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The Selection Model of Scholarship Recipients using a Combination of Best Worst Method, SMART and PROMETHEE

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ABSTRACT

This research aims to develop a model for selecting scholarship recipients using a combination of the Best Worst Method, SMART and PROMETHEE. The topic was chosen due to the importance of an objective and transparent selection process to improve access to higher education for underprivileged students. The Best Worst Method is used to determine criteria weights by comparing the best and worst criteria. SMART evaluates the utility value of alternatives based on the weights obtained from the Best Worst Method. PROMETHEE ranks the alternatives based on preference values calculated from SMART results. The results showed that this combination achieved an accuracy of 96,29%, precision of 96,67%, recall of 96,67%, and specificity of 96,67%. In the sensitivity analysis, based on 20 weight change experiments, resulted in an average value of 0,863, indicating the superiority of this method compared to others. These findings suggest that this combination is more robust to weight changes, making it more effective in maintaining consistency and objectivity during the selection process. Applying Best Worst Method, SMART and PROMETHEE enhances the quality of scholarship selection, ensuring fairness, objectivity and consistency in various decision-making situations.

KEYWORDS: Best Worst Method, SMART, PROMETHEE, Confusion Matrix, Sensitivity Analysis

INTRODUCTION

A scholarship is a financial aid for education provided by a government, company, or foundation that can be in the form of a grant or on the condition of employment after graduation. College scholarships play an important role in improving access to higher education for underprivileged students with the aim of alleviating the cost burden and improving the quality of human resources. The selection of scholarship recipients requires meeting certain criteria and a decision support system can help select the most qualified recipient among the large number of applicants. A decision support system is a part of a computerized information system that helps decision making in an organization or business by processing data into information for semi-structured problems [1].

Simple Multi Attribute Rating Technique (SMART) is a method that supports Multi-Criteria Decision Making efficiently, but has the disadvantage of ignoring the interaction between criteria, which are evaluated independently and linearly [2]. This weakness can be overcome by the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), which allows paired comparisons between alternatives to determine a superior alternative based on the preference of more complex criteria [3]. Although PROMETHEE excels at ranking, the method often faces challenges in dealing with criteria measured on different scales [4]. Therefore, the combination of SMART and PROMETHEE methods allows preference-based ranking as well as normalizing criteria, so as to overcome variations in the characteristics or units of measurement of the criteria used. The Best Worst Method (BWM) method is added in the selection model that uses paired comparisons to assess decision criteria so that it can help overcome bias in weighting by comparing the best and worst criteria to determine the weight of each [5].

Several previous studies have used various decision-making methods to select the best alternative. Research by Liang *et al.* [6] showed that the Best Worst Method requires less comparative data and produces more consistent results than AHP. Zahara *et al.* [7] comparing SMART, SAW and MOORA methods, found that SMART produces higher accuracy and is better suited for cases with a lot of selection data. The combination of Best Worst Method and PROMETHEE proved effective in evaluating and classifying alternatives where Best Worst Method to determine the weight of criteria, while PROMETHEE is used to evaluate and rank alternatives and handle conflicting criteria [8]. The research by Kabassi and Martinis [9] compared the SAW, WPM, PROMETHEE and TOPSIS methods, showing that PROMETHEE has better sensitivity and is more consistent in dealing with changes in weights or criteria values. This finding confirms the superiority of PROMETHEE as a stable and reliable method of decision making with a variety of assessment criteria.

The use of Best Worst Method is necessary to establish the relative weight of criteria in decision making by comparing the most important and unimportant criteria [10]. The SMART method is used to evaluate the utility value of various alternatives, providing a more objective and measurable assessment of the criteria [11]. Selection of prospective scholarship recipients also requires evaluation of alternatives based on established criteria. The PROMETHEE method helps to prioritize and rank the best alternatives [12]. Although these three methods have been applied in various fields, their combination in the selection of prospective scholarship recipients has not been found before, so this research can make a significant contribution to improving the quality and objectivity of the scholarship selection process.

PROPOSED MODEL

Decision Support System for scholarship candidate selection often faces challenges in ensuring objectivity and fairness in the evaluation process due to the complexity of multiple criteria and subjective assessments. To address these challenges, this research proposes a model that combines the Best Worst Method, SMART and PROMETHEE offering a robust framework for ranking and selecting the most suitable scholarship recipients.

