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OPTIMIZING STUDENT PERFORMANCE ASSESSMENT AND RANKING USING THE SAW–TOPSIS APPROACH

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ABSTRACT

Student assessment is a fundamental aspect of education for comprehensively measuring learning progress. Given that conventional assessment systems, which focus solely on academic grades, often neglect other important aspects of student performance, a more objective and holistic approach is necessary. This study aims to explain the implementation of a combined method of SAW and TOPSIS to optimize student performance assessment and ranking. This research uses a descriptive quantitative approach with data collection techniques through interviews and documentation. The results show that the combination of the SAW and TOPSIS methods can provide an objective ranking of students based on the predetermined criteria: academic scores, extracurricular scores, academic or non-academic achievement scores, attendance scores, violation scores, and madrasah scores. From the calculation results, the student with the highest rank is S06 with a preference value of 0,622009183, while the student with the lowest rank is S19 with a preference value of 0,137883342. This ranking provides a clearer picture of each student's performance, which can be used as a basis for evaluation and decision-making by the school.

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INTRODUCTION

Student performance assessment plays a crucial role in supporting educational decision-making processes, particularly in identifying student achievements and determining appropriate academic interventions. However, in many educational institutions, student evaluation still predominantly relies on academic scores as the primary indicator (Boumi & Vela, 2022), which may not fully reflect students' overall competencies and development. Recent studies emphasize that student performance is inherently multidimensional and should be evaluated using multiple criteria (Blasco-Blasco et al., 2021). In the context of education, these criteria may include not only academic achievement but also behavioral aspects, attendance, and participation in extracurricular activities (Sholihat & Gustian, 2021; Angraini et al., 2023). Therefore, relying solely on single-dimensional evaluation criteria can lead to biased or incomplete assessment outcomes.

Interviews at MTs Raudlatul Thalabah reveal that student ranking is primarily based on academic scores, a common practice that inadequately reflects students' overall potential. Performance-based assessment is therefore emphasized in the literature as a more comprehensive approach that evaluates competencies using multiple indicators aligned with real learning contexts (Chahnia et al., 2024). Moreover, comprehensive assessment practices are considered more equitable because they acknowledge broader forms of student engagement, including participation in school activities and consistent attendance (Fahrudin & Warnars, 2020).

From this perspective, student performance should be viewed as a multidimensional construct that includes academic achievement as well as character development, discipline, and social skills fostered through extracurricular activities (Angraini et al., 2023). Based on both theoretical considerations and field findings, this study proposes the inclusion of additional criteria for student performance assessment and ranking, namely academic scores, extracurricular scores, academic and non-academic achievement scores, attendance scores, violation scores, and Madin program scores, in order to produce a more balanced and comprehensive evaluation of student performance.

To make decision-making regarding student performance more effective, an objective and comprehensive ranking system that considers various criteria is needed. A Decision Support System (DSS) can be utilized to analyze intricate scenarios in performance evaluation, as it produces more informative and precise decisions without supplanting the decision-maker's role (Basri, 2017). Evaluating and ranking students' work is seen as a way to make decisions. Simple Additive Weighting (SAW) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are two ways to make decisions using math. The SAW method looks for a weighted sum by taking the performance ratings of each option across all attributes (Gunawan et al., 2023). The reason for choosing this method is that it makes calculations easy to understand and quick (Ilmiyah et al., 2023). This method only needs criterion values and weights that experts have set (Marbun & Hansun, 2019). The SAW method is good for picking the best choice because it can give each criterion an importance weight and then rank the choices from best to worst (Muqorobin et al., 2019). The SAW method works best when used with another method, like TOPSIS (Saputra & Santi, 2022).

TOPSIS is another way to help make decisions with more than one criterion. The TOPSIS method is based on the idea that the best option should be the one that is closest to the positive ideal solution and the farthest from the negative ideal solution (Sukamto et al., 2020). This method has a straightforward and comprehensible calculation principle (Somya & Wardoyo, 2019). Consequently, this study advocates for the integration of the SAW and TOPSIS methods to address these constraints.

The rationale for employing a combination of SAW and TOPSIS lies in the fact that the SAW method facilitates weight determination, whereas the TOPSIS method excels in ranking (Gunawan et al., 2023). SAW is valued for its efficiency and simplicity in calculating weighted scores based on criteria importance, making it particularly suitable for establishing a consistent basis for comparison, while TOPSIS enhances this framework by identifying alternatives closest to the ideal positive solution and furthest from the negative ideal, thus offering a more comprehensive ranking mechanism than SAW alone (Ciardiello & Genovese, 2023; Damanik, 2017). The SAW method assigns weights to criteria based on how important they are to the study. After that, the combination with the TOPSIS method starts by finding the suitability rating and the normalized decision matrix using the formula from the SAW method (Pertiwi et al., 2022).

