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Improving University Ranking Robustness Using Rank Geometric Weight Integration with CoCoSo Method for Reducing Ordinal Weighting Instability

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Abstract

This study lies in the field of decision support systems, focusing on the application of Multi-Criteria Decision Making (MCDM) for ranking alternatives based on predefined organizational criteria. A persistent challenge in this domain is the instability and subjectivity of ordinal weighting methods - such as Rank Order Centroid (ROC), Rank Sum (RS), Rank Reciprocal (RR), and Rank Order Distribution (ROD), which derive weights solely from rank positions, often leading to inconsistent and unreliable outcomes. To address this, this study introduces Rank Geometric (RG) weights, a geometric mean aggregation of ROC, RS, RR, and ROD designed to reduce subjectivity, stabilize weight distribution, and enhance robustness. By using the Combined Compromise Solution (CoCoSo) method, the RG against Times Higher Education's (THE) official weights were evaluated, and the four individual ordinal methods, applied to the top 10 Indonesian universities across five THE 2025 ranking criteria. Empirical results show that RG-CoCoSo produces stronger and more consistent correlations with THE's rankings than THE-CoCoSo, as validated by Spearman and Pearson correlation tests, with a p-value of 0.0251. This study contributes a practical, data-driven weighting framework that strengthens the reliability of MCDM-based institutional performance evaluation and can be generalized to other ranking contexts.

Keywords: CoCoSo, Geometric Mean, Institutional Ranking, MCDM, Ordinal Weighting

1. Introduction

Weight determination of criteria is a critical component in Multi-Criteria Decision-Making (MCDM) systems, as it reflects the relative importance of each criterion in the evaluation process. In practice, various weighting methods have been employed, which are generally classified within the MCDM framework into two main categories: comparative and non-comparative. Comparative methods assess the relative importance of criteria, either explicitly through pairwise comparisons or implicitly through ranking-based approaches. Ordinal weighting, a subset of the comparative method, relies solely on the rank order of criteria without requiring quantitative input [1]. This method has been widely applied across various domains, offering distinct advantages in terms of computational efficiency and ease of use [2]. Although ordinal weighting methods are widely applied, they suffer from instability, subjectivity, and rank reversal, often leading to inconsistent results.

Such limitations raise concerns about the reliability of decision outcomes. To address this issue, this study proposes a composite weighting scheme that integrates four ordinal methods, namely Rank Order Centroid (ROC), Rank Sum (RS), Rank Reciprocal (RR), and Rank Order Distribution (ROD), using the Geometric Mean (GM) approach. This approach is intended to consolidate the strengths of each technique while minimizing potential biases associated with relying on a single method, thereby establishing a more robust weighting framework [3], [4]. MCDM methods provide

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a structured framework designed to address complex decision-making problems by systematically integrating decision-makers' subjective preferences with quantitative data. This approach facilitates more accountable and robust decision outcomes. The hybrid AHP–SMARTER–TOPSIS method has been employed to determine coffee marketing strategies [5]. Similarly, Fuzzy-TOPSIS has been applied for industrial location selection [6]. In another study, four MCDM approaches (CF, VIKOR, TOPSIS, and SAW) were utilized to rank and prioritize 20 sub-watersheds [7]. Hybrid MCDM methods were applied in material selection [8]. For ranking the Top 20 Indonesian universities, the MAIRCA and MABAC methods were employed [9]. Meanwhile, for student ranking assessments within a university, the CoCoSo and CoCoFISo methods have been applied [10].

In addition to these approaches, non-comparative weighting methods such as Entropy, MEREC, and CRITIC are widely employed, as they determine criteria weights objectively based on the information content and variability of the data without relying on direct subjective judgments from decision-makers. On the other hand, comparative methods such as AHP and SWARA derive weights from decision-makers' judgments, while EDAS and CODAS represent comparative MCDM techniques primarily applied to evaluate and rank alternatives. The CoCoSo method has been integrated into various hybrid models, including CRITIC-EDAS-CODAS-CoCoSo [11], MEREC-CoCoSo [12], SWARA-CoCoSo [13], Entropy-CoCoSo [14], [15], and AHP-CoCoSo [16], [17]. The CoCoSo method, which integrates additive and multiplicative utility functions, provides a balanced and comprehensive approach to multi-criteria decision analysis and is well-regarded for its effectiveness in handling complex decision-making problems [18].

In this study, the derived composite weights are incorporated into an MCDM framework using the CoCoSo method to rank the Top 10 Indonesian universities based on five criteria from the Times Higher Education (THE) Rankings 2025, namely research quality, research environment, teaching, industry engagement, and international outlook [19]. To evaluate the consistency and validity of the proposed method, this study applies Spearman's rank correlation and Pearson's correlation coefficient [20]. These tests assess the alignment between rankings derived from GM weights and those from individual ordinal methods. This analysis aims to assess the extent to which the rankings based on the GM weights align with those derived from each ordinal weighting method.

This paper is organized as follows. Section 2 provides a review of related work on weighting techniques and hybrid MCDM approaches. Section 3 describes the proposed methodology, including the construction of composite weights and the application of the CoCoSo framework. Section 4 presents the case studies and empirical results, followed by a discussion of the key findings, correlation analysis, and their broader implications. Finally, Section 5 concludes the study by summarizing the main contributions and outlining potential directions for future research.

