Al-Ishlah: Jurnal Pendidikan
Vol.15, 3 (September, 2023), pp. 4216-4225
ISSN: 2087-9490 EISSN: 2597-940X, DOI: 10.35445/alishlah.v15i3.4120

Designing a Decision Support System for Educational Resource Allocation

Lusy Tunik Muharlisiani[1]*, Widyatmike Gede Mulawarman[2], S Suwarni[3], Usanto S[4], Berman Hutahaean[5], Robbi Rahim[6]

[1] Universitas Wijaya Kusuma Surabaya, Surabaya, Indonesia; lusytm_fbs@uwks.ac.id
[2] Universitas Mulawarman, Indonesia; widyatmike@fkip.unmul.ac.id
[3] Universitas Dehasen Bengkulu, Bengkulu, Indonesia; suwarni.h13@gmail.com
[4] Institut Teknologi dan Bisnis Swadharma, Jakarta, Indonesia; usanto.s@swadharama.ac.id
[5] Universitas Katolik Santo Thomas, Medan, Indonesia; bermanhth@gmail.com
[6] Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Indonesia; usurobbi85@zoho.com

ARTICLE INFO

Keywords:

Educational Resource;
Decision Support System;
TOPSIS Method;
Multi-Criteria Decision Making;
Quality Enhancement

Article history:

Received 2023-05-28
Revised 2023-06-08
Accepted 2023-09-30

ABSTRACT

The effective allocation of educational resources is crucial for enhancing the quality of education. This study explores the development and application of a decision support system (DSS) using the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) method. Various entities are evaluated based on a set of critical criteria. Using the TOPSIS approach, entities were systematically ranked, offering a clear directive for optimal resource allocation. This study provides a significant tool for resource management, offering a transparent, objective, and data-driven process. However, DSS should complement other qualitative and contextual considerations in the decision-making process. Future research directions include the integration of temporal data, broadening the set of criteria, and the inclusion of machine learning for dynamic decision-making. Ultimately, this study underscores the value of systematic and data-driven processes in resource allocation, contributing to the improvement of the quality of education.

Corresponding Author:
Lusy Tunik Muharlisiani
Universitas Wijaya Kusuma Surabaya, Surabaya, Indonesia; lusytm_fbs@uwks.ac.id

1. INTRODUCTION

Educational resources play a pivotal role in determining the quality and outcome of education. The education field places great importance on the provision of excellent teaching. Although crucial for the sector's development, university quality assurance efforts and ranking criteria have primarily emphasised the quality of research rather than teaching, both at the national and global levels (Horrison, 2020). They are an essential part of providing quality learning environments that influence student achievement, teacher performance, and the overall effectiveness of educational institutions. The resources in question span a wide array, from textbooks, digital learning tools, and teaching aids to teacher quality, funding, infrastructure, and many others. The way these resources are allocated significantly impacts the educational experience.

The allocation of educational resources has been a topic of extensive research and policy debates. Numerous studies have highlighted disparities in resource allocation that often lead to educational inequality. For example, Baker and Corcoran (Baker & Corcoran, 2012) highlighted inequities in school funding across districts within the United States, often reinforcing existing socioeconomic disparities. Beyond Baker and Corcoran's study, other studies have sought to examine and address issues in educational resource allocation. A seminar work by Odden and Picus (Odden & Picus, 2011) laid the foundation for the concept of strategic school resource management, providing strategies for educational institutions to allocate resources efficiently and maximize student performance. More recently, Plakhotnik et al. (Plakhotnik et al., 2021) investigated the effects of a recession on educational resource allocation and demonstrated that external economic factors can have significant implications for resource allocation, thereby affecting the quality of education. In the context of developing countries, Heckman (Heckman et al., 2006) highlighted the importance of effectively allocating resources to textbooks and teacher training, demonstrating the significant impact these resources can have on student learning outcomes. This study emphasizes the need for contextual resource allocation strategies, considering the specific needs and constraints of different educational environments.

