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Multi-Criteria Decision Support System for Web-Based Credit Approval: A Study of TOPSIS, MABAC, WASPAS, and MAUT Methods

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Abstract. *The decision-making process in granting credit involves analyzing a series of alternatives using certain criteria.. The goal is to find the best alternative that meets these criteria. One method that can be used in the decision making process is Multi-Criteria Decision Making (MCDM) or Multi-Criteria Decision Analysis (MCDA). There are many MCDM or MCDA methods that can be used for decision making. This research aims to test the MCDM methods, namely TOPSIS, MABAC, WASPAS and MAUT in making decisions regarding credit acceptance. The dataset used in this research is data regarding credit acceptance with 5 criteria and 100 attributes. The method study was carried out by ranking all alternatives based on the best alternative and then comparing the ranking results of the four methods using Spearman and Kendall Tau rank correlations. And carry out sensitivity tests on the four methods to find the most sensitive method. The results of the comparison of the four methods show that there is a strong correlation between the MABAC and WASPAS methods. The sensitivity test results show that the TOPSIS method is the most sensitive method. Based on the correlation results, it can be concluded that the MABAC and WASPAS methods are the methods that produce the most similar rankings. Meanwhile, the most sensitive method is obtained by the TOPSIS method.*

Keywords: *Decision Support System, TOPSIS, MABAC, WASPAS, MAUT*

1. INTRODUCTION

According to Law Number 10 of 1998 Article 1 Paragraph 2 concerning Banking, a bank is a business entity that collects funds from the public in the form of deposits and redistributes them to the public in the form of credit or other forms, with the aim of improving the standard of living in society. [1]. Credit refers to a loan provided by a creditor, which is to be repaid by the debtor according to an agreed-upon schedule, along with compensation through interest, fees, or profit-sharing calculations. Some steps in the decision-making process for credit approval are still done manually. Errors in the credit analysis process can lead to the risk of non-performing loans. Non-performing loans can become a complex issue, potentially causing losses that may even threaten a bank with bankruptcy [2] The use of a decision support system can be an anticipatory measure to address these issues.

The implementation of a computerized system, particularly a decision support system, is considered an appropriate solution to support managers in decision-making. In this context, the decision support system aims to assist managers in the decision-making process regarding financing applications submitted by applicants. With a decision support system in place, the decision-making process for credit approval can become more efficient and effective [[3]. The principle of a decision support system is a computer-based system designed to assist in the decision-making process by utilizing specific data and models to solve semi-structured problems [4].

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The decision-making process involves analyzing a set of alternatives using specific criteria. The goal is to find the best alternative that meets these criteria. One of the methods that can be used in the decision-making process is Multi-Criteria Decision Making (MCDM) or Multi-Criteria Decision Analysis (MCDA). MCDM or MCDA focuses on solving decision and planning problems that involve multiple criteria [5]. There are many MCDM or MCDA methods that can be used, including TOPSIS, PROMETHEE, AHP, ANP, MAUT, MACBETH, MOORA, COPRAS, WASPAS, and MABAC [[6]. Each MCDM method has a different algorithm, making it challenging to select a method to address a particular problem, as different MCDM methods may yield different rankings [7]. Therefore, it is necessary to conduct experiments by comparing the results of alternatives to determine which method can best recommend the optimal alternative. [8]

Thus, the development and implementation of multi-criteria methods in the credit approval process are considered important steps. This effort is expected to enhance the efficiency and effectiveness of the process, as well as contribute to the stability and sustainability of the banking and financial sector as a whole. This research will examine and analyze the correlation of the results from the four methods to provide an overview of credit feasibility determination using MCDA. Therefore, this study discusses a Web-Based Multi-Criteria Decision Support System for Credit Approval: A Study of the TOPSIS, MABAC, WASPAS, and MAUT Methods.

2. RESEACH METHODS

This study uses data from Kaggle, specifically credit approval data. The research compares four different methods using the same dataset to determine which method is most suitable for the data used. The methods employed in this research include TOPSIS, MABAC, WASPAS, MAUT, Rank Correlation Spearman, and Kendall Tau, as well as sensitivity testing. The four methods are used to calculate the rankings of alternatives, while rank correlation is utilized to compare the rankings of the methods, and sensitivity testing is conducted to assess how sensitive these methods are.

Topsis Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method introduced by Yoon and Hwang in 1981 [9] The fundamental principle of the TOPSIS method is that the selected alternative should have the closest distance to the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution is considered the sum of the best values achieved for each attribute. [10].

