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Effective methods for employee performance assessment

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ABSTRACT

This study aims to select the most effective multi-criteria decision-making method used in an employee performance appraisal system. The approach used in this study is a comparative experiment where three multi-criteria decision-making methods simple additive weighting (SAW), analytical hierarchy process (AHP), and technique for order preference similarity to an ideal solution (TOPSIS) are compared. The dataset involves 16 employees, considering input data such as work behavior scores, and performance targets (SKP). The criteria for evaluating work behavior include service quality, accountability, competence, harmony, loyalty, adaptability, collaboration, and achievement of targets. The comparison results were tested using a one-way ANOVA to evaluate whether there are significant differences among the three methods, as well as to provide supporting evidence for the conducted research. The results indicated that the SAW method provides the most accurate and relevant performance assessments while AHP yields less precise rankings as some employees received the same scores despite having different workloads. TOPSIS also produced rankings that did not accurately reflect the relative workloads. Implementing the SAW method in the employee performance information system enhances the assessment process, making it faster, more objective, transparent, and credible. Thus, SAW emerges as the most effective method for aligning performance scores with employee roles and responsibilities.

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1. INTRODUCTION

Employee performance appraisal is a crucial aspect of human resource management that involves evaluating employees' work performance against predefined criteria [1]. Traditionally, performance appraisal systems have relied on quantitative metrics and subjective evaluations [2]. However, integrating multi-criteria decision making (MCDM) techniques into this process enhances the robustness and fairness of assessments by considering various performance dimensions simultaneously [3], [4]. MCDM is a systematic approach that assists decision-makers in evaluating multiple conflicting criteria when making decisions [5]. In the context of performance appraisal, MCDM can help organizations assess not only quantitative outputs but also qualitative factors such as work behavior scores and employees' performance targets [6]. The use of MCDM in performance appraisal offers several benefits, such as improving transparency and promoting career advancement by involving multiple stakeholders in the decision-making process [7]. Furthermore, MCDM frameworks facilitate the identification of training needs and development opportunities, thereby fostering a culture of continuous improvement [8], [9].

Despite its benefits, the implementation of MCDM in performance appraisal requires careful consideration of various factors, including the selection of appropriate criteria, stakeholder involvement, and the complexity of the decision-making process [10]-[12]. Organizations must also ensure that employees are engaged in the appraisal process to enhance acceptance and effectiveness [13]. Given the complexities involved in employee performance appraisal—from variations in workload to the need for tailored criteria—choosing the most effective MCDM method is crucial [14].

A comparative experiment in MCDM involves systematically evaluating various decision-making techniques under the same conditions to determine their relative effectiveness, accuracy, and consistency [15]. The most commonly used MCDM methods include simple additive weighting (SAW), analytic hierarchy process (AHP), and the technique for order of preference by similarity to ideal solution (TOPSIS) [16]. Each method employs different approaches to prioritize criteria and alternatives, which can lead to different outcomes depending on the context and the strategic objectives of the assessment [17]-[19].

In a comparative experiment, decision-makers evaluate the performance of these methods when applied to specific datasets and decision contexts, analyzing the strengths, weaknesses, and potential biases inherent in each technique [20], [21]. Such studies often use statistical analysis tests like analysis of variance (ANOVA) or the Friedman test to validate and compare the results, ensuring that the research is robust and reliable [22].

This comparative experiment approach in MCDM lays the groundwork for a deeper analysis that guides decision-makers in making informed choices about the most effective and relevant MCDM methods according to the specific needs of the research [23], [24]. This article focuses on a comparative experiment approach by comparing the SAW, AHP, and TOPSIS methods to determine the effectiveness and relevance of the methods applied in an employee performance appraisal system. The study aims to provide insights into MCDM methods that can be implemented to enhance performance appraisal systems in organizational environments [25].

The following sections are structured as follows. In section 2, the methodology of this study is presented. It is started with the variable identification and followed by the three MCDM methods: SAW, AHP, and TOPSIS. In section 3, the main results regarding the evaluation of those three MCDM methods are presented. It is then followed by the discussion related to the managerial insights. Finally, section 4 concludes the study and provides recommendations based on the presented study.