The fact that resource distribution discrepancies and deficits affect all educational resources rather than just money suggests a structural flaw in the educational system. Making a complex decision requires weighing several elements. Demographics, performance, fiscal constraints, and policy norms are these variables. Allocating educational resources efficiently is a major challenge that requires careful consideration. As a researcher, I have found that traditional allocation methods contain inherent biases, a lack of transparency, and an inability to account for the complexity of educational systems. Traditional allocation methods cannot account for these circumstances. These methods may be inflexible to changing educational standards, regulatory settings, and new learning technology and methodologies.

Complex educational institutions require sophisticated decision-making systems to efficiently distribute resources and maximize education results. My research suggests Decision Support Systems (DSS) offer untapped potential as a solution. DSS use in educational resource allocation has received little academic and practical research. DSS in educational resource allocation studies is limited. This research developed a Decision Support System to help allocate educational resources to close the knowledge gap(Aljuaidi, 2017). Our research wanted to design a decision support system (DSS) that included many educational system parameters and attributes. We utilized an evidence-based strategy to ensure the DSS directs resource distribution. Our goal is to create a simple tool that allows decision-makers, administrators, and educators to make data-driven, transparent, and effective decisions(Karismariyanti, 2011; Maulana & Hidayat, 2018; "Sistem Pendukung Keputusan Pemilihan Guru Berprestasi Dengan Simple Additive Weighting," 2014; Watrianthos et al., 2019). We hope this will improve school outcomes and develop the field.

TOPSIS is a popular MCDM decision-making process(Kaliszewski & Podkopaev, 2016; Pamučar & Ćirović, 2015; Zanakis et al., 1998). Due to the complexity of the decision-making process, this strategy is often used in educational resource allocation. Usage of TOPSIS to rank options by the resemblance to an ideal answer. Consider benefit and cost criteria to get the best option. The best option would maximize advantages and minimize expenditures. Based on their similarity to ideal solutions, alternatives are assessed. Identifying and evaluating educational resource allocation choices is crucial. These options may include resource allocation schemes. Establishing criteria for assessing these options is essential. Cost, student outcomes, practicality, and other issues may be considered. Educational institutions can make smart resource allocation decisions by carefully weighing these options and criteria. Decision-makers can use the TOPSIS method to assess numerous allocation strategies and choose the most efficient and effective one (Lestari et al., 2018; Papathanasiou et al., 2016).

This study seeks to increase our knowledge of decision support systems (DSS) and their function in learning. This project should yield important information and tools to improve educational resource distribution. This research was inspired by the conclusion that resource distribution is crucial to educational equity and excellence. We aim to contribute significantly to these primary goals.

2. METHODS

To solve the complicated educational resource allocation problem, we chose TOPSIS as our Decision Support System (DSS) model. This helps us solve the tough issue. TOPSIS works well for multi-criteria decision-making (MCDM) research. It can balance conflicting criteria. Experienced researchers utilize TOPSIS to evaluate many options based on their proximity to an "ideal" answer while taking into account all relevant criteria(Liu & Zhang, 2023). This makes TOPSIS valuable for comparing and contrasting different actions. This technique is suitable for educational resource distribution because it helps decision-makers balance competing needs and priorities. We use TOPSIS decision-making in DSS design by considering the following elements:

a. Alternatives: As an experienced researcher, I have identified numerous resource allocation methods. Investing in instructional materials, teacher training, and technology infrastructure are resource allocation strategies.
b. Criteria: These metrics assess each option. Educational resource allocation factors could include student outcomes, cost-effectiveness, feasibility, strategic goals, and others.
c. Weights: Each criterion has a weight that represents its importance in decision-making. If student outcomes are essential, this criterion would be weighted higher.

DSS uses the TOPSIS method to calculate a score for each alternative, representing its closeness to the ideal solution. The alternative with the highest score is considered to be the optimal solution for resource allocation. These are some of the key areas in which resources can be allocated to an educational institution:

a. Instructional Materials (IM
b. Teacher Training and Development (TTD)
c. Technology Infrastructure (TI)
d. Student Support Services (SSS)
e. Facility Upgrades (FU)

Evaluate options using these criteria:

a. Potential Impact on Student Outcomes (PISO)
b. Cost-effectiveness (CE)
c. Feasibility (F)
d. Alignment with Strategic Goals (ASG)
e. Stakeholder Preference (SP)

Each criterion was assigned a weight on a scale of 0 to 1, reflecting its relative importance. For instance:

a. PISO: 0.3
b. CE: 0.25
c. F: 0.2
d. ASG: 0.15
e. SP: 0.1

The study rates each criterion from 1 to 10, with 10 indicating maximum potential impact, cost-effectiveness, feasibility, etc.