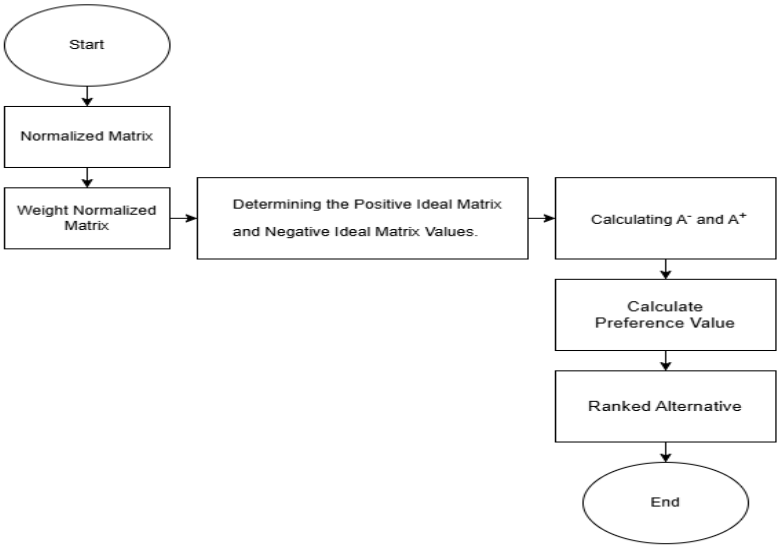

Figure 1. TOPSIS Method Steps

In multi-criteria decision-making (MCDM), comparing criteria with different units is facilitated by normalization, which eliminates units, making the criteria dimensionless. Normalized values are calculated by dividing each value in the decision matrix by the square root of the sum of squares of all values in the criterion. Next, the weighted normalized matrix is obtained by multiplying the normalized values by the weights of each criterion. The positive ideal solution (A^+) and negative ideal solution (A^-) are then determined. For benefit-type criteria, A^+ is the maximum value and A^- is the minimum value in the weighted matrix, while for cost-type criteria, A^+ is the minimum value and A^- is the maximum value. The distance of each alternative from the positive ideal solution (S^+) and negative ideal solution (S^-) is calculated using the Euclidean distance method. The preference value for each alternative is computed by dividing the negative ideal distance (S^-) by the total distance ($S^+ + S^-$), yielding a relative closeness factor (RC) ranging from 0 to 1. The alternatives are then ranked, with the alternative having the highest RC value being the best solution, while the one with the lowest RC value is the least suitable.

Mabac Method

The Multi-Attributive Border Approximation Area Comparison (MABAC) Method developed by Pamucar and Cirovic, evaluates how close each observed alternative is to the boundary of the approximate area defined by the given criteria [11]. The MABAC method consists of six steps: Forming the Initial Decision Matrix, Normalization of the Initial Matrix Calculation of the Weighted Matrix, Determination of the Border Approximate Area Matrix, Calculation of the Matrix Elements of Alternative Distance from the Border Approximate Area, Ranking Alternatives . [12]

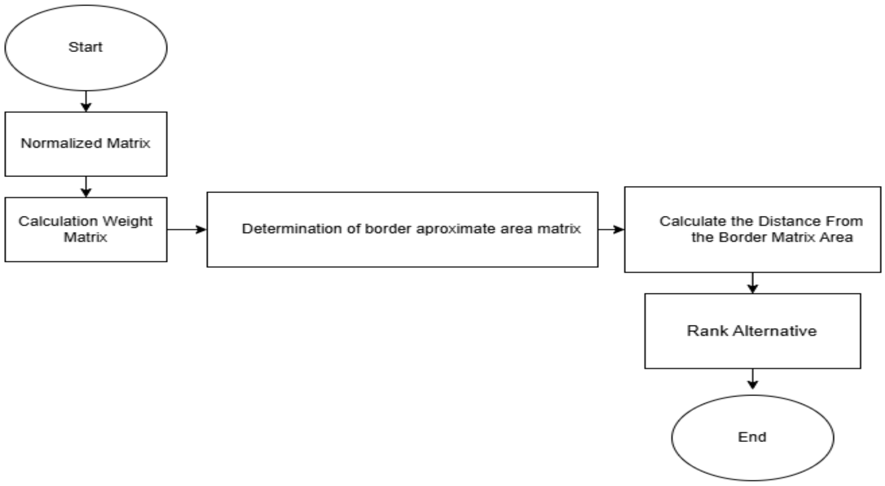

Figure 2. Mabac Method

In multi-criteria decision-making, the normalization of a matrix depends on the type of criteria. Benefit criteria are normalized by comparing each value to the range of observed values, while cost criteria are normalized inversely to reflect their nature. After normalization, the weighted normalized matrix is calculated by incorporating the weights assigned to each criterion. The boundary approximate area matrix

