranged in an ascending order matrix to identify data change patterns for each criterion using (4), followed by determining the ideal value as a reference for evaluation using (5). The next step is to calculate the difference between consecutive values and the indifference threshold to identify significant differences using (6). All significant differences are then summed for each criterion using (7), and the results are normalized against the total significant differences of all criteria to obtain the final weights, which reflect the relative importance of each criterion objectively using (8).

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

$$e_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (2)$$

$$NIT_j = \frac{IT_j}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

$$\beta_{ij} = \begin{bmatrix} \beta_{aspire,1} & \cdots & \beta_{aspire,j} \\ \beta_{11} & & \beta_{1j} \\ \vdots & \ddots & \vdots \\ \beta_{i1} & \cdots & \beta_{ij} \end{bmatrix} \quad (4)$$

$$\gamma_{ij} = \beta_{i+1,j} - \beta_{ij} \quad (5)$$

Setiawansyah: *Corresponding Author

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$$\varepsilon_{ij} = \begin{cases} \gamma_{ij} - NIT_j; for\ \gamma_{ij} > NIT_j \\ 0 \quad ; for\ \gamma_{ij} \leq NIT_j \end{cases} \tag{6}$$

$$v_j = \left(\sum_{i=1}^{m-1} \varepsilon_{ij}{}^{p}\right)^{1/p} \tag{7}$$

$$w_j = \frac{v_j}{\sum_{j=1}^{n} v_j} \tag{8}$$

The symbol $X = [x_{ij}]_{mxn}$ represents the decision matrix, where x_{ij} is the performance value of the i^th^ alternative against the j^th^ criterion, m indicates the number of alternatives, and n represents the number of criteria. The symbol e_{ij} represents the normalized value of x_{ij}, obtained by dividing the value by $\sum_{i=1}^{m} x_{ij}$, which is the total value of all alternatives for the j^th^ criterion. The symbol IT_j indicates the indifference threshold for the j^th^ criterion, while NIT_j is the normalized indifference threshold to be comparable with the value of ε_{ij}. The matrix β_{ij} represents the values of e_{ij} that have been arranged in ascending order for each criterion, with $\beta(aspire, j)$ as the aspiration value or the ideal reference value for the j^th^ criterion. The symbol γ_{ij} denotes the difference between two consecutive values in the βij matrix. The symbol ε_{ij} indicates a significant difference, which is the γ_{ij} value that exceeds NIT_j, while a zero value is given if the difference does not surpass the threshold. The symbol v_j represents the initial importance level of the j^th^ criterion obtained from the aggregation of all ε_{ij} using the parameter p. Finally, the symbol w_j indicates the final weight of the j^th^ criterion obtained by normalizing the v_j values against the total of all criteria.

CODAS Method

The CODAS method is one of the multi-criteria decision-making approaches that evaluates alternatives based on their distance from the negative ideal solution. In CODAS, the best alternative is determined by combining two distance measures, namely Euclidean distance as the primary measure and Taxicab distance as a supporting measure when the Euclidean distance differences among alternatives are not significant. This approach allows for a more sensitive evaluation of variations in alternative performance, especially in situations where the values among alternatives are very close. By relying on the concepts of distance and criteria weighting, the CODAS method can produce stable and logical rankings, making it widely used in decision support systems to solve complex selection and evaluation problems.

The stages of the CODAS method begin with the preparation of a decision matrix containing the performance values of each alternative against all criteria using (1). This matrix is then normalized to equalize the value scales across criteria, allowing a fair comparison using (9). Next, weighted normalization is carried out by multiplying the normalized matrix by the criterion weights to reflect the level of importance of each criterion using (10). Next, the negative ideal solution is determined to reflect the worst performance level of each criterion and is used as a reference for evaluating the alternatives using (11). Based on this weighted matrix, the Euclidean distance and Taxicab distance of each alternative to the negative ideal solution are calculated as the main and supporting measures in the evaluation process using (12) and (13). The distance calculation results are used to form a relative evaluation matrix that shows the degree of superiority of one alternative over another using (14). This entire process produces the final preference values that serve as the basis for ranking the alternatives using (15).

$$n_{ij} = \begin{cases} \frac{x_{ij}}{\max_i x_{ij}}; if\ j \in benefit \\ \frac{\min_i x_{ij}}{x_{ij}}; if\ j \in cost \end{cases} \tag{9}$$

$$r_{ij} = w_j * n_{ij} \tag{10}$$

$$ns_j = \min_i r_{ij} \tag{11}$$

$$E_i = \sqrt{\sum_{j=1}^{m} \left(r_{ij} - ns_j\right)^2} \tag{12}$$

$$T_i = \sum_{j=1}^{m} \left|r_{ij} - ns_j\right| \tag{13}$$

$$h_{ik} = (E_i - E_k) + (\varphi(E_i - E_k)) * (T_i - T_k) \tag{14}$$

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{15}$$

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The symbol x_{ij} represents the performance value of the i[th] alternative against the j[th] criterion, while n_{ij} represents the normalized value adjusted according to the type of criterion, where max x_{ij} is used for benefit-type criteria and min x_{ij} is used for cost-type criteria. The symbol r_{ij} indicates the decision matrix value that has been normalized and weighted, while ns_j represents the negative ideal solution value obtained from the minimum rij for each criterion. The symbol Ei represents the Euclidean distance of the i-th alternative from the negative ideal solution, calculated from the squared difference between r_{ij} and ns_j. The symbol Ti represents the Taxicab distance of the i-th alternative, which is the sum of the absolute differences between rij and ns_j. The symbol h_{ik} represents the relative evaluation value between the i[th] h alternative and the k[th] alternative, which is obtained from a combination of Euclidean distance difference and Taxicab distance with the threshold function φ. Finally, the symbol H_i represents the final preference value of the i[th] alternative, obtained from the sum of all relative evaluation values h_{ik}, and is used as the basis for determining the ranking of alternatives.

TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is one of the multi-criteria decision-making methods that evaluates alternatives based on their closeness to the positive ideal solution and their distance from the negative ideal solution. The basic principle of TOPSIS is that the best alternative should have the shortest distance from the positive ideal solution, which represents the most desirable condition, and the farthest distance from the negative ideal solution, which represents the least desirable condition. This method uses a normalized and weighted decision matrix to ensure that comparisons across criteria are conducted proportionally. With a simple and logical geometric concept, TOPSIS is widely used in decision support systems because it can provide ranking results that are easy to understand and consistent across various multi-criteria evaluation and selection problems.

The steps of the TOPSIS method begin with the preparation of a decision matrix that contains the performance values of each alternative against all the criteria used, using (1). This matrix is then normalized to equalize the differences in scale between criteria so that comparisons can be made fairly, using (16). The normalization results are then multiplied by the criteria weights to obtain a weighted normalized matrix that reflects the importance level of each criterion, using (17). Based on this matrix, the positive ideal value and the negative ideal value are determined as representations of the best and worst conditions for each criterion, using (18) and (19). The distance of each alternative to the ideal and anti-ideal values is then calculated using a distance measure to assess the relative closeness of the alternatives using (20) and (21). The final stage produces the preference values of the alternatives, which serve as the basis for ranking, where the alternative with the highest preference value is considered the best choice using (22).

$$x^*_{ij} = \frac{x_{ij}}{\sqrt{\left[\sum_{i=1}^{j} x_{ij}^2\right]}} \quad (16)$$

$$v_{ij} = w_j * x^*_{ij} \quad (17)$$

$$y_j^+ = \begin{cases} max_i y_{ij} \text{ ; if } j \text{ is a benefit attribute} \\ min_i y_{ij} \text{ ; if } j \text{ is a cost attribute} \end{cases} \quad (18)$$

$$y_j^- = \begin{cases} min_i y_{ij} \text{ ; if } j \text{ is a benefit attribute} \\ max_i y_{ij} \text{ ; if } j \text{ is a cost attribute} \end{cases} \quad (19)$$

