AHP and PROMETHEE Comparison on Decision Support System for Scholarship Selection in Universitas Sebelas Maret Surakarta

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Abstract
Youth awareness regarding the importance of continuing their education in higher institutions is very low. It has been discovered that the biggest factor responsible for this is very expensive price of higher institutions. To overcome this problem, Universitas Sebelas Maret (UNS) offers scholarships to individuals who meet the criteria. Currently, the implementation of scholarship selection in UNS is still performed manually and this often leads to a long selection procedure and has been considered inaccurate. Therefore, a Decision Support System (DSS) is needed to aid the scholarship selection process. The system can compute the criteria score and generate a ranking based on the criteria weight. The results showed that using the AHP algorithm on DSS at school in East Java yielded an accuracy score of 90%, while the PROMETHEE utilization on a system of determining the food aid recipients showed 85% accuracy. This study aims to determine the difference between the accuracies of AHP and PROMETHE in the development of the scholarship system (SIBEA) at UNS. This study showed the SIBEA prototype and the analysis of the comparison algorithm as well as the one that is better to use at UNS.

Keywords
AHP, Algorithm, Decision Support System, PROMETHEE, Scholarship

1. Introduction
Youth awareness concerning the importance of furthering their education in higher institutions is very low (Yunus et al., 2021). The study by (Lestari & Zakso, 2020) discovered the internal factor responsible for this as a lack of motivation to continue the education, while the external factor was the high cost of learning in universities.

As a higher institution, Universitas Sebelas Maret (UNS) offers several scholarships to students who meet certain criteria. Meanwhile, the selection process is conducted manually, especially for non-government scholarships managed by universities, thereby causing a delay and the results are often considered less accurate. Consequently, a Decision Support System (DSS) is required to computerize scores and rank automatically based on the given criteria.

According to the literature reviews, the algorithms that are often used in the DSS scholarship system are the Analytic Hierarchy Process (AHP) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE). AHP works by breaking down complex problems into a hierarchical system that is used to select the best alternative. The study by (Puspitasari et al., 2018) showed that the use of AHP as a Decision Support System on scholarship selection in East Java High School has an accuracy of 90%. Other studies showed that the PROMETHEE algorithm has a more precise ranking because it relies on data and decision-making considerations when determining the preference function for each criterion (Istiqomah & Windarni, 2019). In (Maulachela et al., 2019), using the PROMETHEE as DSS in the food aid reception system showed an accuracy of 85%. It has been observed that the AHP and PROMETHEE methods are MCDM that have been widely utilized due to their high accuracy level in determining the alternative rankings based on weights and criteria (Istiqomah & Windarni, 2019).

1.1. Objective
This study aims to determine the accuracy of the AHP and PROMETHEE algorithms in making scholarship acceptance decisions at Universitas Sebelas Maret. The result is the algorithm that best suits the conditions of scholarship selection.

2. Literature Review

2.1. Scholarship
Scholarships (Sugiyarti et al., 2018) are financial assistance for individuals, which are often used as required tuition fees and are divided into two based on the source of the provider: government and non-government scholarships. Furthermore, they are categorized into 3 based on the terms and criteria requested, which include Underprivileged, Merit, and General scholarships. Underprivileged scholarships are for those who want to continue their education but have economic limitations. Merit scholarships are for those who excel regardless of economic conditions, while that of general are scholarships whose criteria are not based on economic conditions or merit. It is important to note that in UNS, scholarships are divided into 3 based on the selection of the organizers, which include government scholarships such as KIP and Bidikmisi, non-government scholarships managed by the university, and those that are not managed by the university. The case study here is scholarships for the underprivileged that are administered by non-government universities. All the above scholarships generally have the same selection stages as follows.

1) Offering stage, entails providing scholarship offer information to students.
2) The registration stage involves students applying for scholarships. In this phase, there are several sub-stages including filling out personal information, uploading the required files, finalizing, and printing the proof of registration.
3) In the verification stage, biodata is verified by the selection organizer.
4) The nomination stage involves computing the criteria score and determining who is entitled to receive the scholarship. Furthermore, a decision letter is also made for scholarship recipients.
5) The announcement stage deals with providing information to students about the results of the scholarship selection.
6) The disbursement stage involves distributing scholarships to the recipients.
7) The evaluation stage is always after the scholarship has been awarded and it is performed every semester or annually.

