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A Comparative Study of SAW, WP, and TOPSIS Methods for Gaming Laptop Selection

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ABSTRACT

The increasing demand for high-performance gaming laptops requires a systematic decision-making approach to select the most suitable product. This study compares three Multi-Criteria Decision-Making (MCDM) methods: Simple Additive Weighting (SAW), Weighted Product (WP), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to determine the best gaming laptop. A dataset of six premium laptops was evaluated based on seven criteria, including specifications, portability, and price. Numerical scoring and sensitivity analysis were applied to assess method stability. The results indicate differences in rankings produced by each method, providing insight into their reliability for supporting gaming laptop selection decisions

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INTRODUCTION

Technological development has increased the demand for high-performance laptops, especially for gaming purposes, where speed, graphics, and processing capability are critical. Gaming laptops not only cater to gamers but are also widely used by professionals for tasks requiring intensive computational resources such as graphic design, video editing, and software development (Gill et al., 2024).

Choosing the best gaming laptop is a complex decision-making process due to the variety of specifications, such as processor performance, graphics quality, memory capacity, storage, and price. The diversity of available products often leads to confusion for consumers when determining the most suitable option that meets their preferences and budget constraints (Sabandar, 2023).

Decision Support Systems (DSS) have been widely applied to assist consumers in solving multi-criteria problems such as product selection (Laguna Salvadó et al., 2022). Among the popular Multi-Criteria Decision Making (MCDM) techniques, the Simple Additive Weighting (SAW), Weighted Product (WP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods have demonstrated their effectiveness in various selection and ranking problems (Wang et al., 2024).

The SAW method operates by calculating a weighted sum of normalized criteria, providing a straightforward mechanism for evaluating alternatives (Panjaitan, 2019). The WP method, in contrast, utilizes a multiplicative model, where each criterion value is raised to the power of its assigned weight, allowing for a different sensitivity response in the decision-making process (Nuraini et al., 2022). Meanwhile, the TOPSIS method offers an approach based on determining the geometric distance of alternatives from an ideal and negative ideal solution, providing a balanced evaluation between benefit and cost criteria (Waqas Arshad & Rahmanto, 2024).

Numerous studies have compared the effectiveness of MCDM methods in fields such as supplier selection, resource allocation, and technological product evaluation (Tarnanidis et al., 2025). However, comparative studies that specifically focus on selecting high-end gaming laptops using SAW, WP, and TOPSIS simultaneously remain limited in the literature.

This study aims to fill that gap by conducting a comparative analysis of these three MCDM techniques to rank and select the best gaming laptop alternatives based on technical specifications and price. Furthermore, this research incorporates a sensitivity analysis to assess how variations in criteria weights influence the final ranking results, thereby ensuring robustness and reliability in the decision-making process (Hassan et al., 2023).

The expected contribution of this study is to provide insights for both consumers and manufacturers on how structured decision-support tools can facilitate optimal product selection in the gaming laptop market, enhancing satisfaction and minimizing the risk of suboptimal purchases (Jansen et al., 2023).

LITERATURE REVIEW

Simple Additive Weighting (SAW) Method

The Simple Additive Weighting (SAW) method is one of the simplest and most widely used techniques in multi-criteria decision-making (MCDM). This method operates by summing the normalized values of each alternative, which are weighted according to the importance of each criterion (Taherdoost, 2023). The steps involved in the SAW method are as follows:

1. Identify the alternatives to be evaluated.
2. Define the evaluation criteria, classifying them as either benefit criteria or cost criteria.
3. Convert the alternative values into suitability scores for each criterion.
4. Assign the weight for each criterion.
5. Construct a decision matrix based on the suitability scores of each alternative with respect to each criterion.
6. Normalize the decision matrix using the following formulas:

$$r_{ij} = \begin{cases} \dfrac{X_{ij}}{\max(X_{ij})}, if\ benefit \\ \dfrac{X_{ij}}{\min(X_{ij})}, if\ cost \end{cases}$$

Description:
r_{ij} : normalized criteria rating value
X_{ij} : atribute value of each criterion
$\max(X_{ij})$: maximum value of criterion W for each alternative
$\min(X_{ij})$: minimum value of criterion W for each alternative

1. Create a normalized matrix (R) based on the results of the normalized performance ratings, using the formula:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots r_{1j} \\ r_{i1} & r_{i2} & \dots r_{ij} \end{bmatrix}$$

2. Calculate the final score (Vi) for each alternative by summing the product of the normalized values and their corresponding weights:

$$V_i = \Sigma_{j=1}^{n} W_j \, r_{ij}$$

Rank the alternatives based on their Vi values, from the highest to the lowest score.

