Yugoslav Journal of Operations Research
(20##), Number #, #-#
DOI: https://doi.org/10.2298/YJOR250815040T

Research article

CURLIA: A STREAMLINED AGGREGATION METHOD THAT ELEVATES RANKING ACCURACY IN COMPLEX MCDM PROBLEMS

Do Duc TRUNG
Hanoi University of Industry, Cau Dien, Bac Tu Liem, Hanoi, Vietnam,
doductrung@haui.edu.vn, ORCID: 0000-0002-3190-1026

Bui Thi Thu TRANG
Hanoi University of Industry, Cau Dien, Bac Tu Liem, Hanoi, Vietnam,
trangbtt@haui.edu.vn, ORCID: 0000-0002-5483-9966

Mehmet ÖZÇALICI
Kilis 7 Aralık University, Kilis, 79000, Türkiye,
mozcalici@kilis.edu.tr, ORCID: 0000-0003-0384-6872

Nazlı ERSOY*
Osmaniye Korkut Ata University, Osmaniye, 80000, Türkiye,
nazliersoy@osmaniye.edu.tr, ORCID: 0000-0003-0011-2216

Received: August 2025 / Accepted: October 2025

Abstract: Multi-Criteria Decision-Making (MCDM) techniques frequently produce inconsistent rankings due to variations among methods, complicating the identification of the most accurate ranking of alternatives. Thus, effectively aggregating these distinct rankings becomes crucial. This research proposes the CURLI-AGGREGATOR (CURLIA) method, a novel aggregation technique developed as an extension of the existing Collaborative Unbiased Rank List integration (CURLI) method. While CURLI ranks alternatives directly based on multiple criteria, CURLIA aggregates rankings previously determined by different MCDM methods. The effectiveness of CURLIA was validated through three case studies, each differing in application domain, alternative count, and MCDM techniques employed. Additionally, an extensive simulation involving 1,000 randomized scenarios was performed to evaluate its robustness. Results from a statistical analysis demonstrated that CURLIA significantly outperformed the widely used COPELAND aggregation method in approximately 78.3% of these scenarios. Thus, the

*Corresponding author

CURLIA method constitutes a reliable and robust aggregation tool, significantly enhancing decision-making accuracy across complex and diverse MCDM environments.

Keywords: MCDM, ranking aggregation, CURLI, CURLIA, COPELAND.

MSC: 91B06

1. INTRODUCTION

Multi-Criteria Decision-Making (MCDM) is a method used across disciplines to support complex decisions involving multiple, often conflicting criteria. Unlike traditional approaches that focus on a single factor, MCDM evaluates alternatives based on various criteria and their importance, helping decision-makers prioritize options and reach optimal outcomes [1]. MCDM provides a structured framework that accounts for the varying importance levels of criteria when selecting among alternatives. And it can be applied in a variety of areas, such as supply chain optimization [2] and energy planning [3] to resource allocation in healthcare services [4] and sustainable development assessments [5].

An important feature of MCDM techniques is that they can deal with quantitative and qualitative information as well as expert judgments and subjective judgments [6]. The ranks of alternatives obtained by different MCDM methods might also be varied since they are based upon methodological features including normalization approach, weighting pattern, distance measure and computational algorithm [7,8,9]. This condition requires a synthesized overall ranking decision on the alternatives [10].

The aggregation of data plays a crucial role in determining viable solutions across various fields [11]. Different approaches have been developed to combine these rankings, especially when these rankings are generated by MCDM techniques. For example, although half-quadratic (HQ) function theory [12], Kemeny's square rule [13,14] offer mathematically sound foundations, they have limited applicability due to the increased computational burden on large datasets. The Minimum of Ranks (MIRA) method [15], while notable for its simplicity, cannot adequately reflect the subtle differences between alternatives in most cases. Condorcet models [16], while based on pairwise comparisons, provide an unbiased structure, but incur high computational costs when the number of alternatives increases. Probabilistic models such as Luce and Mallows [17] have the advantage of capturing uncertainty, but their results can vary due to sensitivity in parameter selection. Approaches based on Arrow theory [18], although valuable from a normative perspective, are difficult to apply to practical problems. Scoring rules [19] and methods based on expert experience [20] produce more flexible solutions, but can be affected by subjective factors. Average ranking calculations [21,22] are distinguished by their ease of implementation and tend to ignore inconsistencies between rankings. The Borda Count [23], and the Copeland method [24] are the most frequently used methods in the literature. These methods are particularly prevalent for aggregating rankings produced by MCDM techniques.

The Borda Count method is a widely used technique for data aggregation, particularly in political elections [25]. Various examples of this approach can be found in the literature [26][27][28]. Theoretically, Borda Count is a straightforward method of assigning and summing points; however, in practice it can be quite difficult when dealing with large data sets. Efficiently processing the large-number of ranking lists or items to rank, and computing and combining scores can involve a great deal of computational resources.

The COPELAND approach is a prominent voting method that is used for ordering the alternatives in MCDM problems. This consists of comparing pairs between alternatives, where at each comparison the alternative that beats its opponent is awarded one point. The alternative with the highest total number of wins is then ranked highest [29]. This method functions as a summary measure that integrates the results of multiple MCDM methods by conducting pairwise comparisons of rankings [30]. It has been used extensively to establish the rank order of alternatives that had been previously evaluated through MCDM methodologies, for example, integrating rankings of internet cables types [31], corporate sustainable development options in the energy sector [32], alternating current transmission system alternatives [33], and districts of Tehran city for the establishment of financial centers [34], among others. The Copeland method is simple and straightforward because it relies on pairwise comparisons and provides an unbiased summary measure for integrating the outputs of different MCDM methods. However, the computational burden increases as the number of alternatives increases, and ties can lead to unbiasedness problems.