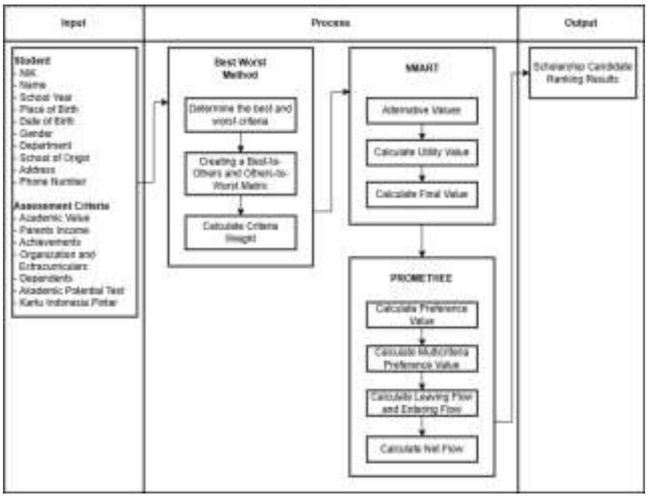

Figure 1 Model Framework of BSMP

The model framework in Figure 1 combines the Best Worst Method, SMART and PROMETHEE. The main input is student data that includes personal data and assessment criteria. The process begins with the Best Worst Method to determine the weight of each criteria based on a comparison of the best and worst criteria. Next, SMART calculates the utility value of each candidate by multiplying the criteria weights from BWM. Finally, PROMETHEE produces an output in the form of a candidate ranking that shows the best candidates based on their suitability for all criteria.

Best Worst Method (BWM) is a multi-criteria decision-making method that has been developed by Rezaei [13]. The reliability of BWM lies in the consistency of its comparisons that provide reliable results. Unlike the AHP approach, BWM requires relatively fewer pairwise comparisons, making it a more efficient choice in criteria assessment [14]. Best Worst Method consists of five main steps that must be followed [15]. The process starts with the identification and definition of all relevant criteria {c1, c2, ..., cn} that have a significant influence on the decision-making process. Then, the best and worst criteria are defined without the need for direct comparisons. Following this, the Best-to-Others are determined with the following equation:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (1)$$

Similarly, identify the Others-to-Worst criteria, which reflects how each criteria compares to the worst criteria, as described in the following equation:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW}) \quad (2)$$

The next step involves calculating the optimal weight for each criteria using the equation:

$$W^* = w_1^*, w_2^*, \dots, w_n^* \quad (3)$$

The optimal weights are determined by satisfying the following conditions in equation:

$$\frac{w_B}{w_j} = a_{Bj} \text{ and } \frac{w_j}{w_W} = a_{jW} \quad (4)$$

Where w_B is the best criteria weight and w_W is the worst criteria weight. The largest absolute difference is minimized to satisfy this condition for j as shown below:

$$min\ max_j (\left| \frac{w_B}{w_j} - a_{Bj} \right| , \left| \frac{w_j}{w_W} - a_{jW} \right|) \quad (5)$$

with conditions,

$$\textstyle\sum_{j=1}^{n} w_j = 1, w_j \geq 0, \forall j \quad (6)$$

this condition ensures that the total weight of all criteria is equal to 1 and each criteria weight is non-negative.

Simple Multi Attribute Rating Technique (SMART) developed by Edward in 1977 is a multiattribute decision-making technique that helps choose from a variety of alternatives. SMART uses several parameters weighted between 0-1 to facilitate calculations and comparisons between alternatives on the basis of which decisions are made [16]. SMART adopts an additive linear model, in which the total value of alternatives is calculated by adding the multiplications between the value of each criteria and its weight, providing an easy and effective way to evaluate alternatives based on the value and weight of each criteria [17]. The process begins by establishing the criteria and assigning appropriate weights to each criteria, which reflect their relative importance in the decision-making process. After that, a normalization process is performed to standardize the values of the criteria, ensuring they are comparable across different alternatives. Once the normalization is completed, each alternative is evaluated based on the established criteria, allowing for a fair comparison. The utility value for each criteria is then calculated using equation:

$$u_i(a_i) = \frac{(C_{out} - C_{min})}{(C_{max} - C_{min})} \quad (7)$$

Description:

$u_i(a_i)$: utility value of the i-th alternaitf for the i-th criteria

C_{max} : maximum value of each criteria

C_{min} : minimum value of each criteria

C_{out} : value of the i-th criteria

Following this, the final value for each alternative is calculated using equation:

$$NA = u_i(a_i)W_j, ij = 1,2, \dots, m \quad (8)$$

Description:

NA : alternative final value

W_j : weighting value of the j-th criteria

$u_i(a_i)$: utility value of the i-th alternaitf for the i-th criteria

Preference Ranking Organization Methods for Enrichment Evaluation (PROMETHEE) is a non-compensatory approach used to handle ranking problems [18]. The main advantages of the PROMETHEE method are simplicity, clarity and stability. The process of selecting alternatives with the PROMETHEE method requires several stages that must be carried out by the decision maker. These stages are important to produce a sequence or priority in accordance with the preferences of the criteria that have been determined [3]. The decision-making process begins by determining a set of alternatives to be evaluated, followed by identifying several criteria that will be used to assess these alternatives. Once the criteria are established, appropriate weights are assigned to reflect their relative importance in the evaluation process. The type of assessment for each criteria is then determined, specifying whether it is a minimization or maximization criteria based on the desired outcomes. Preference values are subsequently calculated using equations:

$$P(a,b) = P(f(a) - f(b)) \quad (9)$$

$$H(d) = \begin{cases} 0 \text{ if } P(a,b) \le 0 \\ P(a,b) \text{ if } P(a,b) > 0 \end{cases} \quad (10)$$

Description:

$P(a,b)$: preference of alternative a to alternative b

$f(a)$: evaluation of a criteria from alternative a

$f(b)$: evaluation of a criteria from alternative b

$H(d)$: criteria difference function between alternatives

d : difference in criteria values $\{d = f(a) - f(b)\}$

After calculating preference values for individual criteria, the multicriteria preference values are determined using equation:

$$\varphi(a,b) = \frac{1}{k}\sum_{i=1}^{k} P_i(a,b); \forall a,b \in A \quad (11)$$

Description:

$\varphi(a,b)$: multicriteria preference index of alternative a is better than alternative b

$P_i(a,b)$: preference of alternative a to alternative b

k : number of criteria

Leaving Flow, Entering Flow and Net Flow are calculated to provide a final assessment of each alternative using equation:

$$\varphi^+(a) = \frac{1}{n-1}\sum_{x \in A} \varphi(a,b) \quad (12)$$

$$\varphi^-(a) = \frac{1}{n-1}\sum_{x \in A} \varphi(b,a) \quad (13)$$

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \quad (14)$$

Description:

$\varphi(a,b)$: indicates the preference of alternative a over alternative b

$\varphi(b,a)$: indicates the preference of alternative b over alternative a

$\varphi^+(a)$: Leaving Flow indicates an alternative advantage

$\varphi^-(a)$: Entering Flow indicates an alternative weakness

$\varphi(a)$: Net Flow is used to determine the final order of alternatives

Confusion Matrix is an evaluation method used in decision support systems to measure the performance of classification models. This method presents information on the number of correct and incorrect predictions for each category and gives a clear picture of the accuracy of the model [19]. Performance measurement using Confusion Matrix there are four terms, namely True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN). True Positive denotes a positive case that was correctly predicted, while False Negative is a positive case that was incorrectly predicted as negative. False positives refer to negative cases that are incorrectly classified as positive, and True negatives reflect precisely identified negative cases [17]. The structure of the Confusion Matrix can be seen in Table 1.

Table 1: Confusion Matrix

Actual	*Prediction*	
	True	*False*
True	True Positive (TP)	False Negative (FN)
False	False Positive (FP)	True Negative (TN)

The information presented in Table 1, the measurement of model performance is carried out through validation tests using the Confusion Matrix method producing various important metrics such as accuracy, precision, recall, and f1-score. The calculation of such matrices can be obtained using the following formula:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \ x\ 100\% \quad (15)$$

$$Precision = \frac{TP}{TP+FP} \ x\ 100\% \quad (16)$$

$$Recall = \frac{TP}{TP+FN} \ x\ 100\% \quad (17)$$

$$F1 - Score = 2\ x\ \frac{Recall\ x\ Precision}{Recall+Precision} \ x\ 100\% \quad (18)$$

Accuracy refers to the percentage of data correctly classified by the algorithm, reflecting the model's effectiveness in identifying the correct category. Precision indicates the proportion of cases predicted positive that are actually positive, assessing the model's positive prediction accuracy. Recall measures the proportion of positive cases identified by the model compared to the total number of positive cases, indicating the model's ability to find all positive cases. F1-Score reflects the proportion of negative cases correctly identified, illustrating the model's ability to accurately recognize negative data.

