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Empowering University Students with Cutting-Edge True Wireless Stereo Selection: A Comparative Analysis of Simple Additive Weighting and TOPSIS Algorithms

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Abstract

Currently, there are a lot of Solid-State Drives or SSDs that are running in the market. Each SSD can come with different features and prices from one another. Hence, this can confuse buyers planning to purchase one for their PC or laptop. It also applies to university students who depend on laptops to do college work and run on a limited budget. Any mistake in deciding which SSD to use can be costly. Henceforth, this paper aims to help decide what SSD would be best for an average university student. Two algorithms will determine which SSDs are best for university students to buy. The algorithms used are Simple Additive Weighting and Technique for Order of Preference by Similarity to Ideal Solution. The results of these algorithms are used to show the top three best SSDs for university students. Therefore, university students can make an informed choice based on the results from both algorithms.

A. Introduction

SSDs, or solid-state drives, are storage devices that rely on semiconductor technology, commonly utilizing NAND flash memory to store data permanently [1]. Every flash memory chip consists of a collection of blocks, and each block contains an array of memory cells referred to as pages or sectors [2].

Since SSDs do not have to seek out data mechanically, SSDs deliver faster load times [3]. Additionally, SSDs do not contain any moving parts, making them far more durable [4], they are more energy efficient [5], they are essentially light in mass [6], and they are far more practical compared to HDDs.

SSDs are generally a memory device and, thus, a very important component in any computer. SSDs are important for university students because they run faster than other memory devices. For starters, SSDs boast quicker read and write velocities compared to conventional hard disk drives (HDDs), thereby enabling students to retrieve files and execute programs more swiftly [7]. It plays a role in improving student productivity, as students can work faster and more efficiently, allowing them to save time and focus more on their work. SSDs also last longer and are a more durable memory device than a traditional hard drive. It makes them the best laptop memory device since laptops tend to be handled roughly due to their portability. Hence, it becomes useful for students who bring their laptops everywhere. Students can work on their laptops without fear of data loss or damage to their memory devices.

However, there lies the issue of deciding which SSD is the best for an average university student. There are a lot of SSDs that multiple brands and stores are currently selling [4], each with its benefits and downsides. Certain SSDs may offer a very generous price, yet in return, provide fewer features compared to those with a higher price. Conversely, some expensive SSDs may have a lot of one feature yet lack another, which is available in cheaper SSDs. Furthermore, certain features on some SSDs may not be needed by certain students. A communications major student, for example, does not require an SDD with a large storage capacity, unlike animation majors. Hence, a question arises: how do we determine which SSD is best for the average university student?

Two algorithms can be applied to determine the best SSD. The SAW algorithm normally decides what SSD to buy based on the available information about each alternative. It normally would be enough, but there are issues in using this method. By deciding through conventional means, there will always be errors in judgment. Therefore may cause someone to pick the wrong product. A better way of deciding which SSD would be the best to buy is through an algorithm. The algorithm would weigh each criterion into a calculation. Ultimately, it would result in ranking several alternatives based on the criteria and the weight of each.

In this research, two computational methods will be employed to assess every option of SSDs in order to identify the top three most favorable choices for university students. The algorithms utilized are Simple Additive Weighting (SAW) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). By applying both approaches, it is expected that both results could be compared and eventually be used to assist university students in deciding which SSD would be the best for them to buy.

B. Methods

This study leverages two decision-making algorithms, specifically the SAW and the TOPSIS. Following the execution of each algorithm, a meticulous comparative assessment of the results ensues, serving as the foundation for subsequent analytical discourse.

B.2. SAW ALGORITHM

SAW is a weighted summation method [8]. It is a multi-criteria decision analysis method to evaluate and compare criteria-based alternatives [9]. The SAW technique seeks the weighted total for each option across all attributes, necessitating the normalization of values for each criterion. These normalized values are then utilized to construct a normalized decision matrix or table. The SAW approach classifies each criterion as either cost or benefit [10]. For attributes regarded as advantageous, greater values indicate superior performance. Conversely, for attributes seen as detrimental, lower values indicate better performance.