2.2. Decision Support System
A Decision Support System (DSS) is a system used in the decision-making process to help the individuals involved (Sibyan, 2020). This concept was first introduced in the 1970s by Michael S. Scot Morton with the name Management Decision System (MSS), featuring a computer-based interactive system that has the ability to make decisions by utilizing data and models to solve unstructured problems (Limbong et al., 2020). It is important to note that DSS is not intended to completely automate decision making, but allows individuals to conduct analysis using available models and data (Saragih, 2013), (Limbong et al., 2020).

2.3. Multi-Criteria Decision Making
Multi-Criteria Decision Making (MCDM) is a decision-making method of determining the best alternative from several ones given based on predetermined criteria and weights. Furthermore, MCDM consists of 5 components including goals, decision-making preferences, alternatives, criteria, and results (Wang et al., 2009).

Based on the difference in the number of alternatives considered, MCDM is classified into 2, namely Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) (Kumar et al., 2017). (Figure 1)

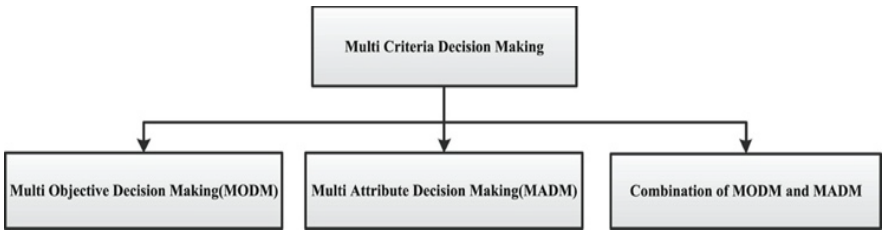

Figure 1 Multi Criteria Decision Making

The MCDM procedure is very complex, and the factors involved include technical, institutional, standard, social, economic, and stakeholder. It is safe to conclude that this process involves technical and managerial analysis. In addition, the MCDM procedure is controversial because its objectives often lead to different solutions at different times, depending on the priorities of the decision makers or those involved in the process. Figure 2 shows the general procedure of MCDM.

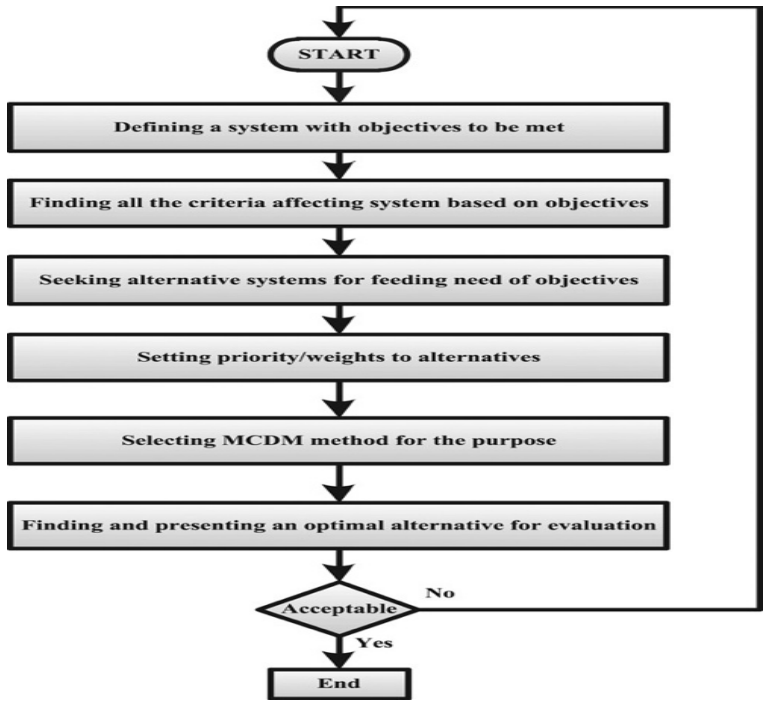

Figure 2 multi-Criteria Decision-making procedure

2.4. Analytic Hierarchy Process (AHP)

AHP is a scientific analytical and decision-making method, which uses consistent hierarchical assessments (Socaciu et al., 2016). It was developed by Thomas Saaty in 1982 and is an effective method that helps decision makers to reduce complex decisions into a series of pairwise comparisons when determining priorities and the best choice. Furthermore, AHP also helps to synthesize the results by capturing the subjective and objective aspects of decision making (Puspitasari et al., 2018).