In the TOPSIS procedure, the decision matrix is normalized to ensure comparability across criteria (Krishnan et al., 2023; Lamrini et al., 2023; Liu et al., 2026). Within the integrated framework, weights obtained from the SAW method are incorporated into the TOPSIS calculations, allowing criterion importance to be consistently represented. Previous studies on hybrid MCDM approaches indicate that this integration effectively addresses trade-offs among criteria and enhances both the stability and discriminative power of the resulting rankings (Ciardiello & Genovese, 2023). Prior research conducted by Pertiwi et al. (2022) and Ilmiyah et al. (2023) has demonstrated that the integration of these two methodologies improves the quality of ranking and the efficiency in identifying optimal alternatives.

Previous studies have applied multi-criteria decision-making (MCDM) methods such as SAW and TOPSIS in various decision support contexts, demonstrating their effectiveness in handling multi-attribute evaluation problems (Fahrudin & Warnars, 2020; Ciardiello & Genovese, 2023). In the context of education, however, student assessment systems still tend to rely predominantly on academic indicators, resulting in a limited representation of overall student performance (Angraini et al., 2023; Blasco-Blasco et al., 2021). Recent studies have begun to incorporate multiple criteria and advanced decision-making techniques in educational evaluation, including the use of TOPSIS and hybrid MCDM approaches (Wang et al., 2022; Sharma et al., 2024; James et al., 2023). Nevertheless, these studies generally apply a single method or focus on specific cases, and do not explicitly integrate a structured hybrid framework that clearly separates the processes of weighting and ranking within a unified student performance evaluation model.

Therefore, a research gap exists in the development of a comprehensive student performance assessment model that systematically integrates both academic and non-academic criteria using a hybrid MCDM approach. This study addresses this gap by proposing a combined SAW–TOPSIS method to optimize student performance assessment and ranking. The novelty of this research lies in: (1) the integration of SAW and TOPSIS within a single analytical framework that distinguishes between weighting and ranking processes, and (2) the application of this hybrid model to a multidimensional student performance dataset that includes academic, behavioral, attendance, extracurricular, and Madrasah-based criteria. Accordingly, this study aims to implement and evaluate the SAW–TOPSIS approach in producing a more comprehensive and structured student ranking system.

METHOD

Data were collected through semi-structured interviews and documentation. The interviews were conducted with school administrators and teachers to identify relevant assessment criteria, determine the weighting of each criterion, and understand the existing evaluation practices. The weighting process was based on expert judgment, where teachers and school administrators assigned relative importance to each criterion according to institutional priorities and educational considerations.

Documentation data were obtained from official school records, including academic scores, extracurricular scores, academic or non-academic achievement scores, attendance scores, violation scores, and Madrasah program scores. Prior to analysis, the data underwent a preprocessing stage, which included checking for completeness, ensuring consistency across data sources, and transforming all criteria into a comparable numerical format suitable for multi-criteria analysis. Missing or inconsistent data entries were verified and corrected through cross-referencing with school records.

To ensure data validity, information obtained from interviews was cross-checked with documented records (data triangulation), while the consistency of data sources was verified through consultation with responsible school personnel. This combined validation and preprocessing process ensures that the data used in the SAW–TOPSIS analysis are accurate, reliable, and appropriate for decision-making purposes.

The measurement scales for non-quantitative criteria are as follows:

a. Academic Scores were measured based on the average report card score for one semester.

b. Scouting Extracurricular Scores were determined by student engagement during the activity, as evidenced by the extracurricular report card. The grading scale for this criterion refers to Table 1:

Table 1: Extracurricular Assessment Guidelines

No.	Category	Points
1.	Very Good	3
2.	Good	2
3.	Fair	1

c. Academic or Non-Academic Achievement Scores were measured by the frequency of student participation and achievement in various fields. The grading scale for this criterion refers to Table 2:

Table 2: Academic or Non-Academic Achievement Assessment Guidelines

No.	Assessment Aspect	Category	Points
1.	Type of Achievement	1st Place	7
		2nd Place	6
		3rd Place	5
		Participated in a competition	4
		Participated in a Training	3
		Participated in a Seminar	2
		Did not participate in a competition, training, or seminar	1
2.	Type of Competition	Individual	2
		Group	1
3.	Competition Level	National	4
		Provincial	3
		City/Regency	2
		Local	1

d. Attendance Scores were calculated based on the total attendance during one semester.
e. Violation Scores were assessed based on violation points recorded in the violation logbook.
f. Madin Scores were measured by student engagement during the program, as evidenced by the Madin extracurricular report card.

