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A Comparative Study of Three Decision Support Methods: Proving Consistency in Decision-Making with Identical Inputs

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ABSTRACT

Decision-making in complex environments often requires evaluating multiple alternatives against various criteria, which can sometimes result in inconsistent outcomes when different decision support methods are employed. Such inconsistencies pose significant challenges for decision-makers in determining the most reliable methodology. To address this gap, the present study examines whether three widely adopted decision support methods, Simple Additive Weighting (SAW), Simple Multi-Attribute Rating Technique (SMART), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), produce consistent results when applied to identical input values, criteria, and alternatives. The primary aim is to explicitly assess the consistency of decision-making outcomes across these methods under controlled conditions. The evaluation was conducted using a set of alternatives, with A1 consistently emerging as the top choice. Specifically, the SAW method produced a final score of 0.8998 for A5, the SMART method assigned a value of 0, and the TOPSIS method yielded a closeness coefficient of 0.826 for the same alternative. The unique contribution of this study lies in its systematic, side-by-side comparison of SAW, SMART, and TOPSIS using precisely the same dataset, an approach seldom addressed in prior research. By empirically demonstrating that these methods generate identical rankings under strictly controlled scenarios, this research provides new evidence supporting the methodological robustness and practical interchangeability of these widely used decision support techniques. The findings underscore the reliability of these methods in facilitating objective decision-making and offer valuable guidance for researchers and practitioners in selecting the most suitable DSS method without concern for inconsistent results.

Keywords: Comparative; Decisions Support System; SAW; SMART; TOPSIS; Consistency

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1. INTRODUCTION

Decision-making remains a critical challenge across diverse domains such as business, healthcare, and public administration, where complex scenarios often demand the evaluation of multiple, sometimes conflicting, criteria[1][2]. Over 70% of decision-making processes in data-driven environments now rely on intelligent systems and analytics frameworks to improve accuracy and reduce subjectivity[1]. This trend reflects a shift toward automated and structured approaches in complex environments where manual judgments often fall short. To address these challenges, Decision Support Systems (DSS) have emerged as vital tools, offering systematic frameworks that enable decision-makers to evaluate options based on multiple criteria, a methodology commonly referred to as Multi-Criteria Decision-Making (MCDM). Among the most widely adopted MCDM methods in DSS are Simple Additive Weighting (SAW), Simple Multi-Attribute Rating Technique (SMART), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)[3]–[5]. These methods are favored for their transparency, repeatability, and adaptability across various sectors.

Each method offers unique advantages: SAW is praised for its simplicity and ease of computation, making it ideal for time-sensitive applications. SMART, originally proposed by Edwards in 1977, allows for more nuanced decision modeling through utility values. TOPSIS, developed by Hwang and Yoon in 1981, evaluates alternatives by measuring their geometric distance from ideal and negative-ideal solutions, a strategy that has proven effective in risk assessment models and environmental policy planning, as demonstrated in red tide risk assessment using TOPSIS-ASSETS[4], For example, in a DSS application for sustainable city evaluation using DARIA-TOPSIS, the variance in ranking among different MCDM methods was reported to be less than 5%[6]–[8]. Recent literature has examined the comparative robustness and consistency of these methods. Taherdoost and Madanchian (2023) provided a taxonomy of over 40 MCDM techniques, stressing the need for empirical evaluations of consistency across methods [3]. In a 2024 study, Cinelli et al. demonstrated that DSS methods, when applied with identical datasets and normalized weights, tend to yield highly consistent rankings, supporting their interchangeability for practitioners seeking reliable results[9]. Similarly, research published in the *European Journal of Operational Research* found that both SAW and TOPSIS, despite methodological differences, often produce closely aligned rankings, particularly when Manhattan or Euclidean distance metrics are used for normalization. Another recent comparative analysis by, systematically assessed normalization techniques within SAW and TOPSIS, confirming that, under consistent input and weighting schemes, the decision outcomes remain stable even across different domains.

However, despite this growing body of evidence, there remains a gap in comprehensive tri-method evaluations involving SAW, SMART, and TOPSIS under strictly controlled, identical conditions. Most research to date focuses on pairwise comparisons or does not fully explore the consistency of all three approaches using precisely the same decision matrices and weighting systems. This study addresses that gap by empirically evaluating the consistency of these three leading DSS methods using identical alternatives, criteria, and weights. The aim is to provide robust evidence regarding their reliability and to inform practitioners about the interchangeability of these popular MCDM techniques in supporting objective and reproducible decision-making.

Despite these comparative studies, a significant research gap remains in the comprehensive analysis involving SAW, SMART, and TOPSIS simultaneously, especially under controlled conditions where input data, criteria, and weights are identical. Most existing research focuses on pairwise comparisons (e.g., SAW vs. TOPSIS), while SMART despite its popularity and theoretical strength—has rarely been included in direct comparisons with both SAW and TOPSIS using the same decision-making dataset. Moreover, few studies have explicitly examined the level of consistency among these methods in producing the same optimal alternative. This lack of in-depth tri-method comparison limits the ability of decision-makers to choose the most appropriate method with confidence, especially when seeking consistent and reproducible results across multiple decision support techniques.