Weighted Product (WP) Method

The Weighted Product (WP) method is an MCDM approach that differs The Weighted Product (WP) method is a popular technique in multi-criteria decision-making (MCDM) that employs a multiplicative model to aggregate the performance scores of each alternative. This method is suitable for handling both benefit and cost criteria, utilizing exponents to reflect the relative importance of each criterion. WP emphasizes proportional comparison among alternatives, making it useful for decision problems where the scale differences between criteria are significant. (Rizal et al., 2021)

The Steps Involved in the WP Method are as Follows:

1. **Identify Alternatives**
   Determine the set of alternatives to be evaluated.
2. Define Evaluation Criteria
   Establish the relevant evaluation criteria, classifying them as either benefit (where higher values are preferred) or cost (where lower values are preferred).
3. Transform Qualitative Data
   Convert qualitative specifications into quantitative scores to ensure uniform interpretation across alternatives.
4. Assign Weights
   Determine the relative importance (weight) of each criterion, with all weights normalized so that their sum equals 1:

$$\boldsymbol{w_j'} = \frac{\boldsymbol{w_j}}{\boldsymbol{\Sigma w_j}}$$

Where:
$\boldsymbol{w_j'}$ = normalized weight of criterion *j*
$\boldsymbol{w_j}$ = original assigned weight of criterion *j*

1. Calculate Preference Score (S_i)
   The overall score for each alternative is calculated using a multiplicative model, where benefit criteria use positive exponents and cost criteria use negative exponents:

$$S_i = \prod_{j=1}^{n} (x_{ij})^{w_j'}$$

Where:
S_i = preference score for alternative i
x_{ij} = performance score of alternative iii on criterion *j*
w_j' = normalized weight for criterion *j*

2. Normalize Preference Values (V_i)
   Normalize the preference scores to facilitate comparison across alternatives:

$$\boldsymbol{V_i} = \frac{\boldsymbol{S_i}}{\boldsymbol{\Sigma S_i}}$$

3. Rank the Alternatives
   Rank the alternatives based on their normalized preference values ViV_iVi , with higher scores indicating more favorable options.

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

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a systematic and widely adopted MCDM approach that evaluates alternatives based on their geometric distance from an ideal solution. The ideal solution represents the hypothetical best performance on all criteria, while the negative ideal solution represents the worst performance (Setiawan & Indrawan, 2023).

The Steps Involved in the TOPSIS Method are as follows:

1. Define Alternatives and Criteria
   Identify the set of alternatives and determine the evaluation criteria, distinguishing between benefit and cost attributes.
2. Construct Decision Matrix
   Build a decision matrix containing the performance scores of each alternative with respect to each criterion.
3. Normalize the Decision Matrix
   Normalize the matrix to eliminate scale differences using the following formula:
   $$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$
   Where:
   r_{ij} = normalized score of alternative i on criterion j
   x_{ij} = original score of alternative i on criterion j
4. Apply Weighting to Normalized Matrix
   Multiply each normalized score by the corresponding criterion weight to obtain the weighted normalized matrix:
   $$\mathbf{Y_{ij} = r_{ij} \times w_j}$$
5. Determine Ideal and Negative Ideal Solutions
   Identify the ideal positive solution ($\mathbf{A^+}$) and the negative ideal solution ($\mathbf{A^-}$) as follows:
   $$\mathbf{A^+} = \{\mathbf{max(Y_{ij})\ if\ benefit, min(Y_{ij})\ if\ cost}\}$$
   $$\mathbf{A^-} = \{\mathbf{min(Y_{ij})\ if\ benefit, max(Y_{ij})\ if\ cost}\}$$
6. Calculate Distance to Ideal Solutions
   Compute the Euclidean distance of each alternative to the ideal and negative ideal solutions:
   $$\mathbf{D_i^+} = \sqrt{\sum_{j=1}^{n} (\mathbf{Y_{ij}} - \mathbf{Y_j^+})^2}$$
   $$\mathbf{D_i^-} = \sqrt{\sum_{j=1}^{n} (\mathbf{Y_{ij}} - \mathbf{Y_j^-})^2}$$
7. Calculate Relative Closeness to Ideal Solution
   Determine the preference score for each alternative, representing its closeness to the ideal solution:
   $$V_i = \frac{D_j^-}{D_j^- + D_j^+}$$
8. Rank the Alternatives
   Rank the alternatives based on V_i, with higher scores indicating better performance relative to the ideal solution.

Sensitivity Test

Sensitivity testing is a procedure used to evaluate how sensitive a decision-making method is to variations in input parameters for a particular case. This analysis aims to compare multiple methods by examining their respective sensitivity levels. A method is considered preferable if slight changes in the input such as the ranking of alternatives cause more noticeable variations in its output compared to other methods (Syifa et al., 2023).

The general procedure for conducting sensitivity analysis includes the following steps:

1. Establish the initial weights for all evaluation criteria.
2. Modify the weight of a specific criterion within a range of 1 to 2 units, while keeping the other criterion weights unchanged.
3. Recalculate the weights by normalizing them so that their total remains equal to 1.
4. Implement the updated normalized weights in the decision-making methods being compared.
5. Assess the percentage change in alternative rankings produced by each method, by comparing the results with the initial baseline when all weights were unchanged.

This research uses the method illustrated in the following figure 1.

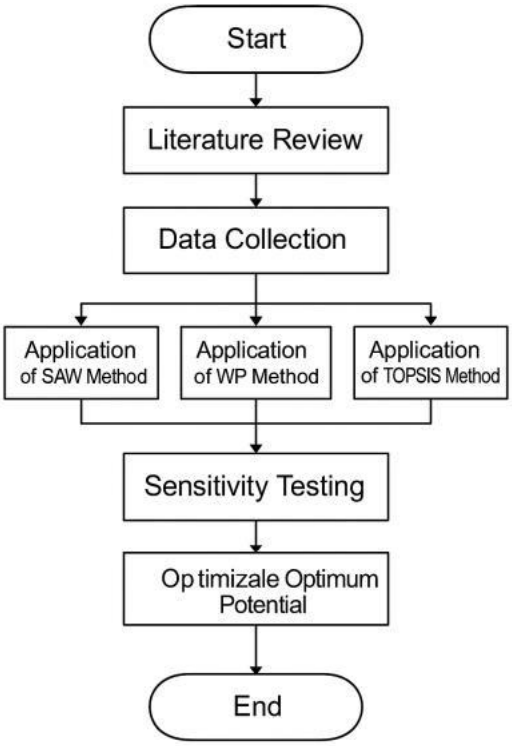

Figure 1. Research Method

METHODOLOGY

Dataset Source

This research utilizes a publicly available dataset from the Kaggle platform, accessible via: https://www.kaggle.com/datasets/muhammetvarl/laptop-price. The dataset consists of **1,320** laptop records, including technical specifications and corresponding prices in Euros (€). The dataset was chosen due to its completeness, structured attributes, and relevance to decision-making models for evaluating laptop performance and pricing.