2. Literature Review

Criterion weighting plays a crucial role in MCDM by influencing the reliability and validity of decisions. Ordinal methods are widely applied due to their simplicity, especially when only ranking information is available. Approximation-based approaches such as ROC, RS, RR, and ROD demonstrate practical relevance when precise quantitative judgments cannot be provided [1]. A detailed comparative analysis of ordinal-based weighting approaches is also available [2]. An empirical extension of this line of analysis demonstrates that, despite their simplicity, rank-based methods can approximate optimal weights in additive models [21]. In terms of practical applications, ROC and RS have been employed in combination with MCDM techniques for hole turning processes, illustrating how variations in weighting schemes influence ranking outcomes [22]. Weighting schemes based on EQUAL, ROC, RS, and entropy have been used to analyze the effects of different weighting approaches on result consistency [23]. Similarly, ROC and RS have been applied in university ranking, with results statistically validated using Spearman correlation against THE benchmarks, revealing a high level of consistency [9]. In another case, the CoCoSo method has been integrated within a multi-model framework for sustainable renewable energy selection, combining CRITIC-based weighting with other evaluative techniques [11]. The GM is commonly used to aggregate values under conditions of uncertainty or when the relationships between data are multiplicative. Its mathematical properties, particularly within the framework of linear algebra, are well described [3]. The efficiency of weighted GM in reciprocal matrices, which is relevant for evaluation techniques such as the AHP, has also been analyzed [24]. A critical review of GM applications, including their interpretational challenges, is provided [4]. A comparison of GM and AM in the context of bandwidth selection for the Nadaraya-Watson kernel regression estimator concludes that the choice of aggregation method is highly dependent on data characteristics [25]. The reviewed literature indicates that both rank-based weighting methods and the GM play significant roles in multi-criteria decision-making contexts. ROC, RS, RR, and ROD are particularly suitable for ordinal information settings and are frequently adopted due to their simplicity. In contrast, GM offers higher accuracy under uncertainty and in nonlinear systems. These two approaches can be effectively integrated, as demonstrated in recent developments such as GM-based FMEA models [26] and unified MCDM frameworks [11].

Table 1 summarizes key studies on weighting methods within the MCDM framework. While prior research highlights the flexibility of various methods and the GM approach, limited work has integrated multiple ordinal methods into a composite framework. Moreover, their integration with the CoCoSo method remains unexplored. To address this gap, this study combines four ordinal weighting techniques using the GM approach and applies the composite weights within CoCoSo for university ranking.

Table 1. Summary of relevant literature on ordinal weighting and MCDM applications

References	Problem	Methods/Weights	Result
[1]	Approximation of weights in multi-attribute decision models	ROC, RS, RR, ROD	Proposed and analyzed surrogate weight approximations; demonstrated usability in multi-attribute models.
[2]	Analysis and comparison of ordinal information-based weighting methods	ROC, RS, RR, ROD	Compared ordinal weighting techniques, highlighted performance differences, and suitability across contexts.
[21]	Empirical evaluation of rank-based surrogate weights in additive decision analysis	ROC, RS, RR, ROD	Provided empirical evidence of inconsistencies; showed impact of weighting choice on stability of results.
[22]	Application of MCDM + weighting methods in manufacturing (hole turning process)	CoCoSo, MABAC, MAIRCA, EAMR, TOPSIS + ROC, RS, FUCOM	Integrated ordinal weighting with MCDM methods; improved ranking robustness and decision accuracy in manufacturing.
[23]	Comparison of MCDM methods using the same data standardization approach	Various MCDM methods	Benchmarked MCDM techniques under identical data preprocessing; clarified relative method performance.
[9]	Enhancing university ranking with MCDM validation	MAIRCA, MABAC, ROC, RS, Spearman's correlation	Improved reliability of university ranking results; validated alignment with THE methodology
[3]	Mathematical formulation of geometric means	Linear algebra approach	Provided theoretical foundations of geometric means; analyzed matrix properties
[24]	Efficiency of weighted geometric means in reciprocal matrices	Weighted geometric mean	Showed efficiency properties of weighted geometric means in reciprocal matrix settings.
[4]	Examination of the geometric mean concept	Statistical perspective	Discussed properties, limitations, and use cases of geometric mean in statistical analysis
[25]	Bandwidth selection in kernel regression	Geometric vs arithmetic mean	Demonstrated geometric mean provides better balance for bandwidth estimation in kernel regression.
[26]	Risk evaluation in FMEA	Geometric mean-based FMEA method	Developed an improved FMEA model; enhanced decision quality using geometric mean with information quality.
[11]	Renewable energy selection in India	CRITIC-EDAS-CODAS-CoCoSo hybrid	Proposed multi-model framework; improved robustness in sustainable energy decision-making.
This study	Enhancing university ranking with MCDM and ordinal weighting methods	CoCoSo, ROC, RS, RR, ROD, Geometric Mean, Spearman's, and Pearson's correlation	University ranking robustness using Rank Geometric weight.