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_i^+ - y_{ij}\right)^2} \quad (20)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_i^-\right)^2} \quad (21)$$

$$V_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (22)$$

The symbol x_{ij} represents the performance value of the i[th] alternative with respect to the j[th] criterion, while x^*_{ij} is the normalized vector value obtained by dividing x_{ij} by the square root of the sum of the squares of all alternative values for the same criterion. The symbol w_j indicates the weight of the j[th] criterion, and v_{ij} is the weighted normalized decision matrix value that reflects the contribution of the

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criterion to each alternative. The symbol y_j^+ represents the positive ideal solution, which is the best value for each criterion, determined as the maximum value for benefit-type criteria and the minimum value for cost-type criteria. Conversely, the symbol y_j^- represents the negative ideal solution, which is the worst value for each criterion, determined as the minimum value for benefit criteria and the maximum value for cost criteria. The symbol D_i^+ indicates the Euclidean distance of the ith alternative to the positive ideal solution, while D_i^- denotes the Euclidean distance of the ith alternative to the negative ideal solution. Finally, the symbol V_i represents the preference value of the i-th alternative, calculated as the ratio of the distance to the negative ideal solution to the total distance to both ideal solutions, and is used as the basis for determining the ranking of alternatives.

COCOSO Method

The COCOSO method is a multi-criteria decision-making method that integrates the concept of weighted addition and multiplication to produce a balanced compromise solution. COCOSO combines the advantages of additive and multiplicative approaches by considering the relative distance of alternatives to the ideal solution, thereby capturing differences in alternative performance more comprehensively. Through the combination of several aggregation indices, this method provides assessments that are not reliant on a single evaluation perspective but rather reflect a balance among all the criteria involved. With these characteristics, COCOSO is widely used in decision support systems to obtain stable and representative ranking results in complex multi-criteria problems.

The stages of the COCOSO method begin with the preparation of a decision matrix that contains the performance values of each alternative against all the criteria used in decision-making using (1). The decision matrix is then normalized to equalize the data scale across criteria, so that each criterion can be compared proportionally using (23) and (24). Next, the positive ideal solution and the negative ideal solution are determined as references for the best and worst values for each criterion using (25) and (26). Based on these two ideal solutions, the relative value of each alternative is calculated, representing the degree of closeness and contribution to the compromise solution using (27), (28), and (29). In the final stage, all relative values are combined to produce the final preference value, which is used as the basis for determining the ranking of alternatives in the COCOSO method using (30).

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{23}$$

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{24}$$

$$S_i = \sum_{j=1}^{n} (W_j r_{ij}) \tag{25}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{26}$$

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{27}$$

$$K_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \tag{28}$$

$$K_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max S_i + (1-\lambda) \max P_i)} \tag{29}$$

$$K_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{30}$$

The symbol x_{ij} represents the performance value of the ith alternative with respect to the jth criterion, while r_{ij} is the normalized value adjusted according to the type of criterion, where equation (23) is used for benefit-type criteria and equation (24) is used for cost-type criteria. The symbols max x_{ij} and min x_{ij} indicate the maximum and minimum values for the jth criterion among all alternatives. The symbol wj represents the weight of the jth criterion. The symbol S_i represents the additive aggregation value of the ith alternative obtained from the summation of the weighted normalized values. The symbol P_i indicates the multiplicative aggregate value of the ith alternative, obtained from raising the normalized value to the weight and combining it across all criteria. The symbols K_{ia}, K_{ib}, and K_{ic} are three compromise indices calculated based on the combination of S_i and P_i values, using normalization approaches, ratio to the minimum value, and a balance parameter λ, that regulates the relative contribution between the additive and multiplicative components. Finally, the symbol K_i represents the final preference value of

Setiawansyah: *Corresponding Author

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the i^{th} alternative, obtained from the combination of the geometric and arithmetic mean, which is used as the basis for determining the ranking of alternatives.

3.RESULTS AND DISCUSSION

Multicriteria decision-making in decision support systems often faces challenges due to differences in ranking results caused by the characteristics of the methods and the weighting of criteria used. The CODAS, TOPSIS, and COCOSO methods have different evaluation approaches, ranging from the concept of distance, closeness to the ideal solution, to compromise solutions, which can result in decisions that are not always consistent for the same problem. Therefore, a comparative analysis is necessary to understand the behavior, reliability, and consistency of these three methods when applied with objective weighting. This approach allows for a more-fair and data-based evaluation, so that the comparison results can provide a clear picture of the method that is most suitable for implementation in a multicriteria decision support system.

Data Collection

Data collection in the assessment of teacher pedagogy is conducted to obtain an objective and comprehensive picture of teaching performance based on seven main criteria, namely Material Mastery (C-1), Teaching Methodology (C-2), Classroom Management (C-3), Interaction and Communication (C-4), Assessment and Evaluation (C-5), Collaboration (C-6), and Creativity and Innovation (C-7). Data is collected through structured assessment instruments designed to capture a teacher's ability to master the material, apply appropriate teaching methods, manage the classroom effectively, and establish active and interactive communication with students. In addition, aspects of learning evaluation, the ability to collaborate with colleagues, and creativity in developing learning innovations are also systematically assessed. This approach ensures that the data obtained is consistent, relevant, and can be reliably used in the teacher pedagogy assessment process. Table 1 is the dataset used in this study.

Table 1. Data Collection[31]

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	85	90	88	89	90	88	93
Teacher GH	87	88	89	91	91	86	94
Teacher NH	89	91	90	94	90	87	95
Teacher PM	90	90	88	90	92	90	93
Teacher DG	88	91	89	92	91	89	93
Teacher AN	93	89	91	91	90	88	92
Teacher TY	92	90	90	93	93	87	91

Based on the data in Table 1, it can be seen that each teacher has a diverse pedagogical performance profile across all evaluated criteria. The scores obtained show variations in mastery of the material, application of teaching methods, classroom management, and other supporting aspects such as collaboration and creativity. This data serves as an important basis for creating a decision matrix for the next stage of analysis, as it reflects the actual quantitative performance of teachers. Using this data, teacher evaluation and ranking can be conducted objectively through the application of the multi-criteria decision-making method employed in this study.

Calculation of Criteria Weights Using the Objective Method

The calculation of criteria weights using the objective method is carried out to ensure that the importance level of each criterion is determined based on the characteristics of the data, rather than the subjective judgment of the decision-maker. This approach utilizes the variation and distribution patterns of the data for each criterion so that the resulting weights reflect the actual contribution of the criteria in the evaluation process. By using the objective weighting method, the assessment process becomes more consistent, transparent, and replicable. This stage plays an important role because the

Setiawansyah: *Corresponding Author

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criteria weights obtained will influence the evaluation results and rankings in the multi-criteria decision-making method applied later.

The calculation of criteria weights using the ITARA method is carried out to obtain weights that truly reflect the importance level of the criteria based on significant data differences between alternatives. This method utilizes the concept of an indifference threshold to distinguish meaningful variations from variations that can be ignored for each criterion. With this approach, ITARA is able to highlight criteria that have a real influence in the decision-making process, while reducing the impact of insignificant data fluctuations. Therefore, the use of the ITARA method provides an objective and consistent basis for weighting before being applied to the evaluation and ranking stages of alternatives.

The implementation of the ITARA method begins with the formation of a decision matrix that represents the performance values of each alternative against all criteria as formulated in (1), with the resulting decision matrix as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} \\ x_{21} & x_{21} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} \end{bmatrix} \quad X = \begin{bmatrix} 85 & 90 & 88 & 89 & 90 & 88 & 93 \\ 87 & 88 & 89 & 91 & 91 & 86 & 94 \\ 89 & 91 & 90 & 94 & 90 & 87 & 95 \\ 90 & 90 & 88 & 90 & 92 & 90 & 93 \\ 88 & 91 & 89 & 92 & 90 & 89 & 93 \\ 93 & 89 & 91 & 91 & 91 & 88 & 92 \\ 92 & 90 & 90 & 93 & 93 & 97 & 91 \end{bmatrix}$$

The next step is to normalize the criterion values as well as the indifference threshold normalization to equalize the data scale and ensure fairness in the comparison between attributes, calculated using (2) and (3). The normalization results are shown in Table 2.