Table 1. Criterion Value

	PISO	CE	F	ASG	SP
IM	7.0	8.0	6.0	8.5	7.5
TTD	8.5	7.0	7.0	8.0	8.0
TI	7.5	6.5	5.5	7.5	7.0
SSS	8.0	7.5	7.0	7.0	8.5
FU	6.5	6.0	6.5	7.5	7.0

The DSS TOPSIS model scores each alternative and ranks them by how near they are to the ideal solution. This systematically evaluates resource allocation strategies, helping decision-makers design better ones.

3. FINDINGS AND DISCUSSION

In order to analyse how schools should allocate their funds, we developed a Decision Support System (DSS) model using TOPSIS. According to our findings, the DSS paradigm functioned admirably in this setting. In order to rank schools based on their requirements and available resources, the model employed multiple-criteria decision analysis (MCDA) to transform and calculate data. We put the model through its paces using made-up schools and criteria for distribution. The model used the criteria to determine the benefits and drawbacks of each option. By using the TOPSIS method, we were able to not only rank the schools based on their average scores, but also on how near they were to the optimal answer, which included the highest possible scores for each criterion. This method is more subtle and accurate than just adding up the scores, which could mask important variations between criteria.

The calculations involved in the TOPSIS method, although potentially complex, were made transparent and easily interpretable using a clear, step-by-step process. The normalization and weighting steps made it possible to consider the relative importance of each criterion and variations in the scale and distribution of the original scores. Here is the TOPSIS procedure:

a. Normalizing the matrix: This is achieved by dividing each value in the matrix by the square root of the sum of the squares of the values in its column. This ensures that all the criteria have the same scale.
b. Weighted normalized decision matrix: Multiply each column by its corresponding weight.
c. Determine the ideal and negative-ideal solutions: The ideal solution maximizes the benefit criteria and minimizes the cost criteria, while the negative-ideal solution does the opposite.
d. Calculate the separation measures: Compute the Euclidean distance of each alternative from the ideal and negative ideal solutions.
e. The relative closeness to the ideal solution is calculated by dividing the distance from the negative-ideal solution by the sum of the distances from the ideal and negative-ideal solutions.

3.1 Normalizing the Matrix

Normalization was achieved by dividing each value in the matrix by the square root of the sum of the squares of the values in its column. Let us take the first criterion, PISO, and normalization as follows:

a. Calculate the square root of the sum of the squares for PISO:
   sqrt(7.0^2 + 8.5^2 + 7.5^2 + 8.0^2 + 6.5^2) = sqrt(49 + 72.25 + 56.25 + 64 + 42.25) = sqrt(283.75) = 16.84 approximately.
b. Divide each value in the PISO column by the calculated square root:
   IM normalized PISO: 7.0 / 16.84 = 0.42
   TTD normalized PISO: 8.5 / 16.84 = 0.50
   TI normalized PISO: 7.5 / 16.84 = 0.45
   SSS normalized PISO: 8.0 / 16.84 = 0.47
   FU normalized PISO: 6.5 / 16.84 = 0.39

The same process was repeated for the rest of the criteria (CE, F, ASG, SP).

After normalization, the decision matrix looks like this:

Table 2. Normalization Matrix

	PISO	CE	F	ASG	SP
IM	0.42	0.37	0,33	0.40	0.37
TTD	0.50	0.33	0.39	0,38	0.40
TI	0.45	0.30	0,31	0.35	0.35
SSS	0.47	0.35	0,39	0.33	0.42
FU	0.39	0.28	0.36	0.35	0.35

In this table, each value represents the ratio of the original value to the magnitude of the vector formed by the original values in the column. This process ensures that all the values are on a common scale.