$$g_i = \left(\prod_{j=1}^{m} V_{ij} \right)^{1/m} \tag{11}$$

Where V_{ij} represents the element of the weighted matrix and m denotes the total number of alternatives. After calculating the g_i based on the criteria, these values form the boundary approximate area matrix in an *n* x 1 format, where "*n*" represents the total number of criteria used in selecting the offered alternatives. The distance from the boundary approximate area is subsequently calculated to assess how far each alternative deviates from the reference point. Finally, alternatives are ranked by summing the distances, with the highest score indicating the most favorable option. This systematic approach ensures an objective evaluation and facilitates decision-making in complex scenarios.

Waspas Method

The Weighted Aggregated Sum Product Assessment (WASPAS) method is a combination of Multi-Criteria Decision-Making (MCDM) models, specifically the weighted sum model and the weighted product model. The WASPAS method aims to reduce errors or improve assessments for selecting the highest and lowest values in decision-making processes [13].

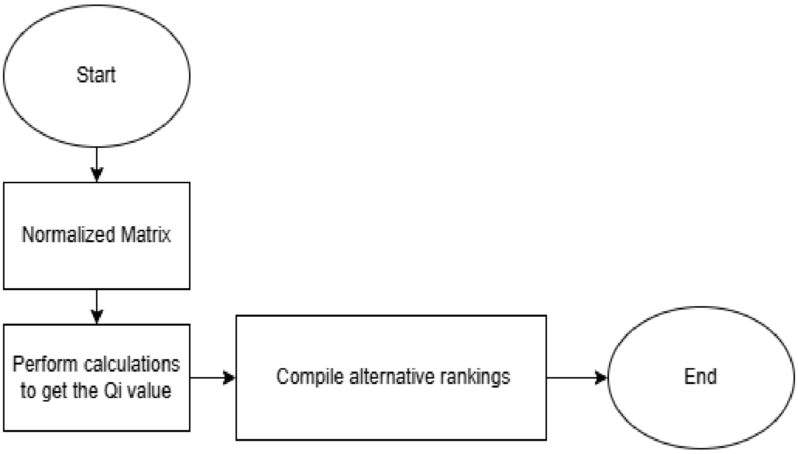

Figure 3. Waspas Method

Normalization is a crucial step in multi-criteria decision-making, ensuring that criteria with different scales are comparable. Each criterion is categorized as either a benefit or a cost. A benefit criterion implies that higher values are preferable, while a cost criterion indicates that lower values are more desirable. For benefit criteria, the performance value of an alternative is normalized by dividing it by the maximum observed value, whereas for cost criteria, normalization is achieved by dividing the minimum observed value by the performance value. After normalization, the preference value (Qi) for each alternative is calculated using the formula:

$$Qi = 0.5 \sum_{j=1}^{n} x_{ij}w + 0.5 \prod_{j=1}^{n} (x_{ij})^{w_j} \qquad (16)$$

Where $x_{ij}w$ is the multiplication of the x_{ij} value with the weight or w. then $(x_{ij})^{wj}$ is the value of x_{ij} raised to the power of weight or w. while Q_i is the value from Q to i. The Q_i value reflects the overall preference of an alternative. Finally, alternatives are ranked based on their Qi values, with the highest value indicating the best choice, ensuring a systematic and objective decision-making process.

Maut Method

The Multi-Attribute Utility Theory (MAUT) method is used to transform multiple criteria into numerical values on a 0-1 scale. In this scale, a value of 0 indicates a less recommended option, while a value of 1 represents the most recommended option [14].