The primary objective of this study is to develop a novel method capable of integrating alternative rankings obtained from different MCDM techniques into a single consolidated ranking. The proposed approach is named CURLIA (CURLI-AGGREGATOR), which is an improved and enhanced version of the existing Collaborative Unbiased Rank List integration (CURLI) method.

The contributions of this study are as follows: i) A novel method called CURLIA has been developed, capable of integrating alternative rankings obtained from different MCDM methods into a single unified and consistent ranking. This represents an original contribution addressing the ranking integration problem in the MCDM field. ii) CURLIA is an improved and enhanced version of its predecessor, the CURLI method, extending its performance and application scope, thereby offering a significant alternative to existing methods in literature. iii) The applicability of CURLIA has been demonstrated through three distinct case studies featuring different application domains, varying numbers of alternatives, and diverse MCDM techniques, illustrating its broad practical relevance. iv) The robustness and reliability of CURLIA have been thoroughly tested via a simulation study involving 1.000 random scenarios. v) By effectively and systematically addressing the problem of integrating different MCDM rankings, this study fills a gap in literature and opens new avenues for future research.

The remainder of this study is organized as follows: Section 2 introduces the CURLIA method, detailing its theoretical foundations, formulation, and implementation steps. Section 3 presents the application of the proposed method. Section 4 provides a comprehensive sensitivity analysis. Finally, Section 5 concludes the study by summarizing the main findings.

2. CURLI-Aggregator (CURLIA) Method

The CURLIA method is an advancement of the CURLI method, which was originally introduced in 2016 to address the challenges of generating collaborative ranked preference lists in medical education selection processes Therefore, before proposing CURLIA, it is essential to describe the CURLI method [35]:

Step 1: Construct the decision matrix as shown in Table 1, where xij is the value of criterion j for alternative i, with j=1…n and i=1…m. Here, m is the number of alternatives, and n is the number of criteria.

Table 1: Sample Decision matrix

Alt.	C_1
A_1	500
A_2	700

Step 2: For each criterion, create an m×m square matrix as shown in Table 2 and assign scores to each cell of the matrix as follows. For each criterion Cj, a scoring matrix is constructed as follows: if the value of Cj for $A1$ is better than that for $A2$, the cell at row 2, column 1 receives a score of 1; if worse, the cell at row 1, column 2 receives -1. In all other cases, a score of 0 is assigned. Diagonal cells (e.g., 1-1, 2-2, ..., m-m) are left blank. This process is repeated for each criterion.

Table 2: Scoring matrix for criterion C_1

Alt.	P_1	P_2
A_1		-1
A_2	1	

	P_1	P_2	…	P_m
A_1		-1	…	…
A_2	1		…	…
…	…	…		…
A_m	…	…	…	

Step 3: Sum all individual scoring matrices corresponding to each criterion to obtain a single aggregated matrix, referred to as the initial sum matrix.

Step 4: Reorder the initial sum matrix by rearranging its rows and columns so that the upper triangular part (above the main diagonal) contains the maximum possible number of negative values. After reordering, the alternative positioned in the first row is identified as the best alternative.

This method ranks alternatives based on pairwise comparisons of values within each criterion, without taking criterion weights into account. However, criterion weights are a critical component in MCDM applications. Nevertheless, the pairwise comparison approach within individual criteria allows the method to be repurposed as a data aggregation technique. Utilizing CURLI not as an MCDM method for ranking alternatives, but as a data aggregation tool, represents a novel perspective. In this new role, the method is referred to as CURLIA. Additionally, the transformation of linguistic descriptions into mathematical formulations at each step to enhance clarity marks another distinctive feature of CURLIA compared to the original CURLI method.

The CURLIA method aggregates alternative rankings derived from various MCDM techniques through a structured four-step procedure, outlined below.

Step 1: Aggregate the ranking data of alternatives previously ranked by different MCDM methods, referred to as the "initial aggregate results matrix," as shown in Formula (1). Here, m is the number of alternatives, l is the number of MCDM methods used, and r_{ij} is the rank of alternative i as determined by method j, with i=1…m and j=1…l.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1l} \\ r_{21} & r_{22} & \cdots & r_{2l} \\ \cdots & \cdots & r_{ij} & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{ml} \end{bmatrix} \quad (1)$$

Step 2: Create l square matrices of size m, called the pairwise comparison matrices for each MCDM method. Then, assign values of -1, 0, or 1 to each cell of these matrices according to the rule described in Formula (2).

$$S_{il} = \begin{cases} -1 & if \quad r_i > r_k, i \neq k \\ 1 & if \quad r_i < r_k, i \neq k \\ 0 & if \quad r_i = r_k, i \neq k \end{cases} \quad (2)$$

Step 3: Calculate the overall scores of the alternatives according to Formula (3).

$$R_i = \sum_{j=1}^{l} S_{il} \quad (3)$$

Step 4: The ranking of the alternatives is determined by arranging them in increasing order of their overall scores. The alternative with the highest overall score is considered the best.