2. METHOD

The methodology used in this study adopts a comparative experiment approach by comparing three multi-criteria decision-making methods based on the same dataset [26]. Comparative experiments can help identify the differences and similarities between the compared methods, leading to a conclusion [27]. This approach involves several processes, including variable identification, data collection, data analysis, and testing. In this section, an ANOVA test is conducted to evaluate the results from the comparison of the three methods [28]. This study focuses on selecting an effective and relevant decision-making method for use in an employee performance appraisal system by comparing the methods used and supporting the findings by reviewing several similar studies as references to ensure the research is relevant. There are four stages in the research: identification variable, data collection, data analysis, and testing [29].

Figure 1 shows the research stages in the comparative experiment approach, in the variable identification stage, the variables used in this approach are the SAW, AHP, and TOPSIS methods. In the data collection stage, the data is based on employee information, SKP data, and employee performance scores. In the data analysis stage, the data is processed according to the calculations of each method. In the testing stage, the results of the calculations for the three methods are subjected to a one-way ANOVA test to obtain optimal results [30].

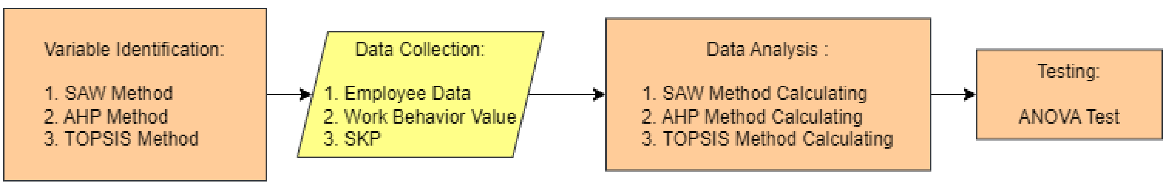

Figure 1. Research stages in comparative experiment

2.1. Variable identification

In a comparative experiment, the identification of variables is a crucial first step to ensure that the analysis is accurate and relevant. Key variables are defined to compare the performance of different methods or techniques under similar conditions. For instance, in a comparative study of MCDM methods like SAW, AHP, and TOPSIS, the variables typically include the criteria used for evaluation, the dataset being analyzed, and the specific metrics or indicators that will be measured [31]. Clearly identifying these variables helps in establishing a structured framework for the experiment, allowing for precise comparisons and ensuring that any observed differences in outcomes are due to the methods themselves rather than external factors.

2.1.1. Simple additive weighting

The SAW method finds the best alternative of all alternative evaluation indices [32]. The basic concept of the SAW method is to find the weighted sum of the performance rankings for each option. The SAW method requires normalizing the decision matrix to a scale that can be compared with all other alternative orders. The SAW method has several stages: analysis, normalization, and ranking. At the analysis stage, first, determine the criteria and alternatives needed. The requirements are divided into benefits (benefits) and costs (cost) [33]. In the normalization stage, the attribute values will be converted into numbers valued from 0 to 1. The SAW normalization is formulated as:

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\mathrm{Max}_i\, x_{ij}} & \text{if } j \text{ is benefit} \\ \dfrac{\mathrm{Min}_i\, x_{ij}}{x_{ij}} & \text{if } j \text{ is cost} \end{cases} \tag{1}$$

where r_{ij} denotes normalized performance rating value and x_{ij} denotes criteria attribute value. The next step is to carry out the ranking stage by using the SAW ring formula shown as follows:

$$V_i = \sum_{j=1}^{n} W_j\, r_{ij} \tag{2}$$

where V_i represents the preference value, W_j represents the ranking weight, and r_{ij} represents the normalized performance ranking.

2.1.2. Analytic hierarchy process

The AHP method is a decision support model describing the multi-attribute decision-making problem or MADM problem. AHP is used to solve a problem in a systematic thinking framework so that effective decisions can be made [34]. The steps in performing the AHP method can be seen in Table 1 [35].

Table 1. The procedure AHP method

Steps	Formula*	Description
Normalization of criteria matrix and priority weight	$w_i = \sum_{i=1}^{n} \frac{a_{ij}}{n}$	Divide each element of the matrix by the total row
Calculation of priority weights and consistency	$\lambda_{max} = \sum_{i=1}^{n} \frac{\left(\frac{a_{ij}}{w_i}\right)}{n}$	Priority weights are obtained from the total criteria normalized by rows divided by the number of measures
Calculating *IC*	*IC* = (λ_{max} − *n*)/*n*	*IC* is the average of the consistency
Calculating *IR* value	*IR*	*IR* value is based on matrix size
Consistency ratio value	*IC* / *IR*	*CR* value 0 – 0.1 is considered consistent; more than that, it is inconsistent
Alternative ranking	The result of multiplying each alternative weight column with the criterion weight	The ranking is sorted from the highest score