Sensitivity analysis studies the impact of changes in input on output in a system typically through mathematical models in software to simulate the functioning of real systems. Its main objectives include the exploration of causal relationships, the reduction of complexity to identify non-influential factors, and the evaluation of data to find the most significant elements. The analysis also supports decision-making by assessing the sensitivity of outcomes to various options, constraints, and assumptions [20].

Spearman's Rho Correlation is a method often used in sensitivity analysis for Multi-Criteria Decision Making that is useful in measuring the strength and direction of relationships between ranking criteria. It provides insight into the effect of changing ranking criteria on decision outcomes, especially when the data are ranked or do not meet the assumption of normality [9]. The formula for calculating Spearman's Rho Correlation is as follows:

$$R = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (19)$$

Description:

R : Spearman's Rho Correlation Coefficient

d_i : difference between ranks for pair of variables i

n : number of variables

RESULT AND DISCUSSION

This research applied 7 assessment criteria in the process of selecting scholarship recipients. These criteria played a crucial role in assessing the eligibility of prospective recipients. Each aspect was assessed carefully to ensure a comprehensive and objective selection. The criteria used included:

1. Academic Value (C1): Based on the average degree score, ranging from 1 (<=75) to 5 (>90).
2. Parents Income (C2): Monthly combined gross income, from 1 (>Rp 5,000,000) to 5 (<Rp 2,500,000).
3. Achievements (C3): Academic and non-academic championships, from 1 (None) to 5 (International).
4. Organization and Extracurriculars (C4): Participation in activities, from 1 (0 Activities) to 5 (>=4 Activities).
5. Dependents (C5): Number of family dependents, from 1 (<=3 People) to 5 (>=7 People).
6. Academic Potential Test (C6): Test scores, from 1 (<=80) to 5 (96-100).
7. Kartu Indonesia Pintar (C7): KIP ownership, 1 (None) or 5 (Have KIP).

As input data, 54 data of students who qualify as prospective scholarship recipients have been collected and analyzed based on these criteria. Details of student data that have been analyzed are shown in Table 2.

Table 2: Data Students

ID	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*
A1	3	5	1	3	1	3	5
A2	3	3	2	2	3	3	5
A3	3	5	1	2	3	5	5
A4	1	3	1	2	3	4	1
A5	3	5	1	2	1	1	1
	...						
A54	1	3	1	2	3	4	1

Best Worst Method (BWM) is employed to determine the weight of each criteria by identifying the best and worst criteria. Based on the process, Parents Income (C2) is chosen as the best criteria, while Academic Potential Test (C6) is identified as the worst criteria. Following this, comparisons are made between each of the other criteria and the best and worst criteria to assess their relative importance. The comparison results are presented in the Best-to-Others and Others-to-Worst matrices, where values represent how each criteria compares to the best and worst criteria, respectively. After obtaining the comparison values, a min-max calculation is conducted to determine the optimal weight for each criteria, as shown in Table 3.

Table 3: Weight of Each Criteria

C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*
0,143	0,250	0,107	0,071	0,214	0,036	0,179

Once the criteria weights are obtained, the SMART method is used to evaluate alternatives based on those weights. Each candidate is assessed by multiplying the criteria weights by the utility value of each criteria, resulting in a final score for each candidate. PROMETHEE is used to sort candidates based on preference values calculated from the final values in the SMART method. This method generates a net flow to obtain the final order of most suitable candidates. The net flow of the combined BWM-SMART-PROMETHEE (BSMP) is then compared with other methods, including BWM-SMART (BSM), BWM-PROMETHEE (BP), BWM-TOPSIS (BT) and BWM-SAW (BS). These comparisons, which highlight the value and ranking of each method are presented in Table 4 to provide a clear overview of the performance and outcomes of each approach.