Accordingly, the CURLIA method differs from the original CURLI method in several important aspects: (i) While CURLI is employed to rank alternatives based on multiple criteria, CURLIA is designed to aggregate the rankings of alternatives that have already been determined by various MCDM methods. (ii) Step 2 of CURLIA is represented by Formula (2), in contrast to the purely textual explanation provided in Step 2 of the CURLI method. (iii) Similarly, Step 3 of CURLIA is illustrated using Formula (3), whereas the corresponding step in CURLI is described solely through text. (iv) Step 4 of the CURLIA method is considerably simpler than the corresponding step in the CURLI method.

This study aims to compare the performance of two MCDM techniques—CURLIA and Copeland—through a structured framework involving real-world case studies and extensive sensitivity analysis. As depicted in Figure 1, three case studies with varying numbers of alternatives (11, 20, and 19) and techniques (4, 5, and 6, respectively) are employed to evaluate each method's decision-support capabilities across different contexts. While the Copeland method offers a straightforward and balanced ranking based on pairwise comparisons, CURLIA introduces a more flexible and insightful approach to evaluating alternatives. To ensure robustness, a sensitivity analysis is conducted using 100 Monte Carlo simulations, systematically varying the number of alternatives (ranging from 2 to 101) and techniques (from 1 to 10). Statistical tests are applied to assess the significance of performance differences, offering a comprehensive evaluation of both methods under diverse decision-making scenarios.

In the comparison with COPELAND, performance was quantified via the Spearman rank correlation coefficient (ρ) computed between the ranking produced by each technique. For every experimental condition, we calculated ρ between our method and each comparator (e.g., COPELAND and CURLIA) and then averaged these correlations over all runs/instances. The mean ρ serves as our primary 'accuracy/consistency' metric: values closer to 1 indicate stronger ordinal agreement (i.e., near-identical rankings), values near 0 indicate weak association, and negative values indicate inverse orderings. Accordingly, the higher average correlations observed with the COPELAND and CURLIA techniques reflect better alignment with our results and thus are interpreted as positive evidence of performance.

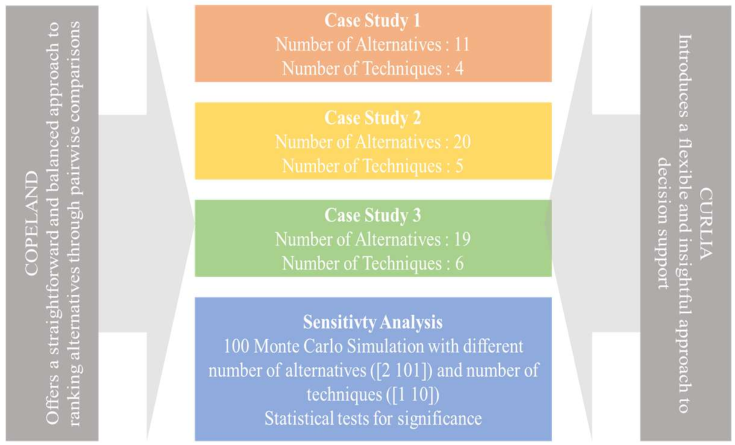


Figure 1: Scheme of the study

3. EVALUATING THE EFFECTIVENESS OF THE PROPOSED METHOD

The primary objective of this study is to propose a novel data aggregation method, CURLIA. To evaluate the performance of the proposed method for aggregating the rankings of alternatives, this section examines the Copeland results obtained in previous studies through the use of various MCDM methods. The outcomes of these studies are comparatively analyzed to assess the effectiveness of the proposed approach. In order to ensure an objective evaluation, the selected datasets cover a range of fields, and within these datasets, the rankings of alternatives were determined using different MCDM techniques.

3.1. Case Study 1

This section evaluates the performance of the CURLIA method in aggregating the rankings of electric vehicles. Table 3 summarizes the rankings of 11 types of electric vehicles (from A1 to A11), previously ranked using the TOPSIS, PROMETHEE, MOORA, and WASPAS methods [29].

Table 3: Rankings of electric vehicles [29]

Alt.	TOPSIS	PROMETHEE	MOORA	WASPAS
A1	9	5	7	7
A2	6	7	8	8
A3	8	9	9	10
A4	3	6	4	4
A5	2	2	2	1
A6	10	3	5	5
A7	11	1	3	3
A8	4	8	6	6
A9	5	11	10	11
A10	1	10	11	9
A11	7	4	1	2

The data presented in Table 3 are used as the initial aggregation results matrix corresponding to Step 1 of the CURLIA method. By applying Equation (2), values were assigned to each cell of the pairwise comparison matrices for each MCDM method, and this process is summarized in Tables 4,5,6 and 7.

Table 4: Pairwise comparison matrix for TOPSIS method

Alt.	S_{ij}									
A1		-1	-1	-1	-1	1	1	-1	-1	-1	-1
A2	1		1	-1	-1	1	1	-1	-1	-1	1
A3	1	-1		-1	-1	1	1	-1	-1	-1	-1
A4	1	1	1		-1	1	1	1	1	-1	1
A5	1	1	1	1		1	1	1	1	-1	1
A6	-1	-1	-1	-1	-1		1	-1	-1	-1	-1
A7	-1	-1	-1	-1	-1	-1		-1	-1	-1	-1
A8	1	1	1	-1	-1	1	1		1	-1	1
A9	1	1	1	-1	-1	1	1	-1		-1	1
A10	1	1	1	1	1	1	1	1	1		1
A11	1	-1	1	-1	-1	1	1	-1	-1	-1	

