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Integration of LODECI Weighting Method and SPOTIS in Employee Performance Evaluation Based on Multi-Criteria Decision Making

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ABSTRACT

Employee performance evaluation in many organizations often faces challenges due to numerous assessment criteria and potential subjectivity in the decision-making process, making the evaluation results less consistent and objective. Multi-Criteria Decision Making (MCDM) methods have been widely used to address this problem; however, previous approaches generally still rely on subjective weight determination and do not fully consider the stability of results against data variation. Therefore, this study aims to develop a more objective and stable decision-making model by integrating the LODECI method to determine criteria weights based on data and the SPOTIS method to rank alternatives based on their distance from the ideal solution. Five evaluation criteria are used, namely productivity, work quality, discipline, teamwork, and responsibility, with data collected from eight employees as alternatives. The analysis process was carried out through the stages of constructing a decision matrix, calculating criterion weights using LODECI, and ranking using SPOTIS which produced a total distance value as a quantitative evaluation metric. The research results show that GS Employee achieved the smallest distance value of 0.058, thus ranking first, followed by CR Employee with a value of 0.086 and AN Employee with a value of 0.321. These findings indicate that the proposed model is capable of providing more measurable and consistent evaluation results. The main contribution of this study lies in the integration of objective weighting and ideal-solution-based ranking methods supported by sensitivity analysis, thereby producing a performance evaluation system that is more reliable, transparent, and robust compared to previous approaches.

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INTRODUCTION

The process of evaluating employee performance is a key element in ensuring effective human resource management practices because it plays a role in assessing the extent of an individual's contribution to achieving organizational goals(Setiawansyah & Rahmanto, 2025; Sithi et al., 2025). Through a systematic and measurable evaluation process, the organization can identify work achievement levels, the competencies possessed, as well as aspects that still need to be improved by each employee. The outcomes of this evaluation serve not only as a foundation for decisions regarding rewards, promotions, and career advancement, but also as a reference for developing more targeted training programs. Thus, performance evaluation helps the organization maintain work quality, increase employee motivation, and encourage the creation of more optimal and sustainable productivity(Hassanpour et al., 2022).

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The performance evaluation process often involves various criteria that reflect an employee's ability and contribution in carrying out their duties(Akbulut & Aydın, 2024). Some commonly used aspects include work productivity, which indicates the employee's ability to complete work according to targets, work quality, which relates to accuracy and the standard of work results, as well as the level of discipline in adhering to established rules and work hours. In addition, the ability to work collaboratively in a team is also an important factor since many tasks require coordination and collaboration with colleagues. Responsibility for assigned tasks also becomes a key indicator in assessing an employee's commitment and professionalism. By considering these various criteria, the performance evaluation process can provide a more comprehensive picture of an employee's performance within the organization(Dündar, 2025).

The process of evaluating employee performance is often hindered by challenges related to subjective evaluator perspectives and inconsistencies in weighting criteria. Such dependence on personal interpretation can compromise objectivity and increase the risk of bias against particular employees(Ajithkumar & GaneshKumar, 2025; Rani et al., 2023). In addition, performance measurement involving multiple criteria also poses difficulties in ensuring that each aspect of assessment can be evaluated consistently, objectively, and proportionally. Variations in the level of importance assigned to different criteria, variations in assessment data, as well as differences in opinions in determining the criteria weights can affect the accuracy of evaluation results and produce inconsistent decisions over time(K. Wang et al., 2023). This condition not only affects the accuracy of assessment results but can also lower employees' trust in the evaluation process conducted by the organization. Hence, the implementation of a systematic and structured framework is necessary to effectively manage diverse evaluation criteria, thereby ensuring more objective, consistent, and accountable decision-making outcomes(Riaz et al., 2024).

Performance evaluation issues that involve numerous criteria can be effectively addressed using the multi-criteria decision-making (MCDM) approach in a systematic and logical way(Abdul et al., 2025; Kara, Yalçın, Simic, Baysal, et al., 2024). By applying this method, decision-makers can assess several alternatives at once using different criteria, which enhances the systematic and quantifiable nature of the evaluation process(Ghanbari et al., 2025; Liu & Shen, 2024). Each criterion is assigned a weight reflecting its importance, and subsequent calculations generate preference scores for each employee. These results provide a more objective evaluation of performance across multiple assessment dimensions. The application of the MCDM method in employee performance evaluation can help organizations make decisions that are fairer, more transparent, and accountable(Kara, Yalçın, Simic, Erbay, et al., 2024; J. Wang et al., 2026). Although MCDM methods are widely used in employee performance evaluation, there are still gaps because the weighting of criteria is often subjective and ranking methods have not fully considered the stability of results against parameter changes. In addition, the integration between objective weighting and ideal-solution-based approaches is still limited. Therefore, the novelty of this research lies in the combination of LODECI as a data-variation-based weighting method and SPOTIS as an ideal-solution-distance-based ranking method. This integration can reduce subjectivity while improving the consistency and reliability of results, which is reinforced through sensitivity analysis.

The Logarithmic Decomposition of Criteria Importance (LODECI) method offers an objective approach to weighting by deriving criterion weights directly from data characteristics(Yalçın et al., 2024). This approach works by analyzing the variation of values in each criterion so that the level of importance of the criterion is no longer determined subjectively by the assessor, but is determined based on the information contained within the assessment data. By leveraging the distribution and variation of values across alternatives, the LODECI method generates criterion weights that are more consistent and better represent the actual data conditions. The application of this method can help reduce bias in the weighting process and increase the reliability of overall employee performance evaluation results.

The stable preference ordering towards ideal solution (SPOTIS) method is employed to rank alternatives by calculating the distance of each alternative from the predefined ideal solution(de Assis et al., 2023). In this approach, each alternative is evaluated based on the criteria values it possesses, then compared with the ideal values that serve as the best reference for each criterion. The calculation process is carried out by determining the distance between the alternative values and the ideal solution, so that the alternative with the smallest distance is considered to have the best performance. Through this mechanism, the SPOTIS method is able to provide a ranking process that is stable, transparent, and easy to understand because the decision is generated from the closeness of the alternative values to the most ideal condition(de Assis et al., 2023).