Initiating the SAW method involves crafting a weight table with meticulously assigned weights [11], ensuring the cumulative weight values sum up to 1. Following this, the subsequent stride generates a normalized decision matrix [12]. It entails determining the normalized value for each criterion across all alternatives, employing equation (1) as a pivotal tool in this calculation process [13]:

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{max_i x_{ij}} \; if\ j\ is\ a\ benefit\ attribute \\ \dfrac{min_i x_{ij}}{x_{ij}} \; if\ j\ is\ a\ cost\ attribute \end{cases} \tag{1}$$

where

r_{ij} = normalized value of a criteria in an alternative

x_{ij} = value of a criteria in an alternative

$max_i\ x_{ij}$ = largest value of criteria among alternatives

$min_i\ x_{ij}$ = smallest value of criteria among alternatives

The next step of the method is to calculate the preference value. It is done by multiplying each criterion's normalized value with each assigned weight, which would then be summarized. It is done for each alternative, by using the equation (2) :

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

where

V_i = preference value for each alternative
w_i = weight for each criterion
r_{ij} = normalized value

The final stage involves ordering all alternatives according to their preference values. Alternatives with elevated preference values (V_i) are positioned higher, while those with lower preference values are ranked lower. The alternative with the utmost preference value is deemed superior to the others.

B.3. TOPSIS ALGORITHM

Technique for Order of Preference by Similarity to Ideal Solution or TOPSIS is an algorithm developed and introduced by Kwangsun Yoon and Dan Hwang Cin-Lai in the 1980s [14]. The central concept of this approach is that the selected alternative exhibits the shortest distance to the ideal positive solution and the greatest distance from the ideal negative solution [15].

The TOPSIS can be summarized into a few steps as described below [16]. The first step in the TOPSIS method is to create a normalized decision matrix of each criterion for each alternative. To do this, we use the equation (3) below:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{3}$$

where

r_{ij} = normalized matrix value
x_{ij} = value of criteria of alternative

The next step is to create a weighted normalized decision matrix. It is done by multiplying each criterion with its assigned weight, as per the equation (4):

$$y_{ij} = w_i r_{ij} \tag{4}$$

where

y_{ij} = weighted matrix value
w_i = weight for each criterion
r_{ij} = normalized matrix value

Next, identify the positive and negative ideal solutions, denoted as A+ and A-. These optimal and suboptimal solutions are represented in equations (5) and (6).

$$y_j^+ = \begin{cases} \max_i y_{ij} \; ; \; if\ j\ is\ a\ benefit\ attribute \\ min_i\, y_{ij} \; ; \; if\ j\ is\ a\ cost\ attribute \end{cases} \tag{5}$$

$$y_j^- = \begin{cases} \min_i y_{ij} \; ; \; if\ j\ is\ a\ benefit\ attribute \\ max_i\, y_{ij} \; ; \; if\ j\ is\ a\ cost\ attribute \end{cases} \tag{6}$$

We then calculate the distance of each alternative rating from both the positive and negative ideal solutions. To do this, we apply the Euclidean distance theory by using the following equations (7) & (8):

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^+\right)^2}\ ,j = 1,2,\dots,J \tag{7}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^-\right)^2}\ ,j = 1,2,\dots,J \tag{8}$$

We then can calculate the preference value for each alternative by using the distance values obtained in step 4). To find the preference value, we utilize the equation (9):

$$V_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{9}$$

where

V_i = preference value for each alternative

D_i^+ = proximity to the optimal positive solution

D_1^- = proximity to the optimal negative solution

The last step is to rank the alternatives based on the obtained preference values. The alternative with the highest preference value is ranked 1st place or best among the other alternatives.

C. Results and Discussion

C.1. SAW Result

The criterions used to calculate both the SAW and TOPSIS algorithms are four, which are average transfer speed, price, storage size, and TBW (Terabytes Written). These criteria are derived from the technical specifications of each alternative, ensuring a standardized basis for comprehensive and objective comparisons. We select ten random SSDs from different online stores for the alternatives. Each SSD alternative will be noted with A, as shown in Table 2. Afterwards, a Decision Matrix is constructed, wherein each alternative is evaluated according to its respective criteria extracted from technical specifications. The results are discernible in Table 3.