Consistency in decision-making is crucial for ensuring reliability and trustworthiness in the outcomes of DSS. The studies mentioned above demonstrate that different MCDM methods, such as SAW, SMART, and TOPSIS, can yield consistent results when applied to the same dataset with identical criteria and weights. This consistency is essential for decision-makers, as it allows them to choose a method that best fits their specific needs without worrying about significant discrepancies in the final decision. The primary objective of this study is to conduct a comparative analysis of SAW, SMART, and TOPSIS methods to evaluate their consistency in decision-making when provided with identical inputs. By applying these methods to the same dataset, this research aims to determine whether they lead to the same optimal decision, thereby validating their reliability and robustness in various decision-making scenarios. Understanding the consistency among different decision support methods is vital for both researchers and practitioners. For researchers, it provides insights into the methodological underpinnings of each technique and their comparative performance. For practitioners, especially those involved in critical decision-making processes, it offers assurance that the choice of method will not adversely affect the outcome, provided that the input data and criteria are consistent. Decision support methods like SAW, SMART, and TOPSIS play a pivotal role in aiding decision-makers to evaluate multiple criteria systematically. This study aims to further explore this consistency by conducting a comparative analysis of the three methods, thereby contributing to the body of knowledge in the field of decision support systems and multi-criteria decision-making.

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2. RESEARCH METHOD

To assess the robustness and stability of the decision support methods, a sensitivity analysis was performed. This process involved systematic variation of the criterion weights and selected input values within a plausible range of ±10% from their original values, reflecting realistic fluctuations that often occur in practical decision-making contexts. The purpose was to observe how these changes influenced the final rankings generated by the three decision support methods: Simple Additive Weighting (SAW), Simple Multi-Attribute Rating Technique (SMART), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The dataset used for this analysis was sourced from Kaggle and comprised five alternatives (A1 to A5) evaluated across five criteria: Price (C1), Customer Rating (C2), Battery Life (C3), Processor Performance (C4), and Display Quality (C5). These criteria included both cost and benefit types, with corresponding weights of 0.30, 0.25, 0.20, 0.15, and 0.10, respectively. A total of 25 normalized data points (5 alternatives × 5 criteria) were used as the decision matrix, ensuring a diverse and representative evaluation basis. To validate the sensitivity analysis, four key steps were undertaken. First, a baseline computation was performed to determine the original rankings using the unaltered weights and input values. Second, during the perturbation rounds, each criterion weight was individually adjusted by ±10% while keeping the others constant, allowing the isolation of each weight's impact on the overall rankings. Third, a comparative evaluation was conducted by comparing the new rankings resulting from the perturbations with the baseline rankings using Spearman's rank correlation coefficient, a non-parametric statistical method that measures the strength and direction of association between two ranked variables. Finally, in the consistency check, a correlation threshold of 0.9 or higher was set to determine whether the rankings remained stable despite parameter variations. This approach follows the robustness testing framework recommended by Taherdoost and Madanchian (2023) in their comprehensive review of Multi-Criteria Decision-Making (MCDM) methodologies[3].

2.1 Dataset Selection

The dataset employed in this study was obtained from Kaggle and represents a realistic multi-criteria decision-making (MCDM) scenario designed to simulate the evaluation and selection process among five alternatives, labeled A1 through A5. Each alternative was assessed based on five distinct criteria commonly encountered in product or service evaluation contexts. The first criterion, C1: Price, is categorized as a cost criterion and was assigned the highest weight of 0.30, reflecting its significant influence in consumer decision-making. The remaining four criteria C2: Customer Rating (weight: 0.25), C3: Battery Life (weight: 0.20), C4: Processor Performance (weight: 0.15), and C5: Display Quality (weight: 0.10) are classified as benefit criteria, meaning higher values are preferred. These weights were chosen to reflect realistic priorities in evaluating technology-based alternatives, ensuring the scenario mirrors actual decision-making environments. The structured weighting system also supports the consistent application of SAW, SMART, and TOPSIS methods in subsequent analyses. Each alternative was assigned numerical values for each criterion. The dataset was crafted to ensure diversity in the attribute values, allowing for an effective comparison across the three decision support methods.

2.2 DSS Methods

A detailed and systematic approach was adopted to evaluate the consistency decision support methods (DSS)[6]. The objective was to apply these methods to the same decision-making problem and assess whether they produced the same best alternative when provided with identical input data. The methodology is designed to ensure that the experiment is reproducible, with sufficient details provided for others to replicate the process.With the data prepared, the next step was to apply each of the three DSS methods[7]. This stage involved following the specific procedures of each method to calculate the decision outcomes. Each method was applied in a manner consistent with its traditional use, ensuring that the core principles behind each approach were preserved.