Table 2. Normalization Results of the ITARA Method

Teacher Name	Criteria Code						
	C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
Teacher RD	0.1362	0.1431	0.1408	0.1391	0.1413	0.1431	0.1429
Teacher GH	0.1394	0.1399	0.1424	0.1422	0.1429	0.1398	0.1444
Teacher NH	0.1426	0.1447	0.1440	0.1469	0.1413	0.1415	0.1459
Teacher PM	0.1442	0.1431	0.1408	0.1406	0.1444	0.1463	0.1429
Teacher DG	0.1410	0.1447	0.1424	0.1438	0.1429	0.1447	0.1429
Teacher AN	0.1490	0.1415	0.1456	0.1422	0.1413	0.1431	0.1413
Teacher TY	0.1474	0.1431	0.1440	0.1453	0.1460	0.1415	0.1398
NIT_j	0.0018	0.0007	0.0007	0.0011	0.0007	0.0009	0.0009

The normalized values are then sorted in ascending order in matrix form to observe the data change patterns for each criterion using (4), with the ascendingly sorted decision matrix results as follows.

$$X = \begin{bmatrix} 0.1362 & 0.1399 & 0.1408 & 0.1391 & 0.1413 & 0.1389 & 0.1389 \\ 0.1394 & 0.1415 & 0.1408 & 0.1406 & 0.1413 & 0.1415 & 0.1413 \\ 0.1410 & 0.1431 & 0.1424 & 0.1422 & 0.1413 & 0.1415 & 0.1429 \\ 0.1424 & 0.1431 & 0.1424 & 0.1422 & 0.1429 & 0.1431 & 0.1429 \\ 0.1462 & 0.1431 & 0.1440 & 0.1438 & 0.1429 & 0.1431 & 0.1429 \\ 0.1474 & 0.1447 & 0.1440 & 0.1453 & 0.1444 & 0.1447 & 0.1444 \\ 0.1490 & 0.1447 & 0.1456 & 0.1469 & 0.1460 & 0.1463 & 0.1459 \end{bmatrix}$$

The next stage continues with determining the ideal values as a reference for evaluation. Next, the differences between successive values are compared with the indifference threshold to identify significant differences using (5). The results of the ideal values are shown in Table 3.

Table 3. Ideal Value of the ITARA Method

Criteria Code						
C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
0.0032	0.0016	0.0000	0.0015	0.0000	0.0017	0.0015
0.0016	0.0016	0.0016	0.0016	0.0000	0.0000	0.0016
0.0016	0.0000	0.0000	0.0000	0.0016	0.0016	0.0000

Setiawansyah: *Corresponding Author

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0.0016	0.0000	0.0016	0.0016	0.0000	0.0000	0.0000
0.0032	0.0016	0.0000	0.0015	0.0015	0.0016	0.0015
0.0016	0.0000	0.0016	0.0016	0.0016	0.0016	0.0015

The next step is to calculate the differences between consecutive values compared to the indifference threshold to identify significant differences using Equation (6). The results of the calculation of differences between consecutive values with the indifference threshold are presented in Table 4.

Table 4. Indifference Threshold of the ITARA Method

Criteria Code						
C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
0.0014	0.0009	0.0000	0.0004	0.0000	0.0008	0.0006
0.0000	0.0009	0.0009	0.0005	0.0000	0.0000	0.0007
0.0000	0.0000	0.0000	0.0000	0.0009	0.0007	0.0000
0.0000	0.0000	0.0009	0.0005	0.0000	0.0000	0.0000
0.0014	0.0009	0.0000	0.0004	0.0008	0.0007	0.0006
0.0000	0.0000	0.0009	0.0005	0.0009	0.0007	0.0006

The next stage continues with aggregating these significant differences for each criterion using (7). The results of the significant difference values are shown in Table 5.

Table 5. Significant Differences of the ITARA Method

Criteria Code						
C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
0.0027	0.0028	0.0027	0.0022	0.0027	0.0014	0.0010

The final stage calculates the final weights that reflect the relative importance of each criterion objectively using (8). The results of the weights using the ITARA method are shown in Table 6.

Table 6. Final Weights of the ITARA Method

Criteria Code						
C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
0.1759	0.1771	0.1762	0.1426	0.1723	0.0896	0.0663

The calculation results of criteria weights using the ITARA method show that Teaching Methodology (C-2) has the highest weight at 0.1771, followed by Classroom Management (C-3) at 0.1762 and Material Mastery (C-1) at 0.1759, indicating that these three criteria have a relatively dominant level of importance in teacher pedagogy assessment. Assessment and Evaluation (C-5) also shows a significant contribution with a weight of 0.1723, while Interaction and Communication (C-4) has a slightly lower weight of 0.1426. The Collaboration (C-6) and Creativity and Innovation (C-7) criteria received smaller weights, 0.0896 and 0.0663 respectively, indicating that the data variation for these two criteria is relatively smaller compared to the other criteria. Overall, this weight distribution reflects the ability of the ITARA method to highlight criteria with the most significant performance differences among teachers objectively.

Implementation of CODAS, TOPSIS, and COCOSO Methods

The implementation of the CODAS, TOPSIS, and COCOSO methods is carried out to evaluate and compare the performance of alternatives systematically based on criteria weights that have been determined objectively. These three methods are applied to the same data so that the ranking results can be analyzed fairly and consistently. CODAS evaluate alternatives based on the distance to the negative ideal solution, TOPSIS measures proximity to the positive ideal solution and distance from the

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negative ideal solution, while COCOSO combines additive and multiplicative approaches to generate a compromise solution. By applying these three methods in parallel, this study aims to observe differences in characteristics, stability, and consistency of ranking results in a multi-criteria decision support system.

The implementation of the CODAS method in teacher pedagogy assessment is carried out to evaluate the performance of each teacher based on the distance of their performance from the worst condition in each evaluation criterion. This method is applied by utilizing pedagogy assessment data that has been objectively weighted, so that the evaluation results reflect the real conditions based on the characteristics of the data. By combining the Euclidean distance as the main measure and the Taxicab distance as a supporting measure, CODAS is able to distinguish teacher performance more accurately, especially when the differences in scores between teachers are relatively small. This approach provides a clear and logical basis for determining teacher rankings based on their overall pedagogical performance.

The stages of the CODAS method begin with the preparation of a decision matrix containing the performance values of each alternative against all criteria using (1), with the CODAS decision matrix being identical to the ITARA decision matrix. This matrix is then normalized to equalize the scale of values across all criteria, allowing for fair comparison using (9), and the normalization results of the CODAS method are shown in Table 7.

Table 7. Normalization Results of the CODAS Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.9140	0.9890	0.9670	0.9468	0.9677	0.9778	0.9789
Teacher GH	0.9355	0.9670	0.9780	0.9681	0.9785	0.9556	0.9895
Teacher NH	0.9570	1.0000	0.9890	1.0000	0.9677	0.9667	1.0000
Teacher PM	0.9677	0.9890	0.9670	0.9574	0.9892	1.0000	0.9789
Teacher DG	0.9462	1.0000	0.9780	0.9787	0.9785	0.9889	0.9789
Teacher AN	1.0000	0.9780	1.0000	0.9681	0.9677	0.9778	0.9684
Teacher TY	0.9892	0.9890	0.9890	0.9894	1.0000	0.9667	0.9579

Next, weighted normalization is carried out by multiplying the normalized matrix by the criteria weights to reflect the level of importance of each criterion using (10), and the results of weighted normalization using the CODAS method are shown in Table 8.