Table 2 Table of Alternatives

Code	Name
A1	WD Black SN750 SE SSD Internal 500GB M.2 NVMe Gen 4x4 2280
A2	Western Digital SSD WD Green 240 GB
A3	Samsung SSD 980 Pro M.2 NVMe 1 TB
A4	HP SSD EX900 M2 NVMe 3D TLC NanD 500GB
A5	V-GeN SSD SATA 3 128GB
A6	ADATA XPG SX6000LNP LITE PCIe Gen3x4 M.2 2280 512 Gb
A7	Midasforce SSD Superlightning 256GB
A8	Team Group MP33 NVME M.2 Pcie Gen3 1TB
A9	Crucial SSD SATA MX500 500GB
A10	Seagate Firecuda 520 M2 NVME 500GB

Table 3. Decision Matrix

Alternative / Criteria	Average Transfer Speed	Price (Thousand IDR)	Storage Size	TBW
A1	2,800	1,150	500	300
A2	485	500	240	40
A3	3,250	1,265	1,000	600
A4	1,700	1,500	500	200
A5	503.5	154	128	60
A6	1,500	297	256	480
A7	550	217	256	180
A8	1,900	830	1,000	600
A9	535	778	500	180
A10	3,750	1,389	500	850

Table 4. Normalized Matrix Table

Divider	3750	154	1000	850

Normalization	Average Transfer speed	Storage size	TBW	Price
	0.74667	0.13391	0.50000	0.35294
	0.12933	0.30800	0.24000	0.04706
	0.86667	0.12174	1.00000	0.70588
	0.45333	0.10267	0.50000	0.23529
	0.13427	1.00000	0.12800	0.07059
	0.40000	0.51852	0.25600	0.56471
	0.14667	0.70968	0.25600	0.21176
	0.50667	0.18554	1.00000	0.70588
	0.14267	0.19794	0.50000	0.21176
	1.00000	0.11087	0.50000	1.00000

The Average Transfer Speed is computed to account for various transfer speed occurrences. Faster transfer speeds are preferred by users, classifying this criterion as a benefit. Conversely, the Price criterion is associated with increased user reluctance as its value rises, placing it within the Cost category. Larger Storage Size is deemed advantageous, designating it as a benefit. Lastly, a higher Total Bytes Written (TBW) is favoured, categorizing TBW as a beneficial criterion. Afterwards, the Decision Table is normalized using Formula (1) according to the respective categories of each criterion.

To determine the weight for each criterion used in the two algorithms, we survey randomly 31 active university students. The survey was done via Google Forms, with each respondent approached via private chat to fill in the survey. Each respondent was required to answer a few questions, some being an importance rating. Respondents must answer between 1 (least important) and 5 (most important). Among the many questions the respondents must answer, only some would be used to calculate both algorithms in this study. Table 5 shows the result of respondents' ratings towards each SSD. The weight is computed as the average rate derived from the respondents and subsequently rounded to the nearest rate.

Table 5. Respondents' Rating for Each Criterion

Rating	Criterion							
	Average Transfer speed		**Storage size**		**TBW**		**Price**	
5	24	77.42%	21	67.74%	13	41.94%	14	45.16%
4	5	16.13%	8	25.81%	13	41.94%	7	22.58%
3	2	6.45%	2	6.45%	5	16.13%	9	29.03%
2	0	0.00%	0	0.00%	0	0%	1	3.23%
1	0	77.42%	0	0.00%	0	0%	0	0%
Weight	5		4		5		4	
	27.8%		22.2%		27.8%		22.2%	

Table 6. Preference Value and Rank Table

Alternative	Preference Value (Vi)	Rank
A1	0.45449	4
A2	0.18149	10
A3	0.70243	1
A4	0.33991	6
A5	0.31076	8
A6	0.42294	5
A7	0.31662	7
A8	0.61661	3
A9	0.26956	9
A10	0.66353	2

After that, we can calculate each alternative's preference values, as shown in Table 6. Based on the preference values from Table 10, we can then pick the top 3 best alternatives among the others. The top 3 SSDs based on the SAW method are Team Group MP33 NVME M.2 Pcie Gen3 1TB (A8) at 3rd place, Seagate Firecuda

520 M2 NVME 500GB (A10) at 2nd place, and Samsung SSD 980 Pro M.2 NVMe 1 TB (A3) at 1st place.

C.2. TOPSIS Result

Initially, the normalization of the decision matrix in Table 3 is executed using Formula (3), thereby producing outcomes as depicted in Table 7. The next step is to weight the normalized decision matrix. Every criterion in every alternative is multiplied by the assigned weight values from Table 5. The Weighted Normalized Decision Matrix can be seen in Table 8.