Combining these two methods leads to a more objective and reliable system for evaluating employee performance. LODECI is utilized to derive criterion weights based on data variation, reducing subjective bias in determining the importance of each criterion. In contrast, SPOTIS ranks alternatives by assessing their distance from the established ideal solution. Together, these methods create a structured, consistent, and data-oriented evaluation process, allowing for more accurate performance insights and improved decision-making in human resource management. The use of the LODECI and SPOTIS methods is based on their ability to produce more objective criteria weighting and a more stable ranking process compared to other MCDM methods. LODECI can capture data variations more adaptively, so the resulting weights reflect real conditions, while SPOTIS offers a distance-based approach to the ideal solution that reduces subjective bias. With this combination, these two methods provide more consistent and reliable evaluation results, making the methodological justification stronger compared to the use of alternative methods.

Although various studies on employee performance evaluation have widely utilized the MCDM approach, most still rely on a criterion weighting process that is subjective, causing the assessment results to often be influenced by the perceptions or preferences of individual evaluators. This condition can lead to inconsistencies in the evaluation process and reduce the level of objectivity in determining overall employee performance. On the other hand, efforts to integrate data-based objective weighting methods with ranking methods that have a high level of stability are still relatively limited in the context of employee performance evaluation. In fact, the combination of objective weighting methods and systematic ranking techniques has the potential to produce a more accurate, transparent, and accountable assessment process. Until now, research that specifically combines the LODECI method as an objective weighting approach with the SPOTIS method as a distance-based ranking technique to the ideal solution in the context of employee performance evaluation is still very limited, thus opening up research opportunities to develop a more comprehensive and data-based evaluation model to support decision-making activities in the context of human resource management.

The objective of this research is to design an employee performance evaluation model using the MCDM approach to achieve a more structured, systematic, and data-oriented assessment process. The LODECI method is applied to derive criterion weights objectively based on data variation, reducing reliance on subjective evaluations. Meanwhile, SPOTIS is used to rank employee performance by calculating the distance of each alternative from the predefined ideal solution. By integrating these two methods, the study examines their effectiveness in generating more consistent, objective, and stable evaluation outcomes. This research contributes by proposing a framework that combines objective weighting and stable ranking techniques, thereby broadening the application of MCDM in human resource management and providing organizations with an alternative method to improve decision-making in performance evaluation.

RESEARCH METHOD

Research stages are a series of processes arranged systematically to help researchers achieve research objectives in a directed and structured manner(Junhai Wang & Setiawansyah, 2025; Oprasto et al., 2025). Through these stages, each research process can be carried out logically, from problem formulation to the analysis and decision-making process. The preparation of research stages also aims to ensure that the methods used can be applied clearly and consistently so that the research results can be scientifically accountable(Hadad et al., 2025; J. Wang et al., 2024). With a structured research flow, the analysis process becomes more directed and makes it easier to understand the relationships between the processes carried out in the research. An overview of the research stage flow used in this study is presented in Figure 1.

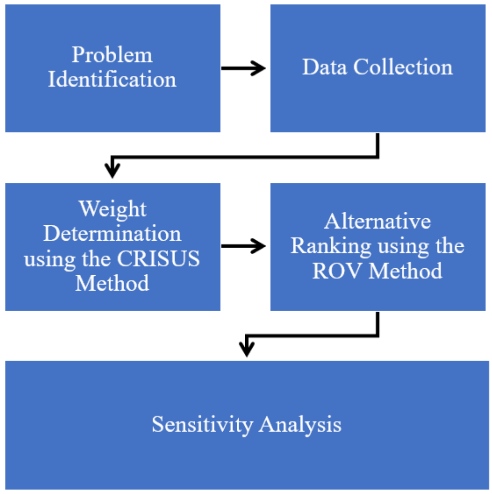

Figure 1. Research Stages

The research stages illustrated in Figure 1 begin with problem identification, focusing on issues in employee performance evaluation involving multiple criteria and potential subjectivity in decision-making. This is followed by data collection, where employee performance data is obtained based on predefined criteria including productivity, work quality, discipline, teamwork, and responsibility as the foundation for analysis. The dataset consists of eight employees, namely AN, BD, CR, DS, EF, FH, GS, and HT, each evaluated using a quantitative scoring scale across the five criteria, resulting in a structured decision matrix that reflects variations in individual performance. Subsequently, criterion weights are determined using the LODECI method, which objectively derives weights through data variation analysis, ensuring that they accurately represent the relative importance of each criterion. The final stage involves ranking alternatives using the SPOTIS method, where employee performance is evaluated by measuring the distance of each alternative from the ideal solution, resulting in a more systematic and stable decision-making process. To strengthen the robustness of the results, a sensitivity analysis is conducted at the end to examine how changes in criteria weights or input data affect the ranking outcomes, thereby ensuring the consistency and reliability of the decision-making model.

1. LODECI Weighting

   LODECI represents an objective weighting method in MCDM that derives criterion importance levels from the underlying characteristics of the dataset(Çilek & Şeyranlıoğlu, 2025; Pala, 2024). By utilizing value variations across each criterion, this method produces weights that are independent of decision-maker subjectivity and are instead computed mathematically based on the available data. With this approach, LODECI is able to provide criterion weights that are more consistent and reflect the contribution of each criterion in the alternative evaluation process.

The LODECI method offers several advantages in determining criterion weights in multi-criteria decision-making problems(Pala, 2024). One of its key strengths lies in its ability to generate weights objectively by utilizing data variation within the decision matrix, thereby minimizing the influence of decision-maker subjectivity. In addition, the application of logarithmic transformation in its computation enables a more proportional representation of differences in data distribution, resulting in weights that are more stable and reflective of actual data conditions. The method is also systematic and relatively easy to implement due to its well-defined computational steps, making it applicable to various evaluation scenarios involving multiple criteria. Consequently, LODECI can improve both the accuracy and consistency of the weighting process in decision-making analysis.