Data Selection

To conduct a focused and relevant analysis, this study selected the **top six laptops with the highest prices** from the dataset. These laptops fall under the high-end category, which generally offers premium specifications and optimal performance.

Data Overview

Table 1. Dataset

laptop_ID	**Company**	**Product**	**TypeName**	**Inches**	**ScreenResolution**
200	Razer	Blade Pro	Gaming	17,3	4K Ultra HD / Touchscreen 3840x2160
243	Asus	ROG G703VI-E5062T	Gaming	17,3	Full HD 1920x1080
731	Dell	Alienware 17	Gaming	17,3	4K Ultra HD 3840x2160
789	Dell	Alienware 17	Gaming	17,3	IPS Panel Full HD 1920x1080
839	Razer	Blade Pro	Gaming	17,3	4K Ultra HD / Touchscreen 3840x2160
1081	Asus	ROG G701VO	Gaming	17,3	IPS Panel Full HD 1920x1080

Cpu	Ram	Memory	Gpu	OpSys	Weight	Price_euros
Intel Core i7 7820HK 2.9GHz	32GB	1TB SSD	Nvidia GeForce GTX 1080	Windows 10	3.49kg	6099
Intel Core i7 7820HK 2.9GHz	32GB	512GB SSD + 1TB HDD	Nvidia GeForce GTX 1080	Windows 10	4.7kg	3890

Intel Core i7 7700HQ 2.8GHz	32GB	1TB SSD + 1TB HDD	Nvidia GeForce GTX 1070	Windows 10	4.36kg	3659,4
Intel Core i7 7700HQ 2.8GHz	32GB	1TB SSD + 1TB HDD	Nvidia GeForce GTX 1070M	Windows 10	4.42kg	3588,8
Intel Core i7 7820HK 2.9GHz	32GB	512GB SSD	Nvidia GeForce GTX 1080	Windows 10	3.49kg	5499
Intel Core i7 6820HK 2.7GHz	64GB	1TB SSD	Nvidia GeForce GTX 980	Windows 10	3.58kg	3975

RESULTS AND DISCUSSION

This section presents the evaluation of six high-end laptops using three MCDM methods: **Weighted Product (WP)**, **Simple Additive Weighting (SAW)**, and **TOPSIS**. The decision-making process incorporates multiple technical specifications converted into measurable criteria with defined benefit and cost types.

Alternatives

The six alternatives analyzed in this study are shown in **Table 2**, which provides an overview of each product along with its specifications.

Table 2. List of Alternatives

No	Name Product	Alternative
1	Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	A1
2	Asus ROG G703VI-E5062T	A2
3	Dell Alienware 17 (4K Ultra HD 3840x2160)	A3
4	Dell Alienware 17 (IPS Panel Full HD 1920x1080)	A4
5	Razer Blade Pro (32 RAM 512 GB SSD)	A5
6	Asus ROG G701VO	A6

Criteria and Weight Distribution

The evaluation employs **seven criteria**, classified as either **benefit** (where higher values are preferable) or **cost** (where lower values are preferable). The weight distribution, shown in **Table 3**, reflects the relative importance of each criterion.

Table 3. Criteria, Type, and Assigned Weights

ID Criteria	Criteria Name	Type of Criteria	Weight
C1	ScreenResolution	Benefit	1
C2	Cpu	Benefit	1
C3	Ram	Benefit	1
C4	Memory	Benefit	2
C5	Gpu	Benefit	2

C6	Weight	Cost	1
C7	Price_euros	Cost	2

A total weight of **10** is distributed across all criteria to balance the impact of technical features, portability, and price considerations.

Scoring Criteria Mapping

For objective assessment, qualitative attributes such as screen resolution, CPU type, and GPU model are transformed into numerical scores based on defined ranges. This scoring system is presented in **Table 4**, ensuring uniform interpretation of specifications across all alternatives.

Table 4. Scoring Range for Each Criterion

Criteria Name	**Score Range**	
	Range	**Score**
ScreenResolution	4K Ultra HD / Touchscreen 3840x2160	4
	4K Ultra HD 3840x2160	3
	IPS Panel Full HD 1920x1080	2
	Full HD 1920x1080	1
Cpu	Intel Core i7 7820HK 2.9GHz	4
	Intel Core i7 7700HQ 2.8GHz	3
	Intel Core i7 6820HK 2.7GHz	2
	< Intel Core i7 6820HK 2.7GHz	1
Ram	64 GB	4
	32 GB	3
	16 GB	2
	< 16 GB	1
Memory	1TB SSD + 1TB HDD	4
	1TB SSD	3
	512GB SSD + 1TB HDD	2
	512GB SSD	1
Gpu	Nvidia GeForce GTX 1080	4
	Nvidia GeForce GTX 1070	3
	Nvidia GeForce GTX 1070M	2
	Nvidia GeForce GTX 980	1
Weight	< 3.5 kg	4
	3.5 kg - < 4 kg	3
	4 kg - < 4.5 kg	2
	>= 4.5 kg	1
Price_euros	< 3700	4
	3700 - < 4000	3
	4000 - < 5500	2
	>= 5500	1

Alternatives Data Conversion

Based on the scoring criteria, the alternatives' specifications are converted into numerical ratings, as shown in **Table 5**. This facilitates a structured comparison across different laptop models.