3. Methodology

To address the lack of robustness and consistency in ordinal weighting within MCDM, this study proposes an integrative approach that combines ordinal weighting techniques with the Geometric Mean (GM) method to produce more stable and consistent composite weights, which are subsequently incorporated into the CoCoSo method within the MCDM framework. Figure 1 summarizes the main stages of the proposed methodology. The process begins with the ordinal weighting methods stage, where criterion weights are determined using four ordinal weighting techniques: ROC, RS, RR, and ROD. These methods are then integrated through the GM Approach, which employs the GM to produce a single set of representative composite weights, referred to as Rank Geometric (RG). Both the ordinal-based weights and the official weights from the THE Rankings 2025 are subsequently used within the CoCoSo method to generate the final rankings of the evaluated alternatives. The next stage, ranking comparison, involves comparing the ranking outcomes to assess variation and the potential for improved decision quality. To evaluate the consistency and strength of relationships among rankings, a correlation analysis is conducted using both Spearman's and Pearson's correlation coefficients. Finally, the evaluation stage concludes the process by assessing the robustness, stability, and reliability of the proposed hybrid weighting approach within the MCDM framework.

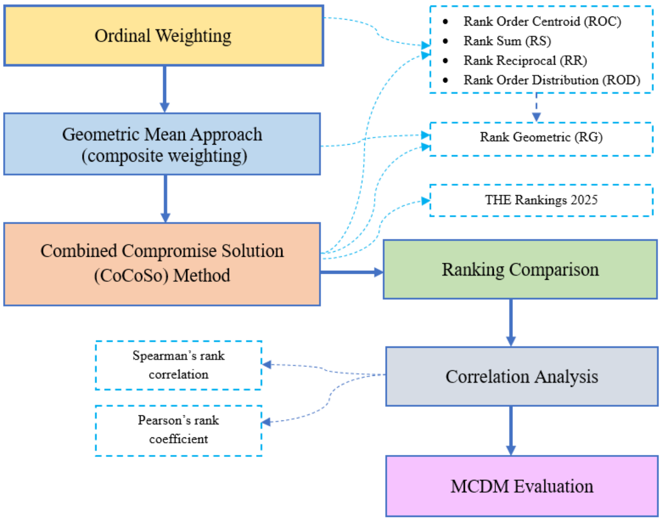


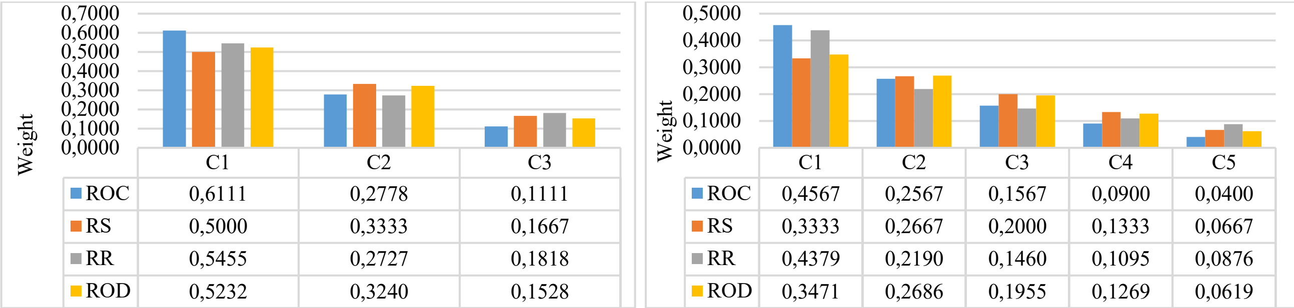
Figure 1. Proposed method using the GM approach

3.1. Ordinal Weighting Methods

Ordinal weights in MCDM represent a method of assigning weights based solely on the rank or order of importance of the criteria, without considering the magnitude of differences between them. In this approach, decision-makers are only required to rank the criteria from most to least important, without assigning precise quantitative values. Ordinal weighting captures relative preferences qualitatively, making it particularly suitable in situations where numerical information is difficult to obtain or when judgments are inherently subjective. The ordinal weighting methods employed in this study include four primary approaches: ROC, RS, RR, and ROD. All four methods rely on rank-order data, where criteria are ordered based on their perceived importance without requiring direct numerical assessments. This makes them particularly useful in contexts where preferences are qualitative [1].

The ROC method generates weights by calculating the average of all weight distributions that are consistent with the given ranking, using the following formula: $W_i = \frac{1}{n}\sum_{j=i}^{n}\left(\frac{1}{j}\right)$. The RS method calculates weights based on a linear transformation of the ranking order, using the following formula: $W_i = \frac{(n+1-Ri)}{\frac{n\,(n+1)}{2}}$, $i = 1, \ldots, n$, where the i-th rank is denoted by Ri. The RR method assigns weights based on the reciprocal of each criterion's rank, using the following formula: $W_i = \frac{\frac{1}{i}}{\sum_{j=1}^{n}\frac{1}{j}}$, $i = 1, \ldots, n.$ $j = 1, \ldots, n.$ Meanwhile, the ROD method assigns weights based on specific proportional distributions derived from the ranking order, aiming to balance the ordinal weight allocation more evenly. By employing all four approaches, this study enables a comprehensive evaluation of the sensitivity and variability in decision outcomes resulting from different ordinal weighting schemes.

Figure 2 presents the criterion weights derived from the ROC, RS, RR, and ROD methods for three and five criteria. This table illustrates the transformation of ordinal rankings into numerical weights according to the principles of the respective ordinal weighting approach. The variations in weight distribution patterns across methods reflect the distinct characteristics of each technique in capturing the relative importance of criteria. These weights are subsequently utilized in the MCDM process to analyze and compare the resulting rankings. This graphical representation highlights how each ordinal weighting technique assigns different proportions of importance to the same set of criteria, thereby revealing the inherent variability in preference modeling within the MCDM process.