The attribute types and weights for each criterion are explained in Table 3 and Table 4:

Table 3. Criteria and Attributes

No.	Criterion Code	Criterion	Atribute
1.	$C1$	Academic Scores	Benefit
2.	$C2$	Extracurricular Scores	Benefit
3.	$C3$	Academic or Non-Academic Achievement Scores	Benefit
4.	$C4$	Attendance Scores	Benefit
5.	$C5$	Violation Scores	Cost
6.	$C6$	Madin Scores	Benefit

All criteria are benefit attributes except Violation Scores, which is treated as a cost attribute, and criterion weights were determined through interviews with school officials and subsequently applied in the SAW and TOPSIS analyses, as presented in Table 4.

Table 4. Preference Weights

No.	Criterion Code	Weight
1.	$C1$	40%
2.	$C2$	10%
3.	$C3$	10%
4.	$C4$	15%
5.	$C5$	15%
6.	$C6$	10%

Based on Table 4, the preference weight matrix F can be structured as follows:

$$F = \begin{bmatrix} 0.40 \\ 0.10 \\ 0.10 \\ 0.15 \\ 0.15 \\ 0.10 \end{bmatrix}$$

The integration of SAW and TOPSIS in this study is designed to separate the processes of weighting and ranking within a unified decision-making framework. The SAW method is utilized to transform the initial decision matrix and to incorporate the relative importance of each criterion through a weighted aggregation process, as it is widely recognized for its simplicity in handling weighted multi-criteria evaluation. Subsequently, the TOPSIS method is applied to perform the ranking process by calculating the relative closeness of each alternative to the ideal solution. In TOPSIS, normalization is required to ensure comparability across criteria and to support distance-based evaluation in a multidimensional space (Hwang & Yoon, 1981; Behzadian et al., 2012).

In this integrated approach, the use of two normalization steps reflects the distinct roles of each method within the analytical framework. The first normalization is associated with the SAW-based transformation and weighting process, while the second normalization follows the standard TOPSIS procedure. This design is intended to enhance the consistency and interpretability of the evaluation process by clearly distinguishing between the weighting and ranking stages.

The implementation of the combined SAW and TOPSIS methods begins with the SAW method stages, as follows:

a. Convert the non-quantitative data into quantitative data based on the defined scale, then create a suitability rating table.
b. Construct the decision matrix S based on the suitability rating table.
c. Normalize the decision matrix S to obtain the normalized decision matrix S_1. The entries in the normalized matrix S_1 are the normalized performance rating values r_{pq} for criterion C_q of alternative S_p. If the attribute of C_q is a benefit and w_{pq} is the rating value of the criterion C_q for alternative S_p, then r_{pq} is calculated using the formula:

$$r_{pq} = \frac{w_{pq}}{\max_{p} w_{pq}} \tag{1}$$

If the attribute of C_q is a cost and w_{pq} is the rating value of criterion C_q for alternative S_p, then r_{pq} is calculated using the formula:

$$r_{pq} = \frac{\min_{p} w_{pq}}{w_{pq}} \tag{2}$$

The calculation continues using the TOPSIS method. This method is implemented through the following steps:

d. Normalize the decision matrix S_1 to obtain the normalized decision matrix S_2. The entries in the normalized decision matrix S_1 are n_{pq} which are calculated using the formula:

$$n_{pq} = \frac{r_{pq}}{\sqrt{\sum_{p=1}^{a} r_{pq}^2}} \tag{3}$$

Where:
n_{pq} = entries in matrix S_2
r_{pq} = entries in matrix S_1
$p = 1,2, \dots, a$ (number of alternatives)
$q = 1,2, \dots, b$ (number of criteria)

e. Create the weighted normalized decision matrix A by multiplying matrix S_2 and the preference weight matrix F using the formula:

$$A = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1q} \\ y_{21} & y_{22} & \cdots & y_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pq} \end{bmatrix} \text{ for } y_{pq} = f_q n_{pq} \tag{4}$$

Where:
f_q = weight of the q-th criterion
n_{pq} = entries in matrix S_2
y_{pq} = elements of the weighted normalized decision matrix A

f. Calculate the positive ideal solution and negative ideal solution using the formulas:

$$y_q^+ = \begin{cases} \max\limits_p y_{pq}, & if\ q\ is\ a\ benefit \\ \min\limits_p y_{pq}, & if\ q\ is\ a\ cost \end{cases} \tag{5}$$

$$y_q^- = \begin{cases} \min\limits_p y_{pq}, & if\ q\ is\ a\ benefit \\ \max\limits_p y_{pq}, & if\ q\ is\ a\ cost \end{cases} \tag{6}$$

Where:
y_{pq} = entries in matrix A
y_q^+ = positive ideal solution
y_q^- = negative ideal solution

g. Calculate the distance to the positive ideal solution and distance to the negative ideal solution using the formulas:

$$g_p^+ = \sqrt{\sum_{q=1}^{b} \left(y_p^+ - y_{pq}\right)^2} \tag{7}$$

$$g_p^- = \sqrt{\sum_{q=1}^{b} \left(y_{pq} - y_p^-\right)^2} \tag{8}$$

Where:
g_p^+ = distance to the positive ideal solution
g_p^- = distance to the negative ideal solution

h. Determine the preference value using the formula:

$$v_p = \frac{g_p^-}{g_p^- + g_p^+} \tag{9}$$

Where:
v_p = preference value
The highest preference value indicates the best alternative.