Table 5: Pairwise Comparison matrix for PROMETHEE method

Alt.	S_{ij}									
A1		1	1	1	-1	-1	-1	1	1	1	-1
A2	-1		1	-1	-1	-1	-1	1	1	1	-1
A3	-1	-1		-1	-1	-1	-1	-1	1	1	-1
A4	-1	1	1		-1	-1	-1	1	1	1	-1
A5	1	1	1	1		1	-1	1	1	1	1
A6	1	1	1	1	-1		-1	1	1	1	1
A7	1	1	1	1	1	1		1	1	1	1
A8	-1	-1	1	-1	-1	-1	-1		1	1	-1
A9	-1	-1	-1	-1	-1	-1	-1	-1		-1	-1
A10	-1	-1	-1	-1	-1	-1	-1	-1	1		-1
A11	1	1	1	1	-1	-1	-1	1	1	1	

Table 6. Pairwise comparison matrix for MOORA method

Alt.	S_{ij}									
A1		1	1	-1	-1	-1	-1	-1	1	1	-1
A2	-1		1	-1	-1	-1	-1	-1	1	1	-1
A3	-1	-1		-1	-1	-1	-1	-1	1	1	-1
A4	1	1	1		-1	1	-1	1	1	1	-1
A5	1	1	1	1		1	1	1	1	1	-1
A6	1	1	1	-1	-1		-1	1	1	1	-1
A7	1	1	1	1	-1	1		1	1	1	-1
A8	1	1	1	-1	-1	-1	-1		1	1	-1
A9	-1	-1	-1	-1	-1	-1	-1	-1		1	-1
A10	-1	-1	-1	-1	-1	-1	-1	-1	-1		-1
A11	1	1	1	1	1	1	1	1	1	1	

Table 7: Pairwise comparison matrix for WASPAS method

Alt.	S_{ij}										
A1		1	1	-1	-1	-1	-1	-1	1	1	-1
A2	-1		1	-1	-1	-1	-1	-1	1	1	-1
A3	-1	-1		-1	-1	-1	-1	-1	1	-1	-1
A4	1	1	1		-1	1	-1	1	1	1	-1
A5	1	1	1	1		1	1	1	1	1	1
A6	1	1	1	-1	-1		-1	1	1	1	-1
A7	1	1	1	1	-1	1		1	1	1	-1
A8	1	1	1	-1	-1	-1	-1		1	1	-1
A9	-1	-1	-1	-1	-1	-1	-1	-1		-1	-1
A10	-1	-1	1	-1	-1	-1	-1	-1	1		-1
A11	1	1	1	1	-1	1	1	1	1	1	

By applying Formula (2), the total scores for each alternative were calculated and summarized in Table 8. The rankings of the alternatives were determined based on these total scores and are presented in the last column of the table. These rankings represent the aggregated rankings obtained using the CURLIA method.

Table 8: Final Rankings of alternatives using the CURLIA method

Alt.	R_i	Rank	Alt.	R_i	Rank
A1	-8	7	A7	12	4
A2	-10	8	A8	0	6
A3	-24	10	A9	-26	11
A4	14	3	A10	-14	9
A5	34	1	A11	20	2
A6	2	5			

Table 9 summarizes the rankings of the alternatives obtained using the TOPSIS, PROMETHEE, MOORA, and WASPAS methods, as well as the aggregated rankings derived using the COPELAND method from the study by [29] and the CURLIA method proposed in this study.

Table 9: Rankings of alternatives (Case Study I)

Alt.	TOPSIS	PROMETHEE	MOORA	WASPAS	COPELAND	CURLIA
A1	9	5	7	7	7	7
A2	6	7	8	8	8	8
A3	8	9	9	10	10	10
A4	3	6	4	4	3	3
A5	2	2	2	1	1	1
A6	10	3	5	5	5	5
A7	11	1	3	3	4	4
A8	4	8	6	6	6	6
A9	5	11	10	11	11	11
A10	1	10	11	9	9	9
A11	7	4	1	2	2	2

It is observed that the rank of each alternative, when aggregated by the CURLIA method, is consistent with its rank when aggregated by the COPELAND method. This indicates that the CURLIA method fully ensures accuracy in aggregating alternative rankings in this case. However, drawing conclusions about the effectiveness of a new method cannot solely rely on a single specific example; it needs to be validated across several other cases.

3.2. Case Study 2

In this section, the performance of the CURLIA method in aggregating mobile phone rankings is evaluated. Table 10 summarizes the rankings of 20 types of mobile phones, which were previously ranked using the TOPSIS-COMET, COCOSO, EDAS, MAIRCA, and MABAC methods [36].

Table 10: Mobile phone rankings by MCDM methods [36]

Alt.	TOPSIS-COMET	COCOSO	EDAS	MAIRCA	MABAC
A1	10	11	11	10	10
A2	14	14	14	14	14
A3	7	7	7	7	7
A4	8	9	9	8	8
A5	13	13	13	13	13
A6	2	1	2	2	2
A7	11	10	10	11	11
A8	17	17	17	17	17
A9	9	8	8	9	9
A10	6	6	6	6	6
A11	15	15	15	15	15
A12	5	5	5	5	5
A13	4	4	4	4	4
A14	16	16	16	16	16
A15	18	19	18	19	19
A16	19	18	19	18	18
A17	1	2	1	1	1
A18	20	20	20	20	20
A19	12	12	12	12	12
A20	3	3	3	3	3

The CURLIA method was applied following a similar procedure to Case Study 1. Table 11 provides a summary of the results obtained from all the methods.