2.2.1 SAW (Simple Additive Weighting)

SAW method is one of the most commonly used techniques in decision support systems for solving multi-criteria decision-making problems[9][10] [11]. SAW is based on the idea of assigning a weight to each criterion based on its importance and then evaluating the alternatives based on how well they perform on each criterion[12][13]. The method is simple, easy to understand, and straightforward in implementation. In the SAW method, the alternatives are rated based on each criterion, and then the weighted sum of the ratings for each alternative is calculated[14][15]. The alternative with the highest total score is considered the best choice. The procedure for applying SAW is as follows:

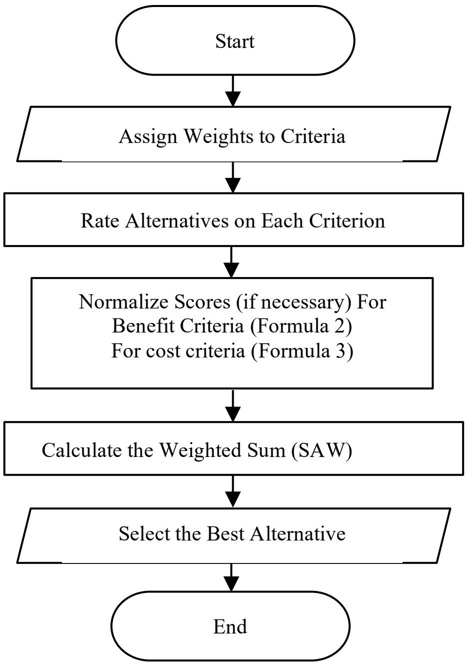

Figure 1. Flowchart of SAW

1. Assign Weights to Criteria: Assign a weight W_j to each criterion based on its importance in the decision-making process. These weights should ideally sum to 1 or be normalized so that they do.
2. Rate Alternatives: Rate each alternative on each criterion, assigning a performance score x_{ij} for each alternative on each criterion. The performance values can be ratings (e.g., 1 to 10) or numerical values based on actual measurements.
3. Normalize the Scores (if necessary): If the criteria have different units or scales, normalization may be needed. The normalized score for each criterion can be calculated using the formula:

$$x_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

For Benefit Criteria:

$$r_{ij} = \frac{x_{ij}}{\max\,(x_j)} \tag{2}$$

For cost criteria (where lower is better):

$$r_{ij} = \frac{\min\,(x_j)}{x_{ij}} \tag{3}$$

In the context of normalization x_{ij}^* is the normalized performance value for the i-th alternative and j-th criterion. The normalization process involves identifying $\min(x_j)$ and $\max(x_j)$are the minimum and maximum values of the j -th criterion across all alternatives.

4. Calculate the Weighted Sum: Using the SAW formula, calculate the weighted sum for each alternative by multiplying the performance score for each criterion by its respective weight and summing the results.
5. Select the Best Alternative: The alternative with the highest total score Si is considered the best choice.

2.2.2 SMART (Simple Multi-Attribute Rating Technique)

SMART is another popular method used in decision-making. The alternatives are evaluated by multiplying their ratings by the respective criterion weights[16], and then summing these weighted values to determine the overall score of each alternative[17]. The procedure for applying SMART is as follows[18][19]:

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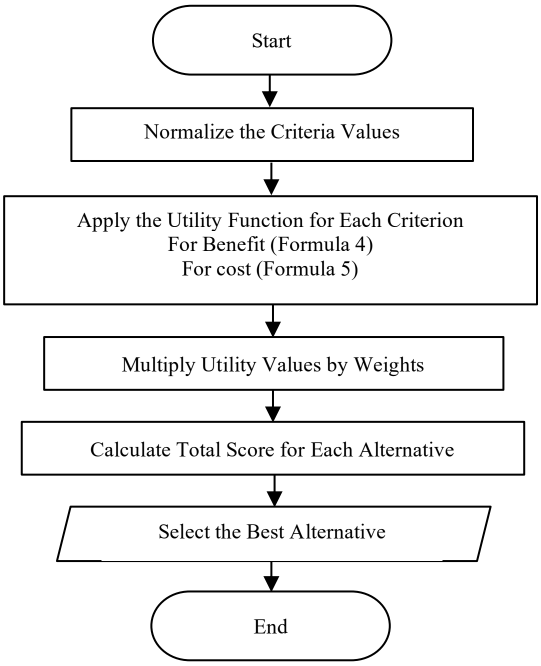

Figure 2. Flowchart of SMART

To evaluate each alternative using the SMART method, the performance values for every criterion must first be normalized. Since C1 (Price) is a cost criterion, lower values are considered more favorable, whereas for the remaining criteria C2 to C5 higher values are preferred, as they represent benefit criteria. The normalization process is followed by the application of a utility function to convert these normalized values into a percentage-based utility score. For benefit criteria, the utility value Ui(ai) is calculated using the formula:

$$\text{Benefit} = U_i\ (a_i) = \frac{C_{max} - C_{out\ i}}{C_{max} - C_{min}} \times 100\% \tag{4}$$