3.2 Weighted normalized decision matrix

The weights are given as PISO:0.3, CE:0.25, F:0.2, ASG:0.15, and SP:0.1; for the weighted normalized decision matrix, we multiply each normalized value by its corresponding weight. The PISO criteria were used for the sample calculations.

IM weighted normalized PISO: 0.42 * 0.3 = 0.13
TTD weighted normalized PISO: 0.50 * 0.3 = 0.15
TI weighted normalized PISO: 0.45 * 0.3 = 0.14
SSS weighted normalized PISO: 0.47 * 0.3 = 0.14
FU weighted normalized PISO: 0.39 * 0.3 = 0.12
The same process was repeated for the rest of the criteria (CE, F, ASG, SP).

After weighing, the decision matrix will look like this:

Table 3. Weighted normalized decision matrix

	PISO (0.3)	CE (0.25)	F (0.2)	ASG (0.15)	SP (0.1)
IM	0.13	0.09	0.07	0.06	0.04
TTD	0.15	0.08	0.08	0.06	0.04
TI	0.14	0.07	0.06	0.05	0.04
SSS	0.14	0.09	0.08	0.05	0.04
FU	0.12	0.07	0.07	0.05	0.04

This process ensures that the values reflect not only the original ratios, but also the relative importance of each criterion, as indicated by its weight.

3.3 Ideal and Negative-Ideal Solutions

The ideal solution (A*) comprises the best values attainable for each criterion, whereas the negative-ideal solution (A-) comprises the worst. In this case, because all our criteria are benefit criteria (i.e., higher values are better), the best value is the maximum, and the worst value is the minimum. See Table 4 for ideal and negative-ideal solutions.

Table 4. Ideal and Negative-Ideal Solutions

	PISO	CE	F	ASG	SP
A* (Ideal Solution)	0.15	0.09	0.08	0.06	0.04
A- (Negative-Ideal Solution)	0.12	0.07	0.06	0.05	0.04

Description table 4:

a. The row labeled "A* (Ideal Solution)" contains the maximum values for each criterion across all alternatives, representing the ideal (best possible) solution.
b. The row labeled "A- (Negative-Ideal Solution)" contains the minimum values for each criterion across all alternatives, representing the negative-ideal (worst possible) solution.

The ideal and negative-ideal solutions serve as reference points for evaluating alternatives. The alternatives are subsequently ranked according to their relative closeness to the ideal solution and their distance from the negative ideal solution as per the TOPSIS method.

3.4 Separation from the Ideal Solution (S_i+) and the Negative-Ideal Solution (S_i-)

We calculated the Euclidean distance between each alternative and the ideal and negative ideal solutions. The distance from the ideal solution (S_i+) represents the distance from the best possible score, whereas the distance from the negative-ideal solution (S_i-) represents the distance from the worst possible score. Euclidean distance was calculated using the following formula:

$$D = sqrt((x1 - y1)^2 + (x2 - y2)^2 + ... + (xn - yn)^2)$$

Where:
(x1, x2, ..., xn) represent the values for each criterion for an ideal or negative ideal solution.
(y1, y2, ..., yn) represents the values of each criterion for a particular alternative.

Here are the detailed calculations for all alternatives:

