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Integration of Data Assessment Method Weighting and Proximity Indexed Value for Best Employee Selection in Decision Support Systems

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Abstract: The selection of the best employee is a multi-criteria decision-making problem because employee performance is evaluated using several criteria with different levels of importance. Subjective criterion weighting may not fully represent the characteristics of the assessment data and can influence the resulting decision. This study proposes the integration of Data Assessment Method (DAM) Weighting and Proximity Indexed Value (PIV) within a Decision Support System for best employee selection. DAM Weighting is employed to determine objective criterion weights based on the information contained in the assessment data, while PIV is used to evaluate the relative proximity of each employee alternative to the reference condition. The results show that the criterion weights are relatively balanced, with R1 obtaining the highest weight of 0.1494 and R4 the lowest weight of 0.1381. The PIV calculation produces different proximity values among the nine employee alternatives, with Alt-08 obtaining the lowest value of -2.2864, followed by Alt-09 at -1.8580 and Alt-06 at -1.7148. Based on the resulting ranking, Alt-08 is identified as the best employee. These findings indicate that the integration of DAM Weighting and PIV can provide an objective, quantitative, and data-oriented mechanism for supporting best employee selection in a Decision Support System.
Keywords: Decision Support System; Best Employee Selection; Data Assessment Method; Proximity Indexed Value; Multi-Criteria Decision Making.

1. INTRODUCTION

Decision Support Systems (DSS) are increasingly used to support organizational decision-making in situations involving multiple alternatives and evaluation criteria[1]–[3]. One important application is the selection of the best employee, where decision makers must evaluate employees based on several performance dimensions, such as work quality, productivity, discipline, attendance, teamwork, responsibility, communication, and initiative[4], [5]. The main research problem arises because employee performance is multidimensional, meaning that an employee who performs well on one criterion may not necessarily demonstrate the same level of performance on other criteria. Consequently, selecting the best employee cannot be adequately represented by a single performance indicator and requires a structured Multi-Criteria Decision Making (MCDM) framework. Although DSS-based MCDM approaches can organize employee evaluation into decision matrices, criterion weights, and alternative rankings, the reliability of the resulting decision remains highly dependent on how the importance of each criterion is determined and how the performance of each employee is aggregated[6]–[8]. Therefore, an objective and data-driven mechanism is required to transform employee assessment data into a reliable ranking that can support managerial decision-making.

A major limitation in employee selection lies in the determination of criterion weights. Since different performance criteria may contribute differently to the final decision, assigning identical or subjectively determined weights may not accurately represent the information contained in the assessment data. Subjective weighting is particularly vulnerable to the preferences, experience, and judgment of decision makers, while conventional objective weighting methods may emphasize specific statistical characteristics of the data without necessarily providing an assessment framework that captures the overall behavior of the criteria[9]–[11]. This limitation becomes important when employee assessment data exhibit different levels of variation, discrimination, and deviation across criteria. A criterion with highly differentiated employee scores may contain greater decision-making information than a criterion in which most employees obtain similar scores, yet this characteristic may not be sufficiently reflected when weights are predetermined or assigned solely through managerial judgment. Thus, the limitation is not only related to the magnitude of the weights but also to whether the weighting mechanism is capable of assessing the actual characteristics of the decision data before assigning criterion importance.

This condition creates a research gap concerning the integration of data assessment into the weighting process for employee selection. Existing MCDM-based employee evaluation approaches commonly focus on applying established weighting methods followed by a ranking method, while the relationship between the characteristics identified through data assessment and the resulting criterion importance remains insufficiently explored. In particular, there is a need for a weighting mechanism that can systematically assess the variation and deviation characteristics of each criterion and subsequently translate those characteristics into objective criterion weights. At the ranking stage, another limitation concerns the mechanism used to distinguish alternatives after the weights have been obtained. Conventional aggregation approaches may produce different ranking outcomes depending on their mathematical structure, normalization procedure, and treatment of the reference condition. Therefore, a research gap exists not only in developing data-driven criterion weights but also in connecting those weights with a ranking mechanism capable of evaluating employee performance according to its proximity to a desired reference condition. Addressing these two gaps within a single DSS framework can provide a more coherent relationship between the information contained in the assessment data and the final employee ranking.