Conversely, for cost criteria, the formula used is:

$$\text{Cost} = U_i\ (a_i) = \frac{C_{out\ i} - C_{min}}{C_{max} - C_{min}} \times 100\% \tag{5}$$

In these formulas, C_{max} and C_{min} refer to the maximum and minimum normalized values for each criterion, respectively, while $C_{out\ i}$ denotes the normalized value of the i-th alternative for the specific criterion. Once all utility scores are obtained, each is multiplied by the corresponding criterion weight to determine the weighted utility score. Finally, the total score for each alternative is derived by summing the weighted scores across all criteria. Based on these total scores, the alternatives are ranked to identify the most optimal choice.

2.2.3 TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is a popular multi-criteria decision-making (MCDM) method[20][21]. It is based on the concept that the best alternative should be the one that is closest to the ideal solution and farthest from the negative ideal solution. The ideal solution is a hypothetical alternative that maximizes the benefits and minimizes the costs for each criterion, while the negative ideal solution is the opposite[22]. TOPSIS calculates the distance between each alternative and these two ideal solutions, and the alternative with the shortest distance to the ideal solution and the farthest distance from the negative ideal solution is considered the best. The procedure for applying TOPSIS is as follows[23][24]:

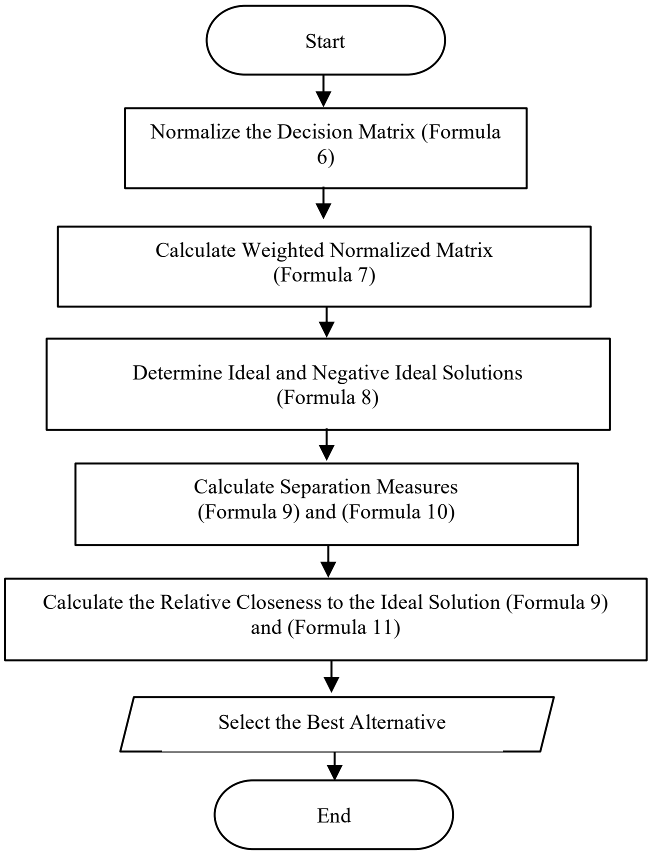

Figure 3. Flowchart of TOPSIS

In the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, the evaluation process begins by normalizing the decision matrix to eliminate differences in scale across criteria. The normalized value for each alternative *i* and criterion *j* is calculated using the formula:

$$rij = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

This step ensures that all performance values are comparable, regardless of their original units. Next, a weighted normalized matrix is generated by multiplying each normalized value r_{ij} with its corresponding criterion weight w_j, as shown in the equation:

$$vij = w_j \cdot r_{ij} \tag{7}$$

Following this, the ideal solution A^+ and negative ideal solution A^- are determined. For benefit criteria, A^+ represents the maximum value across all alternatives, while A^- represents the minimum. The formal representation is:

$$A^+ = (max(v_{ij})), A^- = (min(v_{ij})) \tag{8}$$

These ideal solutions serve as benchmarks for evaluating the proximity of each alternative to the optimal choice. To do this, separation measures are computed. The separation from the ideal solution for alternative i, denoted D_i^+, is calculated as:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2} \tag{9}$$

.

Similarly, the separation measure from the negative ideal solution D_i^- for alternative i is:

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^-)^2} \tag{10}$$

Using these distances, the **relative closeness** of each alternative to the ideal solution is determined through the following formula:

$$C_i^* \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

The value of C_i^* ranges from 0 to 1, where a higher value indicates that the alternative is closer to the ideal solution and, therefore, more preferable. Finally, the alternatives are ranked in descending order based on their relative closeness values to identify the most optimal choice.