Table 4: Ranking of Alternatives

ID	*BSMP*	*BSMP Rank*	*BSM*	*BSM Rank*	*BP*	*BP Rank*	*BT*	*BT Rank*	*BS*	*BS Rank*
A1	0,217	13	0,554	13	0,916	11	0,511	16	0,679	14
A2	0,263	9	0,589	7	0,87	15	0,609	5	0,704	10
A3	0,378	1	0,679	1	1,467	1	0,638	1	0,782	1
A4	-0,12	34	0,295	30	-0,51	37	0,372	27	0,475	33
A5	-0,08	27	0,321	27	-0,19	22	0,409	23	0,504	26
	...									
A54	-0,12	35	0,295	35	-0,51	38	0,372	28	0,475	34

Performance evaluation is done measuring accuracy, precision, recall, and specificity through validation tests using confusion matrix. The classification results obtained were compared with other methods, such as BWM-SMART (BSM), BWM-PROMETHEE (BP), BWM-TOPSIS (BT) and BWM-SAW (BS) which are presented in Table 5 to show the performance of each method.

Table 5: Comparison of Performance Evaluation

Method	*Accuracy*	*Precision*	*Recall*	*F1-Score*
BSMP	96,29%	96,67%	96,67%	96,67%
BSM	92,59%	93,33%	93,33%	93,33%
BP	88,89%	90%	90%	90%
BT	88,89%	90%	90%	90%
BS	92,59%	93,33%	93,33%	93,33%

The results of the performance evaluation comparing several methods showed that the combination of Best Worst Method, SMART and PROMETHEE had better performance among all the methods tested with an accuracy of 96,29%, precision of 96,67%, recall of 96,67%, and f1-score of 96,67%. These outcomes demonstrated the effectiveness and superiority of this combination in delivering highly accurate and reliable performance across the evaluated metrics.

A sensitivity analysis using Spearman's Rho Correlation was carried out to evaluate the consistency of the results obtained from the combination of BWM, SMART and PROMETHEE. In this analysis, the criteria weights of BWM were exchanged 20 times to observe how these changes affected the ranking of alternatives. The results of the sensitivity analysis were generated for various combinations of methods, including BWM-SMART-PROMETHEE (BSMP), BWM-SMART (BSM), BWM-PROMETHEE (BP), BWM-TOPSIS (BT) and BWM-SAW (BS). The average values from these sensitivity analysis results, reflecting the performance consistency of each method are presented in Table 6.

Table 6: Comparison of Sensitivity Analysis Values

Method	*Average Value of Sensitivity Analysis*
BSMP	0,863
BSM	0,860
BP	0,841
BT	0,723
BS	0,852

The results of sensitivity analysis using Spearman's Rho Correlation showed that the combination of BWM, SMART and PROMETHEE is more robust to weight changes with an average sensitivity value of 0,863. For comparison, the BWM-SMART combination has a sensitivity value of 0,860, BWM-PROMETHEE 0,841, BWM-TOPSIS 0,723 and BWM-SAW 0,852. Consistency is considered important when choosing MCDM models because it ensures that alternative ratings remain stable despite changes in criteria weights. These results indicate that the combination of BWM, SMART and PROMETHEE has better resistance to weight changes, making it more stable and consistent in the decision-making process when compared to other methods.

CONCLUSIONS

This research describes the application of a combination of Best Worst Method, SMART and PROMETHEE for the selection of scholarship recipients, accompanied by performance evaluation and sensitivity analysis. The combination of Best Worst Method, SMART and PROMETHEE proved to be effectively implemented in the selection of scholarship recipients based on the results of performance evaluation. This approach has the advantage of combining efficient criteria weighting using Best Worst Method, measurable alternative utility assessment using SMART and alternative ranking by preference with PROMETHEE. The sensitivity analysis proved that the combination of Best Worst Method, SMART and PROMETHEE is more robust to changes in the weight of the criteria when compared with other methods, such as BWM-SMART, BWM-PROMETHEE, BWM-TOPSIS and BWM-SAW. This ensures that the selection process remains fair, objective and consistent across different weighting schemes. The combination of Best Worst Method, SMART and PROMETHEE significantly contributes to improving the quality of scholarship selection, making it a reliable tool for decision-making in selection systems. Furthermore, the approach ensures that the evaluation remains consistent and robust, regardless of variations in the criteria weights, making it a preferred choice for scholarship recipient selection over other methods.

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