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Improving MCDM University Rankings through Statistical Validation Using Spearman's Correlation and THE Benchmark

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Abstract

The evaluation of higher education institutions is a critical field for informing data-driven policy and institutional benchmarking. A key problem in this area is the lack of transparency and consistency in university rankings, particularly when using Multi-Criteria Decision-Making (MCDM) methods such as MABAC and MAIRCA, with limited research on how weighting techniques affect the reliability and alignment of these rankings with international standards like the Times Higher Education (THE) Rankings. This study proposes the use of MABAC and MAIRCA methods combined with two weighting techniques—Rank Order Centroid (ROC) and Rank Sum (RS)—to assess 20 top Indonesian universities based on five performance indicators: research quality, research environment, teaching, industry, and international outlook. Spearman's rank correlation is used to compare the MCDM-generated rankings with THE Rankings 2025. The study contributes empirical evidence on the impact of weighting schemes on the consistency and reliability of university rankings and demonstrates that the MAIRCA-ROC method achieves the highest agreement with THE Rankings, with a correlation coefficient of 0.8135 and a p-value of 0.00001. These results validate the use of MCDM methods in higher education evaluation and emphasize the importance of selecting appropriate weighting techniques to develop transparent and robust ranking frameworks that support evidence-based policy decisions.

Keywords: Consistency And Reliability, MCDM, Spearman's Rank Correlation, University Rankings, Weighting Techniques

1. Introduction

In the context of increasing global competition and public demand for transparency, the evaluation and ranking of Higher Education Institutions (HEIs) have become vital tools for diverse stakeholders. International systems such as the QS World University Rankings (QS WUR) [1] and THE Rankings [2], [3] assess universities based on indicators including academic reputation, faculty-student ratio, research impact, and international outlook. However, these models have been criticized for insufficient alignment with national contexts and priorities In Indonesia, for instance, the Ministry of Education, Culture, Research, and Technology has implemented a national ranking system—the 2023 Higher Education Clustering—which utilizes university performance data from SINTA (2019–2021) alongside institutional accreditation rankings. These differences highlight the need for a ranking methodology that is both methodologically robust and contextually adaptive to local policy objectives and institutional development goals.

To address the need for a more flexible, objective, and locally relevant ranking system, various quantitative approaches are beginning to be used in the evaluation process of higher education institutions. One prominent approach is MCDM, which is capable of handling the complexity of decision-making by considering multiple criteria simultaneously. This method allows for transparent and structured calculations, making the evaluation and ranking results more accountable [4], [5], [6], [7]. MCDM has been widely used in various fields, such as building assessment and retrofitting [8], hospital performance evaluation [9], quality function deployment [10], material selection [11], provider selection [12], and employee ranking [13]. The success of MCDM in handling multidimensional problems makes it an effective and generalizable approach to various contexts. However, selecting the appropriate MCDM method and ensuring the accuracy of the results remain challenges, especially when different weighting techniques are involved. In line with the

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increasing need for transparent and contextual ranking systems, the MCDM method continues to undergo development and adaptation. Various MCDM techniques have been proposed to address the complexity in the evaluation of higher education institutions involving numerous indicators. However, with the abundance of available methods, it becomes crucial to evaluate the extent to which the effectiveness of each approach in generating consistent, credible, and relevant results. In this context, an analysis of specific MCDM methods that possess high potential but have not been extensively researched in the domain of university ranking is necessary.

Two MCDM methods that stand out and offer a systematic approach to the decision-making process are MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis) and MABAC (Multi-Attributive Border Approximation Area Comparison). An interval-valued intuitionistic fuzzy extension of the MAIRCA method has been developed to evaluate sustainable wastewater treatment technologies, thereby enhancing the model's capacity to manage uncertainty and vagueness in expert judgments [14]. A hybrid CRITIC–MAIRCA framework has also been introduced for optimal phase change material selection in solar distillation systems, combining objective weighting techniques with multi-criteria analysis [15]. Furthermore, the MAIRCA method has been applied in various contexts, including the performance assessment of listed insurance companies [16], evaluation of machining processes [17], and analysis of the renewable energy sector [18], and agri-food 4.0 supply chains [19], with a focus on technical, financial, and sustainability aspects project alternatives.