The LODECI algorithm initiates with the formulation of a decision matrix that captures alternative performances across multiple criteria as the analytical baseline (1). A normalization process is subsequently applied to standardize criterion scales, ensuring proportional comparability and eliminating unit disparities (2). Deviation values are then computed from the normalized data to quantify the variation within each criterion, indicating inter-alternative differences (3). These deviations are transformed using a logarithmic function to produce more stable and proportionate measures aligned with data distribution (4). Finally, the logarithmic results are normalized to obtain criterion weights, representing their relative importance in the decision-making framework (5).

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

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

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

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

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

The calculation process in the LODECI method, symbol x_{ij}, indicates the value of the i[th] alternative for the j[th] criterion. The deviation value SD_{ij} is the maximum difference between the normalized value of one alternative and other alternatives on the same criterion to represent the level of data variation. The logarithmic value LSD_j is the average of the deviation values for each criterion. The criterion weight w_j indicates the relative importance of each criterion in the decision-making process.

2. SPOTIS Method

The SPOTIS method is an approach within the MCDM framework used to rank alternatives based on their closeness to predefined ideal solutions for each criterion(Ali et al., 2026; de Oliveira et al., 2025). In this method, each alternative is assessed by computing the distance between its value and the corresponding ideal value within specified preference limits. The resulting distance reflects the degree of proximity to the most desirable condition, where the alternative with the smallest distance is regarded as the best option. This approach enables SPOTIS to provide a clear and systematic ranking mechanism for decision-making problems involving multiple criteria.

One of the main advantages of the SPOTIS method is its ability to produce a stable ranking process because the calculation is based on the distance to a predetermined ideal solution(Kizielewicz et al., 2024). This method is also relatively easy to implement because it does not require complex normalization processes and can still maintain the consistency of calculation results. In addition, SPOTIS is capable of accommodating various types of criteria, both benefit and cost, within the same analytical framework. With these characteristics, this method can provide evaluation results that are more transparent, easy to understand, and support more objective decision-making in various alternative evaluation contexts.

The SPOTIS method starts by constructing a decision matrix that represents the performance values of alternatives across all criteria, which forms the basis for the analysis (1). Next, normalization is conducted by computing the distance between each alternative's value and the predetermined ideal point for each criterion. This step ensures comparability across different scales and reflects how close each alternative is to the target condition (6) and (7). The process continues with the calculation of weighted normalized distances by multiplying the normalized values with their respective criterion weights, producing the overall distance of each alternative from the ideal solution (8). Finally, alternatives are ranked based on these distances, with the smallest value indicating the most desirable option. The mathematical formulation of the SPOTIS method is provided below.

$$x_j{}^* = \begin{cases} \max(x_{ij})\,; benefit \\ min(x_{ij})\,; cost \end{cases} \tag{6}$$

$$d_{ij} = \frac{|x_{ij} - x_j{}^*|}{|x_j{}^{max} - x_j{}^{min}|} \tag{7}$$

$$y_i = \sum_{j=1}^{n} w_j * d_{ij} \tag{8}$$

In the SPOTIS method, the symbol $x_j{}^*$ represents a value determined based on the type of criteria of the alternative, if the criteria are beneficial, or the minimum value if the criteria are of cost nature. The symbol d_{ij} represents the normalization result of each alternative value, and the value y_i represents the overall distance of the alternative to the ideal solution.

RESULTS AND DISCUSSION

Combining the LODECI weighting method with the SPOTIS ranking method under the MCDM framework provides a structured solution for employee performance evaluation when multiple criteria are involved. The process begins with LODECI, which objectively derives criterion weights based on data variation and distribution in the decision matrix, thereby reducing subjectivity in determining importance levels. After obtaining the weights, the SPOTIS method is applied to rank employees by measuring the normalized distance of each alternative from the established ideal solution. Through this mechanism, each employee's performance is evaluated based on how close their performance values are to the ideal condition determined for every criterion. The final ranking is obtained from the total weighted distance values, where alternatives with smaller distances indicate better performance levels. By combining objective weighting through LODECI with the stable preference ordering mechanism of SPOTIS, the proposed evaluation framework is able to support a more consistent, transparent, and data-driven decision-making process in employee performance assessment. This integration not only enhances the reliability of the evaluation results but also helps organizations manage complex performance criteria more effectively while minimizing bias in the decision-making process.

1. Problem Identification
   Identifying problems is an essential first step in research, as it helps to understand the issues present in the object being studied. In employee performance evaluation, the process often includes various criteria such as productivity, quality of work, discipline, teamwork, and responsibility. The involvement of multiple criteria makes the evaluation more complex, as each has a different level of importance and requires a systematic approach for proper analysis. Moreover, many organizations still rely on traditional evaluation methods based on subjective judgment, which can result in inconsistent assessments and may not fully capture an employee's overall performance.
   A common challenge lies in objectively assigning weights to each criterion and combining multiple assessment scores into a unified evaluation result. Errors in determining these weights can affect the final ranking of employees, leading to decisions that may not represent actual performance accurately. Additionally, evaluation methods that lack structure can result in inconsistent decisions over time. To overcome these issues, a more systematic approach is needed, such as the use of multi-criteria decision-making techniques. This approach can help organizations achieve more objective, consistent, and data-based evaluations, ultimately supporting more reliable decision-making.
2. Data Collection
   Data collection constitutes a fundamental phase in the research process, aiming to acquire relevant information for subsequent analysis and decision-making. At this stage, employee performance data is obtained based on predefined criteria, encompassing multiple dimensions such as productivity, work quality, discipline, teamwork, and responsibility. The data may be sourced from internal reports, managerial assessments, or organizational evaluation records. Following collection, the dataset is systematically structured to represent each alternative's performance across all criteria. The processed data is then displayed in a tabular format, summarizing the evaluation results for each alternative, as presented in Table 1.