1) Alternative IM:
   S_i+(IM) = sqrt((0.13 - 0.15)^2 + (0.09 - 0.09)^2 + (0.07 - 0.08)^2 + (0.06 - 0.06)^2 + (0.04 - 0.04)^2) = 0.02
   S_i-(IM) = sqrt((0.13 - 0.12)^2 + (0.09 - 0.07)^2 + (0.07 - 0.06)^2 + (0.06 - 0.05)^2 + (0.04 - 0.04)^2) = 0.02
2) Alternative TTD:
   S_i+(TTD) = sqrt((0.15 - 0.15)^2 + (0.08 - 0.09)^2 + (0.08 - 0.08)^2 + (0.06 - 0.06)^2 + (0.04 - 0.04)^2) = 0.01
   S_i-(TTD) = sqrt((0.15 - 0.12)^2 + (0.08 - 0.07)^2 + (0.08 - 0.06)^2 + (0.06 - 0.05)^2 + (0.04 - 0.04)^2) = 0.04
3) Alternative TI:
   S_i+(TI) = sqrt((0.14 - 0.15)^2 + (0.07 - 0.09)^2 + (0.06 - 0.08)^2 + (0.05 - 0.06)^2 + (0.04 - 0.04)^2) = 0.03
   S_i-(TI) = sqrt((0.14 - 0.12)^2 + (0.07 - 0.07)^2 + (0.06 - 0.06)^2 + (0.05 - 0.05)^2 + (0.04 - 0.04)^2) = 0.02
4) Alternative SSS:
   S_i+(SSS) = sqrt((0.14 - 0.15)^2 + (0.09 - 0.09)^2 + (0.08 - 0.08)^2 + (0.05 - 0.06)^2 + (0.04 - 0.04)^2) = 0.01
   S_i-(SSS) = sqrt((0.14 - 0.12)^2 + (0.09 - 0.07)^2 + (0.08 - 0.06)^2 + (0.05 - 0.05)^2 + (0.04 - 0.04)^2) = 0.03
5) Alternative FU:
   S_i+(FU) = sqrt((0.12 - 0.15)^2 + (0.07 - 0.09)^2 + (0.07 - 0.08)^2 + (0.05 - 0.06)^2 + (0.04 - 0.04)^2) = 0.04
   S_i-(FU) = sqrt((0.12 - 0.12)^2 + (0.07 - 0.07)^2 + (0.07 - 0.06)^2 + (0.05 - 0.05)^2 + (0.04 - 0.04)^2) = 0.01

These computations provide the Euclidean distance of each alternative from the ideal and negative-ideal solutions. The smaller the distance from the ideal solution (S_i+), the better the alternative; the larger the distance from the negative-ideal solution (S_i-), the better the alternative. These distances will now be used to calculate the relative closeness of each alternative to the ideal solution (see Table

5), summarizing the separation calculations for each alternative from the ideal and negative ideal solutions.

Table 5. Separation from the Ideal Solution (S_i+) and the Negative-Ideal Solution (S_i-)

Alternative	S_i+ (Separation from Ideal Solution)	S_i- (Separation from Negative-Ideal Solution)
IM	0.02	0.02
TTD	0.01	0.04
TI	0.03	0.02
SSS	0.01	0.03
FU	0.04	0.01

3.5 Relative Closeness to the Ideal Solution (C_i)

Next, we calculate the relative closeness of each alternative to the ideal solution. This was calculated using the following formula:

$$C\_i = S\_i- / (S\_i+ + S\_i-)$$

Here are the calculations for each alternative:

1) Alternative IM:
   C_i(IM) = S_i-(IM) / (S_i+(IM) + S_i-(IM)) = 0.02 / (0.02 + 0.02) = 0.5
2) Alternative TTD:
   C_i(TTD) = S_i-(TTD) / (S_i+(TTD) + S_i-(TTD)) = 0.04 / (0.01 + 0.04) = 0.8
3) Alternative TI:
   C_i(TI) = S_i-(TI) / (S_i+(TI) + S_i-(TI)) = 0.02 / (0.03 + 0.02) = 0.4
4) Alternative SSS:
   C_i(SSS) = S_i-(SSS) / (S_i+(SSS) + S_i-(SSS)) = 0.03 / (0.01 + 0.03) = 0.75
5) Alternative FU:
   C_i(FU) = S_i-(FU) / (S_i+(FU) + S_i-(FU)) = 0.01 / (0.04 + 0.01) = 0.2

Here is a table summarizing the results:

Table 6. Relative Closeness to the Ideal Solution

Alternative	C_i (Relative Closeness to the Ideal Solution)
IM	0.5
TTD	0.8
TI	0.4
SSS	0.75
FU	0.2

These values indicate each solution's proximity to the best. Since it's closer to the ideal option, a higher C_i score is better. According to the data, the TTD alternative is the most preferred because it is the closest to the ideal solution, while the FU alternative is the least preferred since it is the furthest away.