Innovations to the MABAC method, among others, include its integration with cumulative prospect theory within an intuitionistic fuzzy framework, which substantially enhances its ability to handle uncertainty, risk perception, and subjective biases in group decision-making [20]. Furthermore, hybrid approaches combining MABAC with other methods, such as hesitant fuzzy sets, Data Envelopment Analysis (DEA), and objective weighting techniques, have been successfully applied in the context of sustainable supplier selection [21] in the manufacturing sector, particularly the automotive industry [22]. The application of MABAC is not limited to the industrial sector but has also been extended to the domain of urban planning and development, such as the evaluation of improving urban environmental quality [23], as well as in the optimization of technical parameters in precision machining processes, for example, external cylindrical grinding [24]. The diversity of these case studies reflects the flexibility, robustness, and relevance of the MABAC method in supporting strategic and operational decision-making processes across various sectors. Although methods such as MAIRCA and MABAC have been applied in various domains, their effectiveness in modeling university rankings and how their results align with existing benchmarks has not been extensively explored.

In the multi-criteria decision-making process, determining the weight for each criterion is one of the most crucial components, as the weights reflect the relative importance of the criteria in the evaluation process. Various weighting techniques can be used, both objective and subjective. One widely used objective method is the entropy weighting method [25], which calculates weights based on the level of uncertainty or variation of information within the data. Criteria with a higher diversity of values are considered to provide richer information, thus receiving a greater weight. This approach does not require input from decision-makers and is therefore often considered free from bias. MEREC, EQUAI, ROC, RS, and FUCOM weighting methods are used in the selection of the best alternative in the hole-turning process to compare the ranking results with various MCDM methods [16].

Meanwhile, subjective approaches such as ROC and RS [16], [26], [27] require initial judgments or preferences from decision-makers. ROC assigns weights based on the average centroid of all possible orderings, resulting in a weighting with fairly balanced differences between criteria [28], [29]. On the other hand, RS assigns weights based on the sum of the ranks; the higher the rank of a criterion, the greater the weight assigned [26], [27], [28], [29]. Both of these methods are computationally light and easy to implement, making them widely used in MCDM studies. Although each method has its advantages and disadvantages, these differences in weighting techniques can significantly influence the final ranking results. Therefore, it is important to evaluate the sensitivity and consistency of ranking results when using different weighting methods, especially in the context of the complex and multidimensional ranking of higher education institutions. Furthermore, the impact of different weighting techniques, such as ROC and RS, on the final ranking results has not been comprehensively investigated. This presents a gap in the literature regarding method sensitivity and result validation.

This study implements the MABAC and MAIRCA methods to rank the top 20 universities in Indonesia based on five criteria from THE Rankings. Each method is analyzed using two weighting schemes—ROC and RS—and the ranking results are compared with THE Rankings. The consistency and relevance of the results are evaluated using Spearman's rank correlation analysis, a widely used statistical technique in Multi-Criteria Decision-Making (MCDM) based studies to measure the degree of relationship between two sets of rankings, with a non-parametric approach that is effective across various data conditions [7], [24], [30], [31], [32], [33], [34]. This study aims to examine the performance of MABAC and MAIRCA in the context of ranking higher education institutions, as well as to assess the influence of weighting schemes on the results of each MCDM method. In multi-criteria institutional evaluation, MABAC and MAIRCA have gained attention due to their ability to generate stable rankings under various weight schemes, although systematic comparative studies regarding the performance of these two methods are still limited in the literature. Thus, this research contributes to developing a more contextual and methodological evaluative approach for policymakers and stakeholders in the higher education sector.

2. Method

To provide a clearer overview of the research stages, the flowchart of the proposed method is presented below, as shown in figure 1, illustrating each step involved in the methodology, beginning from the identification and determination of criteria, through to the ranking correlation analysis using Spearman's rank correlation.