The advantage of the AHP algorithm is that it clarifies how a possible change in priority at the top level influences the criteria at the lower. Further AHP's merit includes (Linh, 2019):

1. Combining quantitative and qualitative data, using monetary and non-monetary units for it to utilize several criteria even on very large or limited quantitative data.
2. Efficient use of expert assessment.
3. It involves many stakeholders based on local and academic wisdom.

In addition, the stages of AHP include:

1. Identifying the weight of criteria
   This involves the determination of the criteria that must be present in decision-making based on the problems encountered. For example, when selecting a smartphone, the criteria that the user tends to look out for include the amount of storage memory, camera resolution, price, and design.
2. Determining the Pairwise Comparison Matrix.
   The pairwise comparison matrix is weighted based on the importance of the criteria. The weight of pairwise comparisons is determined using the Saaty scale.

TABLE 1 INDEX RATIO

Intensity of Importance	Definition
1	Equal Importance
2	Somewhat more important
5	Much more important
7	Very much more important
9	Absolutely more important
2,4,6,8	Intermediate values

3. Normalizing the Matrix.
   The matrix is normalized by dividing each element by the number of rows. The result of matrix normalization is 0-1, and then each criterion's weight is calculated by finding the total average of each criterion.
4. Calculating Matrix Consistency
   The consistency of a matrix or CM (Consistency Measure) is calculated by multiplying the matrix by the weight of each row. Then the Consistency Index (CI) is searched. The formula for measuring the CI is expressed as follows:

$$\mathrm{CI} = \frac{\lambda \max - n}{n-1} \quad (1)$$

λ max = average of CM (Consistency Measure).
Based on the Saaty's theory, the index ratio was determined based on the order of the matrix and the results are shown in the Table 2 below.

TABLE 2: INDEX RATIO

Ordo matrix	1	2	3	4	5	6	7	8	9	10
Ratio Matrix	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

5. Alternative Priority Weight Calculation
   In calculating the priority weight of the criteria on the alternative, the criteria number is obtained. The steps are similar to when determining the priority weight of the criteria.
6. Ranking
   To calculate the total value, each row of the alternative priority weight matrix is used between the priority weights of the criteria.

2.5. Promethee

The Promethee is a method of determining priority (sequence) in multi-criteria analysis. This method was developed by Brans in early 1982 using the sequencing method (priority) in a multi-criteria analysis (Priyanto et al., 2017). It produces a more precise ranking because it is based on data and decision-making (Istiqomah & Windarni, 2019). The different versions of PROMETHEE include PROMETHEE I, which discusses spatial ordering, PROMETHEE II deals with complete sorting, PROMETHEE III describes interval sorting with emphasis on neglect, PROMETHEE IV discusses the continuous ordering of alternative possibilities, PROMETHEE V supports controlled optimization, and PROMETHEE VI represents how the human brain works. It is important to note that the PROMETHEE II is utilized in this study as it (Sen et al., 2015) has the ability to simplify many human perceptions and judgments whose decisions are long-term. In addition, it generates full and partial assessments. The steps in this version as described by (Brans et al., 1982) include:

1. Normalize the decision matrix with the equation:

$$Rij = \frac{[X_{ij} - \min(X_{ij})]}{[\max(X_{ij}) - \min(X_{ij})]} \qquad (i = 1,2,..,n; j = 1,2,..,m) \quad (2)$$

   Normalize the decision matrix with the equation:

$$Rij = \frac{[max(X_{ij}) - X_{ij}]}{[\max(X_{ij}) - \min(X_{ij})]} \qquad (i = 1,2,..,n; j = 1,2,..,m) \quad (3)$$