3. RESULTS AND DISCUSSION

3.1 Simple Additive Weighting (SAW)

The decision-making problem involved evaluating five alternatives (A1, A2, A3, A4, A5) based on five criteria: Price in $ (C1), Customer Rating (C2), Battery Life (C3), Processor Performance (C4), and Customer Display Quality (C5). Each criterion was assigned a weight to reflect its importance in the decision process. To reflect the relative importance of each criterion in the overall evaluation, specific weights were assigned: 0.30 for Price, 0.25 for Customer Rating, 0.20 for Battery Life, 0.15 for Processor Performance, and 0.10 for Display Quality. These weights ensured a balanced yet prioritized assessment, where cost considerations held the greatest influence, followed by user satisfaction and technical specifications.
Table. 1 shows the performance ratings for each alternative across the five criteria. The alternatives are labeled A1, A2, A3, A4, and A5, and each row represents the performance of these alternatives for the respective criteria. The weights assigned to each criterion are also indicated to reflect the importance of each factor in the final decision-making process.

Table 1. Data Alternative and Weight of Criteria

Alternative	C1	C2	C3	C4	C5
A1	999	4.5	12	8500	8.5
A2	899	4.2	10	8000	8.0
A3	1099	4.8	14	9000	9.0
A4	799	4.0	9	7500	7.5
A5	1199	4.9	15	9200	9.5

The normalization process is carried out to standardize the values of various criteria in the decision matrix. Since C1 is a cost criterion, its normalization follows the inverse proportion method, where the minimum value is divided by the value of each alternative. Meanwhile, C2, C3, C4, and C5 are benefit criteria, which are normalized by dividing the value of each alternative by the maximum value in each column. The results can be seen in table 2 below:

Table 2. Normalization Process

Alternative	C1 (Cost)	C2 (Benefit)	C3 (Benefit)	C4 (Benefit)	C5 (Benefit)
A1	799 / 999 = 0.799	4.5 / 4.9 = 0.918	12 / 15 = 0.800	8500 / 9200 = 0.924	8.5 / 9.5 = 0.895
A2	799 / 899 = 0.889	4.2 / 4.9 = 0.857	10 / 15 = 0.667	8000 / 9200 = 0.870	8.0 / 9.5 = 0.842
A3	799 / 1099 = 0.727	4.8 / 4.9 = 0.980	14 / 15 = 0.933	9000 / 9200 = 0.978	9.0 / 9.5 = 0.947
A4	799 / 799 = 1.000	4.0 / 4.9 = 0.816	9 / 15 = 0.600	7500 / 9200 = 0.815	7.5 / 9.5 = 0.789
A5	799 / 1199 = 0.666	4.9 / 4.9 = 1.000	15 / 15 = 1.000	9200 / 9200 = 1.000	9.5 / 9.5 = 1.000

The weights assigned to each criterion reflect their importance in the decision-making process. Each normalized value is multiplied by the corresponding weight value for each criterion.

For A1 =
= (0.799 × 0.30) + (0.918 × 0.25) + (0.800 × 0.20) + (0.924 × 0.15) + (0.895 × 0.10)
= 0.2397 + 0.2295 + 0.1600 + 0.1386 + 0.0895
= **0.8573**

For A2:
= (0.889 × 0.30) + (0.857 × 0.25) + (0.667 × 0.20) + (0.870 × 0.15) + (0.842 × 0.10)
= 0.2667 + 0.2143 + 0.1334 + 0.1305 + 0.0842
= **0.8289**

For A3:
= (0.727 × 0.30) + (0.980 × 0.25) + (0.933 × 0.20) + (0.978 × 0.15) + (0.947 × 0.10)
= 0.2181 + 0.2450 + 0.1866 + 0.1467 + 0.0947
= **0.8911**

For A4:
= (1.000 × 0.30) + (0.816 × 0.25) + (0.600 × 0.20) + (0.815 × 0.15) + (0.789 × 0.10)
= 0.3000 + 0.2040 + 0.1200 + 0.1223 + 0.0789
= **0.8252**

For A5:
= (0.666 × 0.30) + (1.000 × 0.25) + (1.000 × 0.20) + (1.000 × 0.15) + (1.000 × 0.10)
= 0.1998 + 0.2500 + 0.2000 + 0.1500 + 0.1000
= **0.8998**