In this case, the rankings obtained using the CURLIA method exhibit a high degree of similarity with those derived from the COPELAND method and the individual MCDM methods. Minor differences in rankings were observed in only 4 out of 20 alternatives; for instance, A6 was ranked 1st by COPELAND and 2nd by CURLIA. These findings indicate that the CURLIA method performs with high accuracy. This finding is further confirmed by the Spearman rank correlation coefficients in Table 12 that express strong independence between the CURLIA and COPELAND methods and the individual MCDM methods. Also, the Spearman coefficient between CURLIA and COPELAND is 0.9970, indicating an almost perfect consistency between the two aggregation approaches.

The average Spearman rank correlation coefficient between the individual MCDM methods and the CURLIA method is 0.9979, which is higher than the corresponding average value between the individual MCDM methods and the COPELAND method, calculated as 0.9967. This suggests that, in this study, the CURLIA method may demonstrate slightly better performance compared to the COPELAND method. This inference is based on the premise that aggregated ranking results should exhibit the highest possible level of agreement with the rankings obtained from various MCDM methods [37].

Table 11: Rankings of alternatives (Case Study 2)

Alt.	TOPSIS-COMET	COCOSO	EDAS	MAIRCA	MABAC	COPELAND	CURLIA
A1	10	11	11	10	10	10	10
A2	14	14	14	14	14	14	14
A3	7	7	7	7	7	7	7
A4	8	9	9	8	8	9	8
A5	13	13	13	13	13	13	13
A6	2	1	2	2	2	1	2
A7	11	10	10	11	11	11	11
A8	17	17	17	17	17	17	17
A9	9	8	8	9	9	8	9
A10	6	6	6	6	6	6	6
A11	15	15	15	15	15	15	15
A12	5	5	5	5	5	5	5
A13	4	4	4	4	4	4	4
A14	16	16	16	16	16	16	16
A15	18	19	18	19	19	19	19
A16	19	18	19	18	18	18	18
A17	1	2	1	1	1	2	1
A18	20	20	20	20	20	20	20
A19	12	12	12	12	12	12	12
A20	3	3	3	3	3	3	3

Table 12: Spearman Correlation Coefficients Among Methods in Case Study 2

Method	COCOSO	EDAS	MAIRCA	MABAC	COPELAND	CURLIA
TOPSIS-COMET	0.9940	0.9970	0.9985	0.9985	0.9955	0.9985
COCOSO		0.9970	0.9955	0.9955	0.9985	0.9955
EDAS			0.9955	0.9955	0.9955	0.9955
MAIRCA				1.0000	0.9970	1.0000
MABAC					0.9970	1.0000
COPELAND						0.9970

3.3. Case Study 3

This section evaluates the performance of the CURLIA method in ranking COVID-19 containment strategies. Table 13 summarizes the rankings of 19 countries in their fight against the COVID-19 pandemic, previously ranked using the TOPSIS, COPRAS, ARAS, WASPAS, MOORA, and MABAC MCDM methods, as well as the aggregation results from the COPELAND [30]. The final column presents the results of the CURLIA method.

The rankings aggregated by both COPELAND and CURLIA methods closely align with those from the individual MCDM methods. Between COPELAND and CURLIA, 12 out of 19 alternatives have identical rankings, while the remaining seven show minor differences. For example, Australia ranks 1st by COPELAND and 2nd by CURLIA; France 9th and 8th; the USA 12th and 13th; Indonesia 15th and 14th; Russia 13th and 12th;

Saudi Arabia 10th and 9th; and Turkey 14th and 15th, respectively. These findings suggest that CURLIA is well-suited for aggregating rankings in this case. Table 14 further supports this by summarizing the Spearman rank correlation coefficients between the methods.

Table 13: Country rankings for COVID-19 containment strategies by MCDM methods [30]

Alternatives	TOPSIS	COPRAS	ARAS	WASPAS	MOORA	MABAC	COPELAND	CURLIA
Australia	1	2	2	6	2	3	1	2
Canada	7	10	10	9	9	7	8	8
France	16	7	7	8	12	10	9	10
Germany	4	5	5	3	4	4	4	4
Italy	9	6	6	5	6	8	7	7
Japan	2	4	3	2	1	1	1	1
South Korea	3	8	8	7	3	2	5	5
United Kingdom	8	3	4	4	7	9	6	6
United States	18	9	9	11	16	17	12	13
Argentina	19	11	11	10	15	11	11	11
Brazil	17	15	14	14	17	16	17	17
China	6	1	1	1	8	5	3	3
India	11	17	18	18	11	14	16	16
Indonesia	10	16	16	17	10	13	15	14
Mexico	14	18	17	16	18	18	18	18
Russia	12	13	12	13	13	15	13	12
Saudi Arabia	5	12	13	12	5	6	10	9
South Africa	13	19	19	19	19	19	19	19
Turkey	15	14	15	15	14	12	14	15

Table 14: Spearman Correlation Coefficients Among Methods in Case Study 2

Method	COPRAS	ARAS	WASPAS	MOORA	MABAC	COPELAND	CURLIA
TOPSIS	0.5579	0.5474	0.5667	0.9035	0.8246	0.7360	0.7737
COPRAS		0.9930	0.9632	0.7228	0.7825	0.9465	0.9281
ARAS			0.9702	0.7018	0.7667	0.9412	0.9246
WASPAS				0.7193	0.8070	0.9360	0.9298
MOORA					0.9368	0.8693	0.8947
MABAC						0.9237	0.9351
COPELAND							0.9939