*Notations:
w_i : Weight value
a_{ij} : Row normalization matrix
λ_{max} : Maximum Eigen value
IC : Consistency index
IR : Ratio index

2.1.3. Technique for order of preference by similarity to ideal solution

The TOPSIS method is a method that can be used to solve problems in decision-making [36]. This method has a concept where the chosen alternative is the best alternative that has the shortest distance from the positive ideal solution (A+) and the farthest distance from the negative perfect solution (A-). The steps in using the TOPSIS method are (1) determining the weighting criteria, (2) determining the value of each alternative, (3) making a normalized decision matrix, (4) making weights on the normalized decision matrix using the formula (5) determining the value of positive and negative ideal solutions using the formulas and (6) determining the distance between values alternatives with the perfect solution matrix and determine the preference value for each option using the formula given as follows [37], [38]:

$$rij = \frac{xij}{\sqrt{\sum_{i=1}^{m} xij}} \; ; y_{ij} = w_i r_{ij} \tag{3}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_i^+ - y_{ij}\right)^2} \tag{4}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_i^-\right)^2} \tag{5}$$

$$V_i = \frac{D_i^-}{D_j^- + D_j^+} \tag{6}$$

where r_{ij} is the normalized decision matrix, y_{ij} is the normalized decision matrix weight, w_i is the criteria weight, D is the distance between alternative values, and V_i is the preference value.

2.2. Data collection

The data used in this study are scores from SKP (*Sasaran Kinerja Pegawai/*employee performance targets), work behavior values, and criteria data, see the forthcoming Table 2. The global atmospheric monitoring station in Sorong has 16 functional employees whose performance assessment will be carried out, see Table 3 for the details of the employees [39]. Table 3 contains the employee data used as the dataset for calculations in the three MCDM methods. The employee data includes the employee's name, position, rank, and length of service.

Table 2. Weight values of the criteria

No.	Criteria	Weight value
1	Public service	10%
2	Accountable	5%
3	Competence	5%
4	Harmony	5%
5	Loyal	5%
6	Adaptability	5%
7	Collaborative	5%
8	SKP	60%

Table 3. Employee data

Name	Code	Category	Years of employment	Position
Rizka	P1	III/c	5 years 8 month	Functional
Shelin	P2	III/c	5 years 4 month	Functional
Ayu	P3	III/b	5 years	Coord. datin
Haris	P4	III/a	3 years	Functional
Pandu	P5	III/a	2 years 6 month	Functional
Harashta	P6	III/a	6 month	Functional
Wahyu	P7	III/a	3 years	Functional
Najma	P8	III/a	3 years 6 month	Functional
Ikhsan	P9	III/a	1 year	Functional
Naufan	P10	III/a	1 year	Functional
Susilo	P11	III/a	3 years	Functional
Risti	P12	III/a	3 years 6 month	Functional
Teja	P13	III/a	1 year	Functional
Agatha	P14	III/a	5 years	Functional
Nury	P15	III/b	5 years 4 month	Coord obs
Rini	P16	III/b	5 years 6 month	Functional

Table 2 shows the weights of each criterion based on the 2019 government regulation. The criteria for assessing employee performance are service, accountability, competence, harmony, loyalty, adaptability, collaboration, and employee work goals [40]. The assessment parameters for each criterion are different. Table 4 shows the assessment parameters for the service criteria, harmonious, loyal, adaptive, collaborative, and SKP. Table 5 shows the assessment parameters for the accountable standards. Table 6 shows the assessment parameters for the competency criteria. Table 7 shows the calculation results of the SKP scores for each employee.

Table 4. Parameters of service criteria, harmony, loyalty, adaptive, collaborative, and SKP

Parameters	Category
91 – 100	Very good
76 – 90	Good
61 - 75	Enough
51 - 60	Less
0 - 50	Bad

Table 5. Accountable criteria parameters

Presence %	Category
91 – 100	1
81 – 90	2
71 - 80	3
61 - 70	4
0 – 60	5

Table 6. Competence criteria parameters

Competence %	Category
91 – 100	1
81 – 90	2
71 – 80	3
61 - 70	4
0 - 60	5

Table 7. Calculation of employee SKP value

Employee	Target (%)	Realization	SKP value
P1	100	85.67	85.67
P2	100	85.72	85.72
P3	100	86	86
P4	100	85.58	85.58
P5	100	85.69	85.69
P6	100	85.72	85.72
P7	100	85.73	85.73
P8	100	85.68	85.68
P9	100	85.55	85.55
P10	100	85.81	85.81
P11	100	85.64	85.64
P12	100	85.69	85.69
P13	100	86	86
P14	100	87.02	87.02
P15	100	86.47	86.47
P16	100	85.68	85.68