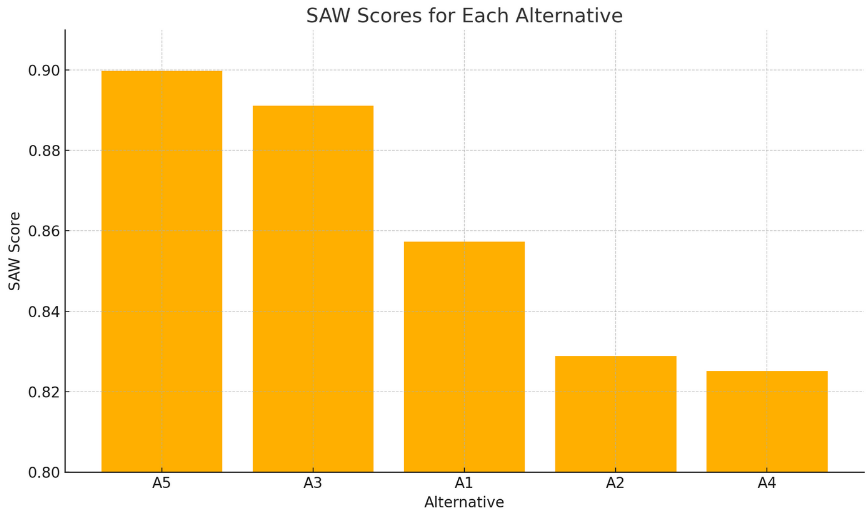

Figure 4. SAW Scores

After calculating the total scores for all alternatives using the Simple Additive Weighting (SAW) method, the alternatives were ranked from highest to lowest based on their scores. Alternative A5 received the highest score of 0.8998, followed closely by A3 with 0.8911, and A1 with 0.8573. A2 and A4 obtained scores of 0.8289 and 0.8252, respectively, placing them in the fourth and fifth positions. Based on this evaluation, and considering both cost and benefit criteria, A5 is identified as the best alternative, demonstrating the most favorable overall performance across all weighted decision factors.

3.2. SMART (Simple Multi-Attribute Rating Technique)

SMART method is a decision-making approach used to evaluate alternatives based on multiple weighted criteria. To calculate the utility value for each alternative and criterion. Use set up in Table 1 and Normalization in Table 2. For the cost (C1) criterion utility function formula (5), and C2-C5 benefit, utility function formula (4):

$C_{max} For\ C1 = 1199\ (maximum\ value\ for\ C1).$
$C_{min} For\ C1 = 799\ (minimum\ value\ for\ C1).$

A1 = $U_{c1}(A1) = \frac{1199-999}{1199-799} \times 100\% = \frac{200}{400} \times 100\% = 50$

A2 = $U_{c1}(A2) = \frac{1199-899}{400} \times 100\% = \frac{300}{400} \times 100\% = 75$

A3 = $U_{c1}(A3) = \frac{1199-1099}{400} \times 100\% = \frac{100}{400} \times 100\% = 25$

.

A4 = $U_{c1}(A4) = \frac{1199-799}{400} \times 100\% = \frac{400}{400} \times 100\% = 100$

A5 = $U_{c1}(A5) = \frac{1199-1199}{400} \times 100\% = \frac{0}{400} \times 100\% = 0$

$C_{max} For\ C2 =$ 4.9 $(maximum\ value\ for\ C2)$.
$C_{min} For\ C2 =$ 4.0 $(minimum\ value\ for\ C2)$.

A1 = $U_{c2}(A1) = \frac{4.9-4.5}{4.9-4.0} \times 100\% = \frac{0.4}{0.9} \times 100\% = 44.44$

A2 = $U_{c2}(A2) = \frac{4.9-4.2}{0.9} \times 100\% = \frac{0.7}{0.9} \times 100\% = 77.78$

A3 = $U_{c2}(A3) = \frac{4.9-4.8}{0.9} \times 100\% = \frac{0.1}{0.9} \times 100\% = 11.11$

A4 = $U_{c2}(A4) = \frac{4.9-4.0}{0.9} \times 100\% = \frac{0.9}{0.9} \times 100\% = 100$

A5 = $U_{c2}(A5) = \frac{4.9-4.9}{0.9} \times 100\% = \frac{0}{0.9} \times 100\% = 0$

The same normalization process applied to C2 was also carried out for C3, C4, and C5. The results of these calculations are summarized and presented in Table 3 below:

Table 3. Utility Values for C1 to C5

Alternative	C1	C2	C3	C4	C5
A1	50	44.44	50	41.18	50
A2	75	77.78	83.33	70.59	75
A3	25	11.11	16.67	11.67	25
A4	100	100	100	100	100
A5	0	0	0	0	0

Next, multiply the utility values for each alternative by the corresponding weights for the criteria.

For A1:
= (50.00 × 0.30) + (44.44 × 0.25) + (50.00 × 0.20) + (41.18 × 0.15) + (50.00 × 0.10)
= 15.00 + 11.11 + 10.00 + 6.18 + 5.00
= 47.29

For A2:
= (75.00 × 0.30) + (77.78 × 0.25) + (83.33 × 0.20) + (70.59 × 0.15) + (75.00 × 0.10)
= 22.50 + 19.44 + 16.67 + 10.59 + 7.50
= 76.70

For A3:
= (25.00 × 0.30) + (11.11 × 0.25) + (16.67 × 0.20) + (11.76 × 0.15) + (25.00 × 0.10)
= 7.50 + 2.78 + 3.33 + 1.76 + 2.50
= 17.87