The Spearman coefficients between both the COPELAND and CURLIA methods and the individual MCDM methods are observed to be very high. Notably, the Spearman coefficient between COPELAND and CURLIA themselves is 0.9939, indicating a strong agreement. This confirms that the CURLIA method reliably and accurately aggregates rankings in this case. The average Spearman coefficient between the individual MCDM methods and the aggregation methods is 0.8977 for CURLIA and 0.8921 for COPELAND, suggesting that CURLIA slightly outperforms COPELAND here. The performance of CURLIA was evaluated across three distinct case studies. Case 1 aggregated rankings of 11 electric bicycle types previously ranked by TOPSIS, PROMETHEE, MOORA, and

WASPAS. Case 2 involved aggregating rankings of 20 mobile phone types ranked by TOPSIS-COMET, COCOSO, EDAS, MAIRCA, and MABAC. Case 3 aggregated rankings of 19 countries based on their COVID-19 containment strategies, previously ranked by COPRAS, ARAS, WASPAS, MOORA, and MABAC. These cases demonstrate diversity in application domains, the number of alternatives, and the MCDM methods employed. Despite this diversity, the results were consistently favorable. In Case 1, CURLIA's aggregated rankings perfectly matched those from COPELAND. In Case 2, CURLIA not only proved accurate but also showed a higher average Spearman coefficient (0.9979) with the MCDM methods than COPELAND (0.9967). Similarly, in Case 3, CURLIA's average Spearman coefficient (0.8977) exceeded that of COPELAND (0.8921). Overall, these findings firmly establish that the proposed CURLIA method ensures high accuracy in aggregating rankings derived from various MCDM approaches.

4. SENSITIVITY ANALYSIS

In this section, we conduct a sensitivity analysis. In previous sections, the superiority of the CURLIA method over the Copeland method was examined using three distinct case studies. However, a sensitivity analysis is required to assess the robustness of these findings.

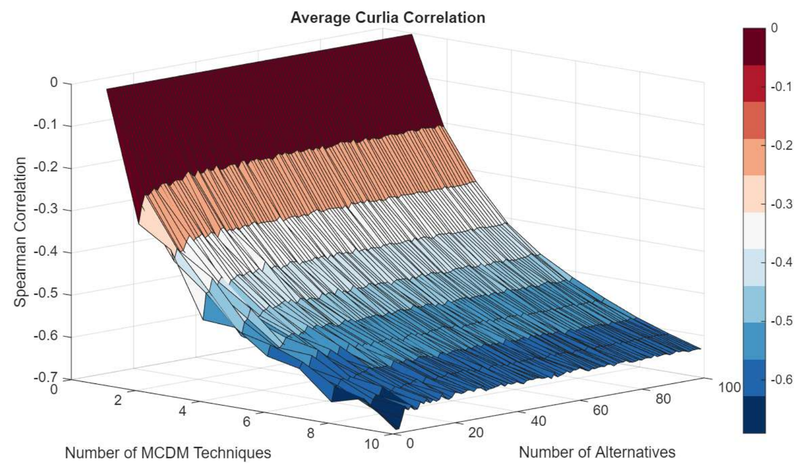
The sensitivity analysis involves generating random rankings to test the stability and consistency of the results under various conditions. The number of alternatives considered ranges from 2 to 101, while the number of techniques evaluated ranges from 1 to 10. This range was intentionally selected since scenarios involving a higher number of techniques are rarely encountered in existing literature.

For each combination of the number of alternatives and techniques, 100 random rankings were generated. It is acknowledged that the chosen approach might be subject to criticism. As observed in the previously conducted case studies, rankings across different techniques tend to exhibit considerable agreement or correlation. For example, certain alternatives consistently appear at the top (or bottom) of rankings, irrespective of the evaluation technique applied. However, in the sensitivity analysis, rankings were deliberately assigned completely randomly. Consequently, this assumption leads to lower correlation coefficients than typically observed in practical situations.

Nevertheless, using random evaluations provides a rigorous test scenario, enabling us to comprehensively examine whether the CURLIA technique continues to outperform the Copeland method under varying conditions. Thus, despite its limitations, the approach chosen for sensitivity analysis creates a robust foundation for evaluating the consistency and robustness of the CURLIA technique compared to the Copeland method across diverse and hypothetical scenarios.

Figure 2 summarize how consensus quality evolves when individual MCDM rankings are purely random. Across both (a) CURLIA and (b) Copeland aggregations, varying the number of alternatives produces little systematic change in the mean Spearman correlation—consistent with the expectation that random permutations yield correlations centered near zero, with list length mainly affecting variance rather than the mean. By contrast, increasing the number of MCDM techniques leads to a clear, monotonic decline in correlation between the aggregate and any single technique, as each added (independent) ranking injects additional noise that the consensus must reconcile. Copeland consistently exhibits slightly more negative correlations than CURLIA, reflecting its greater sensitivity to near ties, whereas CURLIA's score-based smoothing preserves marginally higher alignment. Taken together, these results indicate that, under absence of shared signal, the composition and count of techniques exert far greater influence on consensus behavior than the size of the alternative set, and that unselective aggregation of many heterogeneous methods can systematically reduce agreement with individual rankings.