The global atmospheric monitoring station in Sorong has 16 functional employees whose performance assessments were carried out. Employee performance evaluation is based on SKP values and employee work behavior values. The employee performance is calculated by using the formula as follows:

$$Employee\ performance = SKP\ value * 0.6 + Work\ behavior\ value * 0.4 \quad (7)$$

whereas the SKP achievement is calculated by using the formula as follows:

$$\text{SKP} = \frac{\text{Realization}}{\text{Target}} \times 100 \quad (8)$$

The results are shown in Table 7. As shown in Table 7, the calculation results of the SKP scores for each employee are based on (8).

2.3. Data analysis

The data analysis employed in this study involves examining and interpreting the collected data to identify differences and similarities between the methods being evaluated, c.f. [41]. In the context of a comparative study of MCDM techniques, the data analysis includes applying each method to the same dataset, followed by a systematic evaluation of the outcomes. It provides crucial insights into the strengths and weaknesses of each technique involved in the study, helping to draw conclusions, consistency, and effectiveness in the decision-making, cf. [42]. This stage is conducted to ensure that the experiment's findings are robust and reliable, leading to informed decisions [43]. In this stage, the collected dataset is analyzed using the SAW, AHP, and TOPSIS methods.

2.3.1. SAW method

In the SAW method, the first step is to group the existing criteria into two types of attributes: benefit and cost [44]. The distribution of characteristics on each criterion is shown in Table 8. Meanwhile, the employee appraisal data and the normalized data are shown in Tables 9 and 10, respectively.

After normalizing employee data, the ranking process is carried out. The preference value is obtained by multiplying each criterion weight with the normalized value [45]. Then, a weighted summation of all criteria is performed. The ranking results can be seen in Table 11. Of the 16 employees at PAG Sorong Station, it was found that P15 employees ranked first with a preference value of 0.982224, the second rank was occupied by P14 employees with a preference value of 0.980874 and the third rank was occupied by P2 employees with a preference value 0.97813.

Table 8. Assessment criteria and weight

Code	Attribute	Weight
C1	Benefit	10%
C2	Cost	5%
C3	Cost	5%
C4	Benefit	5%
C5	Benefit	5%
C6	Benefit	5%
C7	Benefit	5%
C8	Benefit	60%

Table 9. Employee appraisal data

	C1	C2	C3	C4	C5	C6	C7	C8
P1	86	1	1	81	80	80	84	85.7
P2	85	1	1	87	82	84	87	85.7
P3	90	1	2	85	85	83	84	86
P4	87	1	2	86	80	82	83	85.6
P5	86	2	2	86	81	84	84	85.7
P6	85	1	2	87	82	88	86	85.7
P7	84	1	3	88	83	86	80	85.7
P8	83	1	3	84	84	81	84	85.7
P9	87	1	3	86	85	82	83	85.6
P10	85	1	2	83	84	84	86	85.8
P11	86	4	4	82	83	84	87	85.6
P12	88	3	3	84	82	85	88	85.7
P13	80	1	1	86	81	86	89	86
P14	82	1	1	84	80	87	84	87
P15	82	1	1	82	86	90	86	86.5
P16	86	1	1	80	82	82	81	85.7

Table 10. Normalization of employee value

	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.96	1	1	81	80	80	84	85.7
P2	0.94	1	1	87	82	84	87	85.7
P3	1	1	0.5	85	85	83	84	86
P4	0.97	1	0.5	86	80	82	83	85.6
P5	0.96	0.5	0.5	86	81	84	84	85.7
P6	0.94	1	0.5	87	82	88	86	85.7
P7	0.93	1	0.33	88	83	86	80	85.7
P8	0.92	1	0.33	84	84	81	84	85.7
P9	0.97	1	0.33	86	85	82	83	85.6
P10	0.94	1	0.5	83	84	84	86	85.8
P11	0.96	0.25	0.25	82	83	84	87	85.6
P12	0.98	0.33	0.33	84	82	85	88	85.7
P13	0.89	1	1	86	81	86	89	86
P14	0.91	1	1	84	80	87	84	87
P15	0.91	1	1	82	86	90	86	86.5
P16	0.96	1	1	80	82	82	81	85.7