The novelty of this research lies in the integration of Data Assessment Method Weighting and Proximity Indexed Value (PIV) into a unified DSS framework for best employee selection. The proposed approach positions Data Assessment Method Weighting as the weighting component, where the decision data are systematically assessed to derive criterion importance from their observed characteristics rather than relying primarily on subjective preferences. The resulting objective weights are subsequently incorporated into PIV, which evaluates the performance of each employee based on proximity to the established reference or ideal condition. This integration establishes a direct methodological relationship between data characteristics, criterion importance, and alternative ranking. Rather than treating weighting and ranking as independent

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computational stages, the proposed framework connects the information obtained during data assessment with the proximity-based evaluation of employee performance. Consequently, the proposed model is expected to provide a more data-responsive decision mechanism in which changes in the characteristics of employee assessment data can influence criterion weights and, subsequently, the ranking results. This integration represents the principal methodological contribution of the study.

Based on these considerations, the objective of this study is to develop and evaluate an integrated Decision Support System that combines Data Assessment Method Weighting with Proximity Indexed Value for selecting the best employee. The study specifically aims to assess employee performance using multiple criteria, derive objective criterion weights through data assessment, apply the resulting weights within the PIV ranking procedure, and identify the employee with the most favorable overall performance. Furthermore, the reliability of the proposed model will be examined through comparative, sensitivity, and robustness analyses to determine whether the resulting ranking remains stable under changes in weighting schemes, criteria, or evaluation methods. The proposed framework is therefore intended not merely to produce a ranking of employees but to establish a transparent and data-driven decision process in which the determination of criterion importance and employee ranking are methodologically connected. The expected outcome is a DSS model that can provide more objective, consistent, and interpretable support for organizational decisions concerning the selection of the best employee.

2. METHODOLOGY

Research Design

This study uses an MCDM approach implemented within a DSS framework to determine the best employees. The developed model integrates DAM Weighting as an objective weighting method and PIV as a ranking method. Employee evaluation data is used as the basis for creating a decision matrix, then an assessment of each criterion's characteristics is conducted to produce objective weights. These weights are then used in the PIV process to obtain preference values and rankings for each employee. The research stages carried out are shown in Figure 1.

Figure 1. Research Stage

The research stages in Best Employee Selection involve a data-driven decision-making process to determine the best employees in an objective and measurable way. This process uses employee evaluation data covering various aspects like performance, skills, attendance, and teamwork, and then considers the importance of each criterion through objective weighting using the DAM Weighting method. After that, the employee assessment results are processed using the PIV method to get the final score and identify the top-performing employee based on the highest score.

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Data Collection

Data collection is the initial stage of the research and is conducted to obtain employee performance assessment data required for the best employee selection process. The data were collected from the organization's employee evaluation records for a specified assessment period and used as the primary input for the proposed Decision Support System. The collected information consists of employee identification and performance scores across several predefined evaluation criteria. The assessment criteria were selected based on their relevance to employee performance and their ability to represent different dimensions of work achievement. The collected data were subsequently organized into a structured dataset to facilitate the construction of the decision matrix and the application of the Data Assessment Method Weighting and Proximity Indexed Value (PIV) methods.

The employee assessment data consist of several criteria representing different aspects of employee performance. In this study, the criteria include Work Quality (R1), Productivity (R2), Discipline (R3), Attendance (R4), Teamwork (R5), Responsibility (R6), and Communication (R7). Each employee is treated as an alternative, while the assessment score for each criterion represents the employee's performance on the corresponding indicator. All criteria are categorized as benefit attributes because higher assessment scores indicate better employee performance. The resulting assessment data form the basis for the decision matrix and are subsequently processed to determine the objective criterion weights and rank the employee alternatives. The employee assessment data are presented in Table 1.

Table 1. Assessment Data

Alternative	R1	R2	R3	R4	R5	R6	R7
Alt-01	85	88	90	95	87	89	84
Alt-02	78	82	85	90	80	84	81
Alt-03	92	90	94	97	91	93	89
Alt-04	81	85	88	92	84	86	82
Alt-05	89	86	91	94	88	90	87
Alt-06	76	80	83	88	79	81	78
Alt-07	94	92	96	98	93	95	91
Alt-08	83	87	89	91	85	88	83
Alt-09	87	84	92	96	86	91	85

The employee assessment data used in this study represent employee performance evaluations across seven assessment criteria. The dataset consists of nine employees, represented as alternatives from Alt-01 to Alt-09, with assessment scores ranging from 76 to 98 for each criterion. Each employee is evaluated using the same seven performance indicators to ensure comparability among alternatives. Based on the assessment framework, all criteria are classified as benefit attributes, meaning that a higher score indicates better employee performance. The assessment scores constitute the initial decision matrix and are subsequently used in the objective weighting process and alternative ranking to identify the employee with the best overall performance.