Table 5. Suitability Ratings for Each Alternative

No	Name Product	Range						
		C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
1	Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	4	4	3	3	4	4	1
2	Asus ROG G703VI-E5062T	1	4	3	2	4	1	3
3	Dell Alienware 17 (4K Ultra HD 3840x2160)	3	3	3	4	3	2	4
4	Dell Alienware 17 (IPS Panel Full HD 1920x1080)	2	3	3	4	2	2	4
5	Razer Blade Pro (32 RAM 512 GB SSD)	4	4	3	1	4	4	2
6	Asus ROG G701VO	3	2	4	3	1	3	3

SAW Calculation
Normalization

$$R_{11} = \frac{4}{4} = 1$$
$$R_{21} = \frac{1}{4} = 0{,}25$$
$$R_{31} = \frac{3}{4} = 0{,}75$$
$$R_{41} = \frac{2}{4} = 0{,}5$$
$$R_{51} = \frac{4}{4} = 1$$
$$R_{61} = \frac{3}{4} = 0{,}75$$

Result of Normalization

$$\begin{bmatrix} 1 & 1 & 0.75 & 0.75 & 1.00 & 0.25 & 1.00 \\ 0.25 & 1 & 0.75 & 0.50 & 1 & 1 & 0.33 \\ 0.75 & 0.75 & 0.75 & 1 & 0.75 & 0.50 & 0.25 \\ 0.50 & 0.75 & 0.75 & 1 & 0.50 & 0.50 & 0.25 \\ 1 & 1 & 0.75 & 0.25 & 1 & 0.25 & 0.50 \\ 0.75 & 0.50 & 1 & 0.75 & 0.25 & 0.33 & 0.33 \end{bmatrix}$$

Determining the preference value for each alternative Here are the calculations:

V1 = (1 × 1) + (1 × 1) + (1 × 0,75) + (2 × 0,75) + (2 × 1) + (1 × 0,25) + (2 × 1) = 8,5
V2 = (1 × 0,75) + (1 × 0,75) + (1 × 0,75) + (2 × 1) + (2 × 0,75) + (1 × 0,5) + (2 × 0,25) = 6,75
V3 = (1 × 0,25) + (1 × 1) + (1 × 0,75) + (2 × 0,5) + (2 × 1) + (1 × 1) + (2 × 0,333) = 6,6667
V4 = (1 × 1) + (1 × 1) + (1 × 0,75) + (2 × 0,25) + (2 × 1) + (1 × 0,25) + (2 × 0,5) = 6,5

V5 = (1 × 0,5) + (1 × 0,75) + (1 × 0,75) + (2 × 1) + (2 × 0,5) + (1 × 0,5) + (2 × 0,25) = 6
V6 = (1 × 0,75) + (1 × 0,5) + (1 × 1) + (2 × 0,75) + (2 × 0,25) + (1 × 0,333) + (2 × 0,333) = 5,25

Based on the analysis using the Simple Additive Weighting (SAW) method, it can be concluded that the best alternative for selecting a high-performance laptop is the **Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)**, which achieved the highest preference score of **8.5**. This indicates that the product offers the best overall performance in meeting the predefined evaluation criteria compared to other alternatives.

Table 6. Rank SAW Calculation

Alternative	Preference Value (V)	Rank
Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	8.5	1
Asus ROG G703VI-E5062T	6.75	2
Dell Alienware 17 (4K Ultra HD 3840x2160)	66.667	3
Dell Alienware 17 (IPS Panel Full HD 1920x1080)	6.5	4
Razer Blade Pro (32 GB RAM 512 GB SSD)	6	5
Asus ROG G701VO	5.25	6

WP Calculation
Normalization

$$w_j' = \frac{w_j}{\Sigma w_j}$$

Total Weight Calculation = 1 + 1 + 1 + 2 + 2 + 1 + 2 = 10

Normalized Weights:

$w_{C1}' = 1 / 10 = 0.1000$
$w_{C2}' = 1 / 10 = 0.1000$
$w_{C3}' = 1 / 10 = 0.1000$
$w_{C4}' = 2 / 10 = 0.2000$
$w_{C5}' = 2 / 10 = 0.2000$
$w_{C6}' = 1 / 10 = 0.1000$
$w_{C7}' = 2 / 10 = 0.2000$

Next, calculations are performed on the value of S for each alternative. In determining the value of S, if the criterion is profit, positive exponentiation is used, while for cost criteria, negative exponentiation will be used. The following are the calculations:

$S_1 = (4)^{0.1000} \times (4)^{0.1000} \times (3)^{0.1000} \times (3)^{0.2000} \times (4)^{0.2000} \times (4)^{-0.1000} \times (1)^{-0.2000}$