Table 1. Data Collection

Employee Name	Productivity (EC-1)	Work Quality (EC-2)	Discipline (EC-3)	Teamwork (EC-4)	Responsibility (EC-5)
AN Employee	85	88	90	84	87
BD Employee	78	82	85	80	83
CR Employee	92	90	88	91	89
DS Employee	80	79	83	77	81
EF Employee	87	85	86	88	84
FH Employee	76	80	78	79	77
GS Employee	90	92	91	89	90
HT Employee	83	81	84	82	85

The criteria used in evaluating employee performance in this study consist of five main aspects that represent various dimensions of work performance. Productivity (EC-1) describes an employee's ability to complete work according to the targets set by the organization. Work Quality (EC-2) reflects the level of accuracy, precision, and standards of the work produced by employees. Discipline (EC-3) relates to employees' compliance with work rules, including punctuality, attendance, and adherence to organizational policies. Next, Teamwork (EC-4) indicates the employees' ability to collaborate with colleagues and contribute to team activities. Finally, Responsibility (EC-5) describes the level of responsibility employees demonstrate in completing tasks and their commitment to the assigned work. These five criteria are used to provide a more comprehensive picture of employee performance within the organization.

The data presented in Table 1 shows the assessment results of eight employees represented by the initials of their names. Each employee is evaluated based on five predetermined criteria using a specific scoring scale to describe performance levels in each aspect. Based on the data, it can be seen that some employees show relatively high scores in most criteria, such as GS Employee and CR Employee, who have high scores in productivity, work quality, and teamwork. Meanwhile, other employees have varying scores in each criterion, indicating differences in performance levels among employees. This variation in scores serves as an important basis in the analysis process using a multi-criteria decision-making method to determine the weight of criteria and to rank employee performance more objectively.

3. Determination of Criteria Weights Using LODECI

The LODECI method is applied to determine criterion weights objectively by utilizing the characteristics of the collected data. The decision matrix obtained during data collection is used as the initial input for analysis. By examining the distribution and variation of values for each criterion, LODECI identifies the extent to which each criterion differentiates alternative performance. Criteria with greater variability typically exert a stronger influence on the evaluation results. This process enables weighting to be performed based on data analysis instead of relying on subjective decision-maker opinions.

The calculation process of the LODECI method begins with the normalization of the decision matrix values to ensure comparability between criteria with different scales using (1), the general form of the decision matrix of assessment data is as follows.

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

The results of the decision matrix from employee assessment data in Table 1 are displayed as follows.

$$X = \begin{bmatrix} 85 & 88 & 88 & 84 & 87 \\ 78 & 82 & 82 & 80 & 83 \\ 92 & 90 & 90 & 91 & 89 \\ 80 & 79 & 79 & 77 & 81 \\ 87 & 85 & 85 & 88 & 84 \\ 76 & 80 & 80 & 79 & 77 \\ 90 & 92 & 92 & 89 & 90 \\ 83 & 81 & 81 & 82 & 85 \end{bmatrix}$$

The calculation process of the LODECI method then calculates the normalization value using (2), the results of the LODECI method normalization value calculation are as follows.

$$d_{11} = \frac{x_{11}}{\max_{1} x_{i1}} = \frac{85}{92} = 0.924.$$

The overall calculation of the LODECI method normalization values for each alternative based on the existing criteria is shown in Table 2.

Table 2. Normalization of the LODECI Method

Employee Name	EC-1	EC-2	EC-3	EC-4	EC-5
AN	0.924	0.957	0.989	0.923	0.967
BD	0.848	0.891	0.934	0.879	0.922
CR	1.000	0.978	0.967	1.000	0.989
DS	0.870	0.859	0.912	0.846	0.900
EF	0.946	0.924	0.945	0.967	0.933
FH	0.826	0.870	0.857	0.868	0.856
GS	0.978	1.000	1.000	0.978	1.000
HT	0.902	0.880	0.923	0.901	0.944

The calculation process of the LODECI method then calculates the deviation values between alternatives to measure the level of dispersion for each criterion using (3). The results of the LODECI method deviation value calculations are as follows.

$$SD_{11} = \max\left\{\left|\begin{matrix}0.0761; 0.0761; 0.0543; 0.0217; \\ 0.0978; 0.0543; 0.0217\end{matrix}\right|\right\}$$

$$SD_{11} = 0.0978$$

The overall calculation of the LODECI method deviation values for each alternative based on the existing criteria is presented in Table 3.

Table 3. Deviation Values of the LODECI Method

Employee Name	EC-1	EC-2	EC-3	EC-4	EC-5
AN	0.098	0.098	0.132	0.077	0.111
BD	0.152	0.109	0.077	0.121	0.078
CR	0.174	0.120	0.110	0.154	0.133
DS	0.130	0.141	0.088	0.154	0.100
EF	0.120	0.076	0.088	0.121	0.078
FH	0.174	0.130	0.143	0.132	0.144
GS	0.152	0.141	0.143	0.132	0.144
HT	0.098	0.120	0.077	0.099	0.089

The calculation process of the LODECI method then computes the logarithmic deviation values that represent the information contribution of each criterion using (4). The results of the logarithmic deviation value calculations of the LODECI method are as follows.

$$LSD_1 = \ln\left(1 + \frac{\sum_{i=1}^{8} SD_{i1}}{8}\right)$$

$$LSD_1 = \ln\left(1 + \frac{1.0978}{8}\right)$$

$LSD_1 = \ln(1.1372)$
$LSD_1 = 0.129$

The overall calculation of the LODECI method's logarithmic deviation values for each alternative based on the existing criteria is presented in Table 4.

Table 4. Logarithmic Deviation Values of the LODECI Method

EC-1	EC-2	EC-3	EC-4	EC-5
0.129	0.111	0.102	0.117	0.104

The next calculation process of the LODECI method calculates the weight value of each criterion using (5), the results of calculating the criterion weight values of the LODECI method are as follows.

$$w_1 = \frac{LSD_1}{\sum_{j=1}^{5} LSD_j} = \frac{0.129}{0.562} = 0.229$$

The overall calculation of the criterion weights of the LODECI method is shown in Table 5.