Data Assessment Method Weighting

The Data Assessment Method Weighting is an objective weighting approach in MCDM that determines the importance level of each criterion based on the characteristics and information contained in the assessment data[12]. This method doesn’t assign weights solely based on the decision maker’s subjective preferences but instead evaluates the data patterns to find each criterion’s relative contribution. That way, criteria with data

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characteristics that better distinguish performance between alternatives can get a more representative importance level, while criteria with less distinguishing information get relatively smaller weights. This approach can be used to produce data-based criterion weights, supporting a more objective, measurable, and consistent decision-making process in various MCDM problems.

The DAM Weighting process starts by creating a decision matrix that represents the performance of each alternative based on all the criteria used in the evaluation through (1). The matrix then goes through a normalization process to equalize the value range between criteria, so that differences in scale do not affect the comparison process using (2). The normalized values then form the basis for determining preference values to identify the relative ability of each criterion in providing distinguishing information between alternatives through (3). Next, the obtained preference values are used to determine the importance level of each criterion, resulting in objective weights that represent the relative contribution of each criterion to the decision-making process through (4).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \quad (1)$$

$$r_{ij} = \frac{x_{ij}}{\sum_{r=1}^{m} x_{rj}} \quad (2)$$

$$P_j = 100 * \left| \frac{\sqrt{\sum_{i=1}^{m} (r_{ij})^2}}{\ln \frac{m}{\sigma_i}} \right| \quad (3)$$

$$w_j = \frac{P_i}{\sum_{k=1}^{m} P_k} \quad (4)$$

The decision matrix X is a matrix that contains the evaluation values of each alternative against each criterion, with x_{ij} showing the performance value of the ith alternative on the jth criterion, while m represents the number of alternatives and j represents the criterion index. The value r_{ij} is the normalized value of x_{ij}, obtained by comparing x_{ij} to the sum of all alternative values on the j-th criterion. Next, P_j is the value used to measure the level of importance or contribution of the jth criterion based on the normalized values, number of alternatives (m), and the standard deviation (σ_i) of the values used in the calculation. Meanwhile, w_j is the final weight of the jth criterion, obtained by comparing P_j to the total P_k values of all criteria, so the resulting weight shows the relative importance of each criterion in the decision-making process.

Proximity Indexed Value Method

The PIV Method is one of the MCDM methods used to evaluate and rank alternatives based on how close their performance values are to a reference value[13]–[15]. This method processes each alternative's values for each criterion through normalization, then combines them with the criterion weights to produce a value that represents how close the alternative is to the desired condition. PIV takes into account the characteristics of each criterion through weighting and the difference between the alternative's value and the reference value, so it can be used to identify the alternative with performance closest to the ideal condition. The final result of the method is a proximity index, which is used as the basis for ranking, so the alternative with the best index value can be chosen as the one that best fits the decision-making goal.

The PIV steps start with normalizing the decision matrix to equalize the value scales across criteria so that all alternatives can be compared proportionally, calculated using (5). The normalization results are then multiplied by the weights of each criterion to form the weighted normalized decision matrix, calculated using (6). Next, the closeness value of each alternative to the ideal solution for each criterion is determined by considering the

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benefit and non-benefit attribute types using (7). These closeness values are then summed to get the overall proximity value for each alternative using (8).