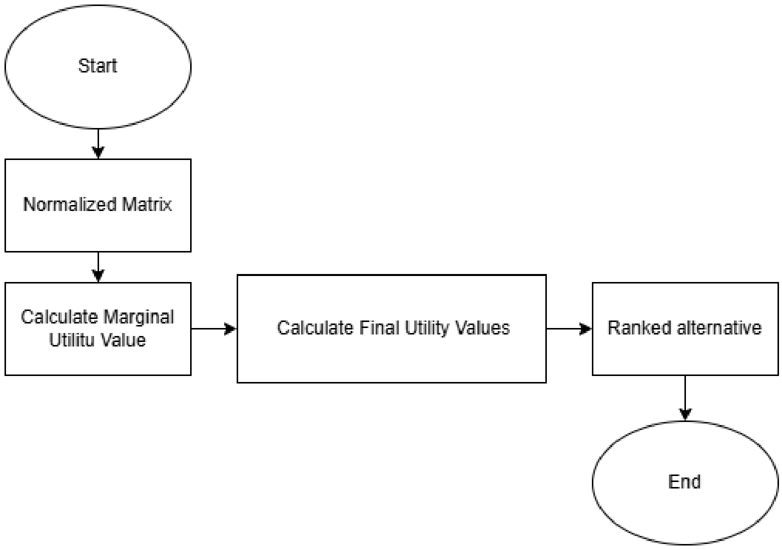

Figure 4. Maut Method

Normalization ensures comparability of criteria using formulas tailored to benefit or cost types. After normalization, the marginal utility for each alternative and criterion is calculated using: Calculating marginal utility value

$$U_{ij}{}^{*} = \frac{exp_{(X_{ij})^2} - 1}{1.71} \quad (19)$$

Where Xij is the normalized value.The final utility value for each alternative is then computed as:

$$U_i = \sum_{j==1}^{n} U_{ij} \,.\, W_j \quad (20)$$

With Wj being the criterion weight. Alternatives are ranked based on their final utility values, with the highest value indicating the best choice.

Rank Correlation

Comparison of four MCDM methods using rank correlation can be compared using rank correlation measure to determine the degree of agreement among the methods. Two common rank correlation methods are spearman’s rank correlation coefficient and kendall’s tau.

1) Spearman rank correlation

   Spearman's rank correlation coefficient (ρ) indicates the strength and direction of the relationship between two variables or MCDM methods being compared. It measures how well the relationship between two rankings can be described by a monotonic function.

$$r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n^2 - n} \quad (21)$$

Description:

d_i: the difference between the ranks of the same alternative

n: The number of alternatives being ranked

2) Kendall rank correlation

Kendall's Tau is a correlation coefficient used to measure the strength of association between two ordinal datasets or to identify how frequently two datasets rank alternatives similarly [15].

$$\tau = \frac{C - D}{\frac{1}{2}n(n-1)} \tag{22}$$

Descriotion:

τ : Kendall Tau correlation
C : number of concordant pais
D : number of discordant pairs
n : the total number of alternatives

Sensitivity Analyst

Sensitivity analysis is a process to evaluate how sensitive an MCDM (Multi-Criteria Decision Making) method is to changes in criterion weights. Sensitivity is assessed by observing changes in the ranking of alternatives when the weight of a specific criterion is altered. The greater change in ranking a method, the more sensitive the chosen method is [16].

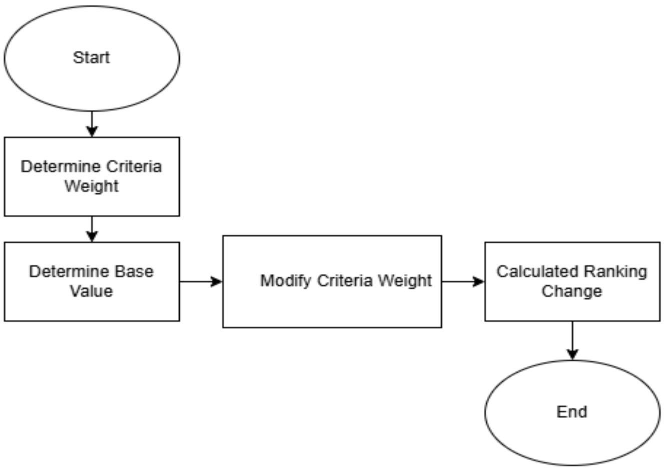

Figure 5. Sensitivity Analyst

The sensitivity analysis proses begins by determining the criteria weights and base values for comparison. Then, the weights are modified according to specific experiments, with each experiment adjusting the weights by a predefined amount. After each modification, the changes in ranking are calculated. This process helps assess the impact of varying criteria weights on the rankings of alternatives, concluding the sensitivity analysis

3. RESULT AND DISCUSSION

This study uses data sourced from Kaggle, consisting of a raw dataset with 32,581 entries and 12 criteria. However, the processed data focuses on 100 entries and 5 criteria. The dataset is filtered based on loan grades A, B, C, and D, resulting in four subsets of data utilized in this research.