For A4:
= (100.00 × 0.30) + (100.00 × 0.25) + (100.00 × 0.20) + (100.00 × 0.15) + (100.00 × 0.10)
= 30.00 + 25.00 + 20.00 + 15.00 + 10.00
= 100

For A5:
= (0.00 × 0.30) + (0.00 × 0.25) + (0.00 × 0.20) + (0.00 × 0.15) + (0.00 × 0.10)
= 0.00 + 0.00 + 0.00 + 0.00 + 0.00
= 0.00

Based on the **SMART (Simple Multi-Attribute Rating Technique)** method with cost and benefit criteria, **Alternative A5** is best alternative with **0**. In the SMART (Simple Multi-Attribute Rating Technique) method, particularly when evaluating cost criteria, alternatives with lower values are considered more favorable. This is because lower values in cost-related attributes indicate reduced expenses or less undesirable outcomes, aligning with the objective of minimizing costs in decision-making processes[25].

3.2 TOPSIS

Before determining the optimal alternative using the TOPSIS method, it is essential to first standardize the varying scales of the decision matrix. By normalizing the decision matrix, we can accurately assess the performance of each alternative relative to the criteria, which forms the foundation for the subsequent calculations in the TOPSIS procedure:

Normalization of C1 (Cost):

Norm of C1 $=$

$$\sqrt{999^2 + 899^2 + 1099^2 + 799^2 + 1199^2 = 998001 + 808201 + 1207801 + 638401 + 1437601 = 5094005}$$

= 2257.53

Normalized values:

$$A1 = \frac{999}{2257.53} = 0.4426$$

$$A2 = \frac{899}{2257.53} = 0.3984$$

$$A3 = \frac{1099}{2257.53} = 0.4869$$

$$A4 = \frac{799}{2257.53} = 0.3541$$

$$A5 = \frac{1199}{2257.53} = 0.5313$$

Complete the normalization for C2 to C5 with the same steps as the normalization of C1, after normalization, the Normalized Performance Matrix looks like table 3.

Table 3. Normalized Performance Matrix

Alternative	C1	C2	C3	C4	C5
A1	999/2257.53 = 0.4426	4.5/10.05 = 0.4483	12/27.32 = 0.4394	8500/18949.06 = 0.4486	8.5/19.07 = 0.4458
A2	899/2257.53 = 0.3984	4.2/10.05 = 0.4182	10/27.32 = 0.3660	8000/18949.06 = 0.4223	8.0/19.07 = 0.4195
A3	1099/2257.53 = 0.4869	4.8/10.05 = 0.4776	14/27.32 = 0.5124	9000/18949.06 = 0.4751	9.0/19.07 = 0.4720
A4	799/2257.53 = 0.3541	4.0/10.05 = 0.3980	9/27.32 = 0.3295	7500/18949.06 = 0.3958	7.5/19.07 = 0.3932
A5	1199/2257.53 = 0.5313	4.9/10.05 = 0.4878	15/27.32 = 0.5492	9200/18949.06 = 0.4854	9.5/19.07 = 0.4983

After obtaining the normalized values for each criterion, the next step in the TOPSIS method is to multiply each normalized value by its corresponding criterion weight. This process ensures that the relative importance of each criterion is accurately reflected in the evaluation of each alternative. By applying these weights, the decision matrix becomes a weighted normalized decision matrix, where each value represents the adjusted performance of an alternative with respect to a specific criterion. The results of this calculation are summarized and presented in Table 4.

Table 4. Weighted Normalized Matrix

Alternative	C1	C2	C3	C4	C5
A1	0.1328	0.1121	0.0879	0.0673	0.0446
A2	0.1195	0.1046	0.0732	0.0633	0.0419
A3	0.1461	0.1194	0.1025	0.0713	0.0472
A4	0.1062	0.0995	0.0659	0.0594	0.0393
A5	0.1594	0.1219	0.1098	0.0728	0.0498

In the next step of the TOPSIS method, it is necessary to identify both the ideal (A^+) and negative ideal (A^-) solutions for each criterion (Formula 8). For cost criteria such as C1, a lower value is preferred, making the minimum value the ideal solution and the maximum value the negative ideal. Conversely, for benefit criteria (C2 through C5), higher values are more desirable, so the maximum value represents the ideal solution and the minimum value represents the negative ideal. Euclidean distance is preferred over Manhattan distance in this context because it more accurately captures the geometric closeness between alternatives in a multidimensional space, allowing for a more precise assessment of their overall similarity to the ideal solution. The ideal and negative ideal solutions for each criterion are summarized in Table 5:

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Table 5. The ideal and negative ideal solutions for each criterion

Criterion	Ideal (A+)	Negative Ideal (A-)
C1	0.1062	0.1594
C2	0.1219	0.0995
C3	0.1098	0.0659
C4	0.0728	0.0594
C5	0.0498	0.0393

Next, the relative closeness of each alternative to the ideal solution, denoted as Ci^+, is calculated using Formula 9 and 10. This step involves determining the ratio of the distance from the negative ideal solution to the sum of the distances from both the ideal and negative ideal solutions. For brevity, here is the calculation for A1 (repeat similarly for others):