$$r_{ij} = \begin{cases} \dfrac{x_{ij}-\min\limits_j x_{ij}}{\max\limits_j x_{ij}-\min\limits_j x_{ij}} \text{ ; } if\ j\ is\ a\ benefit\ attribute \\ \dfrac{\max\limits_j x_{ij}-x_{ij}}{\max\limits_j x_{ij}-\min\limits_j x_{ij}} \text{ ; } if\ j\ is\ a\ cost\ attribute \end{cases} \quad (5)$$

$$n_{ij} = r_{ij} * w_j \quad (6)$$

$$\delta_{ij} = \begin{cases} \max\limits_j n_{ij} - n_{ij} \text{ ; } if\ j\ is\ a\ benefit\ attribute \\ n_{ij} - \min\limits_j n_{ij} \text{ ; } if\ j\ is\ a\ cost\ attribute \end{cases} \quad (7)$$

$$\varphi_i = \sum_{j=1}^{n} \delta_{ij} \quad (8)$$

The symbol r_{ij} represents the normalized performance value of the i^{th} alternative on the j^{th} criterion, which is calculated differently based on the attribute type, namely benefit attributes where a higher value is better, and cost attributes where a lower value is better; x_{ij} indicates the initial value of the i^{th} alternative on the j-th criterion, while $\max\limits_j x_{ij}$ and $\min\limits_j x_{ij}$ represent the maximum and minimum values on the j-th criterion, respectively. The symbol n_{ij} is the performance value of the i-th alternative after normalization and weighting, obtained by multiplying r_{ij} by the criterion weight w_j. The symbol δ_{ij} represents the deviation or distance of the i^{th} alternative from the ideal value on the j^{th} criterion, with the ideal value determined based on whether the attribute is benefit or cost.

3. RESULT AND DISCUSSIONS

The integration of Data Assessment Method Weighting and PIV offers a data-driven approach for supporting the selection of the best employee within a DSS. This integration addresses the need for an objective evaluation mechanism by utilizing employee performance data to represent the relative importance of multiple evaluation criteria and the overall suitability of employee alternatives. Data Assessment Method Weighting provides an objective basis for determining criterion importance according to the characteristics of the assessment data, allowing the resulting weights to represent the relative contribution of each criterion without depending entirely on subjective judgments. Meanwhile, PIV provides a proximity-based decision mechanism for representing the relative performance of employee alternatives in relation to the desired decision condition. The integration of these two approaches creates a relationship between the informational characteristics of employee assessment data and the resulting employee preferences, enabling differences in criterion importance to be reflected in the final decision outcome. In the context of best employee selection, this framework can provide a more objective, consistent, and interpretable representation of employee performance because the decision outcome is determined from the interaction between data-derived criterion importance and the relative performance of each alternative. Therefore, the proposed integration contributes to the development of a DSS that can support employee evaluation and selection through a quantitative and data-oriented decision framework, while also providing a basis for evaluating the consistency and reliability of the resulting decision.

Calculating Criteria Weights Using DAM Weighting

The calculation of criteria weights using DAM Weighting is carried out to determine the importance level of each criterion objectively based on employee assessment data characteristics. This approach is used to reduce reliance on subjective weights and to produce weights that represent the information contained in the decision data. The first

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stage is preparing the decision matrix, which contains the values of each alternative across all evaluation criteria.

This matrix serves as the basis in the DAM Weighting process because all weight calculations are derived from the performance data of the alternatives. The decision matrix is expressed using (1), with each value showing the performance of an alternative against the corresponding criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} \end{bmatrix} \Longleftrightarrow X = \begin{bmatrix} 85 & 88 & 90 & 95 & 87 & 89 & 84 \\ 78 & 82 & 85 & 90 & 80 & 84 & 81 \\ 92 & 90 & 94 & 97 & 91 & 91 & 89 \\ 81 & 85 & 88 & 92 & 84 & 84 & 82 \\ 89 & 86 & 91 & 94 & 88 & 88 & 87 \\ 76 & 80 & 83 & 88 & 79 & 79 & 78 \\ 94 & 92 & 96 & 98 & 93 & 93 & 91 \\ 83 & 87 & 89 & 91 & 85 & 84 & 84 \\ 87 & 84 & 92 & 96 & 86 & 86 & 85 \end{bmatrix}$$

Next, decision matrix normalization is carried out to convert the values of each criterion into a uniform scale. Normalization is needed so that differences in range or units between criteria do not affect the assessment results. The normalized values are then used as a basis to obtain comparable measures between criteria using (2), with the calculation results as follows.

$$r_{11} = \frac{x_{11}}{\sum_{r=1}^{8} x_{r1}} = \frac{85}{85 + 78 + 92 + 81 + 89 + 76 + 94 + 83 + 87} = \frac{85}{765} = 0.1020$$

The normalization results obtained from the decision matrix are presented in Table 2.