Table 1. Data LOAN_GRADE A

Kode	C1	C2	C3	C4	C5
A1	21	9900	OWN	2500	VENTURE
A2	24	83000	RENT	35000	PERSONAL
A3	21	10000	OWN	4500	HOMEIMPROVEMEN
…	…	…	…	…	…
A100	56	65000	RENT	7700	VENTURE

Table *2*. Data LOAN_GRADE B

Kode	C1	C2	C3	C4	C5
A1	21	9600	OWN	1000	EDUCATION
A2	26	77100	RENT	35000	EDUCATION
A3	24	78956	RENT	35000	MEDICAL
…	…	…	…	…	…
A100	54	107000	RENT	10000	VENTURE

Table 3. Data LOAN_GRADE C

Kode	C1	C2	C3	C4	C5
A1	25	9600	MORTAGE	5500	MEDICAL
A2	23	65500	RENT	35000	MEDICAL
A3	24	54400	RENT	35000	MEDICAL
…	…	…	…	…	…
A100	51	60000	MORTAGE	8000	PERSONAL

Table 4. Data LOAN_GRADE D

Kode	C1	C2	C3	C4	C5
A1	22	5900	RENT	35000	PERSONAL
A2	21	10000	OWN	1600	VENTURE
A3	23	113000	RENT	35000	DEBTCONSOLIDATION
…	…	…	…	…	…
A100	53	54000	RENT	10000	MEDICAL

Table 5. Criteria and Weight

Nama	Kode	Jenis	Bobot
person_age	C1	Benefit	0.25
person_income	C2	Benefit	0.3
person_home_ownership	C3	Benefit	0.15
loan_amnt	C4	Benefit	0.2
loan_intent	C5	Benefit	0.1

Table 5, is a breakdown of the criteria used in the research along with their types and weights. The type functions to indicate whether a criterion has the nature of a benefit (profit) or has the nature of a cost (cost). The weight serves to describe how much influence each criterion has.

Table 6. PERSON_AGE and PERSON_INCOME Criteria

Nama Kriteria	Nama Subkriteria	Nilai
person_age	>56	5
person_age	46-55	4
person_age	36-45	3
person_age	25-35	2
person_age	20-25	1
person_income	>969.899	5
person_income	489900 -729899	4
person_income	249900 - 489899	3
person_income	9600 - 249899	2
person_income	<9600	1

Table 7. PERSON_HOME_OWNERSHIP and LOAN_AMNT

Nama Kriteria	Nama Subkriteria	Nilai
person_home_ownership	Own	4
person_home_ownership	Mortage	3
person_home_ownership	Rent	2
person_home_ownership	Other	1
loan_amnt	>28999	5
loan_amnt	22000 - 28999	4
loan_amnt	15000 - 21999	3
loan_amnt	8000 - 14999	2
loan_amnt	<8000	1

Results of applying the TOPSIS, MABAC, WASPAS and MAUT methods

Table 8. TOPSIS, MABAC, WASPAS, and MAUT Method Ranking Results loan_grade A

Rank	TOPSIS		MABAC		WASPAS		MAUT	
1	A21	0.649	A21	0.253	A21	0.625	A21	0.369
2	A41	0.473	A71	0.228	A61	0.610	A88	0.356
3	A88	0.359	A88	0.216	A88	0.608	A85	0.353
4	A99	0.356	A61	0.203	A71	0.598	A97	0.353
5	A87	0.511	A75	0.195	A62	0.589	A71	0.350
…	…	…	…	…	…	…	…	…
96	A8	0.130	A60	-0.133	A40	0.356	A60	0.230
97	A9	0.130	A37	-0.146	A18	0.345	A37	0.221
98	A40	0.113	A40	-0.162	A8	0.334	A40	0.221
99	A18	0.104	A18	-0.175	A9	0.334	A18	0.220
100	A38	0.098	A38	-0.196	A38	0.332	A38	0.218

Table 8 is a table of ranking results from the application of the Topsis, Mabac, Waspas and Maut method based on data loan_grade A.

Table 9. TOPSIS, MABAC, WASPAS, and MAUT Method Ranking Result loan_grade B

Table 9 is a table of ranking results from the application of the Topsis, Mabac, Waspas and Maut method based on data loan_grade b.