Table 5. Criteria Weights of the LODECI Method

EC-1	EC-2	EC-3	EC-4	EC-5
0.229	0.197	0.181	0.208	0.185

The results of the criteria weight calculation using the LODECI method show the relative importance level of each criterion used in employee performance evaluation. Based on these results, Productivity (EC-1) has the highest weight of 0.229, indicating that this criterion has the greatest influence in the performance assessment process. Next, Teamwork (EC-4) has a weight of 0.208, followed by Work Quality (EC-2) with a weight of 0.197. Meanwhile, Responsibility (EC-5) has a weight of 0.185, and Discipline (EC-3) has a weight of 0.181, which is the lowest weight among all the criteria used. Nevertheless, all criteria still contribute to the evaluation process because each weight reflects the relative importance level obtained from data variation analysis using the LODECI method. The results of this weighting are subsequently used in the stage of ranking alternatives to determine employee performance more objectively and proportionally.

4. Ranking Alternatives Using SPOTIS

The Ranking Alternatives stage using SPOTIS is carried out to determine the performance ranking of employees based on the preference values obtained from the SPOTIS method calculation. In this stage, the value of each alternative that has been multiplied by the criteria weights from the LODECI method results is used to calculate the distance of each alternative to the predetermined ideal solution. This process produces a total distance value that indicates how close each employee's performance is to the ideal condition across all assessment criteria. The smaller the distance value obtained by an alternative, the closer that alternative is to the ideal solution and the better its performance level.

The SPOTIS procedure begins by creating a decision matrix that represents the performance values of each alternative with respect to all criteria using (1). The decision matrix results of the SPOTIS method are the same as those of the LODECI method.

The next procedure of the SPOTIS method is to determine the ideal solution values for each criterion using (6), with the results of determining the ideal solution values for the alternatives as follows.

$x_1^* = \max(85; 78; 92; 80; 87; 76; 90; 83)$
$x_1^* = 92$

The overall ideal solution values for each criterion of the SPOTIS method are shown in Table 6.

Table 6. Ideal Solution Values of the SPOTIS Method

EC-1	EC-2	EC-3	EC-4	EC-5
92	92	91	91	90

The next procedure of the SPOTIS method for calculating distance normalization is carried out by determining the difference between the value of each alternative and the ideal point that has been determined for each criterion using (7), the results of the distance normalization calculation are as follows.

$$d_{11} = \frac{|x_{11} - x_1^*|}{|x_1^{max} - x_1^{min}|} = \frac{|85 - 92|}{|92 - 76|} = \frac{7}{16} = 0.438$$

All calculations of the SPOTIS method distance normalization values are shown in Table 7.

Table 7. Distance Normalization of the SPOTIS Method

Employee Name	EC-1	EC-2	EC-3	EC-4	EC-5
AN	0.438	0.308	0.077	0.500	0.231
BD	0.875	0.769	0.462	0.786	0.538
CR	0.000	0.154	0.231	0.000	0.077
DS	0.750	1.000	0.615	1.000	0.692
EF	0.313	0.538	0.385	0.214	0.462
FH	1.000	0.923	1.000	0.857	1.000
GS	0.125	0.000	0.000	0.143	0.000
HT	0.563	0.846	0.538	0.643	0.385

The next procedure of the SPOTIS method calculates the total distance value of each alternative using (7), the results of the total distance value calculation are as follows.

$$y_1 = \sum_{j=1}^{5} w_j * d_{1j}$$

$$y_1 = (0.229 * 0.438) + (0.197 * 0.308) + (0.181 * 0.077) + (0.208 * 0.500) + (0.185 * 0.231)$$

$y_1 = 0.321$

The overall calculation of the total distance value of the SPOTIS method is shown in Table 8.

Table 8. Total Distance Value of the SPOTIS Method

Employee Name	Total Distance Value
AN	0.321
BD	0.698
CR	0.086
DS	0.816
EF	0.377
FH	0.955

Employee Name	Total Distance Value
GS	0.058
HT	0.598

The calculation results of the SPOTIS method shown in Table 8 indicate that each employee has a total distance value representing the performance gap of each employee relative to the ideal solution based on all criteria used in the evaluation. This total distance value is obtained from the distance calculation process, which has been weighted using previously determined criteria weights. From the presented data, it can be seen that AN Employee has a total distance value of 0.321, BD Employee 0.698, CR Employee 0.086, DS Employee 0.816, EF Employee 0.377, FH Employee 0.955, GS Employee 0.058, and HT Employee 0.598. These values indicate differences in the closeness of each employee to the ideal conditions set for each criterion, so this data can be used as a basis for the employee performance evaluation process using the SPOTIS method.

After the total distance values of each alternative are obtained through the SPOTIS method calculation, the next step is to carry out the employee ranking process based on these values. The ranking process is conducted to determine the overall performance order of employees by considering all the criteria used in the evaluation. The total distance values produced reflect the level of closeness of each employee's performance to the ideal solution, so these values can be used as a basis for determining the relative position of each alternative in the evaluation process. Through this process, the organization can gain a clearer picture of the comparison of employee performance in a systematic and measurable way. The final results of the employee ranking process are then presented in Figure 2.

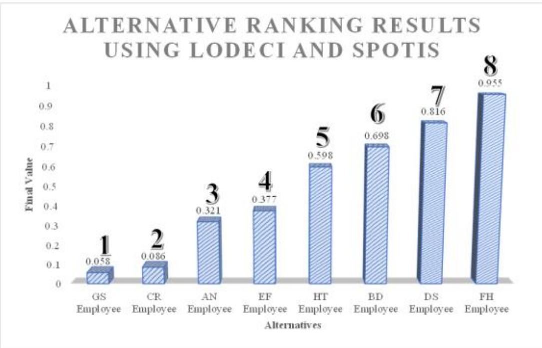

Figure 2. Alternative Ranking

The ranking results in Figure 2 obtained from the integration of the LODECI and SPOTIS methods illustrate the order of employee performance based on the final scores derived from total distance calculations. The results indicate that GS Employee occupies the first position with a score of 0.058, followed by CR Employee in second place with 0.086. AN Employee ranks third with a score of 0.321, while EF Employee is placed fourth with 0.377. HT Employee holds the fifth position with 0.598, followed by BD Employee in sixth place with 0.698. DS Employee ranks seventh with a score of 0.816, and FH Employee is positioned eighth with 0.955. These findings reflect the relative standing of each employee based on performance evaluation using criterion weights derived from LODECI and ranking calculations from the SPOTIS method.