Table 2. Normalization Result

Alternative	R1	R2	R3	R4	R5	R6	R7
Alt-01	0.1111	0.1137	0.1114	0.113	0.1125	0.1117	0.1105
Alt-02	0.1020	0.1059	0.1052	0.1070	0.1035	0.1054	0.1066
Alt-03	0.1203	0.1163	0.1163	0.1153	0.1177	0.1167	0.1171
Alt-04	0.1059	0.1098	0.1089	0.1094	0.1087	0.1079	0.1079
Alt-05	0.1163	0.1111	0.1126	0.1118	0.1138	0.1129	0.1145
Alt-06	0.0993	0.1034	0.1027	0.1046	0.1022	0.1016	0.1026
Alt-07	0.1229	0.1189	0.1188	0.1165	0.1203	0.1192	0.1197
Alt-08	0.1085	0.1124	0.1101	0.1082	0.1100	0.1104	0.1092
Alt-09	0.1137	0.1085	0.1139	0.1141	0.1113	0.1142	0.1118

The next step is to determine the preference values based on the normalization results. These values are used to describe the characteristics of the information provided by each criterion in distinguishing performance among alternatives. The calculation of preference values is done using (3).

$$P_1 = 100 * \left| \frac{\sqrt{\sum_{i=1}^{8} (r_{i1})^2}}{\ln \frac{8}{\sigma_1}} \right| = 100 * \left| \frac{0.3341}{8.5874} \right| = 3.8906$$

The preference values results obtained from the decision matrix are presented in Table 3.

Table 3. Preference Values Result

R1	R2	R3	R4	R5	R6	R7
3.8906	3.6729	3.6893	3.5957	3.7558	3.7212	3.7126

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Based on the preference values obtained, the next step is to calculate the criterion weights to determine the relative importance of each criterion. The weights produced are objective weights derived from the data characteristics, so they don't directly depend on the decision-maker's preferences. The calculation of criterion weights is done using (4).

$$w_1 = \frac{P_1}{\sum_{k=1}^{8} P_k} = \frac{3.8906}{26.0382} = 0.1494$$

The criteria weight results obtained from the decision matrix are presented in Table 4.

Table 4. Criteria Weight Result

R1	R2	R3	R4	R5	R6	R7
0.1494	0.1411	0.1417	0.1381	0.1442	0.1429	0.1426

The results of the weighting using DAM Weighting show that all criteria have relatively close weights, ranging from 0.1381 to 0.1494. Criterion R1 has the highest weight at 0.1494, indicating that it contributes the most to the decision-making process. Next, R5 has a weight of 0.1442, followed by R6 at 0.1429, R7 at 0.1426, R3 at 0.1417, and R2 at 0.1411. Meanwhile, R4 has the lowest weight at 0.1381, making its contribution the smallest compared to the other criteria. Even though there are differences in importance, the weight gaps are small, showing that the seven criteria contribute fairly evenly in representing the performance of the alternatives. The results also show that DAM Weighting can create a weight distribution that isn't too dominated by one criterion, so the next evaluation process can take all the criteria into account more proportionally.

Ranking Alternatives Using the PIV Method

After the criteria weights are obtained through DAM Weighting, the next step is to calculate the value of each alternative using the PIV to determine the relative performance level of each alternative. The PIV method is used to measure how close an alternative's performance is to the ideal condition, considering the objective weights that have been obtained previously. Applying PIV produces index values that represent how close each alternative is to the desired condition, which can then be used as a basis for determining the priority ranking of alternatives. The results of these calculations are then used to identify the best-performing alternatives and to select the best employee based on the ranking results.

The calculation of alternative values using PIV is done by using the criteria weights obtained through DAM Weighting. The first step is to normalize the decision matrix to equalize the performance scale of each alternative across all criteria using (5).

$$r_{11} = \frac{x_{11} - \min_1 n_{1j}}{\max_1 n_{1j} - \min_1 n_{1j}} = \frac{85 - 76}{94 - 76} = \frac{9}{18} = 0.5000$$

The normalization results obtained from the decision matrix are presented in Table 5.