Table 7. Normalized Decision Matrix

Divider	7966.09064	2967363.139	1790.26702	1368.53937
Alternative/Criteria	**Average Transfer speed**	**Storage size**	**TBW**	**Price**
A1	0.35149	0.00039	0.27929	0.21921
A2	0.06088	0.00017	0.13406	0.02923
A3	0.40798	0.00043	0.55858	0.43842
A4	0.21340	0.00051	0.27929	0.14614
A5	0.06321	5.18979E-05	0.07150	0.04384
A6	0.18830	0.00010	0.14300	0.35074
A7	0.06904	7.31289E-05	0.14300	0.13153
A8	0.23851	0.00028	0.55858	0.43842
A9	0.06716	0.00026	0.27929	0.13153
A10	0.47075	0.00047	0.27929	0.62110

Table 8. Weighted Normalized Decision Matrix

Alternative	**Average Transfer speed**	**Storage size**	**TBW**	**Price**
A1	1.75745	0.00155	1.39644	0.87685
A2	0.30442	0.00067	0.67029	0.11691
A3	2.03990	0.00171	2.79288	1.75369
A4	1.06702	0.00202	1.39644	0.58456
A5	0.31603	0.00021	0.35749	0.17536
A6	0.94150	0.00040	0.71498	1.40296
A7	0.34521	0.00029	0.71498	0.52611
A8	1.19255	0.00112	2.79288	1.75369
A9	0.33580	0.00105	1.39644	0.52611
A10	2.35373	0.00187	1.39644	2.48440

Afterward, Table 9 exhibits the optimal positive and suboptimal negative solutions for every criterion. Then, employing the Euclidean distance theory outlined in Table 10, the distance of each alternative rating from both the positive and negative ideal solutions is computed. Consequently, preference values for each alternative are determined, resulting in the ranking of alternatives based on these derived preference values, as explained in Table 11.

Table 9. Positive and Negative Ideal Solutions Table

A+	2.35373	0.00021	2.79288	2.48440
A-	0.30442	0.00202	0.35749	0.11691

Table 10. Distance from positive and negative ideal solutions

Alternative	D_i^+	D_i^-
A1	2.21129	1.94119
A2	3.78286	0.31281
A3	0.79525	3.40912
A4	2.68608	1.37101
A5	3.92619	0.05962
A6	2.73525	1.47904
A7	3.49095	0.54489
A8	1.37195	3.06577
A9	3.13958	1.11707
A10	1.39644	3.29911

Using the preference values from Table 11, we can identify the top three most favorable SSDs. According to the TOPSIS approach, the leading SSD alternatives are the Samsung SSD 980 Pro M.2 NVMe 1 TB (A3) in first position, followed by the Seagate Firecuda 520 M2 NVME 500GB (A10) in second place, and the Team Group MP33 NVME M.2 Pcie Gen3 1TB (A8) in third place.

Table 11. Preference Values and Rank Table

Alternatives	**Preference (Vi)**	**Ranking**
A1	0.46747	4
A2	0.07637	9
A3	0.81085	1
A4	0.33793	6
A5	0.01496	10
A6	0.35096	5
A7	0.13501	8
A8	0.69084	3
A9	0.26243	7
A10	0.70260	2

C.3. Result Comparison

The preference values obtained from both algorithms are used to rank each alternative from the best to worst. The alternative with the highest preference value is the best, while the alternative with the lowest is the worst. Below is a table containing the results of both algorithms, with each alternative ranked based on their preference value.

Table 12. Results Comparison

Alternative	SAW		TOPICS	
	Preference (Vi)	Rank	Preference (Vi)	Rank
A3	0.70243	1	0.81085	1
A10	0.66353	2	0.70260	2
A8	0.61661	3	0.69084	3
A1	0.45449	4	0.46748	4
A6	0.422938	5	0.35096	5
A4	0.33992	6	0.33793	6
A7	0.31662	7	0.13501	8
A5	0.31076	8	0.01496	10
A9	0.26956	9	0.26243	7
A2	0.18149	10	0.07637	9

By analyzing Table 12, it can be inferred that both algorithms have yielded congruent results. The top three alternatives identified by both methodologies align, with the Samsung SSD 980 Pro M.2 NVMe 1 TB (A3) securing the first position, followed by the Seagate Firecuda 520 M2 NVME 500GB (A10) in second place, and the Team Group MP33 NVME M.2 PCIe Gen3 1TB (A8) in the third position. The concordance extends even to the sixth rank. Nevertheless, discrepancies emerge in the lower ranks; alternatives ranked 7 to 10 differ between the two algorithms. In the SAW method, the Western Digital SSD WD Green 240 GB (A2) occupies the last position, whereas the TOPSIS method assigns the V-GeN SSD SATA 3 128GB (A5) to the bottom position.