Rank	TOPSIS		MABAC		WASPAS		MAUT	
1	A61	0.777	A61	0.403	A61	0.771	A61	0.440
2	A21	0.589	A81	0.274	A81	0.677	A81	0.393
3	A41	0.504	A95	0.166	A64	0.601	A95	0.365
4	A5	0.457	A96	0.166	A41	0.597	A96	0.365
5	A81	0.422	A64	0.161	A25	0.580	A85	0.353
…	…	…	…	…	…	…	…	…
96	A22	0.166	A36	-0.121	A22	0.387	A49	0.232
97	A1	0.144	A49	-0.125	A1	0.357	A34	0.230
98	A8	0.134	A8	-0.133	A31	0.356	A36	0.230
99	A31	0.117	A31	-0.188	A8	0.334	A31	0.221
100	A6	0.059	A6	-0.250	A6	0.301	A6	0.217

Table 10. TOPSIS, MABAC, WASPAS, and MAUT Method Ranking Result loan_grade C

Rank	TOPSIS		MABAC		WASPAS		MAUT	
1	A99	0.817	A99	0.440	A99	0.768	A99	0.441
2	A81	0.529	A81	0.306	A81	0.666	A92	0.365
3	A41	0.334	A41	0.206	A41	0.590	A95	0.365
4	A83	0.27	A83	0.206	A83	0.549	A83	0.358
5	A22	0.269	A62	0.177	A62	0.540	A81	0.356
…	…	…	…	…	…	…	…	…
96	A31	0.097	A17	-0.143	A17	0.292	A31	0.225
97	A36	0.078	A36	-0.180	A36	0.289	A36	0.222
98	A8	0.074	A8	-0.193	A8	0.279	A8	0.221
99	A1	0.045	A1	-0.243	A1	0.242	A1	0.218
100	A15	0.041	A5	-0.259	A5	0.232	A5	0.217

Table 10 is a table of ranking results from the application of the Topsis, Mabac, Waspas and Maut method based on data loan_grade C.

Table 11 TOPSIS, MABAC, WASPAS, and MAUT Method Ranking Result loan_grade D

Rank	TOPSIS		MABAC		WASPAS		MAUT	
1	A45	0.634	A45	0.334	A45	0.720	A45	0.415
2	A89	0.552	A89	0.234	A69	0.713	A89	0.390
3	A90	0.552	A90	0.234	A89	0.707	A90	0.390
4	A100	0.527	A69	0.222	A90	0.707	A100	0.340
5	A92	0.514	A100	0.201	A100	0.694	A34	0.338
…	…	…	…	…	…	…	…	…
96	A30	0.203	A11	-0.140	A11	0.433	A47	0.233
97	A21	0.173	A21	-0.140	A39	0.408	A30	0.230
98	A39	0.172	A39	-0.152	A21	0.378	A39	0.227
99	A18	0.103	A18	-0.240	A18	0.367	A18	0.217
100	A13	0.077	A13	-0.256	A13	0.348	A13	0.217

Table 11 is a table of ranking results from the application of the Topsis, Mabac, Waspas and Maut method based on data loan_grade D.

Rank Correlation

Rank correlation is carried out to find out the extent of the ranking relationship between several data sets. This research uses 2 rank correlation methods to compare 4 Multiple Criteria Decision Analysis methods, namely the Spearman's correlation and Kendall Tau correlation methods.

a. Spearman Correlation

Table 12. Comparison of Ranking Result Baed On LOAN_GRADE A

Alternatif	RankTopsis	RankMabac	RankWaspas	RankMaut
A21	1	1	1	1
A71	19	2	4	5
A88	3	3	3	2
A61	10	4	2	22
A75	42	5	8	13
…	…	…	…	…
A60	92	96	94	96
A37	95	97	92	97
A40	98	98	96	98
A18	99	99	97	99
A38	100	100	100	100

Table 13. Ranking Correlation Result Based On LOAN_GRADE A

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.82402	0.848845	0.829883
MABAC	0.820402	-	0.945611	0.758344
WASPAS	0.848845	0.945611	-	0.666535
MAUT	0.829883	0.758344	0.666535	-

Table 14. Comparison of Ranking Result Based On LOAN_GRADE B

Alternatif	RankTopsis	RankMabac	RankWaspas	RankMaut
A61	1	1	1	1
A81	5	2	2	2
A95	10	3	12	3
A96	11	4	13	4
A64	16	5	3	44
…	…	…	…	…
A36	94	96	93	98
A49	90	97	94	96
A8	98	98	99	69
A31	99	99	98	99
A6	100	100	100	100

Table 15**.** Ranking Correlation Result Based On LOAN_GRADE B

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.788203	0.799436	0.734077
MABAC	0.788203	-	0.925389	0.787243
WASPAS	0.799436	0.925389	-	0.628275
MAUT	0.734077	0.787243	0.628275	-

Table 16**.** Comparison of Ranking Result Based On LOAN_GRADE C

Alternatif	RankTopsis	RankMabac	RankWaspas	RankMaut
A99	1	1	1	1
A81	2	2	2	5
A41	3	3	3	31
A83	4	4	4	4
A62	12	5	5	30
…	…	…	…	…
A17	93	96	96	70
A36	97	97	97	97
A8	98	98	98	98
A1	99	99	99	99
A5	100	100	100	100