RESULTS

Raw data for each criterion were collected from 28 students and recorded for each alternative, as summarized in Table 5. The dataset used in this study had been previously validated and prepared to ensure consistency across all evaluation criteria. The selected sample represents students with complete performance records, enabling a reliable comparison within the multi-criteria framework. In this study, six evaluation criteria were applied, with weights reflecting their relative importance as determined by school stakeholders. Based on this prepared dataset, the SAW–TOPSIS procedure was implemented to generate preference values and produce the final student performance rankings.

Table 5. Raw Data of Each Student's Criteria

No.	Student Code	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
1.	S01	83,41	Very Good	-	128	1	87,60
2.	S02	84,06	Very Good	-	130	1	73,17
3.	S03	83,76	Good	-	129	1	72,33
4.	S04	80,88	Good	3rd Place in Kediri Regency Women's Doubles Table Tennis	129	1	62,00
5.	S05	80,53	Very Good	3rd Place in Kediri Regency Women's Doubles Table Tennis	130	1	73,40
6.	S06	80,18	Fair	2nd Place in Kediri Regency Tahfidz Competition	125	1	81,00
7.	S07	80,76	Very Good	-	129	1	72,50
8.	S08	77,35	Very Good	-	125	1	59,00
9.	S09	84,00	Very Good	-	130	1	85,17
10.	S10	81,12	Very Good	-	130	1	64,50
11.	S11	81,24	Very Good	-	130	1	70,33
12.	S12	83,29	Very Good	Participant in Kediri Regency Islamic Singing Competition	128	1	85,83
13.	S13	81,76	Very Good	-	130	1	86,20
14.	S14	82,88	Very Good	-	128	1	83,50
15.	S15	82,71	Very Good	-	130	1	67,50
16.	S16	79,29	Very Good	-	130	1	73,25
17.	S17	80,88	Good	-	127	1	66,25
18.	S18	81,94	Good	Participant in Kediri Regency Men's Volleyball Competition	125	1	74,17
19.	S19	78,41	Good	-	126	1	73,00
20.	S20	78,47	Very Good	-	129	1	65,00
21.	S21	81,18	Good	-	125	1	76,25
22.	S22	83,53	Very Good	-	130	1	86,22
23.	S23	74,35	Fair	-	123	7	61,67
24.	S24	83,76	Very Good	-	128	1	76,25
25.	S25	81,65	Very Good	-	130	1	75,00
26.	S26	80,24	Very Good	-	128	1	74,00
27.	S27	83,65	Very Good	-	130	1	76,83
28.	S28	86,47	Very Good	-	130	1	83,50

SAW Method Implementation

a. Converting Non-Quantitative Data to Quantitative Data

Non-quantitative data were converted into quantitative values using the measurement scales presented in Table 1 and Table 2. These scales assign numerical scores to qualitative indicators such as extracurricular performance and student achievements to ensure comparability across criteria. After the conversion process, a suitability rating matrix was constructed, as shown in Table 6.

To enhance clarity, a sample calculation is provided. For example, student S04 has an extracurricular assessment categorized as “Good”, which, based on Table 1, is assigned a score of 2. For the achievement criterion (C3), S04 is recorded as “3rd Place in Kediri Regency Women’s Doubles Table Tennis”. Based on Table 2, this is converted as follows: 3rd Place = 5 points, competition type (group) = 1 point, and competition level (regency) = 2 points, resulting in a total score of 8.

Table 6. Suitability Ratings for Criteria and Alternatives

No.	Student Code	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
1.	S01	83,41	3	1	128	1	87,60
2.	S02	84,06	3	1	130	1	73,17
3.	S03	83,76	2	1	129	1	72,33
4.	S04	80,88	2	8	129	1	62,00
5.	S05	80,53	3	8	130	1	73,40
6.	S06	80,18	1	10	125	1	81,00
7.	S07	80,76	3	1	129	1	72,50
8.	S08	77,35	3	1	125	1	59,00
9.	S09	84,00	3	1	130	1	85,17
10.	S10	81,12	3	1	130	1	64,50
11.	S11	81,24	3	1	130	1	70,33
12.	S12	83,29	3	8	128	1	85,83
13.	S13	81,76	3	1	130	1	86,20
14.	S14	82,88	3	1	128	1	83,50
15.	S15	82,71	3	1	130	1	67,50
16.	S16	79,29	3	1	130	1	73,25
17.	S17	80,88	2	1	127	1	66,25
18.	S18	81,94	2	7	125	1	74,17
19.	S19	78,41	2	1	126	1	73,00
20.	S20	78,47	3	1	129	1	65,00
21.	S21	81,18	2	1	125	1	76,25
22.	S22	83,53	3	1	130	1	86,22
23.	S23	74,35	1	1	123	7	61,67
24.	S24	83,76	3	1	128	1	76,25
25.	S25	81,65	3	1	130	1	75,00
26.	S26	80,24	3	1	128	1	74,00
27.	S27	83,65	3	1	130	1	76,83
28.	S28	86,47	3	1	130	1	83,50