Table 8. Weighted Normalization Results of the CODAS Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.1607	0.1751	0.1704	0.1350	0.1667	0.0876	0.0649
Teacher GH	0.1645	0.1712	0.1724	0.1381	0.1686	0.0856	0.0656
Teacher NH	0.1683	0.1771	0.1743	0.1426	0.1667	0.0866	0.0663
Teacher PM	0.1702	0.1751	0.1704	0.1365	0.1704	0.0896	0.0649
Teacher DG	0.1664	0.1771	0.1724	0.1396	0.1686	0.0886	0.0649
Teacher AN	0.1759	0.1732	0.1762	0.1381	0.1667	0.0876	0.0642
Teacher TY	0.1740	0.1751	0.1743	0.1411	0.1723	0.0866	0.0635

Next, the negative ideal solution is determined to reflect the worst performance level of each criterion and is used as a reference for evaluating the alternatives using (11), and the results of the negative ideal solution in the CODAS method are presented in Table 9.

Table 9. Negative Ideal Solution Results of the CODAS Method

Criteria Code						
C-1	C-2	C-3	C-4	C-5	C-6	C-7

Setiawansyah: *Corresponding Author

JURNAL ILMIAH INFORMATIKA DAN ILMU KOMPUTER (JIMA-ILKOM)
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0.1607	0.1712	0.1704	0.1350	0.1667	0.0856	0.0635

The Euclidean distance and Taxicab distance of each alternative to the negative ideal solution are calculated as the main and supporting measures in the evaluation process using (12) and (13), and the results of the Euclidean and Taxicab distances in the CODAS method are shown in Table 10.

Table 10. Euclidean and Taxicab Results of the CODAS Method

Teacher Name	Euclidean Result	Taxicab Result
Teacher RD	0.0046	0.0073
Teacher GH	0.0059	0.0127
Teacher NH	0.0131	0.0286
Teacher PM	0.0118	0.0239
Teacher DG	0.0102	0.0242
Teacher AN	0.0167	0.0286
Teacher TY	0.0166	0.0336

The distance calculation results are used to form a relative evaluation matrix that shows the level of superiority of one alternative over another using (13), and the relative evaluation results of the CODAS method are presented in Table 10.

Table 10. Relative Evaluation Results of the CODAS Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.0000	0.0013	0.0086	0.0072	0.0057	0.0123	0.0000
Teacher GH	-0.0013	0.0000	0.0073	0.0059	0.0044	0.0109	-0.0013
Teacher NH	-0.0085	-0.0072	0.0000	-0.0014	-0.0029	0.0036	-0.0085
Teacher PM	-0.0071	-0.0058	0.0014	0.0000	-0.0015	0.0050	-0.0071
Teacher DG	-0.0056	-0.0043	0.0029	0.0015	0.0000	0.0065	-0.0056
Teacher AN	-0.0120	-0.0107	-0.0036	-0.0050	-0.0065	0.0000	-0.0120
Teacher TY	-0.0118	-0.0105	-0.0034	-0.0048	-0.0063	0.0002	-0.0118

This entire process produces the final preference values, which serve as the basis for ranking the alternatives using (14), and the final preference values of the CODAS method are presented in Table 11.

Table 11. Final Preference Values Results of the CODAS Method

Teacher Name	Final Value
Teacher RD	0.0352
Teacher GH	0.0271
Teacher NH	-0.0163
Teacher PM	-0.0081
Teacher DG	0.0010
Teacher AN	-0.0378
Teacher TY	-0.0366

Ranking in the CODAS method is carried out to determine the order of alternatives based on their superiority relative to the negative ideal solution. At this stage, each alternative is evaluated through preference values obtained from a combination of Euclidean distance and Taxicab distance, so that differences in performance between alternatives can be identified more clearly. This ranking process provides a comprehensive overview of the relative position of each alternative within the decision support system. Alternatives with the highest preference values are considered to have the best performance because they are farthest from the worst conditions set by the CODAS method, as shown in Table 12.

Setiawansyah: *Corresponding Author

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Table 12. CODAS Method Ranking Results

Teacher Name	Final Value	Rank
Teacher RD	0.0352	1
Teacher GH	0.0271	2
Teacher DG	0.001	3
Teacher PM	-0.0081	4
Teacher NH	-0.0163	5
Teacher TY	-0.0366	6
Teacher AN	-0.0378	7

Based on the ranking results shown in the table, Teacher RD occupies the first rank with the highest final score of 0.0352, reflecting the best pedagogical performance among all the evaluated teachers. Teacher GH is in second place with a score of 0.0271, followed by Teacher DG in third place with a score of 0.001. Next, Teacher PM and Teacher NH rank fourth and fifth with final scores of −0.0081 and −0.0163, respectively. Teacher TY and Teacher AN are in sixth and seventh place with scores of −0.0366 and −0.0378. Overall, these results indicate a clear ranking pattern, where higher final scores represent better pedagogical performance according to the method used.

The implementation of the TOPSIS method in teacher pedagogy assessment is carried out to rank teachers based on their closeness to an ideal teaching profile. This method utilizes pedagogical assessment data that has been normalized and weighted objectively, so that each criterion contributes according to its level of importance. By comparing each teacher's distance to the best and worst conditions across all criteria, TOPSIS can provide a clear picture of the teacher's overall relative performance. This approach supports a transparent and consistent evaluation process in assessing the quality of teacher pedagogy.

The steps of the TOPSIS method begin with preparing a decision matrix containing the performance values of each alternative against all the criteria used, using (1), with the TOPSIS decision matrix being identical to the ITARA decision matrix. This matrix is then normalized to equalize differences in scale among criteria so that comparisons can be made fairly, using (16), and the decision matrix results of the TOPSIS method are shown in Table 13.

Table 13. Normalization Results of the TOPSIS Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.9140	0.9890	0.9670	0.9468	0.9677	0.9778	0.9789
Teacher GH	0.9355	0.9670	0.9780	0.9681	0.9785	0.9556	0.9895
Teacher NH	0.9570	1.0000	0.9890	1.0000	0.9677	0.9667	1.0000
Teacher PM	0.9677	0.9890	0.9670	0.9574	0.9892	1.0000	0.9789
Teacher DG	0.9462	1.0000	0.9780	0.9787	0.9785	0.9889	0.9789
Teacher AN	1.0000	0.9780	1.0000	0.9681	0.9677	0.9778	0.9684
Teacher TY	0.9892	0.9890	0.9890	0.9894	1.0000	0.9667	0.9579

The normalized results are then multiplied by the criteria weights to obtain a weighted normalized matrix that reflects the importance level of each criterion, using (17), and the weighted normalized matrix results of the TOPSIS method are shown in Table 14.

Table 14. Weighted Normalization Results of the TOPSIS Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.0634	0.0670	0.0656	0.0525	0.0644	0.0339	0.0251
Teacher GH	0.0648	0.0655	0.0664	0.0536	0.0651	0.0331	0.0253
Teacher NH	0.0663	0.0678	0.0671	0.0554	0.0644	0.0335	0.0256

Setiawansyah: *Corresponding Author

Teacher PM	0.0671	0.0670	0.0656	0.0531	0.0658	0.0347	0.0251
Teacher DG	0.0656	0.0678	0.0664	0.0542	0.0651	0.0343	0.0251
Teacher AN	0.0693	0.0663	0.0679	0.0536	0.0644	0.0339	0.0248
Teacher TY	0.0686	0.0670	0.0671	0.0548	0.0666	0.0335	0.0245

Based on this matrix, the positive ideal value and negative ideal value are determined as representations of the best and worst conditions for each criterion, using (18) and (19), and the results of the positive ideal value and negative ideal value of the TOPSIS method are shown in Table 15.