	C1	C2	C3
ROC	0,6111	0,2778	0,1111
RS	0,5000	0,3333	0,1667
RR	0,5455	0,2727	0,1818
ROD	0,5232	0,3240	0,1528

	C1	C2	C3	C4	C5
ROC	0,4567	0,2567	0,1567	0,0900	0,0400
RS	0,3333	0,2667	0,2000	0,1333	0,0667
RR	0,4379	0,2190	0,1460	0,1095	0,0876
ROD	0,3471	0,2686	0,1955	0,1269	0,0619

Figure 2. Four ordinal weighting methods

3.2. Geometric Mean Approach

The Geometric Mean (GM) is a statistical method used to calculate the average of a set of values by considering the product of those values, rather than their sum, as in the arithmetic mean. The use of GM in weighting is particularly important as it reduces the influence of excessively high or low biased assessments, resulting in a more balanced aggregation. This approach is also well-suited for ratio-scaled data and relative comparisons, as it preserves the proportional relationships between values. As such, GM ensures that the resulting weights remain consistent, fair, and representative of the overall set of evaluations. The GM is calculated using the formula: $GM = (\prod_{i=1}^{n} x_i)^{1/n}$, where x_i represents the i-th value in the data set, and n is the total number of values. $\prod_{i=1}^{n} x_i$ represents the product of all values from x_i to x_n. This means that the GM is obtained by multiplying all values in the dataset and then taking the nth root of the product. This method is commonly used in MCDM weighting because it reduces the influence of extreme values, preserves proportionality, and is well-suited for ratio-scale data or relative comparisons. The new weights derived using the GM approach, referred to as Rank Geometric (RG), are calculated based on the weights obtained from the ROC, RS, RR, and ROD methods, as shown in Equation (1). Where RG [i, j] is GM weight for alternative i and criterion j; A [i, j] is ROC weight for the i-th rank among j criteria; B [i, j] is RS weight for the i-th rank among j criteria; C [i, j] is RR weight for the i-th rank among j criteria; D [i, j] is ROD weight for the i-th rank among j criteria; and n is number of ordinal weights.

$$\text{RG}\,[i,j] = \sqrt[n]{A\,[i,j]\ \text{x}\ B\,[i,j]\ \text{x}\ C\,[i,j]\ \text{x}\ D\,[i,j]} \tag{1}$$

3.3. CoCoSo

CoCoSo is an MCDM method that integrates the compromise approach by combining the strengths of Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS), Weighted Product Method (WPM), and Weighted Sum Method (WSM) to generate more accurate and balanced alternative rankings. This integration is operationalized through the use of the lambda (λ) parameter, which is employed in one of the three methods for aggregating the final score (k_i) [18]. Figure 3 illustrates the main steps of the CoCoSo method, starting with the creation of the decision matrix, followed by the normalization of criteria values. For this step, the benefit-type and cost-type criteria are normalized using the min–max method, as shown in Equations (3) and (4), respectively. Next, the weighted comparability sequence is calculated, which represents S_i based on the SAW method, incorporating the weights of each criterion. The values of S_i and P_i are subsequently employed in three aggregation strategies, namely k_{ia}, k_{ib}, and k_{ic}, corresponding to Equations (7), (8), and (9), respectively, with λ= 0.5. These represent compromise approaches based on total synthesis, ratio relative to the minimum, and a λ-based compromise, respectively. Finally, the overall score k_i for each alternative is obtained using the arithmetic and geometric means of the three compromise values, as shown in Equation (10). The alternative with the highest k_i value is considered the optimal choice. The SAW method is a widely used MCDM technique that evaluates alternatives by summing the weighted values of each criterion [27], [28]. These applications highlight the adaptability and relevance of SAW in supporting multi-criteria evaluations across different domains. The WASPAS method is an MCDM technique that combines the strengths of the SAW and WPM methods to enhance evaluation accuracy and stability [29], [30], [31], [32]. These studies collectively emphasize WASPAS's high adaptability across various domains and data types, as well as its capability to improve the systematic reliability of alternative evaluations.