Table 5. Normalization Result

Alternative	R1	R2	R3	R4	R5	R6	R7
Alt-01	0.5000	0.6667	0.5385	0.7000	0.5714	0.5714	0.4615
Alt-02	0.1111	0.1667	0.1538	0.2000	0.0714	0.2143	0.2308
Alt-03	0.8889	0.8333	0.8462	0.9000	0.8571	0.8571	0.8462
Alt-04	0.2778	0.4167	0.3846	0.4000	0.3571	0.3571	0.3077
Alt-05	0.7222	0.5000	0.6154	0.6000	0.6429	0.6429	0.6923
Alt-06	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

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Alt-07	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Alt-08	0.3889	0.5833	0.4615	0.3000	0.4286	0.5000	0.3846
Alt-09	0.6111	0.3333	0.6923	0.8000	0.5000	0.7143	0.5385

Next, the normalized values are combined with the weights of each criterion to get the weighted normalized value using (6), and the calculation results are as follows.

$$n_{11} = r_{11} * w_1 = 0.5000 * 0.1494 = 0.0747$$

The weighted normalization results obtained from the decision matrix are presented in Table 6.

Table 6. Weighted Normalization Result

Alternative	R1	R2	R3	R4	R5	R6	R7
Alt-01	0.0747	0.0940	0.0763	0.0967	0.0824	0.0817	0.0658
Alt-02	0.0166	0.0235	0.0218	0.0276	0.0103	0.0306	0.0329
Alt-03	0.1328	0.1176	0.1199	0.1243	0.1236	0.1225	0.1206
Alt-04	0.0415	0.0588	0.0545	0.0552	0.0515	0.0510	0.0439
Alt-05	0.1079	0.0705	0.0872	0.0829	0.0927	0.0919	0.0987
Alt-06	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Alt-07	0.1494	0.1411	0.1417	0.1381	0.1442	0.1429	0.1426
Alt-08	0.0581	0.0823	0.0654	0.0414	0.0618	0.0715	0.0548
Alt-09	0.0913	0.0470	0.0981	0.1105	0.0721	0.1021	0.0768

The next step is to determine the ideal value as a reference to measure how close each alternative is, then the difference between the alternative values and the ideal value is calculated using (7), with the calculation results as follows.

$$\delta_{11} = \max_{1} n_{1j} - n_{11} = 0.1494 - 0.0747 = 0.0747$$

The ideal values results obtained from the decision matrix are presented in Table 7.

Table 7. Ideal Values Result

Alternative	R1	R2	R3	R4	R5	R6	R7
Alt-01	0.0747	0.0470	0.0654	0.0414	0.0618	0.0612	0.0768
Alt-02	-0.0747	-0.0940	-0.0763	-0.0967	-0.0824	-0.0817	-0.0658
Alt-03	0.0000	-0.0470	-0.0109	-0.0552	-0.0206	-0.0204	0.0110
Alt-04	-0.1494	-0.1881	-0.1526	-0.1933	-0.1648	-0.1633	-0.1316
Alt-05	-0.0747	-0.1411	-0.0872	-0.1519	-0.1030	-0.1021	-0.0548
Alt-06	-0.2241	-0.2821	-0.2289	-0.2900	-0.2473	-0.2450	-0.1974
Alt-07	-0.1494	-0.2351	-0.1635	-0.2486	-0.1855	-0.1837	-0.1206
Alt-08	-0.2988	-0.3762	-0.3052	-0.3867	-0.3297	-0.3267	-0.2632
Alt-09	-0.2241	-0.3291	-0.2398	-0.3452	-0.2679	-0.2654	-0.1865

The resulting difference is then used to obtain the proximity indexed value for each alternative by adding up the closeness values across all criteria using (8), the calculation results are as follows.

$$\varphi_1 = \sum_{j=1}^{8} \delta_{1j} = 0.0747 + 0.0470 + 0.0654 + 0.0414 + 0.0618 + 0.0612 + 0.0768 = 0.4284$$

The proximity indexed value results obtained from the decision matrix are presented in Table 7.