In the SPOTIS method, the process of ranking alternatives is based on the total distance value, which indicates the distance of each alternative from the predetermined ideal solution. The basic principle of this method is that alternatives with smaller distance values have a higher level of closeness to the expected ideal conditions. Therefore, the ranking process is carried out by ordering the total distance values from smallest to largest, where the alternative with the smallest value is placed in the first rank because it is considered to have performance closest to the ideal solution. Conversely, alternatives with larger values indicate a greater distance from the ideal conditions, thus occupying the next rank in the evaluation order. This approach allows the assessment process to be conducted systematically and consistently in determining the best alternative.

5. Sensitivity Analysis

Sensitivity analysis is conducted to test the level of stability and reliability of the ranking results produced by the model by evaluating changes in output against variations in input parameters, particularly the criterion weights. In this stage, the weights obtained from the LODECI method are gradually modified in several scenarios, both by increasing and decreasing the values of certain criterion weights, to observe their effect on the ranking positions of alternatives calculated using the SPOTIS method. This process allows for the identification of the criteria that have the most influence on the final results as well as detecting whether there are significant changes in the ranking order. Sensitivity analysis not only serves as a validation tool but also provides a more comprehensive view of the model's robustness in facing data uncertainty, thereby increasing confidence in the decision-making results. The scenario of sensitivity analysis of weight changes is presented in Table 9.

Table 9. Weight Change Scenario

Scenario	EC-1	EC-2	EC-3	EC-4	EC-5
Initial Weight	0.229	0.197	0.181	0.208	0.185
Scenario 1	0.266	0.188	0.172	0.198	0.176
Scenario 2	0.218	0.235	0.172	0.198	0.176
Scenario 3	0.218	0.188	0.220	0.198	0.176
Scenario 4	0.218	0.188	0.172	0.246	0.176
Scenario 5	0.218	0.188	0.172	0.198	0.224
Scenario 6	0.188	0.207	0.191	0.219	0.195
Scenario 7	0.241	0.155	0.191	0.219	0.195

Scenario	EC-1	EC-2	EC-3	EC-4	EC-5
Scenario 8	0.241	0.207	0.138	0.219	0.195
Scenario 9	0.241	0.207	0.191	0.166	0.195
Scenario 10	0.241	0.207	0.191	0.219	0.142

In the sensitivity analysis, scenarios 1 to 5 were conducted by incrementally adding a weight value of 0.05 to each criterion, with the aim of observing to what extent an increase in the importance of a criterion affects the ranking results of the alternatives. Each addition of weight to one criterion is balanced by proportional adjustments to the other criteria so that the total weight remains consistent, ensuring that the changes truly reflect the relative influence of the tested criterion. Furthermore, in scenarios 6 to 10, the weight of each criterion was reduced by 0.05 sequentially to see the impact of a decrease in the level of importance on the ranking position of the alternatives. Through these two groups of scenarios, it can be analyzed whether the model shows stability in the ranking results or experiences significant changes, thereby providing a clearer picture of the level of sensitivity and robustness of the model to the dynamics of changes in criteria weights.

The ranking of alternatives in each weight change scenario shows how the position of each alternative can shift with increases or decreases in criterion weight values. In the weight increase scenario, alternatives that have superior values in the strengthened criteria tend to rise in rank, while other alternatives may relatively decrease. Conversely, in the weight reduction scenario, the influence of those criteria on the final result diminishes, so alternatives with advantages in other criteria have the potential to rise in rank. Nevertheless, if the model has a good level of stability, weight changes within certain limits will not cause significant shifts in ranking, so the best alternative consistently remains at the top position. This indicates that the method used is capable of producing decisions that are robust against parameter variations. The complete results of the alternative rankings for all scenarios of weight changes are shown in Figure 3.

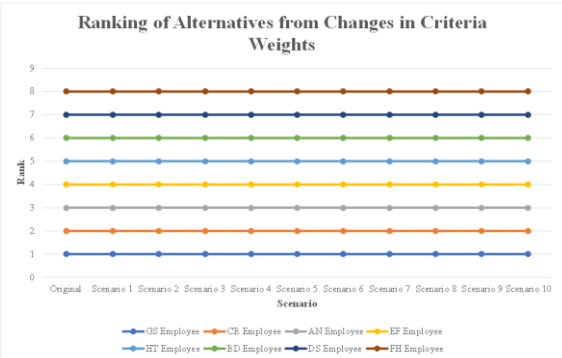

Figure 3. Ranking of Alternatives from Changes in Criteria Weights

Figure 3 shows that the ranking results of the alternatives tend to be very stable across all scenarios of weight changes, both in the initial condition and in scenarios 1 to 10. Each alternative maintains the same ranking position without shifting, even though weighting criteria have been increased or decreased. For example, the alternative with the highest rank consistently remains at the top position, followed by the other alternatives in order down to the lowest rank, with no change in order in any scenario. The parallel, non-intersecting line pattern shows that a weight change of ±0.05 does not have a significant impact on the final ranking results. This indicates that the model used has a very good level of robustness and consistency in facing parameter variations, so the decisions produced can be considered stable and reliable under various conditions of changes in criterion weights.

6. Discussion

The integration of LODECI and SPOTIS within the MCDM framework demonstrates a strong capability to address the inherent complexity of employee performance evaluation involving multiple criteria. One of the main strengths of this approach lies in its ability to reduce subjectivity, particularly in the weighting phase, where LODECI derives criterion importance directly from data variation rather than relying on expert judgment alone. The resulting weights indicate that Productivity (EC-1) and Teamwork (EC-4) have relatively higher influence compared to other criteria, reflecting their stronger discriminative power in the dataset. This data-driven weighting mechanism ensures that the evaluation process is grounded in actual performance patterns rather than assumptions. Furthermore, when these weights are applied in the SPOTIS method, the ranking process becomes more structured, as each employee is evaluated based on their relative distance to the ideal solution. This combination creates a balanced evaluation system that integrates objective weighting with a clear and interpretable ranking logic.