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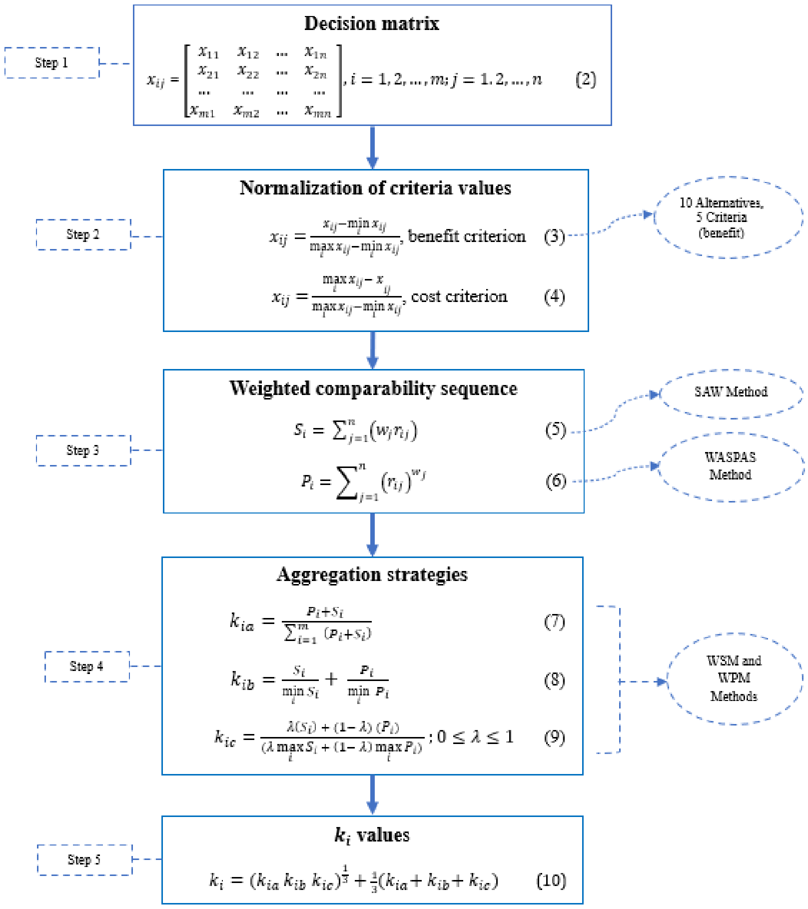

Figure 3. Steps of the CoCoSo Method

3.4. Spearman's rank correlation and Pearson's rank correlation coefficient

In MCDM, the Spearman's correlation, as shown in Equation (11), and the Pearson's correlation, as shown in Equation (12), are used to assess ranking consistency across methods and relationships among criteria.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{11}$$

Where ρ denotes the Spearman's rank correlation coefficient, used to measure the strength and direction of the monotonic relationship between two variables; d_i represents the difference in ranks for the i-th pair of values; $\sum d_i^2$ is the sum of squared differences in ranks for all data pairs, and n is the total number of observations (data pairs).

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \cdot \sum(y_i-\bar{y})^2}} \tag{12}$$

Where x_i and y_i are the i-th observed values of variables x and y; $\bar{x}$ and $\bar{y}$ are the mean values of x and y, respectively; and r is Pearson's correlation coefficient.

4. Results and Discussion

In this study, the RG weight is calculated as the geometric mean of four ordinal weights. The geometric mean is computed using base-10 logarithms, a common approach for analyzing ratio-scaled data. Base-10 logarithms were chosen because they produce values that are easy to interpret in terms of orders of magnitude while yielding the same relative weights. Therefore, the choice of the logarithm base does not affect the normalized RG weight values. Specifically, the average of the logarithms of the four values is first computed, and the RG weight is then derived using the formula (1). For illustration, at rank i = 1 and criterion j = 5, the resulting RG weight is 0.3900.

$$\text{RG}[1,5] = \sqrt[n]{\text{A}[1,5] \text{ x } \text{B}[1,5] \text{ x } \text{C}[1,5] \text{ x } \text{D}[1,5]}$$

$$\text{Log RG }[1,5] = \frac{(\text{Log }(A\,[1,5]) + \text{Log }B\,([1,5]) + \text{Log }(C\,[1,5]) + \text{Log }(D\,[1,5]\,)}{4}$$

$$\text{Log RG }[1,\,5] = \frac{(\text{Log }(0.4567) + \text{Log }(0.3333) + \text{Log }(0.4379) + \text{Log }(0.3471)}{4}$$

$$\text{RG }[1,5] = \text{Antilog }(-\,0.4090) = 0.3900$$

The resulting RG weights are 0.3900, 0.2519, 0.1729, 0.1136, and 0.0617, respectively. RG weights for criteria from 2 to 10 are displayed in table 2, calculated using Equation (1). To evaluate the reliability of the RG weight, a test scenario was conducted using the CoCoSo method with two types of weighting schemes: non-comparative weighting (THE Rankings) and comparative (ordinal) weighting (ROC, RS, RR, ROD, and RG).

Table 2. RG weight from four ordinal weighting methods

Rank	**Criteria**								
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0.6933	0.5434	0.4522	0.3900	0.3447	0.3101	0.2825	0.2600	0.2414
2	0.3038	0.3007	0.2762	0.2519	0.2307	0.2126	0.1974	0.1843	0.1731
3		0.1506	0.1728	0.1729	0.1668	0.1590	0.1510	0.1435	0.1365
4			0.0912	0.1136	0.1201	0.1204	0.1181	0.1148	0.1109
5				0.0617	0.0810	0.0889	0.0916	0.0919	0.0908
6					0.0447	0.0609	0.0687	0.0724	0.0739
7						0.0340	0.0477	0.0550	0.0589
8							0.0269	0.0384	0.0451
9								0.0218	0.0317
10									0.0181

Table 3 presents the normalized results of raw data from 10 universities (U1–U10) based on five main evaluation criteria: C1: Research Quality (30%), C2: Research Environment (28%), C3: Teaching (24.5%), C4: Industry (10%), and C5: International Outlook (7.5%) [9], [19]. All criteria are categorized as benefit criteria, which refer to those for which higher values are considered more favorable. In other words, the greater the value of an alternative with respect to a benefit criterion, the more advantageous it is in the decision-making context [33], [34]. Based on the THE rankings weights, the priority order of the criteria can be determined as C1 ≥ C2 ≥ C3 ≥ C4 ≥ C5. This priority ranking serves as the basis for calculating the weights assigned to each criterion.