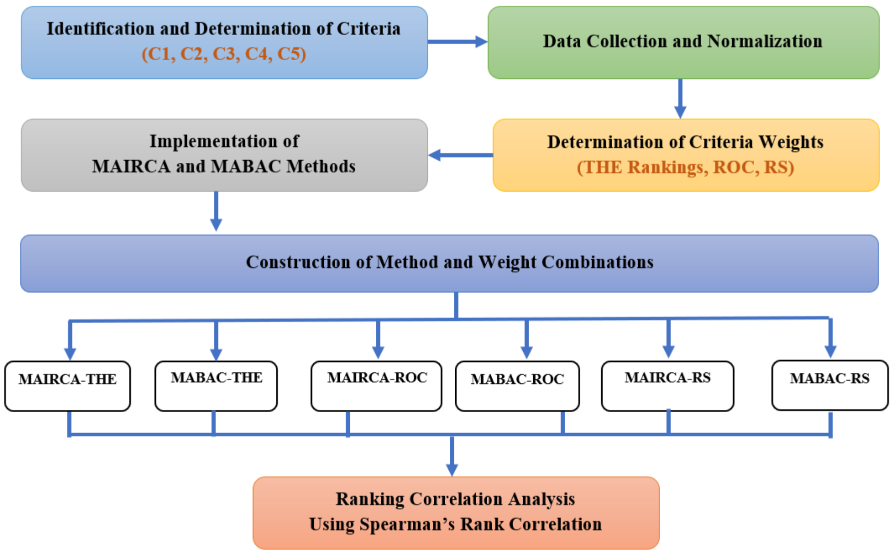

Figure 1. Proposed flowchart of MCDM methods

2.1. Identification and Determination of Criteria

The methodology used to determine the criteria was derived from THE Rankings 2025, which are structured based on five main areas (criteria). Table 1 presents the weights assigned to each criterion [2]. The combined weights of criteria C1, C2, C3, C4, and C5 equal 100%, with criterion C1 receiving the largest weight.

Table 1. Weightings for each criterion in THE rankings 2025

Main Areas (Criteria)		Weighted
Research Quality	C1	30.0%
Research Environment	C2	28.0%
Teaching	C3	24.5%
Industry	C4	10.0%
International outlook	C5	7.5%

Figure 2 illustrates the decision hierarchy consisting of three levels: the objective at the top level, criteria (C1-C5) at the middle level, and alternatives (U1-U20) at the bottom level, referring to detailed classification presented table 1.

This hierarchical structure helps clarify the relationship between the overall goal, the evaluation criteria, and the university alternatives being assessed.

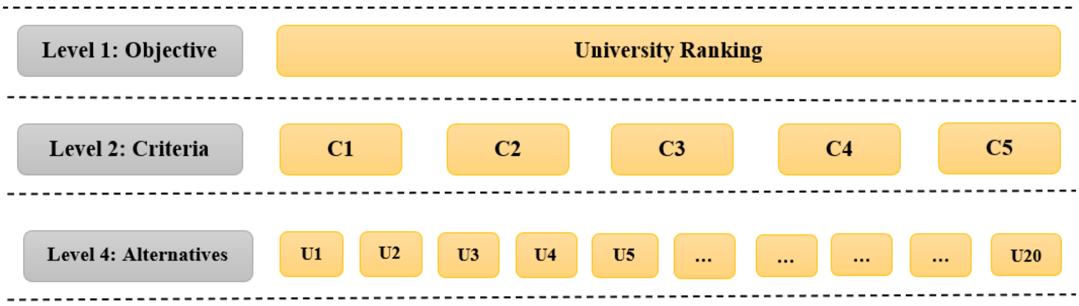

Figure 2. Hierarchy for higher education institution ranking

2.2. Data Collection and Normalization

Quantitative data from each university were collected according to the indicators within the five criteria. As the data originated from different scales, a normalization step was performed to ensure all values were within the same comparative scale (0–1). Max-min normalization was employed for both benefit criteria (1) and cost criteria (2), where x_{ij} is the original value of the *i*-th alternative on the *j*-th criterion; x_{ij}^{*} is the normalized value; $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the *j*-th criterion across all alternatives.

$$x_{ij}^{*} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

$$x_{ij}^{*} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{2}$$

2.3. Determination of Criterion Weights

ROC is a weighting method used to convert the priority order (ranking) of a criterion into a numerical weight. This method is particularly useful in MCDM when only priority order information is available without explicit weight values from decision-makers. ROC assumes that criteria with higher priorities should have greater weights, and the weight of each criterion is calculated based on its rank position in the priority list. If there are n criteria, then the weight W_j for the j-th criterion at rank j is calculated using equation (3).

RS is a weighting method used to transform the priority order of criteria into proportional weight values. This method is very simple and intuitive, and it is suitable for use when only information about the order of importance of the criteria is available, without quantitative data regarding preferences. RS assumes that the higher the priority (the smaller the rank value), the greater the weight assigned. If there are n criteria, then the weight W_j for the j-th criterion at rank j is calculated using equation (4).

$$W_j = \frac{1}{n}\sum_{k=j}^{n}\frac{1}{k}, \qquad j = 1, 2, \ldots, n \tag{3}$$

$$W_j = \frac{2(n+1-j)}{n(n+1)}, \qquad j = 1, 2, \ldots, n \tag{4}$$

W_j is the weight of the *j*-th criterion, *n* is the total number of criteria, and *j* is the rank of the *j*-th criterion based on priority (1 = most important).

The criterion weights using ROC and RS methods are determined based on the importance level of each criterion, under the weight values adopted from the THE ranking. The prioritization follows the order: C1 ≥ C2 ≥ C3 ≥ C4 ≥ C5, which results in weight values satisfying $W_1 \geq W_2 \geq W_3 \geq W_4 \geq W_5$. Table 2 presents the calculated ROC and RS weights for the five criteria used in the ranking, based on the previously established priority order.