Table 15. Positive and Negative Ideal Value Results of the TOPSIS Method

	Criteria Code						
	C-1	**C-2**	**C-3**	**C-4**	**C-5**	**C-6**	**C-7**
Positive Value	0.0693	0.0678	0.0679	0.0554	0.0666	0.0347	0.0256
Negative Value	0.0634	0.0655	0.0656	0.0525	0.0644	0.0331	0.0245

The distance of each alternative to the ideal and anti-ideal values is then calculated using a distance measure to assess the relative closeness of alternatives using (20) and (21), and the ideal and anti-ideal distances of the TOPSIS method alternatives are shown in Table 16.

Table 16. Distance of each Alternative Results of the TOPSIS Method

Teacher Name	**Distance Ideal**	**Distance Anti-Ideal**
Teacher RD	0.0074	0.0018
Teacher GH	0.0059	0.0023
Teacher NH	0.0039	0.0051
Teacher PM	0.0041	0.0046
Teacher DG	0.0045	0.0040
Teacher AN	0.0033	0.0066
Teacher TY	0.0021	0.0065

The final stage produces the preference values of the alternatives, which serve as the basis for ranking, where the alternative with the highest preference value is considered the best choice, using (22), and the results of the preference values of the TOPSIS method alternatives are displayed in Table 17.

Table 17. Preference Value of the Alternative Results of the TOPSIS Method

Teacher Name	**Preference Value**
Teacher RD	0.1915
Teacher GH	0.2812
Teacher NH	0.5657
Teacher PM	0.5279
Teacher DG	0.4707
Teacher AN	0.6625
Teacher TY	0.7531

Ranking in the TOPSIS method is conducted to determine the order of alternatives based on their closeness to the positive ideal solution and their distance from the negative ideal solution. At this stage, each alternative is evaluated through a preference value that represents the balance between these two distances. The alternative with the highest preference value is considered to have the best performance because it is closest to the ideal condition and furthest from the worst condition. This ranking process provides a clear and easily understood basis for comparing the performance of alternatives objectively in a decision support system. The ranking results of the alternatives using the TOPSIS method are shown in Table 18.

Setiawansyah: *Corresponding Author

JURNAL ILMIAH INFORMATIKA DAN ILMU KOMPUTER (JIMA-ILKOM)
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Table 18. TOPSIS Method Ranking Results

Teacher Name	Preference Value	Rank
Teacher TY	0.7531	1
Teacher AN	0.6625	2
Teacher NH	0.5657	3
Teacher PM	0.5279	4
Teacher DG	0.4707	5
Teacher GH	0.2812	6
Teacher RD	0.1915	7

Based on the ranking results using the TOPSIS method in Table 18, Teacher TY ranked first with the highest preference value of 0.7531, indicating the closest proximity to the positive ideal solution. Teacher AN ranked second with a value of 0.6625, followed by Teacher NH in third place with a value of 0.5657. Furthermore, Teacher PM and Teacher DG ranked fourth and fifth with preference values of 0.5279 and 0.4707, respectively. Teacher GH ranked sixth with a value of 0.2812, while Teacher RD occupied the last position with a value of 0.1915. These results indicate the varying degrees of each teacher's closeness to the ideal pedagogical condition, where higher preference values represent better pedagogical performance according to the TOPSIS method.

The implementation of the COCOSO method in assessing teacher pedagogy is carried out to obtain evaluation results that represent a compromise solution from the various assessment criteria used. This method is applied by combining additive and multiplicative approaches on pedagogy evaluation data that has been normalized and weighted objectively. By merging several evaluation indices, COCOSO is able to capture a balanced view of teacher performance across all criteria, without overemphasizing any particular aspect. This approach provides a more comprehensive and stable basis for evaluating teacher rankings based on their pedagogical quality.

The stages of the COCOSO method begin with the preparation of a decision matrix containing the performance values of each alternative against all criteria used in decision-making using (1), with the COCOSO decision matrix being identical to the ITARA decision matrix. The decision matrix is then normalized to equalize the data scale across all criteria, so that each criterion can be compared proportionally using (23) and (24), and the results of the COCOSO normalization values are shown in Table 19.

Table 19. Normalization Results of the COCOSO Method

Teacher Name	Criteria Code						
	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Teacher RD	0.0000	0.6667	0.0000	0.0000	0.0000	0.5000	0.5000
Teacher GH	0.2500	0.0000	0.3333	0.4000	0.3333	0.0000	0.7500
Teacher NH	0.5000	1.0000	0.6667	1.0000	0.0000	0.2500	1.0000
Teacher PM	0.6250	0.6667	0.0000	0.2000	0.6667	1.0000	0.5000
Teacher DG	0.3750	1.0000	0.3333	0.6000	0.3333	0.7500	0.5000
Teacher AN	1.0000	0.3333	1.0000	0.4000	0.0000	0.5000	0.2500
Teacher TY	0.8750	0.6667	0.6667	0.8000	1.0000	0.2500	0.0000

Next, the positive ideal solution and the negative ideal solution are determined as references for the best and worst values for each criterion using (25) and (26), with the results of the positive and negative ideal solution values of the COCOSO method shown in Table 20.

Table 20. Positive and Negative Ideal Solution Results of the COCOSO Method

Teacher Name	Positive Ideal Solution	Negative Ideal Solution
Teacher RD	0.1960	2.8256
Teacher GH	0.2669	4.2938

Setiawansyah: *Corresponding Author

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Teacher NH	0.6138	5.6995
Teacher PM	0.4941	5.5339
Teacher DG	0.5451	6.3525
Teacher AN	0.5295	5.5527
Teacher TY	0.6982	5.6904

Based on these two ideal solutions, the relative value of each alternative is calculated, which represents the level of closeness and contribution to the compromise solution using (27), (28), and (29), and the results of the COCOSO method's compromise solution values are presented in Table 21.

Table 21. Compromise Solution Results of the COCOSO Method

Teacher Name	K_{ia}	K_{ib}	K_{ic}
Teacher RD	0.2679	2.0000	0.4286
Teacher GH	0.3762	2.8814	0.6468
Teacher NH	0.7589	5.1488	0.8954
Teacher PM	0.6349	4.4794	0.8550
Teacher DG	0.7068	5.0294	0.9783
Teacher AN	0.6709	4.6668	0.8626
Teacher TY	0.8430	5.5761	0.9061

In the final stage, all relative values are combined to produce a final preference value, which is used as a basis for ranking alternatives in the COCOSO method using (30), and the results of the COCOSO method's alternative preference values are presented in Table 22.

Table 22. Compromise Solution Results of the COCOSO Method

Teacher Name	Final Preference Value
Teacher RD	1.5112
Teacher GH	2.1899
Teacher NH	3.7858
Teacher PM	3.3345
Teacher DG	3.7532
Teacher AN	3.4594
Teacher TY	4.0628

Ranking in the COCOSO method is carried out to determine the order of alternatives based on the final preference values that represent a compromise solution across all evaluation criteria. At this stage, each alternative is evaluated through the combination of several aggregation indices that reflect a balance between additive and multiplicative approaches. The alternative with the highest preference value is considered to have the best performance because it demonstrates the most balanced performance across all criteria. This ranking process provides a comprehensive and stable evaluation basis for assessing the performance of alternatives in a multi-criteria decision support system. The ranking results of the alternatives using the COCOSO method are shown in Table 23.