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Table 7. Proximity Indexed Value Result

Alternative	PIV Value
Alt-01	0.4284
Alt-02	-0.5716
Alt-03	-0.1432
Alt-04	-1.1432
Alt-05	-0.7148
Alt-06	-1.7148
Alt-07	-1.2864
Alt-08	-2.2864
Alt-09	-1.8580

The calculation results of the PIV in Table 7 show different PIV values for each alternative, ranging from 0.4284 to -2.2864. Alt-01 has a PIV of 0.4284, while Alt-02 has -0.5716 and Alt-03 has -0.1432. Meanwhile, the PIV values for Alt-04, Alt-05, and Alt-06 are -1.1432, -0.7148, and -1.7148 respectively, and Alt-07 has -1.2864. Even lower values are seen in Alt-08 with -2.2864 and Alt-09 with -1.8580. These variations indicate differences in the level of performance proximity among the alternatives compared to the reference conditions used in the PIV method. A lower PIV value shows a smaller closeness to the reference condition, giving a quantitative picture of the relative performance differences for each alternative based on the criterion weights obtained from DAM Weighting.

After the PIV scores for each alternative are obtained, the next step is to rank them based on the final scores generated by the PIV method. These scores are used to arrange the alternatives according to how close they are to the ideal condition, so that the relative position of each alternative in the best employee selection process can be known. Alternatives with lower PIV scores indicate better closeness to the reference condition and get a higher position in the ranking results. The ranking results of the alternatives based on the PIV scores are shown in Table 8.

Table 8. Alternative Ranking Results

Alternative	PIV Value	Rank
Alt-08	-2.2864	1
Alt-09	-1.8580	2
Alt-06	-1.7148	3
Alt-07	-1.2864	4
Alt-04	-1.1432	5
Alt-05	-0.7148	6
Alt-02	-0.5716	7
Alt-03	-0.1432	8
Alt-01	0.4284	9

The ranking results show that alternative Alt-08 takes the first place with a PIV score of -2.2864, indicating the lowest proximity value compared to the other alternatives. Next in line is Alt-09 with a value of -1.8580 and Alt-06 with -1.7148, while Alt-07 ranks fourth with a score of -1.2864. Following that, Alt-04 is in fifth place with -1.1432, then Alt-05 with -0.7148, Alt-02 with -0.5716, and Alt-03 with -0.1432. Meanwhile, Alt-01 holds the ninth place with a PIV value of 0.4284. These results show differences in proximity values among the alternatives, with Alt-08 having the lowest PIV score, making it the best alternative based on the integrated DAM Weighting and PIV model.

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After the PIV scores for each alternative are obtained, the alternatives are ranked in ascending order of their final PIV scores. The PIV value represents the deviation of each alternative from the reference or ideal condition; therefore, a lower PIV value indicates a smaller deviation and a closer position to the desired condition. Consequently, the alternative with the lowest PIV score is considered the best alternative and receives the highest ranking. Based on this principle, Alt-08, with the lowest PIV value of −2.2864, is ranked first, followed by Alt-09 with −1.8580 and Alt-06 with −1.7148. The complete ranking results are presented in Table 8.

4. CONCLUSION

The integration of DAM Weighting and PIV is used as an objective approach to support the process of selecting the best employees in a Decision Support System. DAM Weighting produces relatively balanced criteria weights, with R1 getting the highest weight of 0.1494 and R4 the lowest at 0.1381, showing that all criteria contribute to employee evaluation with relatively close levels of importance. Furthermore, applying PIV results in different closeness values for each alternative, with Alt-08 getting the lowest PIV value of -2.2864 and ranking first, followed by Alt-09 at -1.8580 and Alt-06 at -1.7148. The results show that the integration of DAM Weighting and PIV can link data characteristics in determining criteria weights with the evaluation of alternative performance closeness, thus creating a decision-making mechanism that is objective, measurable, and can be used to choose Alt-08 as the best employee based on the evaluation data used.

5. REFERENCES

[1] S. Dündar, "Prioritizing the Regional Preferences of Turkish Investors Regarding Foreign Direct Investment by ARLON Method," *Konya J. Eng. Sci.*, vol. 13, no. 3, pp. 927–946, 2025, doi: 10.36306/konjes.1648279.

[2] G. Demir, D. Pamucar, and P. Chatterjee, "An Integrated Fuzzy Multi-Criteria Framework for Evaluation of Sustainable Communication Technologies," *Spectr. Oper. Res.*, vol. 2, no. 1 SE-Articles, pp. 326–345, Feb. 2025, doi: 10.31181/sor21202529.