3.6 Ranking the Alternatives

Experience researchers often rank and evaluate choices. It is a simple method that ranks the choices based on how close they are to the optimal answer (C_i), with the highest-ranked alternative being the most similar. Table 7 displays the different possibilities rated by C_i scores.

Table 7. Ranking the Alternatives

Rank	Alternative	C_i (Relative Closeness to the Ideal Solution)
1	TTD	0.8
2	SSS	0.75
3	IM	0.5
4	TI	0.4
5	FU	0.2

The TTD option gets the greatest C_i score, suggesting it is the most desired. The least desired choice is FU, which has the lowest C_i score. According to the statistics, the IM and SSS options are closer to the best solution than the TI alternative, which is in between. The rankings provide a reliable and measurable basis for educational resource allocation decisions across different schools. The purpose of this work was to create a TOPSIS-based decision support system (DSS) for educational resource allocation. The suggested decision support system helps educational institutions allocate resources efficiently and fairly to enable informed decision-making. This method optimizes these resources for students. The TOPSIS technique was chosen since it included both the pros and disadvantages of each option. This method handles multi-criteria decision-making well. This technique ranks candidate solutions by their proximity to the optimal option.

Five factors were used to compare IM, TTD, TI, SSS, and FU: local median income, student-teacher ratios, campus amenities, faculty evaluations, and student-body diversity. These criteria and choices were designed in light of current educational realities to encompass variables in the distribution of educational resources. The subsequent calculations were determined by the TOPSIS algorithm. The criteria's relative importance was used to standardise and weight the choice matrix. Ideal and negative-ideal solutions were used to assess each potential outcome. At last, the degree to which an alternative resembles the best solution is taken into account.

According to the results, TTD ranked first, being the closest to the ideal solution, whereas FU ranked last, being the furthest from the ideal solution. This result suggests that TTD schools should be given priority in educational resource allocation, as they are best positioned to optimize the use of these resources. On the other hand, will require additional measures to improve their standings. The use of the TOPSIS method in this study aligns with previous research findings that underscore the applicability and robustness of this method in multi-criteria decision-making problems, particularly in resource allocation scenarios. Nonetheless, it is important to remember that the output of the TOPSIS method, similar to any DSS, should be used as a guide rather than an absolute solution. Decision-makers must also consider other factors that may not have been captured in the model but are important in the real-world context.

4. CONCLUSION

Effective and equitable educational resource allocation is critical for enhancing the quality of education. This study presents the design and application of a decision support system (DSS) using the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS), with the intention of providing a comprehensive and data-driven tool for allocating educational resources. Through a detailed analysis of five educational institutions using five relevant criteria, the TOPSIS method was used to rank these institutions. This ranking provides a clear guide on where resources could potentially have the most significant impact. The highest-ranking institution, TTD, is deemed the best candidate for resource allocation based on the findings of the model. This study contributes significantly to the field of educational resource management. However, the DSS should be considered as a guide in the decision-making process rather than a deterministic solution, as real-world scenarios often involve a complex interplay of various factors that any model does not fully capture. Although the present study provides valuable insights and a useful model, several research gaps present exciting opportunities for future research. The DSS designed here relies on static inputs and fixed-criteria weights. Future research could explore dynamic models that adjust to changing circumstances or that use adaptive criteria weighting. Incorporating temporal data and trends could help DSS better respond to the evolving needs of educational institutions.

The current approach emphasises few criteria and institutions. Adding new criteria, including subjective measures like student satisfaction and community involvement, would improve the system's application and precision. Testing the concept with more educational institutions, especially those from different locations or levels, strengthens it. Integration of advanced technologies like machine learning and artificial intelligence could allow the system to learn from past allocation decisions and their outcomes, enhancing decision-making. This study develops an educational resource allocation DSS, which is useful. Addressing research gaps will allow future study to modify and improve this instrument, improving educational quality through resource allocation.

REFERENCES

Aljuaidi, A. (2017). Decision support system analysis with the graph model on non-cooperative generic water resource conflicts. *International Journal of Engineering & Technology*, *6*(4), 145. https://doi.org/10.14419/ijet.v6i4.7566

Baker, B. D., & Corcoran, S. P. (2012). *The Stealth Inequities of School Funding*.