b. Constructing the Decision Matrix S

The decision matrix S of size $m \times n$ is constructed, where m represents the number of students and n the performance criteria, resulting in a 28×6 matrix as follows:

$$S = \begin{bmatrix} 83,41 & 3 & 1 & 128 & 1 & 87,60 \\ 84,06 & 3 & 1 & 130 & 1 & 73,17 \\ 83,76 & 2 & 1 & 129 & 1 & 72,33 \\ 80,88 & 2 & 8 & 129 & 1 & 62,00 \\ 80,53 & 3 & 8 & 130 & 1 & 73,40 \\ 80,18 & 1 & 10 & 125 & 1 & 81,00 \\ 80,76 & 3 & 1 & 129 & 1 & 72,50 \\ 77,35 & 3 & 1 & 125 & 1 & 59,00 \\ 84,00 & 3 & 1 & 130 & 1 & 85,17 \\ 81,12 & 3 & 1 & 130 & 1 & 64,50 \\ 81,24 & 3 & 1 & 130 & 1 & 70,33 \\ 83,29 & 3 & 8 & 128 & 1 & 85,83 \\ 81,76 & 3 & 1 & 130 & 1 & 86,20 \\ 82,88 & 3 & 1 & 128 & 1 & 83,50 \\ 82,71 & 3 & 1 & 130 & 1 & 67,50 \\ 79,29 & 3 & 1 & 130 & 1 & 73,25 \\ 80,88 & 2 & 1 & 127 & 1 & 66,25 \\ 81,94 & 2 & 7 & 125 & 1 & 71,17 \\ 78,41 & 2 & 1 & 126 & 1 & 73,00 \\ 78,47 & 3 & 1 & 129 & 1 & 65,00 \\ 81,18 & 2 & 1 & 125 & 1 & 76,25 \\ 83,53 & 3 & 1 & 130 & 1 & 86,22 \\ 74,35 & 1 & 1 & 123 & 7 & 61,67 \\ 83,76 & 3 & 1 & 128 & 1 & 76,25 \\ 81,65 & 3 & 1 & 130 & 1 & 75,00 \\ 80,24 & 3 & 1 & 128 & 1 & 74,00 \\ 83,65 & 3 & 1 & 130 & 1 & 76,83 \\ 86,47 & 3 & 1 & 130 & 1 & 83,50 \end{bmatrix}$$

c. Normalizing the decision matrix S

The decision matrix S was normalized using Formula (1) for benefit criteria and Formula (2) for cost criteria, producing normalized performance ratings (r_{pq}) summarized in the normalized matrix S_1 as follows:

$$S_1 = \begin{bmatrix} 0,96 & 1,00 & 0,10 & 0,98 & 1,00 & 1,00 \\ 0,97 & 1,00 & 0,10 & 1,00 & 1,00 & 0,84 \\ 0,97 & 0,67 & 0,10 & 0,99 & 1,00 & 0,83 \\ 0,94 & 0,67 & 0,80 & 0,99 & 1,00 & 0,71 \\ 0,93 & 1,00 & 0,80 & 1,00 & 1,00 & 0,84 \\ 0,93 & 0,33 & 1,00 & 0,96 & 1,00 & 0,92 \\ 0,93 & 1,00 & 0,10 & 0,99 & 1,00 & 0,83 \\ 0,89 & 1,00 & 0,10 & 0,96 & 1,00 & 0,67 \\ 0,97 & 1,00 & 0,10 & 1,00 & 1,00 & 0,97 \\ 0,94 & 1,00 & 0,10 & 1,00 & 1,00 & 0,74 \\ 0,94 & 1,00 & 0,10 & 1,00 & 1,00 & 0,80 \\ 0,96 & 1,00 & 0,80 & 0,98 & 1,00 & 0,98 \\ 0,95 & 1,00 & 0,10 & 1,00 & 1,00 & 0,98 \\ 0,96 & 1,00 & 0,10 & 0,98 & 1,00 & 0,95 \\ 0,96 & 1,00 & 0,10 & 1,00 & 1,00 & 0,77 \\ 0,92 & 1,00 & 0,10 & 1,00 & 1,00 & 0,84 \\ 0,94 & 0,67 & 0,10 & 0,98 & 1,00 & 0,76 \\ 0,95 & 0,67 & 0,70 & 0,98 & 1,00 & 0,85 \\ 0,91 & 0,67 & 0,10 & 0,97 & 1,00 & 0,83 \\ 0,91 & 1,00 & 0,10 & 0,99 & 1,00 & 0,74 \\ 0,95 & 0,67 & 0,10 & 0,96 & 1,00 & 0,87 \\ 0,97 & 1,00 & 0,10 & 1,00 & 1,00 & 0,99 \\ 0,86 & 0,33 & 0,10 & 0,95 & 0,14 & 0,70 \\ 0,97 & 1,00 & 0,10 & 0,98 & 1,00 & 0,87 \\ 0,94 & 1,00 & 0,10 & 1,00 & 1,00 & 0,86 \\ 0,93 & 1,00 & 0,10 & 0,98 & 1,00 & 0,84 \\ 0,97 & 1,00 & 0,10 & 1,00 & 1,00 & 0,88 \\ 1,00 & 1,00 & 0,10 & 1,00 & 1,00 & 0,95 \end{bmatrix}$$