Table 23. COCOSO Method Ranking Results

Teacher Name	Preference Value	Rank
Teacher TY	4.0628	1
Teacher NH	3.7858	2
Teacher DG	3.7532	3
Teacher AN	3.4594	4
Teacher PM	3.3345	5
Teacher GH	2.1899	6
Teacher RD	1.5112	7

Setiawansyah: *Corresponding Author

JURNAL ILMIAH INFORMATIKA DAN ILMU KOMPUTER (JIMA-ILKOM)
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Based on the ranking results using the COCOSO method in Table 23, Teacher TY ranked first with the highest preference score of 4.0628, indicating the most balanced pedagogical performance based on the compromise solution across all criteria. Teacher NH ranked second with a score of 3.7858, followed by Teacher DG in third place with a score of 3.7532. Next, Teacher AN and Teacher PM ranked fourth and fifth with preference scores of 3.4594 and 3.3345, respectively. Teacher GH ranked sixth with a score of 2.1899, while Teacher RD occupied the last position with a score of 1.5112. These results show differences in pedagogical performance levels among teachers, where higher preference scores represent better pedagogical quality according to the COCOSO method.

Analysis of Ranking Results Comparison

Comparative analysis of ranking results is an important stage in this research because it provides a deeper understanding of the behavior and characteristics of the CODAS, TOPSIS, and COCOSO methods in evaluating alternatives. Although all three methods are applied to the same data and criteria weights, differences in mathematical approaches and underlying concepts can result in ranking orders that are not always consistent. Therefore, this stage focuses not only on who occupies the highest or lowest rank but also on how and why those ranking differences occur. This analysis helps identify the tendencies of each method in assessing the performance of alternatives based on distance, closeness to the ideal solution, or compromise solutions.

Through a comparative analysis of the ranking results, the consistency and stability of the decisions produced by each method can be evaluated more objectively. This stage allows researchers to assess the level of agreement between methods, observe patterns in ranking changes, and reveal the strengths and limitations of each approach in the context of teacher pedagogy assessment. Thus, this analysis serves as an important basis for drawing more comprehensive conclusions and providing appropriate recommendations regarding the use of the most suitable multi-criteria decision-making methods to be applied in data-based decision support systems. The comparison of rankings from the CODAS, TOPSIS, and COCOSO methods is shown in Figure 2.

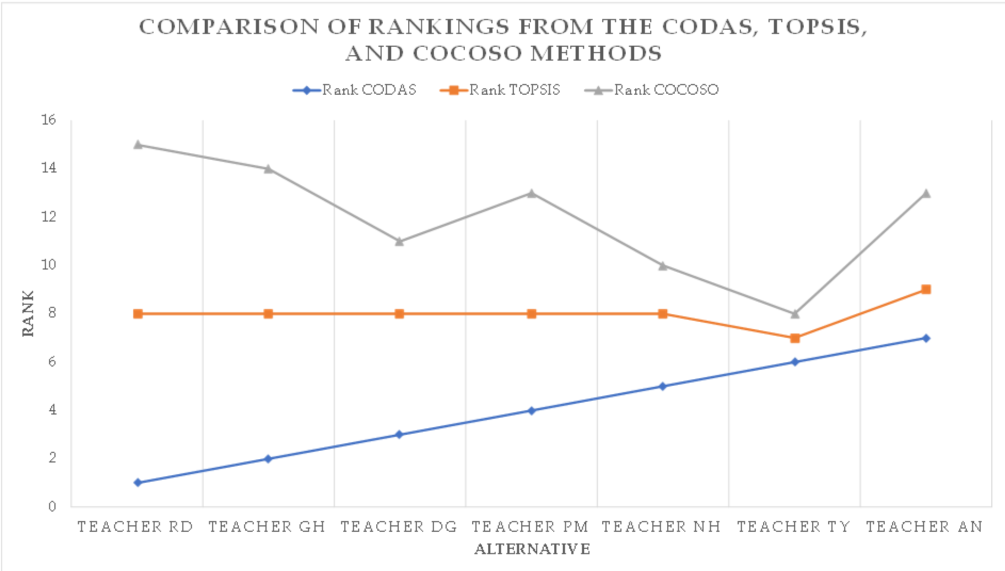

Figure 2. Comparison of rankings from the CODAS, TOPSIS, and COCOSO methods

The comparison of teacher rankings based on the CODAS, TOPSIS, and COCOSO methods shows a fairly clear difference in order among the methods. Teacher RD ranks first in the CODAS method but is in the last position in TOPSIS and COCOSO, indicating that this teacher's performance is considered very good when evaluated based on the distance from the worst solution, but less outstanding in terms of closeness to the ideal solution and compromise solution. Conversely, Teacher TY ranks first in TOPSIS and COCOSO but is ranked sixth in CODAS, showing a difference in assessment characteristics

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among the methods. Teacher NH also showed a significant improvement in ranking from CODAS to TOPSIS and COCOSO. Meanwhile, Teacher DG and Teacher PM tend to have more stable rankings across the three methods. These results confirm that each method has a different evaluation perspective, making the use of comparative analysis important for obtaining a more comprehensive and balanced decision.

Rank correlation comparison is an important step in multi-criteria decision support system analysis to evaluate the level of consistency and alignment of ranking results produced by different methods. Each method has different mechanisms for normalization, aggregation, and distance or utility assessment, which can potentially produce alternative ranking orders that are not exactly the same even when using identical criteria and weights. Through rank correlation analysis, the relationships between ranking results can be measured quantitatively to determine the extent to which these methods provide consistent or divergent decisions. This approach not only helps identify the stability of decision results but also provides a more objective basis for evaluating the reliability and sensitivity of each method to data changes. Rank correlation comparison serves as an additional validation tool that reinforces the interpretation of results and supports the selection of the most appropriate method for a particular decision-making context.

The comparison of rank correlations between the CODAS, TOPSIS, and COCOSO methods was conducted to evaluate the level of alignment of the ranking results produced by the three approaches within a multi-criteria decision-making framework. Although all three methods are used to determine the best alternative, differences in basic concepts such as distance measurement to the ideal solution, dominance-based assessment, and compromise aggregation can influence the resulting ranking order. Rank correlation analysis allows for a quantitative assessment of the strength of the relationship between ranking results, enabling an understanding of the extent to which these methods provide consistent decisions or show significant differences. This approach is important for evaluating the stability of results, reducing doubt about biases from certain methods, and providing a more objective basis for interpreting the reliability of CODAS, TOPSIS, and COCOSO when applied to the same decision problem. Figure 3 shows the comparison results of correlation values between the CODAS, TOPSIS, and COCOSO methods using Spearman correlation.

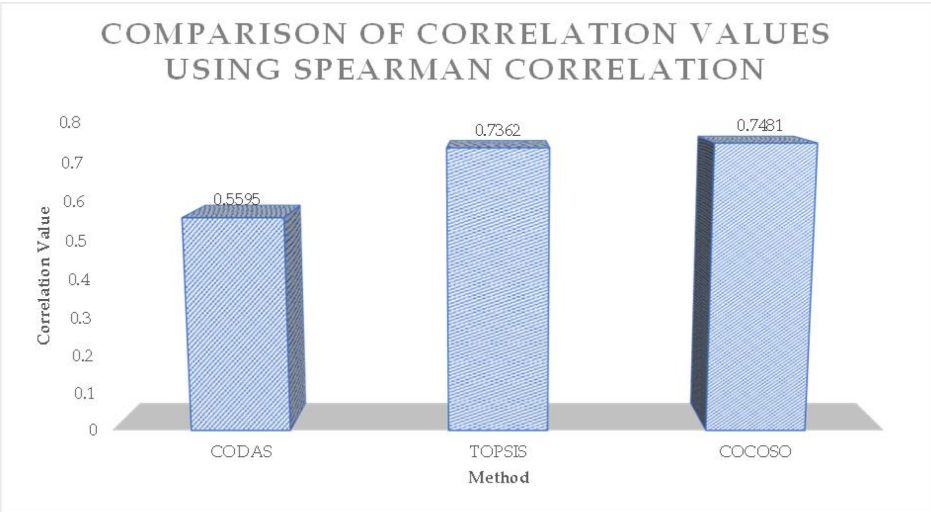

Figure 3. Comparison Correlation Value

The comparison results of ranking correlation values using Spearman correlation show differences in the level of agreement in ranking results among the CODAS, TOPSIS, and COCOSO methods. The CODAS method obtained a correlation value of 0.5595, indicating a moderate relationship between the rankings produced by CODAS and the reference rankings, meaning there is still a noticeable variation in the order of alternatives. Meanwhile, the TOPSIS method showed a higher correlation value of 0.7362, indicating a strong level of alignment and better consistency in representing the ranking order of alternatives. The highest correlation value was obtained by the COCOSO method at 0.7481, reflecting

Setiawansyah: *Corresponding Author

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Volume 5, Nomor 1, Maret 2026, Page 25-45
DOI: https://doi.org/10.58602/jima-ilkom.v5i1.78

the strongest relationship among the three methods and indicating that the COCOSO ranking results are closest to the reference ranking pattern. This finding suggests that although all three methods can be used in a multi-criteria decision support system, COCOSO and TOPSIS tend to produce more stable and consistent rankings compared to CODAS, making them more reliable when applied to decision-making cases with similar criteria structures and data.