Table 11. Ranking using SAW method

Employee	Result	Rank
P1	0.970417	6
P2	0.97813	3
P3	0.95893	7
P4	0.949298	10
P5	0.9262	14
P6	0.954791	8
P7	0.942083	12
P8	0.938405	13
P9	0.943665	11
P10	0.952079	9
P11	0.90143	16
P12	0.914003	15
P13	0.97559	4
P14	0.980874	2
P15	0.982224	1
P16	0.790506	5

2.3.2. AHP method

Calculations using the AHP method in the employee performance assessment system were carried out to determine the resulting comparison from the three techniques, namely the AHP, SAW, and TOPSIS methods. In the AHP method, the first step is to determine the comparison matrix between criteria [46]. The criteria comparison matrix can be seen in Table 12, and the calculation results of priority seen in Table 13.

Obtaining an alternative ranking requires the consistency index value (CI), the index ratio value (RI), and the consistency ratio value (CR). If the CR value ranges from 0 to 0.1, then hierarchical consistency is acceptable, but if the CR value is more than 0.1, then it is considered inconsistent [47]. The CR value in this calculation is 0.0120, which means that the consistency of the hierarchy is acceptable. The alternative ranking is done to find the highest score based on the employee performance appraisal system. After obtaining the alternative values, the last step is to determine the alternative ranking results by multiplying the value of each criterion against each priority value of the criteria matrix. The results can be seen in Table 14. The first rank was obtained by six employees with the same preference value of 0.2837. P11 employees received the lowest score with a preference value of 0.2350.

Table 12. Criteria comparison matrix

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	3	3	3	3	3	3	0.2
C2	0.33	1	1	1	1	1	1	0.14
C3	0.33	1	1	1	1	1	1	0.14
C4	0.33	1	1	1	1	1	1	0.14
C5	0.33	1	1	1	1	1	1	0.14
C6	0.33	1	1	1	1	1	1	0.14
C7	0.33	1	1	1	1	1	1	0.14
C8	5	7	7	7	7	7	7	1
Total	7.98	16	16	16	16	16	16	2.04

Table 13. The result of calculating priority value and eigen value

Criteria	Eigen value	Priority value
Public service	1.046822	0.149546
Accountable	0.994529	0.076502
Competence	0.994529	0.076502
Harmony	0.994529	0.076502
Loyal	0.994529	0.076502
Adaptability	0.994529	0.076502
Collaborative	0.994529	0.076502
SKP	0.990343	0.391440

Table 14. Ranking using AHP method

Employee	Result	Rank
P1	0.2837	1
P2	0.2837	1
P3	0.2719	2
P4	0.2719	2
P5	0.2600	4
P6	0.2719	2
P7	0.2641	3
P8	0.2641	3
P9	0.2641	3
P10	0.2719	2
P11	0.2350	6
P12	0.2446	5
P13	0.2837	1
P14	0.2837	1
P15	0.2837	1
P16	0.2837	1

2.3.3. TOPSIS method

Calculations using the TOPSIS method in the performance assessment system are carried out to determine which way has the accuracy and precision of use in solving problems [48]. In the TOPSIS method, the first step is to determine the weight criteria and determine the value of each alternative. After selecting the requirements and value of each option, then create a normalized decision matrix which can be seen in

Table 15. The next step is to create a weighted normalized decision matrix by multiplying each alternative normalized decision matrix against the weight of each criterion [49]. The results can be seen in Table 16. The next step is determining the distance between the alternative values and the ideal solution matrix shown in Tables 17 and 18. The last step is to determine the preference value or ranking in Table 19.