Table 2. ROC and RS weights for 5 criteria

Degree of importance	Number of criteria/Weighted (W_j)									
	1		2		3		4		5	
	ROC	RS	ROC	RS	ROC	RS	ROC	RS	ROC	RS
1	1.000	1.000	0.7500	0.6667	0.6111	0.5000	0.5208	0.4000	0.4567	0.3333
2			0.2500	0.3333	0.2778	0.3333	0.2708	0.3000	0.2567	0.2667
3					0.1111	0.1667	0.1458	0.2000	0.1567	0.2000
4							0.0625	0.1000	0.0900	0.1333
5									0.0400	0.0667

2.4. Implementation of MAIRCA and MABAC Methods

2.4.1. MAIRCA

The MAIRCA method is based on the principle of comparison between the ideal solution and the actual solution, where each alternative is evaluated based on how closely its performance aligns with the expected or ideal preferences of the decision-maker. It is implemented through a series of structured steps, beginning with the formation of the initial decision matrix, The application of the MAIRCA method in this study begins with the construction of the initial decision matrix, $X = [x_{ij}]$,, where x_{ij} represents the performance value of the i-th alternative under j-th criterion, with $i = 1, 2, \ldots, m$ (number of alternatives) and $j = 1, 2, \ldots, n$ (number of criteria). Since the performance values originate from different scales, a normalization process is applied using the min-max method to transform the values into a comparable range between 0 and 1. Once normalized, the ideal (or theoretical) preference is determined under the assumption that all alternatives have equal opportunity. The ideal preference for each criterion is calculated as $T_{ij} = w_j . \frac{1}{m}$, where w_j denotes the weight of criterion j, and m is the number of alternatives. Following this, the real preference values are computed by multiplying the normalized scores by their respective criterion weights, resulting in $P_{ij} = w_j . r_{ij}$, where r_{ij} is the normalized value. The absolute difference between the ideal and real preferences for each criterion is then calculated as the preference deviation, expressed as $D_{ij} = |T_{ij} - P_{ij}|$. These deviations are aggregated across all criteria to obtain the total deviation for each alternative, denoted by $S_i = \sum_{j=1}^{n} D_{ij}$. The total deviation score S_i reflects how far an alternative is from the ideal condition; the smaller the value of S_i, the better the performance of the alternative. Consequently, alternatives are ranked in ascending order based on their respective S_i values.

2.4.2. MABAC

The MABAC method employs the concept of a boundary area between actual attribute values and a reference point, evaluating alternatives based on their relative distance from this area. It is recognized for producing stable and interpretable rankings through a straightforward computational procedure. In this study, the method is applied through a series of structured steps, beginning with the construction of a decision matrix, followed by normalization to bring all criteria values onto a comparable scale, similar to the process used in the MAIRCA method. Subsequently, the normalized values are multiplied by their respective criterion weights to generate the weighted normalized matrix, where $v_{ij} = n_{ij} . w_j$ denotes the weighted score of alternative *i* under criterion *j*.

To determine a reference point for evaluation, the border approximation area for each criterion is calculated as the average of the weighted normalized values across all alternatives, expressed as $g_j = \frac{1}{m} \sum_{i=1}^{m} v_{ij}$. The deviation of each alternative from this border is then computed through the proximity measure $q_{ij} = v_{ij} - g_j$, which reflects the relative performance of alternative *i* on criterion *j*. Finally, the overall performance score for each alternative, denoted as $Q_i =$

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$\sum_{j=1}^{n} q_{ij}$, is obtained by aggregating its proximity values across all criteria. Alternatives are ranked in descending order based on their Q_i scores, with higher values, indicating better performance relative to the ideal border approximation area.

2.5. Construction of Method and Weight Combinations

In this research, a combination of two MCDM methods (MAIRCA and MABAC) with two weighting approaches (ROC and RS) was used to evaluate and rank the performance of universities based on the five criteria of THE Rankings. Table 3 presents the combinations of methods and weighting techniques used in the study.