[3] V. Simic, A. Ebadi Torkayesh, and A. Ijadi Maghsoodi, "Locating a disinfection facility for hazardous healthcare waste in the COVID-19 era: a novel approach based on Fermatean fuzzy ITARA-MARCOS and random forest recursive feature elimination algorithm," *Ann. Oper. Res.*, vol. 328, no. 1, pp. 1105–1150, 2023, doi: 10.1007/s10479-022-04822-0.

[4] P. Zofaisal Hamid and H. Sulistiani, "Kombinasi Metode Pembobotan Entropy dan Multi-Attribute Utility Theory Dalam Penentuan Karyawan Terbaik," *JUSTINDO*, vol. 9, no. 2, pp. 121–132, Aug. 2024, doi: 10.32528/justindo.v9i2.1963.

[5] N. P. Siburian and L. Sahriani, "Sistem Pendukung Keputusan Pemilihan Pegawai Honorer Kelurahan Menerapkan Metode MOORA," *TIN Terap. Inform. Nusant.*, vol. 3, no. 10, pp. 395–404, Mar. 2023, doi: 10.47065/tin.v3i10.4148.

[6] 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.

[7] M. A. M. Al-Gerafi *et al.*, "Promoting inclusivity in education amid the post-COVID-19 challenges: An interval-valued fuzzy model for pedagogy method selection," *Int. J. Manag. Educ.*, vol. 22, no. 3, p. 101018, 2024, doi: https://doi.org/10.1016/j.ijme.2024.101018.

[8] J. Jin, L. Zou, Z. Long, T. Shi, and Y. Chang, "A Parameterized Intuitionistic Fuzzy Distance Measure-Based CoCoSo Method and Its Application in Stock Selection," *Mathematics*, vol. 14, no. 5. p. 810, 2026. doi: 10.3390/math14050810.

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Volume 4, Number 4, October 2027
DOI : **https://doi.org/10.58602/chain.v4i4.378**
Page 530-541

[9] P. Rani, A. R. Mishra, E. B. Tirkolaee, A. M. Alshamrani, and A. F. Alrasheedi, "Pythagorean fuzzy comprehensive distance-based ranking approach for assessing industry 4.0 adoption strategies in the automotive manufacturing sector," *Adv. Eng. Informatics*, vol. 65, p. 103359, 2025, doi: https://doi.org/10.1016/j.aei.2025.103359.
[10] G. C. Yalçın, K. Kara, E. K. Özekenci, V. Simic, and D. Pamucar, "Promoting biodiversity-based trade: A fuzzy multi-criteria decision analytics for performance measurement of sustainable development in megadiverse countries," *J. Clean. Prod.*, vol. 547, p. 147831, 2026, doi: https://doi.org/10.1016/j.jclepro.2026.147831.
[11] T. T. Worku, "Formwork material selection and optimization by a comprehensive integrated subjective–objective criteria weighting MCDM model," *Discov. Mater.*, vol. 5, no. 1, p. 2, 2025, doi: 10.1007/s43939-024-00162-x.
[12] D. A. Megawaty *et al.*, "DAM Weighting: A New Approach to Determining Criteria Weighting in Multi-Criteria Decision Making," *Evergreen*, vol. 13, no. 2, pp. 788–800, 2026, doi: 10.5109/7432655.
[13] D. D. Trung, N. T. P. Giang, D. Van Duc, T. Van Dua, and H. X. Thinh, "The Use of SAW, RAM and PIV Decision Methods in Determining the Optimal Choice of Materials for the Manufacture of Screw Gearbox Acceleration Boxes," *Int. J. Mech. Eng. Robot. Res.*, vol. 13, no. 3, pp. 338–347, 2024, doi: 10.18178/ijmerr.13.3.338-347.
[14] N. Ersoy and S. Taslak, "Comparative Analysis of MCDM Methods for the Assessment of Corporate Sustainability Performance in Energy Sector," *Ege Acad. Rev.*, vol. 23, no. 3, pp. 341–362, 2023, doi: 10.21121/eab.986122.
[15] D. T. Do, "Assessing the Impact of Criterion Weights on the Ranking of the Top Ten Universities in Vietnam," *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 4 SE-, pp. 14899–14903, Aug. 2024, doi: 10.48084/etasr.7607.

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