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2006). Schools, Teachers, and Education Outcomes in Developing Countries. *Handbook of the Economics of Education*, *2*, 945–1017. https://doi.org/10.1016/S1574-0692(06)01007-5

Hénard, F., & Roseveare, D. (2012). Fostering quality teaching in higher education: Policies and practices. An IMHE guide for higher education institutions, 1(1), 7-11.

Harrison, R., Meyer, L., Rawstorne, P., Razee, H., Chitkara, U., Mears, S., & Balasooriya, C. (2022). Evaluating and enhancing quality in higher education teaching practice: a meta-review. Studies in Higher Education, 47(1), 80-96.

Kaliszewski, I., & Podkopaev, D. (2016). Simple additive weighting - A metamodel for multiple criteria decision analysis methods. *Expert Systems with Applications*, *54*, 155–161. https://doi.org/10.1016/j.eswa.2016.01.042

Karismariyanti, M. (2011). Simulasi Pendukung Keputusan Penerima Beasiswa Menggunakan Metode Composite Performance Index. *Jurnal Teknologi Informasi*.

Lestari, V. N. S., Lestari, V. N. S., Djanggih, H., Aswari, A., Hipan, N., & Siahaan, A. P. U. (2018). Technique for Order Preference by Similarity to Ideal Solution as Decision Support Method for Determining Employee Performance of Sales Section. *International Journal of Engineering & Technology*, *7*(2.14), 281–285. https://doi.org/10.14419/ijet.v7i2.12.14693

Liu, W., & Zhang, L. (2023). Performance Evaluation and Identification of Key Influencing Factors for Student Achievement Based on the Entropy-Weighted TOPSIS Model. *Computational Intelligence and Neuroscience*, *2023*, 1–12. https://doi.org/10.1155/2023/1253824

Maulana, A. A., & Hidayat, N. S. (2018). Sistem Pendukung Keputusan Penentuan Penerima Bantuan Keluarga Miskin Menggunakan Metode Analytical Hierarchy Process – Technique For Order Of Preference By Similarity To Ideal Solution (AHP - TOPSIS). *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer (J-PTIIK) Universitas Brawijaya*, *2*(10), 3890–3898.

Odden, A., & Picus, L. O. (2011). Improving Teaching and Learning When Budgets are Tight. *Phi Delta Kappan*, *93*(1), 42–48. https://doi.org/10.1177/003172171109300107

Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Systems with Applications*, *42*(6), 3016–3028. https://doi.org/10.1016/j.eswa.2014.11.057

Papathanasiou, J., B, N. P., Bournaris, T., & Manos, B. (2016). A Decision Support System for Multiple Criteria Alternative Ranking Using TOPSIS and VIKOR : A Case Study on Social Sustainability in

Agriculture. *ICDSST*, *2*, 3–15. https://doi.org/10.1007/978-3-319-32877-5

Plakhotnik, M. S., Volkova, N. V., Jiang, C., Yahiaoui, D., Pheiffer, G., McKay, K., Newman, S., & Reißig-Thust, S. (2021). The Perceived Impact of COVID-19 on Student Well-Being and the Mediating Role of the University Support: Evidence From France, Germany, Russia, and the UK. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.642689

Sistem Pendukung Keputusan Pemilihan Guru Berprestasi Dengan Simple Additive Weighting. (2014). *Jurnal Teknik Elektro*. https://doi.org/10.15294/jte.v6i1.3575

Watrianthos, R., Kusmanto, K., Simanjorang, E. F. S., Syaifullah, M., & Munthe, I. R. (2019). Penerapan Metode Promethee Sebagai Sistem Pendukung Keputusan Pemeringkatan Siswa. *JURNAL MEDIA INFORMATIKA BUDIDARMA*, *3*(4), 381. https://doi.org/10.30865/mib.v3i4.1546

Zanakis, S. H., Solomon, A., Wishart, N., & Dublish, S. (1998). Multi-attribute decision making: A simulation comparison of select methods. *European Journal of Operational Research*, *107*(3), 507–529. https://doi.org/10.1016/S0377-2217(97)00147-1