Table 3. Combinations of methods and weighting techniques

Evaluation Method	THE Rankings	ROC	RS
MAIRCA	MAIRCA-THE	MAIRCA-ROC	MAIRCA-RS
MABAC	MABAC-THE	MABAC-ROC	MABAC-RS

2.6. Ranking Correlation Analysis Using Spearman's Rank Correlation

To evaluate the degree of agreement between the ranking results obtained from each combination of method and weighting scheme and the official THE Rankings 2025 results, Spearman's rank correlation coefficient (ρ) was employed. The evaluation began by determining the rankings of alternatives based on the outcomes of the six method–weighting combinations. These rankings were then compared to a reference ranking constructed from the official THE Rankings 2025, which served as the benchmark for correlation analysis. The differences in rank positions between the proposed methods and the benchmark were calculated using the formula $d_i = R_i^{(X)} - R_i^{(Y)}$, where $R_i^{(X)}$ denotes the rank of the i-th alternative according to the proposed method, and $R_i^{(Y)}$ represents the corresponding rank in the official THE Rankings. Each rank difference was then squared to obtain $d_i^2 = (R_i^{(X)} - R_i^{(Y)})^2$, which was used in the computation of Spearman's rank correlation coefficient, given by $\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$, where n is the number of alternatives being compared. To assess the statistical significance of the correlation, a p-value was calculated using the t-distribution, expressed as $t = \rho\sqrt{\frac{n-2}{1-\rho^2}}$. This allowed for hypothesis testing to determine whether the observed correlation was statistically meaningful. The null hypothesis (H0) stated that there was no significant Spearman's rank correlation between the rankings generated by the method and the official reference ranking (ρ=0) while the alternative hypothesis (H1) posited a significant correlation (ρ≠0). The null hypothesis was rejected if the computed p-value was less than the predetermined significance level of (α=0.01). Interpretation of the p-value provided insight into the strength of the relationship between the two rankings: a value approaching 1 indicated a strong positive correlation, whereas a value near 0 or negative suggested a weak or statistically insignificant relationship.

3. Results and Discussion

3.1. Decision Matrix

The decision matrix in this study was constructed based on the data presented in table 4, which lists the top 20 universities in Indonesia according to the THE Rankings 2025 [2]. The evaluation criteria are aligned with the assessment dimensions utilized in the THE ranking system, thereby ensuring consistency with internationally recognized benchmarks.

Table 4. Top 20 Indonesian universities based on THE rankings 2025

University	Rank	Research Quality (30%)	Research Environment (28%)	Teaching (24.5%)	Industry (10%)	International Outlook (7.5%)
U1	1	33.3	23.9	45.6	59.0	64.2

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University	Rank	Research Quality (30%)	Research Environment (28%)	Teaching (24.5%)	Industry (10%)	International Outlook (7.5%)
U2	2	30.3	17.5	22.6	39.4	39.5
U3	3	35.2	21.0	21.1	49.6	35.8
U4	4	34.9	14.1	27.7	27.9	60.1
U5	5	26.2	21.8	30.9	56.4	44.0
U6	6	58.2	9.2	16.3	17.6	31.2
U7	7	33.8	22.0	20.0	49.7	37.3
U8	8	21.8	15.9	29.4	43.6	38.3
U9	9	26.4	9.9	18.9	19.0	19.5
U10	10	28.5	10.7	25.4	41.2	45.1
U11	11	24.8	10.5	30.8	41.8	44.1
U12	12	15.1	10.3	15.0	17.7	35.2
U13	13	17.7	9.4	10.7	19.6	21.7
U14	14	30.1	11.4	19.2	19.8	34.6
U15	15	36.0	12.2	15.2	32.0	50.6
U16	16	38.8	10.4	10.1	22.3	40.2
U17	17	18.6	9.9	23.5	26.9	32.2
U18	18	39.6	8.2	12.3	15.8	28.5
U19	19	21.2	10.8	12.0	16.8	44.4
U20	20	30.9	8.1	12.1	16.6	25.3

The alternatives U1, U2, U3, ..., U20 represent the selected universities based on THE Rankings 2025, evaluated across five criteria: research quality (C1), research environment (C2), teaching (C3), industry (C4), and international outlook (C5), with respective weights of 30%, 28%, 24.5%, 10%, and 7.5%. To enable fair comparison among criteria measured on different scales, a normalization of the decision matrix was applied to the data presented in table 4.

Table 5. Normalized matrix with 20 alternatives

Alternatives	C1	C2	C3	C4	C5
U1	0.4223	1.0000	1.0000	1.0000	1.0000
U2	0.3527	0.5949	0.3521	0.5463	0.4474
U3	0.4664	0.8165	0.3099	0.7824	0.3647
U4	0.4594	0.3797	0.4958	0.2801	0.9083
U5	0.2575	0.8671	0.5859	0.9398	0.5481
...	...	...	...	...	...
U20	0.3666	0.0000	0.0563	0.0185	0.1298

Table 5 presents the normalized matrix according to C1–C5, where C1–C5 are “benefit” criteria, with i representing the alternatives and j representing the criteria. Thus, i = 1, 2, 3, ..., 20 and j = 1, 2, 3, 4, 5.