Table 3. Normalized matrix with 10 alternatives

Alternatives	**Criteria**				
	C1 (Research Quality (30%)	**C2 (Research Environment (28%)**	**C3 (Teaching (24.5%)**	**C4 (Industry (10%)**	**C5 (International Outlook (7.5%)**
U1	0.3159	1.0000	1.0000	1.0000	1.0000
U2	0.2335	0.5646	0.2150	0.5266	0.4474
U3	0.3681	0.8027	0.1638	0.7729	0.3647
U4	0.3599	0.3333	0.3891	0.2488	0.9083
U5	0.1209	0.8571	0.4983	0.9372	0.5481
U6	1.0000	0.0000	0.0000	0.0000	0.2617
U7	0.3297	0.8707	0.1263	0.7754	0.3982
U8	0.0000	0.4558	0.4471	0.6280	0.4206
U9	0.1264	0.0476	0.0887	0.0338	0.0000
U10	0.1841	0.1020	0.3106	0.5700	0.5727

Figure 4 illustrates the comparative weight distribution for five criteria (C1–C5) obtained from multiple ordinal weighting methods. Across all methods, C1 consistently received the highest weight, ranging from approximately 0.30 to 0.45, indicating its dominant role in the decision-making process. C2 ranked second, with weights between 0.24 and 0.29, followed by C3 with intermediate values ranging from 0.15 to 0.22. In contrast, C4 and C5 consistently obtained the lowest weights (0.05–0.12 and 0.05–0.08, respectively), suggesting limited influence on the final ranking outcomes. These differences in weight distribution have important implications for MCDM outcomes. Since C1 and C2 dominate the weighting structure, alternatives scoring highly on these criteria are likely to benefit the most, whereas the low and stable weights of C4 and C5 reduce their role as differentiating factors in the ranking process.

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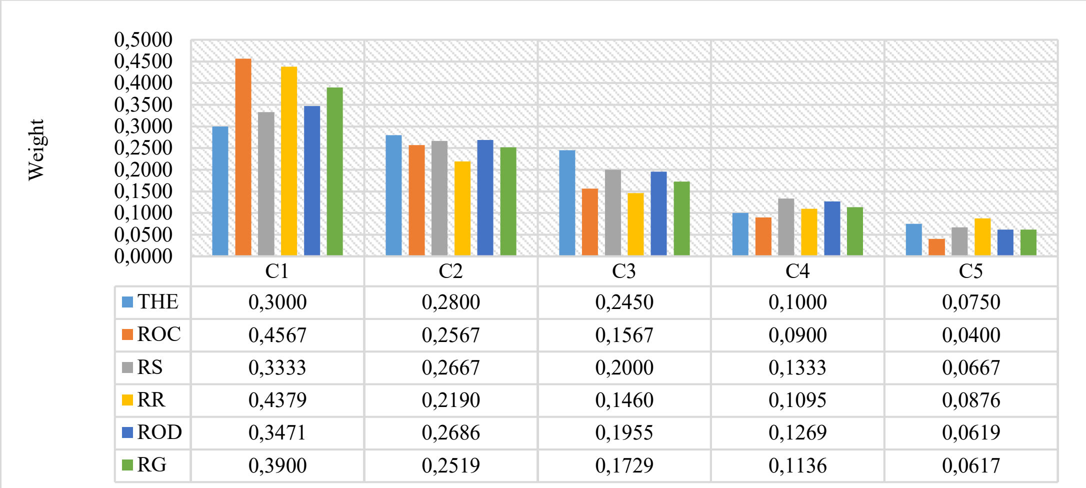

Figure 4. Weighted comparability for five criteria

4.1. MCDM Evaluation

After obtaining the normalized decision matrix and the criterion weights from each method, the next step is to integrate both into the evaluation process using the CoCoSo approach. Table 4 and table 5 present a comparison of the scores for each alternative based on the computed S_i and P_i values. It also shows the ranking results derived from the k_i values, where the alternative with the highest score ranks first. The ranking results indicate that alternative U1 consistently holds the first position across all methods, suggesting a dominant and stable performance regardless of weighting variations. Alternative U3 also demonstrates a high level of consistency, maintaining relatively stable top-tier rankings. In contrast, alternatives U6, U9, and U10 consistently appear at the bottom of the rankings. Furthermore, the rankings generated by THE-CoCoSo, RS-CoCoSo, ROD-CoCoSo, and RG-CoCoSo follow an identical order: U1, U5, U3, U7, U4, U2, U8, U10, U6, and U9.

Although U2 has high values in several criteria, differences in the calculation of weights and aggregation across methods cause its overall score to change. Comparative methods take into account the relative comparison of alternatives for each criterion, so the applied weights may differ from non-comparative weights, which rely solely on absolute values. These differences collectively explain the drop in U2's ranking from 2nd to 6th across all weighting methods.