TOPSIS Method Implementation

d. Normalizing the Decision Matrix S_1

The normalized decision matrix S_2 was obtained from S_1 using Formula (3), yielding normalized performance ratings (n_{pq}) for each criterion and alternative as follows:

$$S_2 = \begin{bmatrix} 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,22 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,19 & 0,14 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,19 & 0,14 & 0,42 & 0,19 & 0,19 & 0,16 \\ 0,19 & 0,21 & 0,42 & 0,19 & 0,19 & 0,19 \\ 0,19 & 0,07 & 0,52 & 0,18 & 0,19 & 0,20 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,18 & 0,21 & 0,05 & 0,18 & 0,19 & 0,15 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,21 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,16 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,19 & 0,21 & 0,42 & 0,19 & 0,19 & 0,22 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,22 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,21 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,17 \\ 0,18 & 0,21 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,19 & 0,14 & 0,05 & 0,19 & 0,19 & 0,17 \\ 0,19 & 0,14 & 0,37 & 0,18 & 0,19 & 0,19 \\ 0,18 & 0,14 & 0,05 & 0,19 & 0,19 & 0,18 \\ 0,18 & 0,21 & 0,05 & 0,19 & 0,19 & 0,16 \\ 0,19 & 0,14 & 0,05 & 0,18 & 0,19 & 0,19 \\ 0,19 & 0,14 & 0,05 & 0,18 & 0,19 & 0,19 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,22 \\ 0,17 & 0,07 & 0,05 & 0,18 & 0,03 & 0,16 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,19 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,19 \\ 0,19 & 0,21 & 0,05 & 0,19 & 0,19 & 0,19 \\ 0,20 & 0,21 & 0,05 & 0,19 & 0,19 & 0,21 \end{bmatrix}$$

e. Constructing the Weighted Normalized Decision Matrix A

The weighted normalized decision matrix A is created by multiplying the normalized decision matrix S_2 with the preference weight matrix F (Formula (4)). The results are as follows:

$$A = \begin{bmatrix} 0,077305891 & 0,020901990 & 0,005241424 & 0,028280650 & 0,028856610 & 0,022098018 \\ 0,077905584 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,018457899 \\ 0,077632996 & 0,013934660 & 0,005241424 & 0,028501593 & 0,028856610 & 0,018246001 \\ 0,074961636 & 0,013934660 & 0,041931393 & 0,028501593 & 0,028856610 & 0,015640150 \\ 0,074634531 & 0,020901990 & 0,041931393 & 0,028722536 & 0,028856610 & 0,018515919 \\ 0,074307425 & 0,006967330 & 0,052414242 & 0,027617823 & 0,028856610 & 0,020433099 \\ 0,074852601 & 0,020901990 & 0,005241424 & 0,028501593 & 0,028856610 & 0,018288885 \\ 0,071690583 & 0,020901990 & 0,005241424 & 0,027617823 & 0,028856610 & 0,014883368 \\ 0,077851066 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,021485025 \\ 0,075179706 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,016270801 \\ 0,075288741 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,017741480 \\ 0,077196856 & 0,020901990 & 0,041931393 & 0,028280650 & 0,028856610 & 0,021651517 \\ 0,075779399 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,021744853 \\ 0,076815233 & 0,020901990 & 0,005241424 & 0,028280650 & 0,028856610 & 0,021063750 \\ 0,076651680 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,017027582 \\ 0,073489662 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,018478080 \\ 0,074961636 & 0,013934660 & 0,005241424 & 0,028059708 & 0,028856610 & 0,016712257 \\ 0,075942952 & 0,013934660 & 0,036689969 & 0,027617823 & 0,028856610 & 0,018710160 \\ 0,072671899 & 0,013934660 & 0,005241424 & 0,027838765 & 0,028856610 & 0,018415015 \\ 0,072726416 & 0,020901990 & 0,005241424 & 0,028501593 & 0,028856610 & 0,016396931 \\ 0,076161022 & 0,013934660 & 0,005241424 & 0,027617823 & 0,028856610 & 0,019234862 \\ 0,077414926 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,021777647 \\ 0,068910187 & 0,006967330 & 0,005241424 & 0,027175938 & 0,004122373 & 0,015556904 \\ 0,077632996 & 0,020901990 & 0,005241424 & 0,028280650 & 0,028856610 & 0,019234862 \\ 0,075670364 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,018919536 \\ 0,074361943 & 0,020901990 & 0,005241424 & 0,028280650 & 0,028856610 & 0,018667276 \\ 0,077523961 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,019381173 \\ 0,080140803 & 0,020901990 & 0,005241424 & 0,028722536 & 0,028856610 & 0,021063750 \end{bmatrix}$$