   Xij denotes the ith alternative performance measure with respect to the j criterion.
2. Calculate the difference in the alternative evaluation i against other ones. Furthermore, it involves calculating the difference in criterion values between different alternatives in pairs. For example, D(M1-M2) means the difference between alternative 1 and alternative 2.
3. Calculate the preference function $P_j(i, i^\iota)$ with equations:

$$P_j(i, i^\iota) = 0 \qquad if\ R_{ij} \le R_{i^\iota j} \rightarrow\ D(M1 - M2) \le 0 \quad (4)$$

$$P_j(i, i^\iota) = R_{ij} - R_{i^\iota j} \quad if\ R_{ij} > R_{i^\iota j} \rightarrow\ D(M1 - M2) > 0 \quad (5)$$

4. Calculate the preference aggregate function by considering the criteria weight using the equation below:

$$\Pi_{(i,i^\iota)} = \left[\sum_{j=1}^{m} W_j x P_j(i, i^\iota)\right] / \sum_{j=1}^{m} Wj \quad (6)$$

   Wj represents the weight of criteria i th.
5. Calculate the *Leaving Flow* and *Entering Flow* with the equation below:
   Leaving (Positive) Flow for every criterion i th

$$\varphi^+(i) = \frac{i}{n-1} \sum_{i^\iota}^{n} \Pi(i, i^\iota) \qquad (i \neq i^\iota) \quad (7)$$

   Entering (Negative) Flow for every alternative i th.

$$\varphi^-(i) = \frac{i}{n-1} \sum_{i^\iota}^{n} \Pi(i^\iota, i) \qquad (i \neq i^\iota) \quad (8)$$

   n represents the number of alternatives. Every alternative is divided by *n-1.* The *Leaving flow* denotes how much one alternative dominates the other, while the *Entering flow* shows how much alternative is dominated by others.

6. Calculate the *outranking flow* for every alternative with the equation below:

$$\emptyset(i) = \emptyset^+(i) - \emptyset^-(i) \quad (9)$$

7. Rank all alternatives according to the value of $\emptyset(i)$. As the value of $\emptyset(i)$ increases, the alternative becomes better. Therefore, the highest $\emptyset(i)$ value is the best alternative.

2.6. Confusion Matrix

Confusion Matrix is a method for measuring the accuracy of a data mining concept (Priyanto et al., 2017). Furthermore, it is used for evaluating, visualizing the behavior, and determining the performance of the classification model (Davis & Goadrich, 2006). The comparison of accuracy in the confusion matrix is shown in Figure 3.

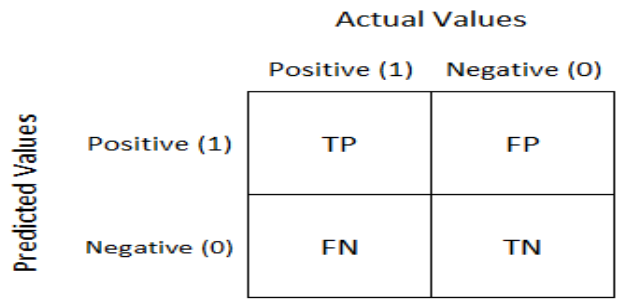

Figure 3 Confusion Matrix

The figure above represents the predicted values and the actual values, in which T(true) and F(false) are representations of actual values, while P(positive) and N(negative) are representations of predicted values. The explanation of the table above is as follows:

1. TP (True Positive) → The amount of data with positive true and positive predicted values.
2. FP (False Positive) → Amount of data with negative true and positive predicted values.
3. FN (False Negative) → The amount of data with positive true and negative predicted values.
4. TN (True Negative) → Amount of data with negative true and negative predicted values.
   The confusion matrix's evaluation produces the following values of accuracy, precision, recall, and f- measure.