Table 15. Values in determining the normalized decision matrix

Weight	[x_1]	[x_2]	[x_3]	[x_4]	[x_5]	[x_6]	[x_7]	[x_8]
Value	340.6376	6.480741	8.831761	337.8713	330.0818	337.1587	339.13124	343.4157
Employee	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.252468	0.154303	0.113228	0.239736	0.242364	0.237277	0.2476917	0.249464
P2	0.249532	0.154303	0.113228	0.257495	0.248423	0.249141	0.2565379	0.24961
P3	0.26421	0.154303	0.226455	0.251575	0.257512	0.246175	0.2476917	0.250425
P4	0.255403	0.154303	0.226455	0.254535	0.242364	0.243209	0.244743	0.249202
P5	0.252468	0.308607	0.226455	0.254535	0.245394	0.249141	0.2476917	0.249523
P6	0.249532	0.154303	0.226455	0.257495	0.248423	0.261005	0.2535891	0.24961
P7	0.246596	0.154303	0.339683	0.260454	0.251453	0.255073	0.2358969	0.249639
P8	0.243661	0.154303	0.339683	0.248615	0.254482	0.240243	0.2476917	0.249494
P9	0.255403	0.154303	0.339683	0.254535	0.257512	0.243209	0.244743	0.249115
P10	0.249532	0.154303	0.226455	0.245656	0.254482	0.249141	0.2535891	0.249872
P11	0.252468	0.617213	0.452911	0.242696	0.251453	0.249141	0.2565379	0.249377
P12	0.258339	0.46291	0.339683	0.248615	0.248423	0.252107	0.2594866	0.249523
P13	0.234854	0.154303	0.113228	0.254535	0.245394	0.255073	0.2624353	0.250425
P14	0.240725	0.154303	0.113228	0.248615	0.242364	0.258039	0.2476917	0.253396
P15	0.240725	0.154303	0.113228	0.242696	0.260541	0.266937	0.2535891	0.251794
P16	0.252468	0.154303	0.113228	0.236777	0.248423	0.243209	0.2388456	0.249494

Table 16. The weighted normalized decision matrix

Employee	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.02524677	0.00771517	0.00566139	0.01198681	0.01211821	0.01186385	0.01238459	0.14967866
P2	0.024953203	0.00771517	0.00566139	0.01287473	0.01242116	0.01245704	0.01282689	0.14976601
P3	0.026421038	0.00771517	0.01132277	0.01257875	0.0128756	0.01230874	0.01238459	0.15025522
P4	0.025540337	0.00771517	0.01132277	0.01272674	0.01211821	0.01216044	0.01223715	0.14952141
P5	0.02524677	0.01543033	0.01132277	0.01272674	0.01226969	0.01245704	0.01238459	0.1497136
P6	0.024953203	0.00771517	0.01132277	0.01287473	0.01242116	0.01305023	0.01267946	0.14976601
P7	0.024659636	0.00771517	0.01698416	0.01302271	0.01257264	0.01275364	0.01179484	0.14978348
P8	0.024366068	0.00771517	0.01698416	0.01243077	0.01272412	0.01201215	0.01238459	0.14969613
P9	0.025540337	0.00771517	0.01698416	0.01272674	0.0128756	0.01216044	0.01223715	0.149469
P10	0.024953203	0.00771517	0.01132277	0.01228278	0.01272412	0.01245704	0.01267946	0.14992326
P11	0.02524677	0.03086067	0.02264554	0.0121348	0.01257264	0.01245704	0.01282689	0.14962624
P12	0.025833904	0.0231455	0.01698416	0.01243077	0.01242116	0.01260534	0.01297433	0.1497136
P13	0.023485367	0.00771517	0.00566139	0.01272674	0.01226969	0.01275364	0.01312176	0.15025522
P14	0.024072501	0.00771517	0.00566139	0.01243077	0.01211821	0.01290194	0.01238459	0.15203731
P15	0.024072501	0.00771517	0.00566139	0.0121348	0.01302707	0.01334683	0.01267946	0.15107638
P16	0.02524677	0.00771517	0.00566139	0.01183883	0.01242116	0.01216044	0.01194228	0.14969613

Table 17. The ideal matrix solution

Category	C1	C2	C3	C4	C5	C6	C7	C8
	Benefit	Cost	Cost	Benefit	Benefit	Benefit	Benefit	Benefit
Positive	0.026421038	0.00771517	0.00566139	0.01302271	0.01302707	0.01334683	0.01312176	0.15203731
Negative	0.023485367	0.03086067	0.02264554	0.01183883	0.01211821	0.01186385	0.01179484	0.149469

2.4. ANOVA testing

ANOVA testing is used to determine whether there are statistically significant differences between the methods being evaluated [50]. By analyzing the variance among multiple groups, ANOVA helps identify if the differences in outcomes are due to the specific method applied rather than random chance. In the context of comparing MCDM techniques, a one-way ANOVA test can assess whether methods like SAW, AHP, and TOPSIS produce significantly different results when applied to the same dataset. This statistical test is crucial for validating the effectiveness and reliability of each method under the same conditions, ensuring that conclusions drawn from the comparative study are robust and accurate [51].