As an example: $x_{11}^{*} = \frac{33.3-15.1}{58.2-15.1} = 0.4223$; $x_{12}^{*} = \frac{23.9-8.1}{23.9-8.1} = 1.000$; $x_{33}^{*} = \frac{21.1-10.1}{45.6-10.1} = 0.3099$; $x_{54}^{*} = \frac{56.4-15.8}{59-15.8} = 0.9398$; $x_{55}^{*} = \frac{44-19.5}{64.2-19.5} = 0.5481$.

This normalization ensures that the data are transformed into a common scale, facilitating meaningful comparisons across all alternatives and criteria.

3.2. Influence of Weighting on Ranking

The determination of criterion weights using the ROC and RS methods reveals differences in the emphasis on the importance values among the criteria. The ROC method yields a more proportionally distributed set of weights, whereas RS places greater emphasis on the top-ranked criteria. This directly influences the final scores and the resulting ranking

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order of the universities. The priority order of the criteria is presented in table 1, where C1 ≥ C2 ≥ C3 ≥ C4 ≥ C5. Accordingly, the ROC weights are as follows: C1 = 0.4567, C2 = 0.2567, C3 = 0.1567, C4 = 0.0900, and C5 = 0.0400. In contrast, the RS weights are: C1 = 0.3333, C2 = 0.2667, C3 = 0.2000, C4 = 0.1333, and C5 = 0.0667, as shown in table 2. The results are summarized in Tables 6 and 7, and illustrated in figure 3.

Based on table 6, the ranking results reveal that U1 and U5 consistently occupy the top ranks across both methods (MAIRCA-THE and MABAC-THE), indicating a stable and outstanding performance by these institutions. Furthermore, the ranks of all universities are identical across the two methods, demonstrating a high level of consistency in the evaluation results when using THE weighting approach.

Table 6. Ranking of MAIRCA and MABAC with THE rankings weight

Alternatives	MAIRCA-THE		MABAC-THE	
	S_i	Rank	Q_i	Rank
U1	0.0087	1	0.5106	1
U2	0.0277	6	0.1308	6
U3	0.0225	4	0.2340	4
U4	0.0269	5	0.1457	5
U5	0.0201	2	0.2826	2
...	...	...	...	...
U20	0.0432	18	-0.1807	18

Based on table 7, the university ranking results obtained using the ROC weighting method indicate that U1 consistently ranked first across both decision-making approaches (MAIRCA-ROC and MABAC-ROC). In contrast, U5 was ranked fourth under the MABAC-ROC method. Under the RS weighting scheme, U1 and U5 also demonstrated strong and consistent performance, ranking first and second, respectively, in both MAIRCA-RS and MABAC-RS methods. These findings underscore the sustained excellence and competitiveness of both institutions, regardless of the weighting technique applied.

Table 7. Ranking of MAIRCA and MABAC with ROC and RS weights

Alternatives	MAIRCA-ROC		MABAC-ROC		MAIRCA-RS		MABAC-RS	
	Si	Rank	Qi	Rank	Si	Rank	Qi	Rank
U1	0.0045	1	0.4180	1	0.0058	1	0.4896	1
U2	0.0282	7	0.1178	7	0.0275	7	0.1314	6
U3	0.0245	3	0.2379	2	0.0229	4	0.2459	4
U4	0.0271	6	0.1282	6	0.0272	6	0.1336	5
U5	0.0182	2	0.2202	4	0.0180	2	0.2783	2
...	...	...	...	...			...	...
U20	0.0455	19	-0.1352	16	0.0448	19	-0.1733	17

Figure 3 illustrates the ranking patterns of six methods, which are generally consistent, although minor variations exist in the middle ranks. In the context of sensitivity to weight distribution, the use of THE Rankings weights resulted in identical ranking outcomes between the MAIRCA and MABAC methods. In contrast, the application of ROC and RS weights produced different rankings for the two methods.