The results of the ranking process provide meaningful insights into employee performance differences, where GS Employee consistently achieves the best position, followed by CR Employee and AN Employee. The relatively small distance values obtained by these top-ranked employees indicate that their performance is closely aligned with the ideal criteria benchmarks across all evaluation aspects. In contrast, employees with larger distance values, such as DS and FH, demonstrate a wider gap from the ideal performance, highlighting areas that may require improvement. This ranking not only serves as a decision-support tool but also provides actionable information for organizational management, such as identifying high-performing employees for rewards and recognizing those who may benefit from further training or development. The SPOTIS method, in particular, offers a transparent evaluation mechanism since the ranking is directly based on measurable distances, making it easier for decision-makers to justify the results and communicate them within the organization.

The sensitivity analysis further strengthens the reliability of the proposed model by demonstrating that the ranking results remain unchanged across all weight variation scenarios. Despite systematic increases and decreases in criterion weights, the positions of all employees remain consistent, indicating that the model is highly robust to parameter changes. This stability suggests that the decision outcomes are not overly dependent on specific weight configurations, which is a common concern in many MCDM applications. From a practical perspective, this finding enhances confidence in the model's applicability in real-world scenarios where uncertainty or slight variations in judgment may occur. However, this study is still limited by the scope of data and the assumption of deterministic values, which may not fully capture uncertainty in human judgment. Therefore, future research could explore the integration of fuzzy or probabilistic approaches, expand the dataset with more alternatives and criteria, and compare the performance of this hybrid model with other MCDM methods to further validate its effectiveness and generalizability.

CONCLUSION

The combined use of the LODECI and SPOTIS methods within the MCDM framework has proven effective in producing employee performance evaluations that are objective, systematic, and consistent. Based on the initial criterion weights obtained through LODECI, namely EC-1 at 0.229, EC-2 at 0.197, EC-3 at 0.181, EC-4 at 0.208, and EC-5 at 0.185, it is evident that each criterion has a different contribution according to the level of variation in its data. These weights are then implemented in the SPOTIS method to calculate the distance of each alternative from the ideal solution. The calculation results show that the top three ranks are consecutively held by GS Employee with a value of 0.058, CR Employee with a value of 0.086, and AN Employee with a value of 0.321, reflecting that GS Employee has performance closest to the ideal condition. Furthermore, the results of the sensitivity analysis indicate that changes in the criteria weights, whether an increase or decrease of 0.05, do not cause significant changes in the ranking order of the alternatives. This confirms that the model used has a high level of stability and robustness, making it capable of providing consistent and reliable decision-making results under various parameter changes. This integration offers a structured and data-driven approach that enhances consistency and reliability in decision-making. Nevertheless, this study has limitations, including the use of a still limited number of criteria and alternatives, and it has not yet considered factors of uncertainty or data ambiguity in the assessment process. The implications of this study indicate that an approach based on LODECI and SPOTIS can be a practical solution for organizations in improving the objectivity and consistency of employee performance evaluations. For future research, it is recommended to develop a model by integrating a fuzzy-based approach or other methods capable of handling uncertainty, expanding the amount of data and criteria, and conducting comparisons with other MCDM methods to obtain a more comprehensive understanding of model performance.

REFERENCES

Abdul, D., Wenqi, J., Tanveer, A., & Sharaf, I. M. (2025). Analyzing the sustainability factors to prioritize sustainable energy source: A novel integrated MCDM model. *Energy*, *337*, 138637. https://doi.org/https://doi.org/10.1016/j.energy.2025.138637

Ajithkumar, A., & GaneshKumar, P. (2025). A systematic framework for the optimum selection of organic PCM in sustainable solar drying process: A multi-criteria decision-making methodology. *Journal of Energy Storage*, *116*, 116080. https://doi.org/https://doi.org/10.1016/j.est.2025.116080

Akbulut, O. Y., & Aydın, Y. (2024). A Hybrid Multidimensional Performance Measurement Model Using the MSD-MPSI-RAWEC Model for Turkish Banks. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty*, *11*(3), 1157–1183. https://doi.org/10.30798/makuiibf.1464469

Ali, T., Aytekin, A., & Demidionov, M. (2026). Optimal siting of wind powered green hydrogen production in Bangladesh using interval-valued T-spherical fuzzy multi-criteria decision-making method. *International Journal of Hydrogen Energy*, *217*, 153931. https://doi.org/https://doi.org/10.1016/j.ijhydene.2026.153931

Çilek, A., & Şeyranlıoğlu, O. (2025). Measuring the Financial Performance of Reinsurance Companies in Türkiye with LODECI, CRADIS and AROMAN MCDM Methods TT - LODECI, CRADIS ve AROMAN. *International Journal of Business and Economic Studies*, *7*(1), 1–18. https://doi.org/10.54821/uiecd.1587675

de Assis, G. S., dos Santos, M., & Basilio, M. P. (2023). Use of the WASPAS Method to Select Suitable Helicopters for Aerial Activity Carried Out by the Military Police of the State of Rio de Janeiro. In *Axioms* (Vol. 12, Issue 1). https://doi.org/10.3390/axioms12010077

de Oliveira, P. L., Moreira, M. Â. L., de Araújo Costa,

I. P., de Moura Pereira, D. A., Gomes, C. F. S., & dos Santos, M. (2025). *Human Resources Selection Through the PSI-SPOTIS Hybrid Modelling: Multi-criteria Analysis of Sellers for Technological Market BT - Proceedings of International Conference on Information Technology and Applications* (A. Ullah & S. Anwar (eds.); pp. 445–459). Springer Nature Singapore. https://doi.org/10.1007/978-981-96-1758-6_37

Dündar, S. (2025). Prioritizing the Regional Preferences of Turkish Investors Regarding Foreign Direct Investment by ARLON Method. *Konya Journal of Engineering Sciences*, *13*(3), 927–946. https://doi.org/10.36306/konjes.1648279