f. Calculating the Positive and Negative Ideal Solutions

The positive ideal solution (y_q^+) and negative ideal solution (y_q^-) are calculated using Formula (5) and Formula (6), respectively. The results are shown in Table 7.

Table 7. Positive and Negative Ideal Solution Calculation Results

No.	Criterion	y_q^+	y_q^-
1.	$C1$	0,080140803	0,068910187
2.	$C2$	0,02090199	0,00696733
3.	$C3$	0,052414242	0,052414242
4.	$C4$	0,028722536	0,027175938
5.	$C5$	0,004122373	0,02885661
6.	$C6$	0,022098018	0,014883368

g. Calculating the Distance to the Positive and Negative Ideal Solutions

The distances to the positive ideal solution (g_p^+) and negative ideal solution (g_p^-) are calculated using Formula (7) and Formula (8). The results of these calculations are presented in Table 8.

Table 8. Results of Distance Calculation to Positive and Negative Ideal Solutions

No.	Student Code	(g_p^+)	(g_p^-)
1.	S01	$\mathbf{0,053341252}$	$\mathbf{0,017830708}$
2.	S02	$\mathbf{0,053435044}$	$\mathbf{0,017037052}$
3.	S03	$\mathbf{0,053914533}$	$\mathbf{0,011734383}$
4.	S04	$\mathbf{0,028961922}$	$\mathbf{0,03786354}$
5.	S05	$\mathbf{0,027655435}$	$\mathbf{0,0398583}$
6.	S06	$\mathbf{0,029051297}$	$\mathbf{0,047805854}$
7.	S07	$\mathbf{0,053661724}$	$\mathbf{0,015583387}$
8.	S08	$\mathbf{0,054421825}$	$\mathbf{0,01421621}$
9.	S09	$\mathbf{0,05331675}$	$\mathbf{0,017891001}$
10.	S10	$\mathbf{0,053811023}$	$\mathbf{0,015420718}$
11.	S11	$\mathbf{0,05366171}$	$\mathbf{0,015665933}$
12.	S12	$\mathbf{0,027032093}$	$\mathbf{0,040694296}$
13.	S13	$\mathbf{0,053443463}$	$\mathbf{0,01705382}$
14.	S14	$\mathbf{0,053379599}$	$\mathbf{0,017207034}$
15.	S15	$\mathbf{0,053618472}$	$\mathbf{0,016158437}$
16.	S16	$\mathbf{0,053799617}$	$\mathbf{0,015180918}$
17.	S17	$\mathbf{0,054239012}$	$\mathbf{0,009449317}$
18.	S18	$\mathbf{0,030625134}$	$\mathbf{0,033194187}$
19.	S19	$\mathbf{0,054366635}$	$\mathbf{0,008695173}$
20.	S20	$\mathbf{0,0540794}$	$\mathbf{0,014587207}$
21.	S21	$\mathbf{0,053952364}$	$\mathbf{0,010965813}$
22.	S22	$\mathbf{0,0533347}$	$\mathbf{0,017788434}$
23.	S23	$\mathbf{0,050899453}$	$\mathbf{0,024743406}$
24.	S24	$\mathbf{0,053401678}$	$\mathbf{0,017041656}$
25.	S25	$\mathbf{0,053545726}$	$\mathbf{0,016079719}$
26.	S26	$\mathbf{0,053688152}$	$\mathbf{0,015473679}$
27.	S27	$\mathbf{0,053397437}$	$\mathbf{0,017058548}$
28.	S28	$\mathbf{0,053274074}$	$\mathbf{0,01899712}$

h. Determining Preference Values and Ranking

The final step is to determine the preference value (v_p) for each alternative using Formula (9). The calculation results show that the alternative with the highest preference value is the best. The preference values, which represent student performance, and their corresponding ranks are presented in Table 9.