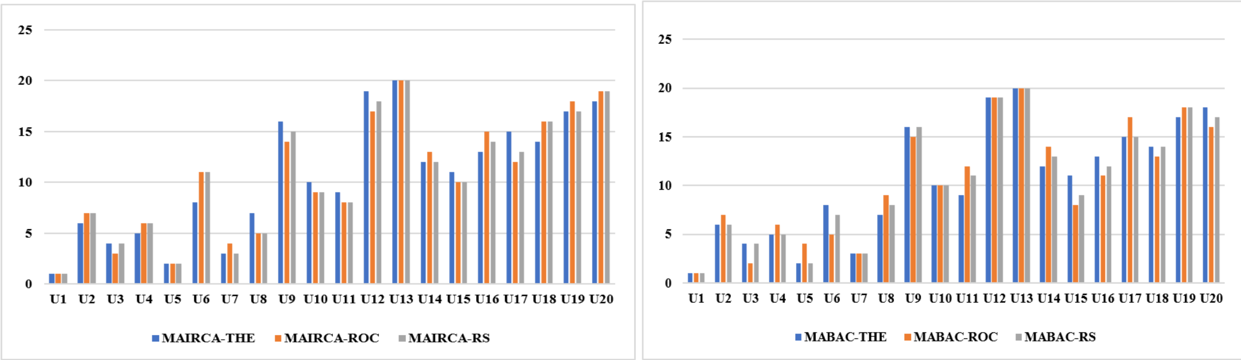

Figure 3. Ranking of MAIRCA and MABAC with THE rankings, ROC, and RS weighting

3.3. Comparison of Ranking Combinations

Table 8 and the graph in figure 4 present the ranking results of the 20 alternatives based on various MCDM methods and weighting techniques. The analysis reveals that alternative U1 consistently holds the first rank across all methods used, including THE Rankings, indicating that U1 is the most superior alternative overall. Additionally, alternatives U3, U5, and U7 demonstrate relatively stable performance by securing ranks within the top five across nearly all methods, reflecting their strong and consistent performance. In contrast, significant discrepancies were observed between the THE Rankings and the analytical methods for certain alternatives. For instance, U2, which holds rank second in the THE Rankings, drops to rank sixth and seventh in the other methods. The consistent top-ranking position of U1 can be attributed to its excellent performance in criteria C2, C3, C4, and C5. Meanwhile, U5 ranks second in criteria C2, C3, and C4. Consequently, U1 and U5 occupy the first and second positions, respectively.

Table 8. A Combination of Rankings from Six Methods

Alternatives	THE Rankings	MAIRCA-THE	MABAC-THE	MAIRCA-ROC	MABAC-ROC	MAIRCA-RS	MABAC-RS
U1	1	1	1	1	1	1	1
U2	2	6	6	7	7	7	6
U3	3	4	4	3	2	4	4
U4	4	5	5	6	6	6	5
U5	5	2	2	2	4	2	2
U6	6	8	11	5	11	7	8
U7	7	3	4	3	3	3	3
...	...	...	...	...	...	...	...
U20	20	18	19	16	19	17	18

The graph in figure 4 reinforces the findings from the previous table analysis, indicating that U1 and U5 are the most consistent and superior alternatives. This graph also confirms that the MAIRCA and MABAC methods, along with their variations, demonstrate strong internal consistency in the ranking of alternatives.

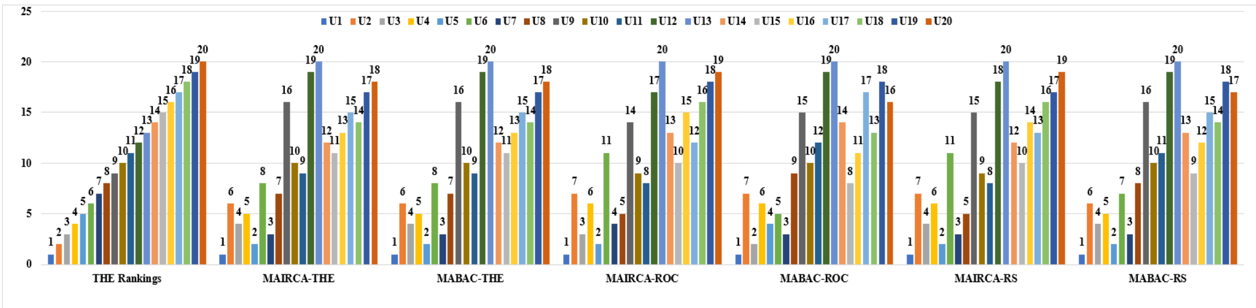

Figure 4. Comparison of University Rankings Across Six Methods

3.4. Evaluation of Ranking Consistency with Spearman's Rank Correlation

The results of Spearman's rank correlation analysis in table 9 indicate varying levels of consistency between the rankings generated by the MCDM methods and the official THE Rankings. The MAIRCA-ROC method demonstrates the best performance in terms of agreement with THE, with the highest correlation coefficient (ρ) = 0.8135 dan p-value = 0.00001.

This suggests that the ranking order produced by MAIRCA-THE, MABAC-THE, and MAIRCA-ROC shows very strong correlations, with values of 0.8075, 0.8075, and 0.8135, respectively. On the other hand, MABAC-ROC, MAIRCA-RS, and MABAC-RS exhibit strong correlations, with values of 0.7744, 0.7910, and 0.7940, respectively.