Ghanbari, H., Seiti, H., Mohammadi, E., & Elkamel, A. (2025). Selecting a sustainable hydrogen production method using a novel dual evaluation EDAS approach. *Annals of Operations Research*. https://doi.org/10.1007/s10479-025-06616-6

Hadad, S. H., Chandra, I., Wang, J., Megawaty, D. A., Setiawansyah, S., & Yudhistira, A. (2025). Dynamic Weight Allocation In Modified Multi-Atributive Ideal-Real Comparative Analysis With Symmetry Point For Real-Time Decision Support . *Jurnal Teknik Informatika (Jutif)*, *6*(1 SE-Articles), 63–74. https://doi.org/10.52436/1.jutif.2025.6.1.4170

Hassanpour, N., Shaemi Barzoki, A., Moshref Javadi, M. H., & Safari, A. (2022). Designing employee performance evaluation model in Isfahan municipality: an interorganizational experience. *International Journal of Productivity and Performance Management*, *71*(6), 2558–2581. https://doi.org/10.1108/IJPPM-08-2020-0411

Junhai Wang, & Setiawansyah. (2025). Integration of LOPCOW and ARAS Methods for Selecting the Best Employees in the Finance Division. *Journal of Decision Support System Research*, *2*(3), 125–134. https://doi.org/10.64366/dss.v2i3.102

Kara, K., Yalçın, G. C., Simic, V., Baysal, Z., & Pamucar, D. (2024). The alternative ranking using two-step logarithmic normalization method for benchmarking the supply chain performance of countries. *Socio-Economic Planning Sciences*, *92*, 101822. https://doi.org/https://doi.org/10.1016/j.seps.2024.101822

Kara, K., Yalçın, G. C., Simic, V., Erbay, M., & Pamucar, D. (2024). A type-2 neutrosophic entropy-based group decision analytics model for sustainable aquaculture engineering. *Engineering Applications of Artificial Intelligence*, *134*, 108615. https://doi.org/https://doi.org/10.1016/j.engappai.2024.108615

Kizielewicz, B., Więckowski, J., & Sałabun, W. (2024). *SESP-SPOTIS: Advancing Stochastic Approach for Re-identifying MCDA Models BT - Computational Science – ICCS 2024* (L. Franco, C. de Mulatier, M. Paszynski, V. V Krzhizhanovskaya, J. J. Dongarra, & P. M. A. Sloot (eds.); pp. 281–295). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-63751-3_19

Liu, P., & Shen, J. (2024). GHF-COPRAS Multiple Attribute Decision-Making Method Based on Cumulative Prospect Theory and Its Application to Enterprise Digital Asset Valuation. In *Axioms* (Vol. 13, Issue 5). https://doi.org/10.3390/axioms13050297

Oprasto, R. R., Wang, J., Pasaribu, A. F. O., Setiawansyah, S., Aryanti, R., & Sumanto. (2025). An Entropy-Assisted COBRA Framework to Support Complex Bounded Rationality in Employee Recruitment. *Bulletin of Computer Science Research*, *5*(3 SE-), 207–218. https://doi.org/10.47065/bulletincsr.v5i3.505

Pala, O. (2024). Assessment of the social progress on European Union by logarithmic decomposition of criteria importance. *Expert Systems with Applications*, *238*, 121846. https://doi.org/https://doi.org/10.1016/j.eswa.2023.121846

Rani, P., Mishra, A. R., Pamucar, D., Ali, J., & Hezam, I. M. (2023). Interval-valued intuitionistic fuzzy symmetric point criterion-based MULTIMOORA method for sustainable recycling partner selection in SMEs. *Soft Computing*. https://doi.org/10.1007/s00500-023-08189-7

Riaz, M., Qamar, F., Tariq, S., & Alsager, K. (2024). AI-Driven LOPCOW-AROMAN Framework and Topological Data Analysis Using Circular Intuitionistic Fuzzy Information: Healthcare Supply Chain Innovation. In *Mathematics* (Vol. 12, Issue 22). https://doi.org/10.3390/math12223593

Setiawansyah, S., & Rahmanto, Y. (2025). Implementation of the Geometric Mean Multi-Attribute Utility Theory (G-MAUT) in Determining the Best Honorary Employees. *Jurnal Ilmiah Computer Science*, *3*(2 SE-Articles), 111–119. https://doi.org/10.58602/jics.v3i2.50

Sithi, S. S., Ara, M. A., Dhrubo, A. T., Rony, A. H., & Shabur, M. A. (2025). Sustainable supplier selection in the textile industry using triple bottom line and SWARA-TOPSIS approaches. *Discover Sustainability*, *6*(1), 344. https://doi.org/10.1007/s43621-025-01206-9

Wang, J., Isnain, A. R., Suryono, R. R., Rahmanto, Y., Mesran, M., & Setiawansyah, S. (2024). Decision Support System for Platform Selection in E-Commerce Using the OWH-TOPSIS Method. *Journal of Computer System and Informatics (JoSYC)*, *6*(1), 172–181. https://doi.org/10.47065/josyc.v6i1.5990

Wang, J., Setiawansyah, S., & Sumanto, S. (2026). Comparison of Objective Weighting Methods in SAW and Their Effect on Alternative Ranking Results. *Jurnal Masyarakat Informatika*, *17*(1), 89–112. https://doi.org/10.14710/jmasif.17.1.78414

Wang, K., Li, B., Tian, T., Zakuan, N., & Rani, P. (2023). Evaluate the drivers for digital transformation in higher education institutions in the era of industry 4.0 based on decision-making method. *Journal of Innovation & Knowledge*, *8*(3), 100364. https://doi.org/https://doi.org/10.1016/j.jik.2023.100364

Yalçın, G. C., Kara, K., & Senapati, T. (2024). A hybrid spherical fuzzy logarithmic decomposition of criteria importance and alternative ranking technique based on Adaptive Standardized Intervals model with application. *Decision Analytics Journal*, *11*, 100441. https://doi.org/https://doi.org/10.1016/j.dajour.2024.100441