(a)



(b)

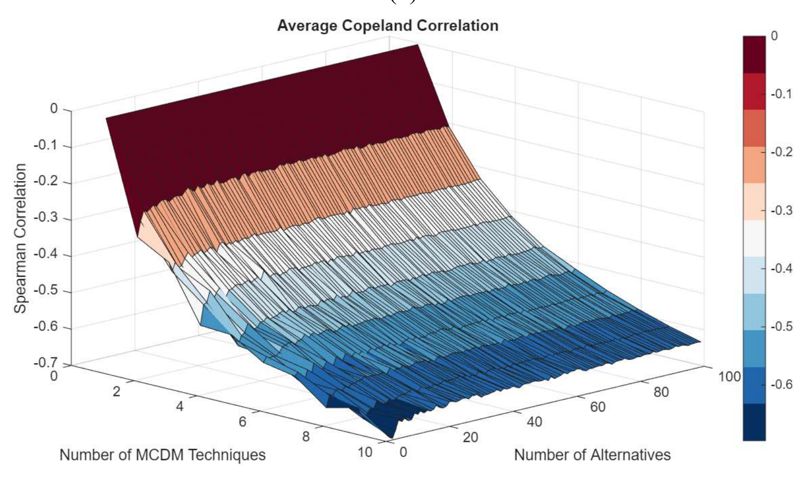


Figure 2: Average Spearman Coefficients observed during Simulation (a) CURLIA (b) Copeland

Although this assumption of completely random rankings could be viewed as unrealistic or overly conservative—especially since practical applications usually show some degree of correlation across methods—it nevertheless offers a distinct advantage. By intentionally creating the most unfavorable or least correlated scenario, we ensure that the CURLIA technique is rigorously tested under highly varied and challenging conditions.

Thus, this conservative approach allows us to robustly evaluate the performance of CURLIA compared to Copeland, providing a strong foundation to demonstrate CURLIA's effectiveness even in highly uncertain or randomized decision-making contexts.

Across a total of 1,000 different scenarios, each involving 100 individual simulations whose results were averaged to obtain robust correlation measures, the CURLIA method outperformed the Copeland method in 783 scenarios (approximately 78.3%).

Clearly stating, this methodology highlights the rigorous nature of our analysis and underscores that the observed advantage of CURLIA is consistently replicable under a broad range of simulated conditions.

To statistically verify whether the CURLIA technique significantly outperforms the Copeland technique, we formulated the following hypotheses and performed a one-tailed Wilcoxon Signed-Rank Test:

- Null Hypothesis (H_0): There is no significant difference in performance between the CURLIA and Copeland methods.
- Alternative Hypothesis (H_1): The CURLIA method provides significantly better results than the Copeland method.

The one-tailed Wilcoxon Signed-Rank test yielded the following result: Wilcoxon Signed-Rank Test: z=24.24, p=4.124×10^(-130). Given that the p-value (p≈4.12×10^(-130))) is far below any conventional significance threshold (e.g.,α=0.05), we strongly reject the null hypothesis in favor of the alternative hypothesis. These findings clearly demonstrate that the Curlia technique consistently and significantly outperforms the Copeland technique across diverse and randomized scenarios. Figure 3 is a binary 'superiority mask' (1 ⇒ CURLIA > Copeland) based on the mean Spearman rank correlation (ρ) with the reference rankings across simulation runs.

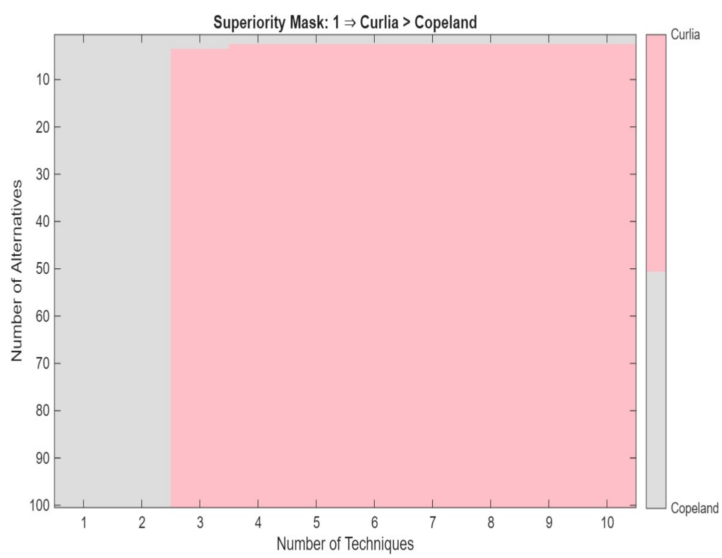


Figure 3: Comparative Superiority of CURLIA over Copeland Technique Across Different Numbers of Alternatives and MCDM Techniques

The x-axis varies the number of aggregated techniques, and the y-axis varies the number of alternatives. The large pastel-red block shows that once ≥3 techniques are combined, CURLIA delivers higher average ρ than Copeland almost uniformly across 10–100 alternatives—i.e., its advantage is robust to the problem size. The gray columns at 1–2 techniques indicate parity or a slight Copeland edge in these very small ensembles; this is expected because pairwise/majority-type aggregation tends not to benefit from cross-technique structure until the ensemble is large enough. Importantly, there is no visible erosion of CURLIA's superiority as the number of alternatives grows, suggesting scalability in both accuracy and stability. Practically, if only one or two techniques are available, Copeland remains a reasonable baseline; with three or more techniques, CURLIA should be preferred due to its consistently higher ordinal agreement.

This clear delineation in the superiority mask reinforces our earlier statistical findings and demonstrates CURLIA's robustness, particularly as the complexity (number of techniques) increases. It also underscores CURLIA 's suitability for more complex decision-making environments, supporting its practical applicability and reliability.