The formula for the one-way ANOVA test is primarily based on partitioning the total variance into between-group variance and within-group variance. The formula calculates the F-ratio, which is the ratio of these two variances to determine if the means of different groups are significantly different. The formula is stated as follows:

$$F = \frac{MS\ between}{MS\ within} \tag{9}$$

where F is the ANOVA statistic value, *MS between* is the the mean square between groups, and *MS within is* the mean square within groups. The criteria is shown in Table 20.

Table 18. The distance between alternative values and the ideal solution

Category	Employee	Value
D+	P1	0.00340352
	P2	0.00292934
	P3	0.00608837
	P4	0.0065008
	P5	0.01001749
	P6	0.0063275
	P7	0.01177737
	P8	0.0118607
	P9	0.01174213
	P10	0.00634836
	P11	0.02886592
	P12	0.01932185
	P13	0.00357871
	P14	0.00272643
	P15	0.00272453
	P16	0.00338045
D-	P1	0.02876964
	P2	0.02879237
	P3	0.02597735
	P4	0.02586923
	P5	0.01926068
	P6	0.02587503
	P7	0.02390906
	P8	0.02386797
	P9	0.02395066
	P10	0.02584529
	P11	0.00219963
	P12	0.00997666
	P13	0.02877773
	P14	0.02885988
	P15	0.02882706
	P16	0.02876685

Table 19. Determining the preference value

Alternative	Preference	Rank
P1	0.894212	5
P2	0.907655	3
P3	0.810128	7
P4	0.799172	10
P5	0.657851	14
P6	0.803509	8
P7	0.669976	12
P8	0.668034	13
P9	0.671022	11
P10	0.802807	9
P11	0.070806	16
P12	0.340518	15
P13	0.889397	6
P14	0.913683	1
P15	0.913649	2
P16	0.894845	4

Table 20. ANOVA testing criteria

Alpha testing criteria 5%	
P-Value <0.05	There is a significant difference
P-Value >0.05	No difference

3. RESULTS AND DISCUSSION

The comparison between the SAW, AHP, and TOPSIS methods was conducted using the same dataset within the context of an employee performance appraisal system [52]. The dataset included criteria such as service, accountability, competence, alignment, loyalty, adaptability, collaboration, and achievement of targets.

3.1. Comparison between SAW, AHP, and TOPSIS method

The comparison results between the SAW, AHP, and TOPSIS methods in the employee performance assessment can be seen in Figure 2 [53]. In Figure 2, it can be seen that the best employee based on calculation using the SAW method was given to P15, who ranked first with a value range of 0.98222. Different results were obtained when calculating employee performance assessment using the AHP method. The first rank is given to employees P1, P2, P13, P14, P15, and P16 because they have the same values.

TOPSIS method, the first rank was given to P14 employee with a preference value of 0.91368. There is different compared to the SAW method and the TOPSIS method in determining the best employee; in the SAW method, the best employee was given to P15, while in the TOPSIS method, the best employee was assigned to P14. However, based on the assessment of work behavior between P14 and P15 in the accountable or attendance category, P15 has an attendance percentage of 100% whereas P14 has the 95% attendance percentage. In addition, P15 has the position as the observation field coordinator with a larger workload than P14, and his working hour is also longer than P14.

The SAW method has been proved to be the most effective and relevant approach for evaluating employee performance in this context. The preference values calculated using SAW showed a high level of accuracy, aligning well with the expected outcomes for the given dataset. This method directly aggregates the weighted scores of each criterion, providing a straightforward and transparent ranking system. The SAW method consistently ranked employees based on their performance criteria without overlapping scores, accurately reflecting variations in workloads and responsibilities. Preference values in the SAW method were closely aligned with the dataset, showing that this method effectively captured the nuances of each employee's performance. SAW’s simple calculation process facilitated quick evaluations and minimized complexity, making it a practical choice for organizational settings [54]. The AHP method was found to be less precise in this specific case due to the nature of its pairwise comparisons and complex weighting structure. Although AHP allows for detailed comparison and ranking of criteria based on their relative importance. In some instances, AHP assigned equal ranks to employees despite differences in workload and performance, reducing its effectiveness in distinguishing between top and bottom performers [55]. The pairwise comparison process in AHP is more time-intensive and requires extensive input from decision-makers, which may not be suitable for scenarios requiring quick decision-making. The reliance on subjective judgments for assigning relative weights introduced potential bias, making it less objective compared to SAW.