1. *Accuracy* shows the number of correctly predicted classes (positive and negative), and it is calculated with the equation below:

$$\frac{TP+TN}{TP+FP+FN+TN} \quad (10)$$

2. *Precision* shows all the classes that are predicted to be positive and the number of classes that are truly positive. It is calculated with the equation:

$$\frac{TP}{TP+FP} \quad (11)$$

3. *Recall* shows all positive classes and the numbers that are correctly predicted. It is calculated using this equation:

$$\frac{TP}{TP+FN} \quad (12)$$

4. *Specificity* is the accuracy of negative prediction compared to the overall negative data, and it is calculated using this equation:

$$\frac{TN}{TN+FP} \quad (13)$$

5. *F-measure* or *F-score* describes the average comparison between precision and weighted recall. It is calculated using the equation below:

$$F-measure = \frac{2*recall*precision}{recall+precision} \quad (14)$$

The options for selecting a performance matrix include:
1. When the dataset has several false negatives and false positives that are close or symmetric, then accuracy needs to be used. But when the numbers are not close, then use the F-measure.
2. Select an algorithm that has high recall when it performs better than False Negative in the case of False Positive.
3. Indicate an algorithm that selects high precision when True Positive is highly desired and True Negative is highly undesirable
4. Choose an algorithm with high specificity when preventing False Positives from occurring.

The standard for measuring the level of accuracy (Gorunescu, 2011) is as follows:
1. Accuracy 90% - 100% = *Excellent Classification*
2. Accuracy 80% - 90% = *Best Classification*
3. Accuracy 70% - 80% = *Fair Classification*
4. Accuracy 60% - 70% = *Poor Classification*
5. Accuracy 50% - 60% = *Failure.*

3. Methods

This study consists of 3 sections, namely study literature and data collection, algorithm implementation, and algorithm testing.

3.1. Study Literature

The literature review was conducted by referring to previous studies that discussed similar topics, those related to the comparison of algorithms to be utilized, and the ones that discussed the methods of measuring the algorithm's quality. Furthermore, the data collected are presented, which include scholarship criteria and the requirements for the scholarship system.

3.2. Algorithm Implementation

Implementation was conducted by development application with PHP and Laravel framework based on the results of study literature and requirement analysis by result of studies with Sebelas Maret student institutions. Using Laravel for application development is quickly with latest technology.

3.3. Algorithm Testing

The testing was conducted by calculating confusion matrix to find out the level of accuracy AHP and PROMETHEE algorithm in scholarship selection system.

3. Data Collection

Data collection in this research is secondary data in the form of scholarship criteria scores and scholarship applicants from Universitas Sebelas Maret Student institute.

4.1. **Scholarship Criteria Score** (Tables 3 – 9)

1. Parents Living Scores

TABLE 3: PARENTS LIVING SCORES

Criteria	Live	Divorced	Died
Score	3	6	10

2. Parents Education Scores

TABLE 4: PARENTS EDUCATION SCORES

Criteria	No School	Elementary School	Junior High School	Senior High School	Associate's degree 1	Associate's degree 2	Associate's degree 1	Bachelor's degree	Master's degree
Score	10	9	8	7	6	5	4	2	1

3. Parents Works Scores

TABLE 5: PARENTS WORK SCORES

Criteria	No Work	Other	Farmers/ Fishermen	Businessman	Private Employees Not Teachers /Lecturers	Private Teacher /Lecturer	Civil Servants Not Teachers /Lecturers	Civil servant teacher /lecturer	soldier Abri/Tni
Score	10	8.3	6.64	4.98	3.32	3.32	1.66	1.66	1.66

4. Parents Income Scores

TABLE 6: PARENTS INCOME SCORES

Criteria*	250 –500	500 – 750	750 – 1000	1000 – 1250	1250 – 1500	1500 – 1750	1750 – 2000	2000 – 2250	2250 – 2500	2500 – 2750	2750 – 3000	3000 – 3250	3250 – 3500	3500 – 3750	3750 – 4000	4000 – 4250	4250 – 4500	4500 – 4750	4750 - 5000	0 - < 250
Score	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	1	19

*In thousand IDR.

5. Home Ownership Scores

TABLE 7: HOME OWNERSHIP SCORES

Criteria	Own House	Crashing	Crashing without permission	Annual rent	Monthly rent	No House
Score	2	4	6	8	10	4

6. Number of Dependent Scores

TABLE 8: NUMBER OF DEPENDENT SCORES

Criteria	1	2	3	4	5	6	7	8	9	0
Score	1	2	3	4	5	6	7	8	9	1

7. Income per Capita Scores

TABLE 9: INCOME PER CAPITA

Criteria	0 - 150	150 - 300	300 - 450	450 - 600	600 - 750	750 - 900	900 - 1050	1050 - 1200	1200 - 1350	1350 - 1500	> 1500
Score	10	9	8	7	6	5	4	3	2	1	1

*In thousand IDR.