Discussion

This discussion section highlights the differences in ranking results produced by the CODAS, TOPSIS, and COCOSO methods, even though all three are applied to the same data and criteria weights. The study results show that each method has different tendencies in evaluating teachers' pedagogical performance. CODAS emphasize the distance of alternatives from the negative ideal solution, so teachers who can avoid the worst values in most criteria receive higher rankings. In contrast, TOPSIS prioritizes closeness to the positive ideal solution and distance from the negative ideal solution simultaneously, which causes teachers with the most balanced performance across all criteria to tend to occupy the top positions. COCOSO, with its compromise solution approach, generates rankings that reflect a balance between the additive and multiplicative contributions of all criteria, thereby highlighting alternatives with stable and consistent performance.

The quite contrasting ranking differences, as seen with Teacher RD and Teacher TY, indicate that the interpretation of 'best performance' highly depends on the evaluation perspective used by each method. Teacher RD achieved the highest rank in CODAS because of having the greatest distance from the worst conditions, yet ranked at the bottom in TOPSIS and COCOSO, which place more emphasis on proximity to ideal conditions and balance among criteria. Conversely, Teacher TY showed superior performance in TOPSIS and COCOSO but did not occupy a high position in CODAS. These findings suggest that there is no single method that is absolutely correct; rather, each method provides a different evaluative perspective on the same data. Therefore, understanding the characteristics of each method becomes crucial before applying it in a specific assessment context.

In addition, the use of ITARA-based objective weighting plays an important role in maintaining the consistency and transparency of evaluation results. With weights determined based on significant differences in data among criteria, the influence of subjectivity can be minimized, so that differences in rankings reflect the characteristics of the methods rather than assessment bias. Overall, the results of this discussion confirm that comparative analysis between MCDM methods provides significant added value in decision support systems, particularly in evaluating teacher pedagogy. This approach allows decision-makers to obtain a more comprehensive overview and select the method that best matches the evaluation objectives and the characteristics of the data used.

Based on the results of the rank correlation analysis, the differences in Spearman correlation values produced by the CODAS, TOPSIS, and COCOSO methods indicate varying levels of consistency in generating alternative ranking orders. The lower correlation value in CODAS suggests that the distance and threshold-based evaluation mechanism used by this method is more sensitive to changes in criterion values, potentially resulting in greater differences in rankings. In contrast, TOPSIS and COCOSO show higher correlation values, indicating that both methods are able to maintain a more stable and consistent ranking pattern in line with the reference ranking. These findings reinforce the argument that the choice of MCDM method not only affects the final ranking results but also the reliability and consistency of the decisions, so TOPSIS and especially COCOSO can be considered as a more robust approach for decision problems with similar data characteristics.

4.CONCLUSION

The results of this study confirm that the use of the CODAS, TOPSIS, and COCOSO methods produces different ranking patterns even though they are based on the same data and criteria weights, thereby enriching perspectives in teacher performance assessment. In the CODAS method, Teacher RD ranks first, followed by Teacher GH and Teacher DG, while Teacher AN is in the last position. In contrast, the TOPSIS method ranks Teacher TY highest with a preference value of 0.7531, followed by Teacher AN and Teacher NH, whereas Teacher RD is in seventh place. Furthermore, the COCOSO

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DOI: https://doi.org/10.58602/jima-ilkom.v5i1.78

method also shows consistency in evaluating Teacher TY as the best alternative with a preference value of 4.0628, followed by Teacher NH and Teacher DG, while Teacher RD again occupies the lowest position. These result differences indicate that each method has different sensitivities and evaluation focuses regarding distance, proximity to the ideal solution, and performance aggregation, making comparative analysis important to ensure that the decisions made are more objective, balanced, and aligned with the evaluation goals in the educational decision support system. The comparison results of the CODAS, TOPSIS, and COCOSO methods can be used in a multi-criteria decision support system, but they show different levels of ranking consistency. Rank correlation analysis indicates that TOPSIS and COCOSO produce stronger and more stable ranking relationships compared to CODAS. Therefore, COCOSO, followed by TOPSIS, can be recommended as a more reliable method for producing consistent decisions in cases with similar criteria structures and data.

5.REFERENCES

[1] A. Ulutaş, A. Topal, and F. Ecer, "The Alternative Prioritization and Assessment System (ALPAS) Method for Environmental Performance Evaluation," *Mathematics*, vol. 13, no. 20. p. 3333, 2025. doi: 10.3390/math13203333.

[2] M. Riaz, F. Qamar, S. Tariq, and K. Alsager, "AI-Driven LOPCOW-AROMAN Framework and Topological Data Analysis Using Circular Intuitionistic Fuzzy Information: Healthcare Supply Chain Innovation," *Mathematics*, vol. 12, no. 22. 2024. doi: 10.3390/math12223593.

[3] C.-N. Wang, T. Q. Le, K.-H. Chang, and T.-T. Dang, "Measuring Road Transport Sustainability Using MCDM-Based Entropy Objective Weighting Method," *Symmetry*, vol. 14, no. 5. 2022. doi: 10.3390/sym14051033.

[4] J. Liu, B. Gu, and J. Chen, "Enablers for maritime supply chain resilience during pandemic: An integrated MCDM approach," *Transp. Res. Part A Policy Pract.*, vol. 175, p. 103777, 2023, doi: https://doi.org/10.1016/j.tra.2023.103777.

[5] A. Katrancı, N. Kundakcı, and D. Pamucar, "Financial performance evaluation of firms in BIST 100 index with ITARA and COBRA methods," *Financ. Innov.*, vol. 11, no. 1, p. 34, 2025, doi: 10.1186/s40854-024-00704-5.

[6] H. Onuoha *et al.*, "Integrating GIS and AHP for Photovoltaic Farm Site Selection: A Case Study of Ikorodu, Nigeria," *Processes*, vol. 13, no. 1. 2025. doi: 10.3390/pr13010164.

[7] J. Wang, A. R. Isnain, and S. Setiawansyah, "Multi-Criteria Decision Support System for Best Warehouse Performance Selection Using Combined Compromise Solution Method," *Bull. Data Sci.*, vol. 4, no. 2, pp. 86–93, 2025, doi: 10.47065/bulletinds.v4i2.7196.

[8] S. Dündar, "Performance evaluation of IPARD-II rural development programs with integrated DIBR-RAWEC methods TT - IPARD-II kırsal kalkınma programlarının bütünleşik DIBR-RAWEC yöntemleriyle performans değerlendirmesi," *Pamukkale Üniversitesi Mühendislik Bilim. Derg.*, vol. 31, no. 3, pp. 339–350, 2025, [Online]. Available: https://dergipark.org.tr/en/pub/pajes/article/1727829

[9] G. C. Yalçın, P. Gürol, and K. Kara, "Chapter 6 - Developing a GIS-supported SVN-WENSLO-ARLON hybrid method for bicycle pooling location selection: A case study in Turkey," M. B. T.-I. U. M. Deveci, Ed. Academic Press, 2025, pp. 103–148. doi: https://doi.org/10.1016/B978-0-443-34160-1.00014-6.