The TOPSIS method, while useful for creating a visual gap analysis between each employee and an ideal solution, showed limitations when applied to this dataset. TOPSIS rankings did not accurately reflect the relative workloads and responsibilities of the employees, leading to potentially misleading results [56]. This method was highly sensitive to the weightings assigned to criteria, which influenced the final rankings significantly, making it challenging to maintain consistency across different contexts. TOPSIS involves more complex calculations compared to SAW, which can increase the likelihood of errors during implementation.

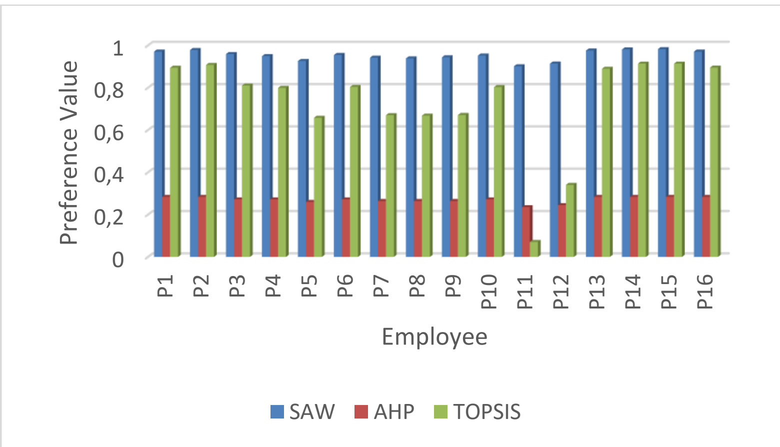

Figure 2. Comparison chart of SAW, AHP, and TOPSIS method

3.2. One-way ANOVA testing

To test the significant differences between the three MCDM methods (SAW, AHP, and TOPSIS) in generating rankings, a statistical analysis was conducted using one-way ANOVA. The ANOVA analysis was used to determine if there were significant differences in the average scores produced by the three methods. In Figure 3, The ANOVA test indicated that there were significant differences between the ranking scores produced by SAW compared to AHP and TOPSIS [57]. The p-value obtained was below the significance level of 0.05, indicating that the results from the three methods are not statistically similar. These results strengthen the findings that the SAW method provides more accurate and consistent performance evaluations, aligning well with the characteristics of the dataset used [58], [59]. In contrast, the AHP and TOPSIS methods produced rankings that were less suitable for capturing individual employee performance nuances.

Alpha Testing Criteria 5%						
P-Value < 0,05	There is a Significant Difference					
P-Value > 0,05	No Difference					
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
SAW	16	15,23867978	0,952	0,001		
AHP	16	4,32213407	0,270	0,000		
TOPSIS	16	11,707264	0,732	0,054		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3,87879191	2	1,939	107,115	0,000	3,204
Within Groups	0,814755493	45	0,018			
Total	4,693547403	47				

Figure 3. One-way ANOVA testing

4. CONCLUSION

Based on the conducted comparative analysis, the SAW method emerged as the most effective and relevant for the performance appraisal system in this case study. SAW correctly calculated preference values for the dataset, resulting in clear and distinguishable rankings that accurately reflected each employee's performance. The simplicity and transparency of the SAW calculations make it ideal for performance appraisal systems, especially in environments where quick, objective, and reliable evaluations are needed. SAW demonstrated consistent results with minimal bias, making it the preferred choice for aligning performance scores with organizational goals.

Organizations seeking to enhance their performance appraisal systems should consider the advantages of the SAW method, especially when dealing with complex datasets requiring clear differentiation of performance levels. While AHP and TOPSIS provide valuable insights for decision-making in certain contexts, their complexity and subjectivity can limit their practical application in straightforward performance evaluations. This study confirms that the SAW method offers a more reliable and effective approach for employee performance appraisal, balancing accuracy, ease of application, and relevance to organizational needs. The results of the ANOVA test support this conclusion, highlighting the superiority of SAW in delivering the most relevant and appropriate assessments in the evaluated context.

Future research directions can include other parameters in determining the ranking. Furthermore, fuzzy parameters can also be included in the criteria. In particular, some further methods can be integrated in the ranking such as fuzzy aggregation methods.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Rinta Kridalukmana	✓	✓		✓	✓	✓			✓	✓		✓		
Toni Prahasto		✓		✓						✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Access to the data is restricted and available upon request. Interested parties can request the data by contacting the corresponding author via email at agathabenyhimawan@students.undip.ac.id.

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