Table 9. Spearman's Rank Correlation Analysis of Ranking Methods

Methods	Spearman's Rank Correlation Coefficient (ρ)	t-Student	p-Value	Hypothesis Result	Interpretation of Consistency and Reliability
MAIRCA-THE	0.8075	5.807	0.00002	Rejected	Very Strong
MABAC-THE	0.8075	5.807	0.00002	Rejected	Very Strong
MAIRCA-ROC	**0.8135**	5.935	**0.00001**	Rejected	**Very Strong**
MABAC-ROC	0.7744	5.474	0.00006	Rejected	Strong
MAIRCA-RS	0.7910	5.635	0.00003	Rejected	Strong
MABAC-RS	0.7940	5.673	0.00003	Rejected	Strong

The consistency and reliability of these interpretations are based on the criteria provided in table 10, where correlation values between 0.80 and 1.00 indicate a "very strong" relationship and values between 0.60 and 0.79 indicate a "strong" relationship, according to Spearman's rank correlation interpretation.

Table 10. Interpretation of Spearman's Rank Correlation Coefficients

Spearman's Rank Correlation Coefficient (ρ)	Interpretation of Consistency and Reliability
0.00 – 0.19	Very Weak
0.20 – 0.39	Weak
0.40 – 0.59	Moderate
0.60 – 0.79	Strong
0.80 – 1.00	Very Strong

These findings indicate that while both methods are capable of producing rankings that positively correlate with THE Rankings, MAIRCA-ROC demonstrates superior performance in replicating the international ranking pattern. Moreover, the variation in correlation coefficients across methods highlights the significant influence of both the weighting technique and the MCDM algorithm on the final ranking outcomes of higher education institutions. Rankings generated using ROC weights consistently exhibit a higher level of alignment with THE Rankings compared to those using RS weights. Specifically, MAIRCA-ROC achieves a stronger correlation with THE Rankings (ρ = 0.8135) than MAIRCA-RS (ρ = 0.7910). Conversely, MABAC-RS shows a slightly higher correlation (ρ = 0.7940) with THE Rankings compared to MABAC-ROC (ρ = 0.7744), indicating that the impact of weighting schemes may vary depending on the decision-making method employed.

4. Conclusion

This study is situated within the domain of MCDM, with a focus on its application to institutional rankings in higher education. It addresses the critical issue of selecting appropriate MCDM methods and weighting schemes that align with established benchmarks. The objective of this research is to evaluate the consistency of rankings produced by two MCDM methods—MAIRCA and MABAC—when integrated with three different weighting approaches: THE Rankings 2025, ROC, and RS. Employing a comparative analysis framework, both MCDM methods were applied to

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generate institutional rankings, followed by correlation testing using Spearman's rank correlation coefficient. The results indicate that while all tested approaches showed statistically significant correlations with the official THE Rankings, the MAIRCA-ROC method achieves the highest level of consistency and reliability, with a Spearman's rank correlation coefficient of approximately 0.8315. and a p-value of 0.00001.

These findings suggest that the selection of both MCDM algorithms and weighting techniques plays a crucial role in shaping the accuracy and validity of institutional ranking outcomes, particularly when aligned with established international benchmarks. The study offers practical insights for policymakers and higher education managers by emphasizing the importance of method selection and the weighting scheme in enhancing the credibility of internal evaluations. In particular, the use of MAIRCA and MABAC methods with appropriate weighting enhances the robustness and alignment of institutional rankings with recognized global standards.

Future research may consider extending the range of MCDM methods by incorporating other established approaches, investigating dynamic or participatory weighting schemes, and conducting more in-depth sensitivity analyses on weight variations. Additionally, the inclusion of further evaluation criteria—particularly qualitative and region-specific indicators—as well as the use of alternative correlation measures such as Kendall's Tau or Pearson's coefficient, may provide broader insights and improve the generalizability of the results. It is also recommended to expand the set of university alternatives, including institutions from across Indonesia and global rankings, to enhance the comprehensiveness and applicability of the findings.

5. Declarations

5.1. Author Contributions

Conceptualization: S.A., T.M.; Methodology: S.A., A.G.; Software: A.E.R.; Validation: T.M., A.G.; Formal Analysis: S.A.; Investigation: S.A.; Resources: T.M., A.G.; Data Curation: A.E.R.; Writing – Original Draft Preparation: S.A.; Writing – Review and Editing: T.M., A.G., A.E.R.; Visualization: A.E.R.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

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5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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