S1 = 2.107436

$S_2 = (1)^{0.1000} \times (4)^{0.1000} \times (3)^{0.1000} \times (2)^{0.2000} \times (4)^{0.2000} \times (1)^{-0.1000} \times (3)^{-0.2000}$

S2 = 1.559954

$S_3 = (3)^{0.1000} \times (3)^{0.1000} \times (3)^{0.1000} \times (4)^{0.2000} \times (3)^{0.2000} \times (2)^{-0.1000} \times (4)^{-0.2000}$

S3 = 1.616061

$S_4 = (2)^{0.1000} \times (3)^{0.1000} \times (3)^{0.1000} \times (4)^{0.2000} \times (2)^{0.2000} \times (2)^{-0.1000} \times (4)^{-0.2000}$

S4 = 1.430969

$S_5 = (4)^{0.1000} \times (4)^{0.1000} \times (3)^{0.1000} \times (1)^{0.2000} \times (4)^{0.2000} \times (4)^{-0.1000} \times (2)^{-0.2000}$

S5 = 1.472733

$S_6 = (3)^{0.1000} \times (2)^{0.1000} \times (4)^{0.1000} \times (3)^{0.2000} \times (1)^{0.2000} \times (3)^{-0.1000} \times (3)^{-0.2000}$

S6 = 1.231144

ΣS = 9.418298

Calculation of Preference Values (V)

$$\boldsymbol{V_i = \frac{S_i}{\Sigma S_i}}$$

Preference Values:

V1 = 2.107436 / 9.418298 = 0.223759749
V3 = 1.616061 / 9.418298 = 0.171587331
V2 = 1.559954 / 9.418298 = 0.165630176
V5 = 1.472733 / 9.418298 = 0.156369380
V4 = 1.430969 / 9.418298 = 0.151935004
V6 = 1.231144 / 9.418298 = 0.130718360

The results clearly demonstrate that the **Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)** is the most suitable laptop according to the defined multi-criteria decision-making framework, achieving the highest preference value of **0.223759749**.

Table 7. Rank WP Calculation

Alternative	Preference Value (V)	Rank
Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	0.223759749	1
Dell Alienware 17 (4K Ultra HD 3840x2160)	0.171587331	2
Asus ROG G703VI-E5062T	0.165630176	3
Razer Blade Pro (32 GB RAM 512 GB SSD)	0.156369380	4
Dell Alienware 17 (IPS Panel Full HD 1920x1080)	0.151935004	5
Asus ROG G701VO	0.130718360	6

TOPSIS Calculation
Normalization Matrix

$$\boldsymbol{r_{ij} = \frac{x_{ij}}{\sqrt{\Sigma_{i=1}^{m} x_{ij}^2}}}$$

$$r_1C1 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$

$$r_1C2 = \frac{0.47809144373376}{\sqrt{1.0000}} = \frac{0.47809144373376}{1.0000} = 0.4781$$

$$r_1C3 = \frac{0.38411063979869}{\sqrt{1.0000}} = \frac{0.38411063979869}{1.0000} = 0.3841$$

$$r_1C4 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$

$$r_1C5 = \frac{0.50800050800076}{\sqrt{1.0000}} = \frac{0.50800050800076}{1.0000} = 0.5080$$
$$r_1C6 = \frac{0.56568542494924}{\sqrt{1.0000}} = \frac{0.56568542494924}{1.0000} = 0.5657$$
$$r_1C7 = \frac{0.13483997249265}{\sqrt{1.0000}} = \frac{0.13483997249265}{1.0000} = 0.1348$$

$$r_2C1 = \frac{0.13483997249265}{\sqrt{1.0000}} = \frac{0.13483997249265}{1.0000} = 0.1348$$
$$r_2C2 = \frac{0.47809144373376}{\sqrt{1.0000}} = \frac{0.47809144373376}{1.0000} = 0.4781$$
$$r_2C3 = \frac{0.38411063979869}{\sqrt{1.0000}} = \frac{0.38411063979869}{1.0000} = 0.3841$$
$$r_2C4 = \frac{0.2696799449853}{\sqrt{1.0000}} = \frac{0.2696799449853}{1.0000} = 0.2697$$
$$r_2C5 = \frac{0.50800050800076}{\sqrt{1.0000}} = \frac{0.50800050800076}{1.0000} = 0.5080$$
$$r_2C6 = \frac{0.14142135623731}{\sqrt{1.0000}} = \frac{0.14142135623731}{1.0000} = 0.1414$$
$$r_2C7 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$

$$r_3C1 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$
$$r_3C2 = \frac{0.35856858280032}{\sqrt{1.0000}} = \frac{0.35856858280032}{1.0000} = 0.3586$$
$$r_3C3 = \frac{0.38411063979869}{\sqrt{1.0000}} = \frac{0.38411063979869}{1.0000} = 0.3841$$
$$r_3C4 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$
$$r_3C5 = \frac{0.38100038100057}{\sqrt{1.0000}} = \frac{0.38100038100057}{1.0000} = 0.3810$$
$$r_3C6 = \frac{0.28284271247462}{\sqrt{1.0000}} = \frac{0.28284271247462}{1.0000} = 0.2828$$
$$r_3C7 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$

$$r_4C1 = \frac{0.2696799449853}{\sqrt{1.0000}} = \frac{0.2696799449853}{1.0000} = 0.2697$$
$$r_4C2 = \frac{0.35856858280032}{\sqrt{1.0000}} = \frac{0.35856858280032}{1.0000} = 0.3586$$
$$r_4C3 = \frac{0.38411063979869}{\sqrt{1.0000}} = \frac{0.38411063979869}{1.0000} = 0.3841$$
$$r_4C4 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$