4.2. System Requirement Analysis

The scholarship application system requirements are shown with the Use Case Diagram as follows: (Figure 4)

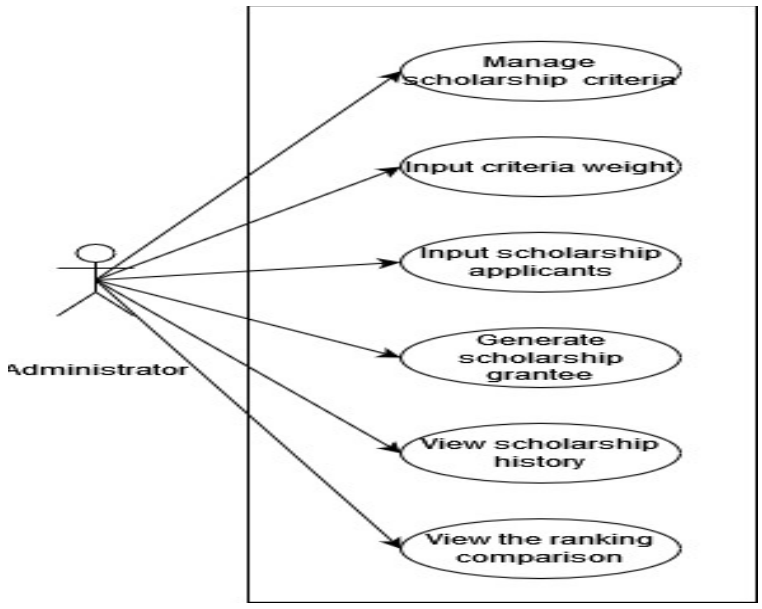

Figure 4 Use Case Diagram

4. Results and Discussion

This study uses 30 alternative data and 13 criteria for applicants. The scholarships considered as case studies were the unprivileged with a quota of 20 participants. The data was obtained from the results of interviews with Universitas Sebelas Maret.

4.1. Graphical Results

1. AHP Implementation

The necessary criteria were identified before performing the calculations, followed by AHP weighting according to the criteria desired by the expert. The weighting process was conducted by making a criterion comparison matrix as shown in Figure 5.

	STA	STI	SPA	SPI	SKA	SKI	SHA	SHI	SHO	SKR	SJT	SKJ
STA	1	2	4	4	1	2	2	2	3	4	4	3
STI	0.5	1	3	3	0.5	1	1	1	2	3	3	2
SPA	0.25	0.33333333333333	1	1	0.25	0.3333333333	0.3333333333	0.3333333333	0.5	1	1	0.5
SPI	0.25	0.33333333333333	1	1	0.25	0.3333333333	0.3333333333	0.3333333333	0.5	1	1	0.5
SKA	1	2	4	4	1	2	2	2	3	4	4	3
SKI	0.5	1	3.0000000003	3.0000000003	0.5	1	1	1	2	3	3	2
SHA	0.5	1	3.0000000003	3.0000000003	0.5	1	1	1	2	3	3	2
SHI	0.5	1	3.0000000003	3.0000000003	0.5	1	1	1	2	3	3	2
SHO	0.33333333333333	0.5	2	2	0.33333333333333	0.5	0.5	0.5	1	2	2	1
SKR	0.25	0.33333333333333	1	1	0.25	0.33333333333333	0.33333333333333	0.33333333333333	0.5	1	1	0.5
SJT	0.25	0.33333333333333	1	1	0.25	0.33333333333333	0.33333333333333	0.33333333333333	0.5	1	1	0.5
SKJ	0.33333333333333	0.5	2	2	0.33333333333333	0.5	0.5	0.5	1	2	2	1
	5.6666666666667	10.333333333333	28.0000000009	28.0000000009	5.6666666666667	10.333333333267	10.333333333267	10.333333333267	18	28	28	18