Table 4. S_i dan P_i value of the CoCoSo method

Alternatives	THE Rankings	THE-CoCoSo		ROC-CoCoSo		RS-CoCoSo		RR-CoCoSo		ROD-CoCoSo		RG-CoCoSo	
		S_i	P_i	S_i	P_i	S_i	P_i	S_i	P_i	S_i	P_i	S_i	P_i
U1	1	0.7948	4.7077	0.6877	4.5908	0.7720	4.6811	0.7004	4.6038	0.7626	4.6704	0.7233	4.6380
U2	2	0.3670	4.0640	0.3506	4.0764	0.3715	4.0756	0.3542	4.0744	0.3693	4.0750	0.3579	4.0809
U3	3	0.4800	4.2250	0.4840	4.2694	0.4969	4.2574	0.4775	4.2541	0.4961	4.2590	0.4844	4.2656
U4	4	0.3896	4.1276	0.3696	4.1223	0.3804	4.1097	0.3942	4.1469	0.3783	4.1095	0.3759	4.1268
U5	5	0.5332	4.2808	0.4596	4.2092	0.5300	4.2762	0.4640	4.2081	0.5225	4.2677	0.4895	4.2433
U6	6	0.3196	1.9044	0.4672	1.9478	0.3508	1.9145	0.4608	1.8892	0.3633	1.9204	0.4061	1.9206
U7	7	0.4811	4.1893	0.4796	4.2318	0.4973	4.2228	0.4733	4.2196	0.4960	4.2240	0.4824	4.2300
U8	8	0.3315	3.5152	0.2604	3.6238	0.3227	3.5460	0.2707	3.6083	0.3156	3.5546	0.2894	3.5870
U9	9	0.0764	2.2292	0.0869	2.2679	0.0771	2.1986	0.0824	2.3099	0.0783	2.2026	0.0805	2.2492
U10	10	0.2598	3.7849	0.2331	3.7795	0.2649	3.7957	0.2609	3.8189	0.2598	3.7903	0.2513	3.8009

Table 5. Evaluation of university rankings

Alternatives	THE Rankings	THE-CoCoSo		ROC-CoCoSo		RS-CoCoSo		RR-CoCoSo		ROD-CoCoSo		RG-CoCoSo	
		k_i	Rank	k_i	Rank	k_i	Rank	k_i	Rank	k_i	Rank	k_i	Rank
U1	1	5.8707	1	4.8978	1	5.7133	1	5.1432	1	5.6062	1	5.3199	1
U2	2	3.4627	6	3.1798	6	3.4732	6	3.2998	6	3.4338	6	3.3406	6
U3	3	4.0988	3	3.8587	2	4.1754	3	3.9559	2	4.1347	3	4.0260	3
U4	4	3.6026	5	3.2842	5	3.5318	5	3.5190	5	3.4923	5	3.4462	5
U5	5	4.3891	2	3.7250	4	4.3485	2	3.8740	4	4.2682	2	4.0417	2
U6	6	2.3654	9	2.8537	7	2.5097	9	2.9145	7	2.5475	9	2.7091	9
U7	7	4.0900	4	3.8239	3	4.1635	4	3.9222	3	4.1206	4	4.0022	4

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U8	8	3.0665	7	2.5930	8	3.0196	7	2.7172	9	2.9626	7	2.8136	7
U9	9	1.2529	10	1.2707	10	1.2411	10	1.2986	10	1.2425	10	1.2643	10
U10	10	2.8053	8	2.5279	9	2.8232	8	2.7528	8	2.7751	8	2.7100	8

Figure 5 presents the rankings of 10 universities based on six weighting methods, in which alternatives U1, U2, U4, and U9 occupy consistent rankings across the methods, namely U1 ranks 1st, U4 ranks 5th, U2 ranks 6th, and U9 ranks 10th.

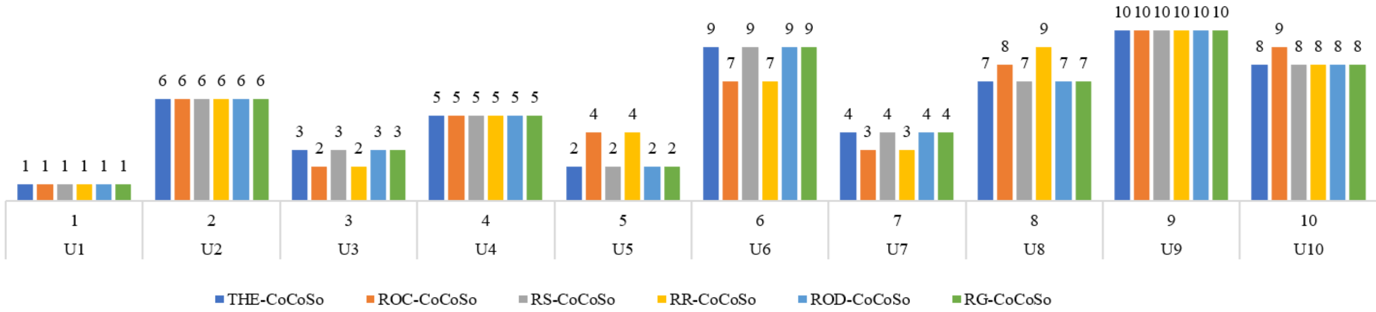

Figure 5. Top 10 university ranking

In general, the RG-CoCoSo method provides reliable results in representing university performance evaluations, with a logical and consistent ranking distribution relative to external benchmarks. The geometric weighting approach employed effectively balances the contributions of individual criteria, resulting in an aggregated score that reflects the overall performance of each alternative. Based on the ranking results in Table 9, U1 ranks 1st and U3 ranks 3rd in the RG-CoCoSo method, consistent with their rankings in THE. This indicates that the method is relatively effective in capturing the dominant characteristics of top-performing universities. In addition to U1, U5 ranks 2nd and U7 ranks 4th in both approaches, demonstrating stable positions. Conversely, a slight shift is observed for U2, which ranks 6th in RG-CoCoSo compared to 2nd in THE.