$$r_4C5 = \frac{0.25400025400038}{\sqrt{1.0000}} = \frac{0.25400025400038}{1.0000} = 0.2540$$
$$r_4C6 = \frac{0.28284271247462}{\sqrt{1.0000}} = \frac{0.28284271247462}{1.0000} = 0.2828$$
$$r_4C7 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$

$$r_5C1 = \frac{0.53935988997059}{\sqrt{1.0000}} = \frac{0.53935988997059}{1.0000} = 0.5394$$
$$r_5C2 = \frac{0.47809144373376}{\sqrt{1.0000}} = \frac{0.47809144373376}{1.0000} = 0.4781$$
$$r_5C3 = \frac{0.38411063979869}{\sqrt{1.0000}} = \frac{0.38411063979869}{1.0000} = 0.3841$$
$$r_5C4 = \frac{0.13483997249265}{\sqrt{1.0000}} = \frac{0.13483997249265}{1.0000} = 0.1348$$
$$r_5C5 = \frac{0.50800050800076}{\sqrt{1.0000}} = \frac{0.50800050800076}{1.0000} = 0.5080$$
$$r_5C6 = \frac{0.56568542494924}{\sqrt{1.0000}} = \frac{0.56568542494924}{1.0000} = 0.5657$$
$$r_5C7 = \frac{0.2696799449853}{\sqrt{1.0000}} = \frac{0.2696799449853}{1.0000} = 0.2697$$

$$r_6C1 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$
$$r_6C2 = \frac{0.23904572186688}{\sqrt{1.0000}} = \frac{0.23904572186688}{1.0000} = 0.2390$$
$$r_6C3 = \frac{0.51214751973158}{\sqrt{1.0000}} = \frac{0.51214751973158}{1.0000} = 0.5121$$
$$r_6C4 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$
$$r_6C5 = \frac{0.12700012700019}{\sqrt{1.0000}} = \frac{0.12700012700019}{1.0000} = 0.1270$$
$$r_6C6 = \frac{0.42426406871193}{\sqrt{1.0000}} = \frac{0.42426406871193}{1.0000} = 0.4243$$
$$r_6C7 = \frac{0.40451991747795}{\sqrt{1.0000}} = \frac{0.40451991747795}{1.0000} = 0.4045$$

Weighted Normalization Matrix

$$\mathbf{Y_{ij} = r_{ij} \times w_j}$$

$$Y_1C1 = 0.5394 \times 1 = 0.5394$$
$$Y_1C2 = 0.4781 \times 1 = 0.4781$$
$$Y_1C3 = 0.3841 \times 1 = 0.3841$$
$$Y_1C4 = 0.4045 \times 2 = 0.8090$$
$$Y_1C5 = 0.5080 \times 2 = 1.0160$$
$$Y_1C6 = 0.5657 \times 1 = 0.5657$$

$$Y_1C7 = 0.1348 \times 2 = 0.2697$$

$$Y_2C1 = 0.1348 \times 1 = 0.1348$$
$$Y_2C2 = 0.4781 \times 1 = 0.4781$$
$$Y_2C3 = 0.3841 \times 1 = 0.3841$$
$$Y_2C4 = 0.2697 \times 2 = 0.5394$$
$$Y_2C5 = 0.5080 \times 2 = 1.0160$$
$$Y_2C6 = 0.1414 \times 1 = 0.1414$$
$$Y_2C7 = 0.4045 \times 2 = 0.8090$$

$$Y_3C1 = 0.4045 \times 1 = 0.4045$$
$$Y_3C2 = 0.3586 \times 1 = 0.3586$$
$$Y_3C3 = 0.3841 \times 1 = 0.3841$$
$$Y_3C4 = 0.5394 \times 2 = 1.0787$$
$$Y_3C5 = 0.3810 \times 2 = 0.7620$$
$$Y_3C6 = 0.2828 \times 1 = 0.2828$$
$$Y_3C7 = 0.5394 \times 2 = 1.0787$$

$$Y_4C1 = 0.2697 \times 1 = 0.2697$$
$$Y_4C2 = 0.3586 \times 1 = 0.3586$$
$$Y_4C3 = 0.3841 \times 1 = 0.3841$$
$$Y_4C4 = 0.5394 \times 2 = 1.0787$$
$$Y_4C5 = 0.2540 \times 2 = 0.5080$$
$$Y_4C6 = 0.2828 \times 1 = 0.2828$$
$$Y_4C7 = 0.5394 \times 2 = 1.0787$$

$$Y_5C1 = 0.5394 \times 1 = 0.5394$$
$$Y_5C2 = 0.4781 \times 1 = 0.4781$$
$$Y_5C3 = 0.3841 \times 1 = 0.3841$$
$$Y_5C4 = 0.1348 \times 2 = 0.2697$$
$$Y_5C5 = 0.5080 \times 2 = 1.0160$$
$$Y_5C6 = 0.5657 \times 1 = 0.5657$$
$$Y_5C7 = 0.2697 \times 2 = 0.5394$$

$$Y_6C1 = 0.4045 \times 1 = 0.4045$$
$$Y_6C2 = 0.2390 \times 1 = 0.2390$$
$$Y_6C3 = 0.5121 \times 1 = 0.5121$$
$$Y_6C4 = 0.4045 \times 2 = 0.8090$$
$$Y_6C5 = 0.1270 \times 2 = 0.2540$$
$$Y_6C6 = 0.4243 \times 1 = 0.4243$$
$$Y_6C7 = 0.4045 \times 2 = 0.8090$$