Figure 5 AHP Criteria

Furthermore, this AHP calculation was performed in several stages, which include:

a. Decision Matrix Normalization: Based on the comparison matrix, the criteria that have been formed are normalized by dividing the value of the alternative criteria with the highest value.
b. Look for matrix consistency: This is intended to check whether the specified comparison value is consistent. In this study the consistency value is below 0.1.
c. Determine the criteria priority matrix: In this case the UNS provides data in the form of a finished scale to obtain a priority value
d. Calculating the weight of the criteria for each alternative: This is achieved by matching the criteria data with the values for the comparison results from the previous stage.
e. Ranking stage: This stage is done by adding up all the data on each criterion in one alternative. Furthermore, the total value for each alternative is sorted to obtain ranking results as shown below. (Figure 6)

Ranking	Nama	Total	Status
1	nana	0.399	diterima
2	didi	0.384	diterima
3	doni	0.368	diterima
4	tini	0.364	diterima
5	salsa	0.359	diterima
6	hana	0.347	diterima
7	dinda	0.342	diterima
8	dewi	0.342	diterima
9	tata	0.328	diterima
10	nuri	0.32	diterima
11	dodi	0.317	diterima
12	dian	0.317	diterima
13	tita	0.304	diterima
14	cika	0.292	diterima
15	ninda	0.29	diterima
16	zeina	0.269	diterima
17	dona	0.267	diterima
18	dina	0.264	diterima
19	tira	0.261	diterima
20	danang	0.254	diterima
21	dini	0.252	ditolak
22	tono	0.236	ditolak
23	nita	0.23	ditolak
24	tina	0.224	ditolak
25	joni	0.218	ditolak
26	salma	0.204	ditolak
27	titi	0.189	ditolak
28	nian	0.161	ditolak
29	toni	0.156	ditolak
30	nanda	0.108	ditolak

Figure 6 Ranking AHP Algorithm

2. Promethee Implementation

The desired criteria have been weighted prior to the calculation. It is important to note that the criteria need to have the same weight as those in the AHP with different scales and rules. The PROMETHEE weighting is shown in Figure 7.

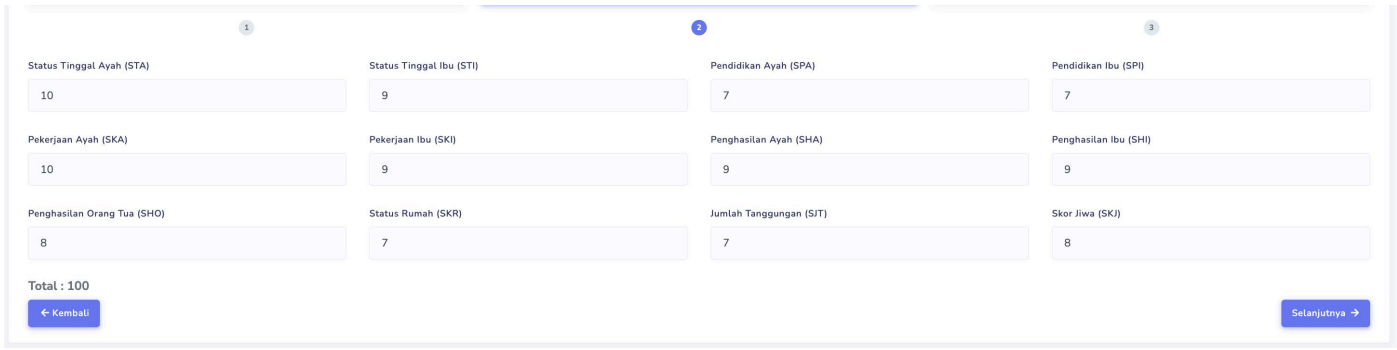

Figure 7 Promethee Criteria

Furthermore, the Promethee calculation is performed in several stages, as follows: (Figure 8)

a. The decision matrix normalization stage: This is conducted to normalize the data obtained. After normalization is conducted, the results of the normalization table are multiplied by the weight for each criterion.
b. Alternative comparison stage: This involves finding the difference between the two alternatives selected for each criterion. The number of comparisons or the amount of data is calculated by n2 – n. In this study, only the first 30 data are shown.
c. Preference function calculation stage: This is conducted by entering the equation. The calculation results obtained was a value of 0 – 1.
d. Aggregate function calculation stage: This is done in accordance with the procedure described in the literature study.
e. Leaving Flow and Entering Flow calculation stages
f. Outranking flow calculation stage: Outranking flow is obtained from the difference between leaving and entering flows.
g. Ranking stage: Ranking is obtained from the highest outranking flow.