A1 and A+:

$= \sqrt{[(0.1328-0.1062)^2 + (0.1121-0.1219)^2 + (0.0879-0.1098)^2 + (0.0673-0.0728)^2 + (0.0446-0.0498)^2]}$

$= \sqrt{[(0.0266)^2 + (-0.0098)^2 + (-0.0219)^2 + (-0.0055)^2 + (-0.0052)^2]}$

$= \sqrt{[0.000707 + 0.000096 + 0.000480 + 0.000030 + 0.000027]}$

$= \sqrt{[0.001340]} = \mathbf{0.0366}$

A1 and A-:

$= \sqrt{[(0.1328-0.1594)^2 + (0.1121-0.0995)^2 + (0.0879-0.0659)^2 + (0.0673-0.0594)^2 + (0.0446-0.0393)^2]}$

$= \sqrt{[(-0.0266)^2 + (0.0126)^2 + (0.0220)^2 + (0.0079)^2 + (0.0053)^2]}$

$= \sqrt{[0.000707 + 0.000159 + 0.000484 + 0.000062 + 0.000028]}$

$= \sqrt{[0.001440]} = \mathbf{0.0379}$

This calculation is then repeated for all alternatives to ensure a consistent and comprehensive evaluation across the entire set of options. By applying the same process to each alternative and rounding the results as needed, we obtain a clear comparison of their relative closeness values. These calculated values enable us to objectively rank the alternatives, facilitating the selection of the most optimal choice. The complete results of this analysis are presented in Table 6.

Table 6. Distance from A+ and A-

Alternative	D+	D-
A1	0.0366	0.0379
A2	0.0520	0.0214
A3	0.0243	0.0500
A4	0.0726	0.0000
A5	0.0136	0.0647

Next, the relative closeness (C*) of each alternative to the ideal solution is calculated to provide a final ranking (Formula 11). This value represents how close each alternative is to the ideal solution based on the previously computed distances. By analyzing the relative closeness scores, we can identify which alternative most closely aligns with the optimal criteria. The results of these calculations are displayed in Table 7.

Tabel 7. Relative Closeness

Alternative	D+	D-	C*	Rank
A1	0.0366	0.0379	0.508	3
A2	0.0520	0.0214	0.292	4
A3	0.0243	0.0500	0.673	2
A4	0.0726	0.0000	0.000	5
A5	0.0136	0.0647	0.826	1

Based on the **TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)** method with cost and benefit criteria, **Alternative A5** ranks the highest with a total score of **0.826** making it the best alternative.

The results presented below show clear consistency across all SAW, SMART, and TOPSIS methods in recognizing Alternative A5 as the best option. This consistency strengthens the validity of the decision-making process and confirms the robustness of the evaluation. Table 8 below summarizes the final scores obtained by each alternative using the three methods:

Table 8. Final Result

Alternative	SAW	SMART	TOPSIS
A1	0.8573	47.29	0.508
A2	0.8289	76.70	0.292
A3	0.8911	17.87	0.673
A4	0.8252	100	0.000
A5	**0.8998**	**0**	**0.826**

4. CONCLUSION

This study aimed to evaluate the consistency of decision-making across three Decision Support System (DSS) methods: Simple Additive Weighting (SAW), Simple Multi-Attribute Rating Technique (SMART), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The results indicate that despite differences in computational approaches, all three methods consistently identified A1 as the best alternative. The SAW method produced a final score of 0.8998 for A5, the SMART method assigned a value of 0, and the TOPSIS method resulted in a closeness coefficient of 0.826. Although the numerical values differ due to variations in methodological calculations, the consistency in ranking confirms that all three methods lead to the same decision outcome. This finding suggests that decision-makers can apply any of these methods with confidence, knowing that their final choice will remain stable across different DSS techniques. The practical implications of this study are significant for decision-makers across business, engineering, and public administration. The demonstrated consistency among SAW, SMART, and TOPSIS confirms that any of these methods can be used with confidence for multi-criteria decision-making, regardless of their computational differences. SAW is recommended for rapid and straightforward decision-making due to its simplicity and transparency, making it suitable for environments with limited resources or urgent timelines. SMART offers greater flexibility when subjective utility or stakeholder preferences are important, while TOPSIS is best applied in strategic contexts where proximity to an ideal solution is crucial for evaluating alternatives. Ultimately, the choice of method can be guided by the specific needs of the decision-making scenario, such as ease of computation, the importance of subjective input, or the need for nuanced analysis. However, decision-makers should remain aware that criteria weighting and normalization techniques may still influence outcomes. Future research should focus on sensitivity analyses, the integration of hybrid decision support models, and real-world case studies to further strengthen the reliability and applicability of these techniques in complex, dynamic environments.

CONFLICT OF INTEREST STATEMENT

The Authors state no conflict of interest.

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