4.1. Correlation analysis

To evaluate the consistency between the alternative ranking results and the THE rankings, a correlation analysis was conducted using Spearman's and Pearson's tests. These tests aim to measure the strength and direction of the relationship between the results of each method and the THE rankings. The correlation results are presented in Table 6.

Table 6. Spearmans and Pearson's rank correlation coefficients between CoCoSo methods and THE ranking

Weighting Methods	Spearman's rank correlation					Pearson's rank correlation				
	(ρ)	p-value	t-student	Interpretation	Hypothesis	(ρ)	p-value	t-student	Interpretation	Hypothesis
THE-CoCoSo	0.6970	0.0251	2.7490	Strong	Rejected	0.6970	0.0251	2.7490	Strong	Rejected
ROC-CoCoSo	0.7697	0.0092	3.4101	Strong	Rejected	0.7697	0.0092	3.4101	Strong	Rejected
RS-CoCoSo	0.6970	0.0251	2.7490	Strong	Rejected	0.6970	0.0251	2.7490	Strong	Rejected
RR-CoCoSo	0.7455	0.0133	3.1632	Strong	Rejected	0.7455	0.0133	3.1632	Strong	Rejected
ROD-CoCoSo	0.6970	0.0251	2.7490	Strong	Rejected	0.6970	0.0251	2.7490	Strong	Rejected
RG-CoCoSo	0.6970	0.0251	2.7490	Strong	Rejected	0.6970	0.0251	2.7490	Strong	Rejected

All weighting methods in Table 6 exhibit a strong and positive correlation, with correlation coefficients ranging from 0.6970 to 0.7697. All p-values are below 0.05, indicating statistical significance according to both Spearman's and Pearson's tests. Therefore, the null hypothesis of no correlation is rejected for all methods, reinforcing the confidence that the results of these methods are indeed consistent with the THE rankings. The ROC-CoCoSo method consistently yields the highest correlation values in both tests (Spearman and Pearson), with $\rho = 0.7697$ and a p-value of 0.0092. This result is also accompanied by a t-statistic of 3.4101, the highest among all methods. These findings indicate that ROC-CoCoSo is the most consistent and reliable method in reflecting the actual THE rankings. The RR-CoCoSo method also demonstrates a high correlation ($\rho = 0.7455$), although slightly lower than that of ROC-CoCoSo. Meanwhile, other methods such as THE-CoCoSo, RS-CoCoSo, ROD-CoCoSo, and RG-CoCoSo exhibit identical correlation values ($\rho = 0.6970$) and p-values (0.0251), indicating a strong relationship, although not as strong as that of the ROC-CoCoSo method. RG-CoCoSo, which is derived by calculating the geometric mean of the ordinal weights from ROC, RS, RR, and ROD, demonstrates a positive and significant correlation coefficient in both Spearman and Pearson tests. Although its correlation is not as high as that of the individual ROC-CoCoSo method (ρ = 0.7697), RG-CoCoSo still exhibits a strong relationship with the THE rankings. Although the differences in Spearman correlation coefficients (0.7697 and 0.6970) are statistically noticeable, their practical significance lies in the stability of the rankings and ranking reliability. High correlation values indicate that the relative ordering of alternatives remains generally consistent across the methods used, ensuring that the ranking reliability is maintained. Therefore, small numerical differences in correlation do not substantially affect the overall ranking reliability, and decisions based on these rankings remain valid.

5. Conclusion

This study introduces the RG-CoCoSo method, which integrates four objective weighting techniques (ROC, RS, RR, and ROD) through geometric mean aggregation to evaluate university performance. Compared to previous studies, specifically THE Rankings 2025, Spearman and Pearson correlation coefficients among the weighting methods range from 0.6970 to 0.7697, indicating that the method is robust and consistent. Among the eight weighting methods used, six produced the same ranking of alternatives. ROC-CoCoSo achieved the highest correlation with the reference rankings, while RG-CoCoSo provided a balanced alternative by maintaining strong and stable performance. The main contribution of this study is the demonstration of RG-CoCoSo's ability to synthesize various weighting schemes to produce reliable rankings, while also providing quantitative evidence of ranking robustness and consistency. These quantitative findings confirm the reliability of the proposed method in Multi-Criteria Decision-Making (MCDM) contexts. This study also opens avenues for further development, such as applying hybrid weighting methods, learning-based approaches, or sensitivity analyses to deepen understanding of ranking stability and interpretability.

Future studies may focus on applying the RG-CoCoSo method to other sectors, such as healthcare, finance, or energy management, to evaluate its adaptability across different decision-making contexts. Researchers can also develop a dynamic version of RG-CoCoSo that updates rankings in real-time using streaming data, enabling more context-aware decision-making. In addition, the integration of hybrid or learning-based weighting approaches can be explored to assess their impact on ranking stability compared to traditional methods. More detailed sensitivity and rank reversal analyses can also be conducted to measure the influence of individual criteria on overall rankings. Finally, advanced correlation metrics, such as Kendall's tau or non-linear measures, can be used to capture subtle differences in ranking consistency across methods.

6. Declarations

6.1. Author Contributions

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

6.2. Data Availability Statement

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

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. 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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