Ranking	Nama	Outranking Flow	Status
1	nanda	3.273	diterima
2	toni	2.442	diterima
3	nian	1.965	diterima
4	titi	1.857	diterima
5	salma	0.989	diterima
6	danang	0.938	diterima
7	joni	0.763	diterima
8	nita	0.727	diterima
9	dina	0.71	diterima
10	tira	0.352	diterima

Figure 8 Ranking Promethee Algorithm

3. Confusion Matrix

This test was conducted to determine the accuracy of the algorithm and to determine the one suitable for the scholarship system at Universitas Sebelas Maret. The Confusion Matrix calculation in this study is based on the similarities between the accepted and rejected participants from the algorithm and the actual data. The TP, TN, FP, and FN determined in this case include:

a. TP denoting that the applicants were predicted to receive a scholarship and it turns out that they received the scholarship.
b. TN indicated that the applicants were predicted to not receive, and it turns out that they did not receive the scholarship.
c. FP represents that the applicants were predicted to receive, but it turns out that they did not receive the scholarship.
d. FN is that the applicants were predicted not to receive, but it turns out that they received a scholarship.

The results of the calculation of the confusion matrix in the two algorithms are shown in Table 10 and 11.

TABLE 10: COMPARATION OF ACCURACY ON CONFUSION MATRIX

	TP	TN	FP	FN
PROMETHEE	10	0	10	10
AHP	19	9	1	1

TABLE 11 CONFUSION MATRIX

	Accuration	Precision	Sensitivity	F-Score
PROMETHEE	33,33%	50%	50%	50%
AHP	93,33	95%	95%	95%

After calculating the confusion matrix for each algorithm, an analysis is then performed to determine the best. In this scenario, two points were used as a reference. The first is regarding scholarship receipts, it was observed that the prediction results of the False Positive data number. For example, not receiving a scholarship but predicting incorrectly is close to that of False Negative, which is receiving a scholarship but predicted otherwise. Therefore, to determine the best algorithm in this case, the Accuracy calculation needs to be used. The scholarship recipient's selection shows that out of the 30 data used by the PROMETHEE algorithm, the FP and FN values were 10, respectively with an accuracy value of 33.33%. Therefore, the result is considered a failure. Meanwhile, the AHP algorithm shows the FP and FN values were 1, respectively with an accuracy of 93.33%, and was therefore considered Excellent. This simply signifies that the AHP algorithm is superior to PROMETHEE as it has higher accuracy.

The second is the case of receiving a scholarship in which True Positive representing predicted to receive and receiving the scholarship is highly desirable than True Negative denoting predicted not to receive and not actually receiving the scholarship. In this scenario, the algorithm with high precision was chosen. It was observed that the PROMETHEE algorithm has a precision value of 50% while the AHP has 95%. This means that the AHP is superior to the PROMETHEE algorithm because it has a higher precision value.

5. Conclusion

The accuracy calculation of the AHP and PROMETHEE algorithms in the SIBEA application has been conducted using a confusion matrix. It involves representing the actual scholarship recipient data with True and False as well as the scholarship recipients' predicted data as Positive and Negative. This helps in performing the Accuracy, Precision, Recall, Sensitivity, and F-score calculations.

The comparison results of the algorithm with the confusion matrix in this aspect are based on 2 things, namely the number of adjacent FP and FN to obtain the best algorithm from the highest Accuracy value. In this case, the AHP with 93.33% accuracy was better than PROMETHEE which obtained 33.33%. Second, it was determined from the highest precision value because TP was more desirable than TN. The result showed that the AHP algorithm was better as it has a precision value of 95% compared to the PROMETHEE with 50%. Therefore, in the case of receiving a scholarship at Universitas Sebelas Maret, Surakarta, the use of the AHP is better than the PROMETHEE algorithm.

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