Tabel 9. Student Performance Assessment and Ranking Results

No.	Student Code	Preference Value	Rank	No.	Student Code	Preference Value	Rank
1.	$S01$	0,250529956	9	15.	$S15$	0,231572841	16
2.	$S02$	0,241756004	15	16.	$S16$	0,220075383	22
3.	$S03$	0,178744501	25	17.	$S17$	0,148368116	27
4.	$S04$	0,566603488	4	18.	$S18$	0,520127547	5
5.	$S05$	0,590373209	3	19.	$S19$	0,137883342	28
6.	$S06$	0,622009183	1	20.	$S20$	0,212435231	23
7.	$S07$	0,225046744	19	21.	$S21$	0,168917447	26
8.	$S08$	0,207118543	24	22.	$S22$	0,250107565	10
9.	$S09$	0,251250749	8	23.	$S23$	0,327108282	6
10.	$S10$	0,222740584	21	24.	$S24$	0,241920063	13
11.	$S11$	0,225969507	18	25.	$S25$	0,230946013	17
12.	$S12$	0,600863217	2	26.	$S26$	0,223731481	20
13.	$S13$	0,241907476	14	27.	$S27$	0,242116378	12
14.	$S14$	0,243771844	11	28.	$S28$	0,262858813	7

DISCUSSION

Table 9 presents the student performance ranking results based on preference values obtained from the combined SAW–TOPSIS method. The highest-ranked student is S06 (0,622009183), while the lowest-ranked is S19 (0,137883342). When compared to rankings based solely on academic scores, noticeable differences are observed. In this context, the term “difference” refers to practical differences in ranking positions rather than statistical significance. For example, student S28, who achieved the highest academic score, is ranked seventh in the multi-criteria evaluation. This indicates that high academic performance alone does not necessarily guarantee the highest overall ranking when multiple criteria are considered.

A closer examination reveals that these ranking shifts are influenced by the contribution of non-academic criteria. For instance, student S06, who ranks first overall, is positioned relatively low in terms of academic score compared to other students, yet demonstrates stronger performance in other criteria, particularly in achievement-related indicators. In contrast, student S28, despite having the highest academic score, shows relatively limited contributions in non-academic criteria, which reduces the overall preference value. This finding highlights that the combined SAW–TOPSIS method captures trade-offs among criteria, allowing students with more balanced performance profiles to achieve higher rankings.

The use of the SAW–TOPSIS method in this study provides a structured mechanism for integrating multiple criteria into a single evaluation framework. Rather than claiming absolute superiority, the results suggest that this approach offers a more comprehensive basis for comparison by considering both academic and non-academic aspects. However, the effectiveness of the method in this study is demonstrated descriptively through its ability to differentiate student performance profiles, and not through statistical validation or benchmarking against alternative methods. Therefore, the interpretation of effectiveness should be limited to the context of this dataset.

From a practical perspective, these results can support schools in making more informed decisions regarding student evaluation and development. The ranking outcomes may assist educators in identifying students with balanced performance as well as those who may require additional support in specific areas. However, the application of this model should be accompanied by professional judgment to ensure that decisions remain contextually appropriate.

This study has several limitations that may affect the interpretation of the results. First, the analysis is based on a relatively small sample of 28 students, which may limit the generalizability of the findings. Second, the model incorporates only six criteria, which may not fully represent all dimensions of student performance. Third, the determination of criterion weights is based on expert judgment, which introduces subjectivity into the evaluation process. These limitations suggest that the resulting rankings should be interpreted as indicative rather than definitive. Future research is recommended to include a larger dataset, incorporate additional performance indicators, and compare the proposed approach with other MCDM methods to further evaluate its robustness and consistency.

CONCLUSION

This study shows that the application of a combined SAW–TOPSIS method provides a structured approach for evaluating and ranking student performance based on multiple criteria. The results indicate that incorporating both academic and non-academic aspects leads to differences in ranking outcomes compared to evaluations based solely on academic scores. In particular, students with more balanced performance across criteria tend to achieve higher overall rankings, highlighting the importance of a multidimensional assessment framework.

These findings suggest that the proposed approach can support more comprehensive and transparent decision-making in student evaluation. Rather than relying on a single indicator, the integration of multiple criteria allows schools to better capture the complexity of student performance. However, the results should be interpreted within the context of the dataset used in this study.

Future research is recommended to involve larger and more diverse samples, incorporate additional relevant criteria, and compare the proposed method with other multi-criteria decision-making approaches to further examine its robustness and consistency.

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INFORMED CONSENT

The authors have obtained informed consent from all participants.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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