[10] A. Aytekin, "DETERMINING CRITERIA WEIGHTS FOR VEHICLE TRACKING SYSTEM SELECTION USING PIPRECIA-S," *J. Process Manag. new Technol.*, vol. 10, no. 1–2, pp. 115–124, Jun. 2022, doi: 10.5937/jpmnt10-38145.

[11] S. Chen, "The Application of Big Data and Fuzzy Decision Support Systems in the Innovation of Personalized Music Teaching in Universities," *Int. J. Comput. Intell. Syst.*, vol. 17, no. 1, p. 215, 2024, doi: 10.1007/s44196-024-00623-4.

[12] I. Granado, L. Hernando, Z. Uriondo, and J. A. Fernandes-Salvador, "A fishing route optimization decision support system: The case of the tuna purse seiner," *Eur. J. Oper. Res.*, vol. 312, no. 2, pp. 718–732, 2024, doi: https://doi.org/10.1016/j.ejor.2023.07.009.

[13] T. Sharma and A. Sarin, "Multi-criteria decision making for solar site selection in Punjab, India: An evaluation of site suitability using hybrid MCDM techniques towards the goal of sustainable energy development," *Results Eng.*, vol. 27, p. 106288, 2025, doi: https://doi.org/10.1016/j.rineng.2025.106288.

[14] Hongling Jiang, "Digital Twin-Enhanced MCDM Framework for Circular Construction Dynamic Lifecycle Optimization of Hybrid Concrete Mix Design," *Decis. Mak. Appl. Manag. Eng.*, vol. 8, no. 2 SE-Regular articles, pp. 53–70, Aug. 2025, doi: 10.31181/dmame8220251476.

[15] P. Pisal *et al.*, "An integrated TOPSIS and ARAS method multi-criteria decision-making approach for optimizing investment portfolios using goal programming and genetic algorithm model," *Sci. Rep.*, vol. 15, no. 1, p. 34450, 2025, doi: 10.1038/s41598-025-17604-y.

Setiawansyah: *Corresponding Author

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DOI: https://doi.org/10.58602/jima-ilkom.v5i1.78

[16] P. Rani, A. R. Mishra, A. M. Alshamrani, A. F. Alrasheedi, and D. Pamucar, "Adoption of Smart Manufacturing Technologies in Small and Medium Enterprises Using Picture Fuzzy Combinative Distance-Based Assessment Model," *J. Knowl. Econ.*, 2025, doi: 10.1007/s13132-025-02693-x.

[17] J. Wang, S. Setiawansyah, F. Ulum, A. Yudhistira, and A. D. Wahyudi, "Optimization of Production Operator Performance Assessment with Grey Geometric Mean Weighting and Combinative Distance-based Assessment," *Komputika J. Sist. Komput.*, vol. 14, no. 2 SE-Articles, Nov. 2025, doi: 10.34010/komputika.v14i2.15977.

[18] H. Wang, L. Feng, M. Deveci, K. Ullah, and H. Garg, "A novel CODAS approach based on Heronian Minkowski distance operator for T-spherical fuzzy multiple attribute group decision-making," *Expert Syst. Appl.*, vol. 244, p. 122928, 2024, doi: https://doi.org/10.1016/j.eswa.2023.122928.

[19] K. Yu, Q. Wu, X. Chen, W. Wang, and A. Mardani, "An integrated MCDM framework for evaluating the environmental, social, and governance (ESG) sustainable business performance," *Ann. Oper. Res.*, vol. 342, no. 1, pp. 987–1018, 2024, doi: 10.1007/s10479-023-05616-8.

[20] Q. Wang, T. Cheng, Y. Lu, H. Liu, R. Zhang, and J. Huang, "Underground Mine Safety and Health: A Hybrid MEREC–CoCoSo System for the Selection of Best Sensor," *Sensors*, vol. 24, no. 4, p. 1285, Feb. 2024, doi: 10.3390/s24041285.

[21] S. Dhruva, R. Krishankumar, E. K. Zavadskas, K. S. Ravichandran, and A. H. Gandomi, "Selection of Suitable Cloud Vendors for Health Centre: A Personalized Decision Framework with Fermatean Fuzzy Set, LOPCOW, and CoCoSo," *Informatica*, vol. 35, no. 1, pp. 65–98, Nov. 2024, doi: 10.15388/23-INFOR537.

[22] O. Y. Akbulut and Y. Aydın, "A Hybrid Multidimensional Performance Measurement Model Using the MSD-MPSI-RAWEC Model for Turkish Banks," *J. Mehmet Akif Ersoy Univ. Econ. Adm. Sci. Fac.*, vol. 11, no. 3, pp. 1157–1183, 2024, doi: 10.30798/makuiibf.1464469.

[23] B. Kizielewicz, J. Wątróbski, and W. Sałabun, "Multi-criteria decision support system for the evaluation of UAV intelligent agricultural sensors," *Artif. Intell. Rev.*, vol. 58, no. 7, p. 194, 2025, doi: 10.1007/s10462-025-11201-1.

[24] T. Van Dua, "Combination of design of experiments and simple additive weighting methods: a new method for rapid multi-criteria decision making," *EUREKA Phys. Eng.*, no. 1 SE-Engineering, pp. 120–133, Jan. 2023, doi: 10.21303/2461-4262.2023.002733.

[25] J. Wang, S. Setiawansyah, T. Ardiansah, F. Ulum, and S. Sumanto, "Decision Support System for Determining Strategic Warehouse Locations Using a Combination of the WENSLO Weighting and RAWEC Method," *JUTI J. Ilm. Teknol. Inf.*, vol. 24, no. 1 SE-Articles, pp. 165–184, 2026, doi: 10.12962/j24068535.v24i1.a1456.

[26] P. Rani, A. R. Mishra, D. Pamucar, A. M. Alshamrani, and A. F. Alrasheedi, "Assessment of digital transformation indicators to prioritize sustainable financial services using q-rung orthopair fuzzy rough decision-making model," *Appl. Soft Comput.*, vol. 170, p. 112715, 2025, doi: https://doi.org/10.1016/j.asoc.2025.112715.

[27] Z. Turskis and V. Keršulienė, "SHARDA–ARAS: A Methodology for Prioritising Project Managers in Sustainable Development," *Mathematics*, vol. 12, no. 2, p. 219, Jan. 2024, doi: 10.3390/math12020219.

[28] T. Ahmadi Pargo and S. Hashemkhani Zolfani, "Developing an Expert System for Hardware Selection in Internet of Things-Based System Design: Grey ITARA-COBRA Approach (With an Example in the Agricultural Domain)," *Information*, vol. 16, no. 6. 2025. doi: 10.3390/info16060425.

[29] N. Hendrastuty, J. Wang, A. Sulistiyawati, D. Darwis, and Y. Jumaryadi, "Combination of MOORA and ITARA Methods in Decision Support Systems for Measuring the Performance of Quality Control Teams," vol. 6, no. 6, pp. 727–739, 2025, doi: 10.47065/tin.v6i6.8382.

[30] M. Wu, J. Song, and J. Fan, "Three-way decision based on ITARA and public weights DEA under picture fuzzy environment and its application in new energy vehicles selection," *Complex Intell. Syst.*, vol. 10, no. 1, pp. 927–947, 2024, doi: 10.1007/s40747-023-01188-z.

[31] N. Hendrastuty, M. G. Ar'nars, Setiawansyah, Mesran, T. A. Putra, and M. W. Arshad, "Decision Support System in Teacher Pedagogy Assessment Using MAIRCA with Geometric Mean Weighting," in *2024 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, 2024, pp. 265–270. doi: 10.1109/ICIMCIS63449.2024.10957630.

Setiawansyah: *Corresponding Author