Ideal Solutions Positive and Negative

$$\mathbf{A^+ = \{max(Y_{ij})\ if\ benefit, min(Y_{ij})\ if\ cost\}}$$

$$\mathbf{A^- = \{min(Y_{ij})\ if\ benefit, max(Y_{ij})\ if\ cost\}}$$

Table 8. Positive and negative ideal solution

Criteria	A^+ (Ideal Positive)	A^- (Ideal Negative)
C1	0.5394	0.1348
C2	0.4781	0.2390
C3	0.5121	0.3841
C4	10.787	0.2697
C5	10.160	0.2540
C6	0.1414	0.5657
C7	0.2697	10.787

Distance to Positive and Negative Ideal Solution

$$\mathbf{D_i^+} = \sqrt{\sum_{j=1}^{n} (\mathbf{Y_{ij}} - \mathbf{Y_j^+})^2}$$

$$\mathbf{D_i^-} = \sqrt{\sum_{j=1}^{n} (\mathbf{Y_{ij}} - \mathbf{Y_j^-})^2}$$

$$D^+ = \sqrt{0.2691} = 0.5188$$
$$D^- = \sqrt{1.7469} = 1.3217$$

$$D^+ = \sqrt{0.7618} = 0.8728$$
$$D^- = \sqrt{0.9632} = 0.9814$$

$$D^+ = \sqrt{0.7879} = 0.8877$$
$$D^- = \sqrt{1.0796} = 1.0390$$

$$D^+ = \sqrt{1.0360} = 1.0178$$
$$D^- = \sqrt{0.8315} = 0.9119$$

$$D^+ = \sqrt{0.9237} = 0.9611$$
$$D^- = \sqrt{1.0923} = 1.0451$$

$$D^+ = \sqrt{1.0996} = 1.0486$$
$$D^- = \sqrt{0.4728} = 0.6876$$

Table 9. Positive and negative ideal solution

Alternative	Distance to $A^+(D^+)$	Distance to $A^-(D^-)$
Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	0.5188	1.3217
Asus ROG G703VI-E5062T	0.8728	0.9814
Dell Alienware 17 (4K Ultra HD 3840x2160)	0.8877	1.0390

Alternative	Distance to $A^{+}(D^{+})$	Distance to $A^{-}(D^{-})$
Dell Alienware 17 (IPS Panel Full HD 1920x1080)	1.0178	0.9119
Razer Blade Pro (32 RAM 512 GB SSD)	0.9611	1.0451
Asus ROG G701VO	1.0486	0.6876

Preference Value

$$V_i = \frac{D_j^-}{D_j^- + D_j^+}$$

$$V_1 = \frac{1.3217}{0.5188 + 1.3217} = 0.7181$$

$$V_2 = \frac{0.9814}{0.8728 + 0.9814} = 0.5293$$

$$V_3 = \frac{1.0390}{0.8877 + 1.0390} = 0.5393$$

$$V_4 = \frac{0.9119}{1.0178 + 0.9119} = 0.4725$$

$$V_5 = \frac{1.0451}{0.9611 + 1.0451} = 0.5210$$

$$V_6 = \frac{0.6876}{1.0486 + 0.6876} = 0.3960$$

Table 10. Preference Value

Alternative	D^{+}	D^{-}	V_i
Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	0.5188	1.3217	0.7181
Asus ROG G703VI-E5062T	0.8728	0.9814	0.5293
Dell Alienware 17 (4K Ultra HD 3840x2160)	0.8877	1.0390	0.5393
Dell Alienware 17 (IPS Panel Full HD 1920x1080)	1.0178	0.9119	0.4725
Razer Blade Pro (32 RAM 512 GB SSD)	0.9611	1.0451	0.5210
Asus ROG G701VO	1.0486	0.6876	0.3960

Table 11. Rangking TOPSIS

Ranking	Alternative	Nilai Preferensi (V_i)
1	Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	0.7181
2	Dell Alienware 17 (4K Ultra HD 3840x2160)	0.5393
3	Asus ROG G703VI-E5062T	0.5293
4	Razer Blade Pro (32 RAM 512 GB SSD)	0.5210
5	Dell Alienware 17 (IPS Panel Full HD 1920x1080)	0.4725
6	Asus ROG G701VO	0.3960

The results demonstrate that **Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)** achieved the highest preference value of **0.7181**, making it the best-performing alternative among the available options. This indicates that this alternative is closest to the ideal solution in terms of the decision criteria considered.

Sensivity Test

Table 12. Results of SAW, WP, TOPSIS Methods

Name Product	Alternative	SAW	WP	TOPSIS
Razer Blade Pro Gaming (32 GB RAM 1 TB SSD)	A1	8.5	0.223759749	0.7181
Asus ROG G703VI-E5062T	A2	6.75	0.165630176	0.5293
Dell Alienware 17 (4K Ultra HD 3840x2160)	A3	66.667	0.171587331	0.5393
Dell Alienware 17 (IPS Panel Full HD 1920x1080)	A4	6.5	0.151935004	0.4725
Razer Blade Pro (32 RAM 512 GB SSD)	A5	6	0.156369380	0.5210
Asus ROG G701VO	A6	5.25	0.130718360	0.3960

This study compares the performance of three Multi-Criteria Decision Making (MCDM) methods SAW, WP, and TOPSIS for selecting high-performance laptops. Across all methods, the Razer Blade Pro Gaming (A1) consistently ranked first, while the Asus ROG G701VO (A6) remained the lowest-ranked product. Other alternatives such as the Dell Alienware 17 (A3) and Asus ROG G703VI-E5062T (A2) showed varying positions but remained within the top three across methods.