Table 17. Ranking Correlation Result Based On LOAN_GRADE C

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.803432	0.786211	0.822946
MABAC	0.803432	-	0.982886	0.783462
WASPAS	0.786211	0.982886	-	0.706343
MAUT	0.822946	0.783462	0.706343	-

Table 18**.** Comparison of Ranking Result Based On LOAN_GRADE D

Alternatif	RankTopsis	RankMabac	RankWaspas	RankMaut
A45	1	1	1	1
A89	2	2	3	2
A90	3	3	4	3
A69	6	4	2	6
A100	4	5	5	4
…	…	…	…	…
A11	93	96	96	93
A21	97	97	98	64
A39	98	98	97	98
A18	99	99	99	99
A13	100	100	100	100

Table 19**.** Ranking Correlation Result Based On LOAN_GRADE D

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.793891	0.822466	0.661254
MABAC	0.793891	-	0.926049	0.743306
WASPAS	0.822466	0.926049	-	0.585911
MAUT	0.661254	0.743306	0.585911	-

Based on Table 13, Table 15, Table 17, Table 19, Table High correlation indicates that the ranking of alternatives obtained by both methods has many of the same or similar ranking orders. Meanwhile, the lowest correlation is the correlation between the WASPAS method and MAUT. The low correlation indicates that the ranking results of the two methods have many differences.

b. Kendall Tau Correlation

Table 20.Comparison of Ranking Result Based On LOAN_GRADE A

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.606869	0.669091	0.410505
MABAC	0.606869	-	0.831111	0.446465
WASPAS	0.669091	0.831111	-	0.35596
MAUT	0.410505	0446465	035596	-

Table 21**.** Comparison of Ranking Result Based On LOAN_GRADE B

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.623838	0.633939	0.589091
MABAC	0.623838	-	0.774141	0.617778
WASPAS	0.633939	0.774141	-	0.466263
MAUT	0.589091	0.617778	0.466263	-

Table 22**.** Comparison of Ranking Result Based On LOAN_GRADE C

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.669495	0.642424	0.726869
MABAC	0.669495	-	0.916364	0.608889
WASPAS	0.642424	0.916364	-	0.54303
MAUT	0.726869	0.608889	0.54303	-

Table 23**.** Comparison of Ranking Result Based On LOAN_GRADE D

	TOPSIS	MABAC	WASPAS	MAUT
TOPSIS	-	0.622626	0.658586	0.526061
MABAC	0.622626	-	0.794343	0.582626
WASPAS	0.658586	0.794343	-	0.450505
MAUT	0.526061	0.582626	0.450505	-

Based on Table 20, Table 21, Table 22, Table 23, Table High correlation indicates that the ranking of alternatives obtained by both methods has many of the same or similar ranking orders. Meanwhile, the lowest correlation is the correlation between the WASPAS method and MAUT. The low correlation indicates that the ranking results of the two methods have many differences.

Sensitivity Analyst

The steps for carrying out a sensitivity test are as follows:

a) Determine all criteria weights
b) Determine the initial base value

The initial base value is the value used as a reference for ranking changes in the sensitivity test.

c) Change the weight of the criteria

Criteria weight changes are made in the range 1-2. This research used 10 trials by adding different weights to the criteria.

1) Experiment 1: change the weight of the criteria by adding a weight of 1 with the weight addition process starting from 0.5
2) Experiment 2: change the weight of the criteria by adding a weight of 1 starting from 0.2
3) Experiment 3: change the weight of the criteria by adding a weight of 1 with the weight addition process starting from 0.25
4) Experiment 4: change the weight of the criteria by adding a weight of 1.25 with the weight addition process starting from 0.25
5) Experiment 5: change the weight of the criteria by adding a weight of 1.5 with the weight addition process starting from 0.25
6) Experiment 6: change the weight of the criteria by adding a weight of 1.5 with the weight addition process starting from 0.5
7) Experiment 7: change the weight of the criteria by adding a weight of 1.75 with the weight addition process starting from 0.25
8) Experiment 8: change the weight of the criteria by adding a weight of 2 with the weight addition process starting from 0.25
9) Experiment 9: change the weight of the criteria by adding a weight of 2 with the weight addition process starting from 0.4
10) Experiment 10: change the weight of the criteria by adding a weight of 2 with the weight addition process starting from 0.5

d) Calculate Ranking Changes

Table 24. Result Experiment 1 Data LOAN_GRADE A

Iterasi	Changes Weight	Perubahan ranking			
		TOPSIS	MABAC	WASPAS	MAUT
1	C1 0.5	92	99	89	99
2	C1 0.5	92	100	92	99