C.4. Discussion

We can conclude from the results of both algorithms that a university student could buy the top 3 best SSDs. Table 13 illustrates a list of the top 3 best SSD alternatives based on the SAW and TOPSIS algorithms.

Table 13. Top 3 Best SSDs based on the SAW & TOPSIS method

Code	Alternative	Rank
A3	Samsung SSD 980 Pro M.2 NVMe 1 TB	1
A10	Seagate Firecuda 520 M2 NVME 500GB	2
A8	Team Group MP33 NVME M.2 Pcie Gen3 1TB	3

The Samsung SSD 980 Pro M.2 MVMe with 1 Terabyte of capacity is ranked first, indicating it is the best alternative among other SSD models. The other two, the Seagate Firecuda 520 M2 NVME 500GB and Team Group MP33 NVME M.2 Pcie Gen3 1 TB came at second and third, respectively. However, the results of this research do not fully reflect which SSDs are best or worst for university students in specific cases. The data collected from respondents record only four criteria related to SSDs. It does not address the subjective criteria of SSD brands or hardware compatibility (if the hardware can support the SSD). The results provide general insight for university students based on objective data, but any additional point of consideration still falls on their subjectivity.

In the SSD purchasing context, SAW and TOPSIS algorithms offer distinct approaches. First, with SAW, buyers assign weights to criteria [17], then evaluate SSD options accordingly, summing weighted scores for comparison. Conversely, TOPSIS identifies the most favourable SSD by measuring its distance to ideal performance benchmarks [18]. The SSD closest to the positive ideal solution and farthest from the negative is considered the optimal choice. Secondly, the SAW method involves subjective decisions from buyers to assign importance to criteria like speed, capacity, durability, and price, which may introduce bias based on individual preferences [19]. Contrastly, the TOPSIS algorithm relies more on mathematical calculations [20], providing a more objective evaluation approach that personal biases may be less influenced. Thirdly, SAW is simpler [21], requiring only the determination of criteria weights and performance data for each SSD. This simplicity makes it accessible for buyers to conduct evaluations based on their preferences and priorities. On the other hand, TOPSIS involves more intricate calculations [22], especially when determining ideal solutions and computing distances. This complexity may require specialized knowledge or tools to implement effectively. While TOPSIS offers a more nuanced analysis, its complexity might deter some buyers who prioritize simplicity in their decision-making process when selecting an SSD.

D. Conclusion

For both results, we can conclude that the Samsung SSD 980 Pro M.2 MVMe 1TB is the best SSD for a university student to buy, as it has been ranked first in both calculation algorithms. The Simple Additive Weighting and Technique for Order of Preference by Similarity to Ideal Solution algorithms are applicable in determining which SSD is the best for a university student to buy based on four distinct criteria. Both algorithms are simple and flexible, with the Simple Additive Weighting method being the simplest. However, both algorithms do not come without their limitations. The SAW algorithm has fewer calculation algorithms, thus being less thorough than TOPSIS.

In SSD purchasing, SAW and TOPSIS offer distinct approaches. SAW involves assigning weights to criteria and summing scores, while TOPSIS assesses SSDs based on their distance to ideal benchmarks. SAW relies on subjective decisions, introducing potential bias, while TOPSIS employs mathematical calculations for a more objective evaluation. SAW is simpler, requiring only weights and performance data, whereas TOPSIS involves more complex calculations, which may deter some buyers from seeking simplicity.

Additionally, limitation occurs as the data pool used in this research is rather limited. The results are formulated from the responses of 31 university students, which are applied to review a sample of 10 alternatives. The results may differ if the number of respondents is more than currently available and if the number of alternatives being ranked is greater than it currently is.

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