The SAW method ranked A1 as the best with a preference value of 8.5, while the WP and TOPSIS methods confirmed the same alternative (A1) as superior with preference values of 0.22376 and 0.7181, respectively. The lowest preference values in all three methods were consistently associated with A6, indicating its lower suitability compared to other alternatives.

To assess the stability of the ranking results, a sensitivity analysis was performed by adjusting the weight of each criterion by 0.5 and 1, while keeping other weights constant. This process evaluated how changes in weight influenced the final rankings, with the detailed results of the sensitivity test presented in the following table.

The table below presents the outcomes of the sensitivity analysis for the three decision-making methods:

Table 13. Sensitivity Analysis Results for SAW, WP, and TOPSIS

Criteria Modified	SAW	WP	TOPSIS
ScreenResolution +0,5	0,86	0,23	0,73
ScreenResolution +1	0,86	0,23	0,74
Cpu +0,5	0,86	0,22	0,72
Cpu +1	0,86	0,22	0,73

Ram +0,5	0,85	0,22	0,71
Ram +1	0,84	0,22	0,70
Memory +0,5	0,85	0,22	0,71
Memory +1	0,84	0,22	0,71
Gpu +0,5	0,86	0,22	0,74
Gpu +1	0,86	0,22	0,75
Weight +0,5	0,82	0,22	0,65
Weight +1	0,80	0,21	0,60
Price_euros +0,5	0,86	0,23	0,74
Price_euros +1	0,86	0,24	0,76
SUM	11,87	3,12	9,98

The results of the sensitivity analysis demonstrate that the ranking stability of the SAW, WP, and TOPSIS methods varies with changes in the weights of specific criteria. Overall, SAW and TOPSIS show greater robustness to weight fluctuations, particularly for criteria such as Screen Resolution, CPU, GPU, and Price, where minimal variations in ranking scores were observed. Conversely, changes in RAM, Memory, and Weight criteria resulted in more noticeable impacts, especially on the TOPSIS and SAW outcomes. Among the three methods, SAW consistently achieved the highest cumulative sensitivity score (11.87), followed by TOPSIS (9.98) and WP (3.12), indicating that SAW is more responsive to changes in criteria weights but still maintains ranking consistency. These findings confirm the practical reliability of the applied decision-making models while highlighting the importance of carefully considering criteria weighting in multi-criteria decision-making processes.

CONCLUSION AND RECOMMENDATION

This study presents a comparative evaluation of three Multi-Criteria Decision Making (MCDM) methods Simple Additive Weighting (SAW), Weighted Product (WP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) applied to the selection of high-performance laptops. The findings reveal that all three methods consistently ranked the Razer Blade Pro Gaming (A1) as the top-performing alternative, while the Asus ROG G701VO (A6) received the lowest ranking across all evaluation models. Other alternatives, including Dell Alienware 17 (A3) and Asus ROG G703VI-E5062T (A2), showed slight variations but remained within the top three rankings, confirming the robustness of the decision-making outcomes.

Sensitivity analysis was conducted by adjusting individual criterion weights to evaluate the stability of the ranking results. The SAW and TOPSIS methods demonstrated higher robustness to weight changes, particularly for key criteria such as Screen Resolution, CPU, GPU, and Price, where minimal ranking fluctuations were observed. In contrast, criteria such as RAM, Memory, and Weight introduced more noticeable variations, especially affecting the SAW and TOPSIS results.

Among the tested methods, SAW produced the highest cumulative sensitivity score (11.87), followed by TOPSIS (9.98) and WP (3.12), indicating that SAW is the most responsive to weight adjustments while still maintaining ranking consistency. Based on these outcomes, the SAW method can be recommended as a reliable and practical tool for decision-making in scenarios where weight prioritization may evolve.

It is recommended that decision-makers applying these MCDM methods carefully define the criteria and weight distributions, as improper weight assignments can significantly influence the selection process. The integration of sensitivity analysis is also advisable to ensure ranking stability and to validate the robustness of the chosen method in real-world applications.

FUTHER STUDY

While this research provides valuable insights into the application of SAW, WP, and TOPSIS methods for selecting high-performance laptops, several limitations should be acknowledged. First, the study focuses on a specific set of criteria, including Screen Resolution, CPU, RAM, Memory, GPU, Weight, and Price, which may not comprehensively represent all factors influencing consumer preferences or technical performance in diverse usage scenarios.

Additionally, the sensitivity analysis only considered incremental weight adjustments of +0.5 and +1, which may not fully capture more dynamic or extreme changes in decision-making environments. Future research is encouraged to explore a broader range of criteria, including qualitative factors such as brand reputation, durability, and after-sales service, which could further enhance the decision model's comprehensiveness.

Moreover, applying these methods to larger datasets and different product categories could provide a deeper understanding of their generalizability and robustness. Investigating hybrid approaches that combine MCDM techniques or integrate machine learning for automated weighting could also be promising directions to improve decision-making accuracy in complex multi-criteria environments.

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