3	C2 0.5	94	81	81	84
4	C2 0.5	92	79	86	84
5	C3 0.5	100	99	99	98
6	C3 0.5	98	99	98	98
7	C4 0.5	88	82	86	93
8	C4 0.5	88	83	86	93
9	C5 0.5	97	97	96	95
10	C5 0.5	99	98	86	97
Total		940	917	899	940

The table above shows the total ranking changes from Experiment 1 using test data with loan grade A. After making adjustments to each criterion, it is clear that criteria C1 and C3 cause significant changes in rankings, indicating that C1 and C3 are the most sensitive criteria. The same method is applied to loan grades B, C, and D.

Table 25. The Average Changes in Ranking

Experiment Number	**The Average Changes in Ranking**							
	Loan Grade A				**Loan Grade B**			
	Topsis	Mabac	Waspas	Maut	Topsis	Mabac	Waspas	Maut
1	94	91,7	89,9	94	94,7	89,6	90,6	81,8
2	93,04	90,84	88,88	93,48	93.72	88.52	90.6	81.28
3	88,8	91,5	89,3	93,5	94.15	88.3	90.6	81.15
4	93,76	91,6	90	93,56	94.32	88.72	90.68	81.48
5	93,83	91,7	90,6	93,66	94.4	89.16	91.0	81.7
6	94,13	92	90	94	94.73	90.4	89.86	82.13
7	93,94	91,97	90,91	93,8	94.48	89.54	91.11	81.85
8	94	92,12	91,15	93,9	94.55	89.85	91.55	81.95
9	94,08	92,04	91,4	94	94.64	90.4	91.68	82.04
10	94,7	92,3	89,95	94,2	95.05	90.9	89.5	82.3
Experiment Number	**Loan Grade C**				**Loan Grade D**			
	Topsis	Mabac	Waspas	Maut	Topsis	Mabac	Waspas	Maut
1	95,8	80	86,8	77,3	94,6	84,1	86,1	77,5
2	95.24	80.24	86.16	76.4	94.08	82.6	86.28	76.28
3	95.6	84.85	86.75	76.7	94.4	84.1	86.25	77.05
4	95.56	85.32	87	76.88	94.44	83.92	86.44	77.2
5	95.5	85.63	87.23	77.06	94.5	83.73	86.53	77.4
6	95.66	80.93	84.86	77.6	94.66	83.66	83.13	77.8
7	95.51	86.08	87.42	77.2	94.6	83.6	86.6	77.54
8	95.52	86.45	87.65	77.3	94.72	83.52	86.65	77.65
9	95.6	81.44	87.96	77.6	94.72	83.04	86.36	77.68
10	95.65	81.1	85.95	77.7	94.9	83.5	81.65	77.95

Based on the sensitivity test results, each method shows different average ranking changes. The TOPSIS method demonstrates ranking changes with an average range from 88 to 95.66, MABAC shows a range from 80.24 to 92.12, WASPAS ranges from 83.13 to 91.68, and MAUT shows ranking changes from 76.28 to 94.2.

The results indicate that TOPSIS is the most sensitive method, with the highest average ranking change, reaching up to 95.66. This suggests that TOPSIS is the most responsive to changes in the criteria weights. In contrast, MABAC, WASPAS, and MAUT exhibit lower ranking changes, making them more stable methods.

In practice, the high sensitivity of TOPSIS is useful in situations where criteria weights frequently change, such as in credit decision-making in dynamic market conditions. On the other hand, more stable methods like MABAC, WASPAS, and MAUT are better suited for contexts where decision stability is prioritized. This research provides practical guidance for choosing the most suitable method based on the specific needs of the decision-making process.

4. CONCLUSION

Based on the correlation and sensitivity tests conducted, it can be concluded that the MABAC method shows the highest similarity in ranking results when compared to the WASPAS method, as indicated by rank correlation using both Spearman's and Kendall's Tau correlations. Additionally, the sensitivity test, which included 10 different experiments with varying weights, demonstrated that the TOPSIS method resulted in the most significant ranking changes. This indicates that TOPSIS is the most responsive method to changes in criteria weights. Therefore, when decision-making requires high sensitivity to variations in criteria weights, the TOPSIS method is recommended due to its responsiveness, as evidenced by the sensitivity analysis.

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