5. CONCLUSION

MCDM methods are widely used and it is possible to see examples of application of these methods in different fields in the literature [38,39,40,41,42], and in these methods, the consistent combination of rankings obtained from different decision makers or criteria is critical to increase the reliability and accuracy of the multi-criteria decision-making process. Aggregating the rankings of alternatives, initially evaluated by various MCDM methods, is crucial for obtaining a reliable and accurate final ranking. This research introduced a novel aggregation technique named CURLIA, specifically designed to address the inherent complexities of consolidating multiple alternative rankings. The effectiveness of the CURLIA method was thoroughly validated using three distinct case studies from distinct domains: electric vehicle rankings, mobile phone rankings, and COVID-19 containment strategy rankings. These case studies differed significantly in terms of their application domains, the number of alternatives involved, and the specific MCDM methods originally employed to produce the rankings.

All conducted tests consistently demonstrated that the CURLIA method delivers comparable, and in many cases superior, results compared to the widely adopted COPELAND aggregation technique. Beyond these practical evaluations, an extensive sensitivity analysis was also performed to assess the robustness of CURLIA under varying conditions. This analysis involved simulations with randomly generated rankings for scenarios covering a broad spectrum—specifically, the number of alternatives ranging from 2 to 100, and the number of MCDM techniques ranging from 1 to 10. Each scenario involved averaging results over 100 randomized simulations, resulting in 1,000 unique scenarios. In each simulation, we generated an independent random vector of length equal to the number of criteria by drawing values from a uniform distribution on [0,1] and then normalized this vector by its sum so that the resulting random weights were non-negative and summed to one.

Specifically, CURLIA showed advantages compared to the Copeland method in terms of accuracy, measured as the closeness of the aggregated rankings to reference rankings; consistency, assessed through the stability of results across repeated trials; and statistical significance, confirmed by the one-tailed Wilcoxon Signed-Rank test ($p < 0.0001$). Notably, CURLIA consistently demonstrated superior performance in 78.3% of the tested scenarios, indicating not only its effectiveness but also its reliability under diverse and uncertain conditions.

In conclusion, the proposed CURLIA method significantly enhances the accuracy and reliability of aggregated alternative rankings in MCDM contexts. This method constitutes a meaningful contribution to the field by providing decision-makers and practitioners with an efficient, robust, and statistically validated aggregation tool suitable for complex decision-making scenarios. In future research, the CURLIA method can be tested on different datasets and compared with methods such as Borda and Kemeny-Young, as well as Copeland. Furthermore, hybrid applications can be developed using fuzzy logic, gray system theory, or artificial intelligence-based approaches.

Funding: This research received no external funding.

REFERENCES

[1] S. Zakeri, D. Konstantas, P. Chatterjee, and E. K. Zavadskas, "Soft cluster-rectangle method for eliciting criteria weights in multi-criteria decision-making," *Scientific Reports*, vol. 15, no. 1, p. 284, Jan. 2025, doi: 10.1038/s41598-024-81027-4.

[2] M. Wang, L. Ji, Y. Xie, and G. Huang, "Regional bioethanol supply chain optimization with the integration of GIS-MCDM method and quantile-based scenario analysis," J*ournal of Environmental Management*, vol. 351, p. 119883, Feb. 2024, doi: 10.1016/j.jenvman.2023.119883.

[3] R. Akpahou, L. D. Mensah, D. A. Quansah, and F. Kemausuor, "Long-term energy demand modeling and optimal evaluation of solutions to renewable energy deployment barriers in Benin: A LEAP-MCDM approach," *Energy Reports*, vol. 12, pp. 1888–1904, Dec. 2024, doi: 10.1016/j.egyr.2024.07.055.

[4] C.-H. Yang, W. Hsu, and Y.-L. Wu, "A hybrid multiple-criteria decision portfolio with the resource constraints model of a smart healthcare management system for public medical centers," *Socio-economic Planning Sciences*, vol. 80, p. 101073, Mar. 2022, doi: 10.1016/j.seps.2021.101073.

[5] S. Seker, "Evaluation of agile attributes for low-cost carriers to achieve sustainable development using an integrated MCDM approach," *Management Decision*, vol. 63, no. 4, pp. 1229–1261, Mar. 2025, doi: 10.1108/MD-10-2023-1896.

[6] A. I. Marqués, V. García, and J. S. Sánchez, "Ranking-based MCDM models in financial management applications: analysis and emerging challenges," *Progress in Artificial Intelligence*, vol. 9, no. 3, pp. 171–193, Sep. 2020, doi: 10.1007/s13748-020-00207-1.

[7] J. Więckowski and W. Sałabun, "Aggregating Multi-Criteria Decision Analysis results with a novel fuzzy ranking approach," in *2024 IEEE 63rd Conference on Decision and Control (CDC)*, IEEE, Dec. 2024, pp. 2958–2963. doi: 10.1109/CDC56724.2024.10886467.

[8] H.-J. Shyur and H.-S. Shih, "Resolving Rank Reversal in TOPSIS: A Comprehensive Analysis of Distance Metrics and Normalization Methods," *Informatica*, pp. 837–858, Nov. 2024, doi: 10.15388/24-INFOR576.

[9] M. Baydaş, T. Eren, Ž. Stević, V. Starčević, and R. Parlakkaya, "Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics," *PeerJ Computer Science*, vol. 9, p. e1350, Apr. 2023, doi: 10.7717/peerj-cs.1350.

[10] M. Mohammadi and J. Rezaei, "Ensemble ranking: Aggregation of rankings produced by different multi-criteria decision-making methods," *Omega (Westport)*, vol. 96, p. 102254, Oct. 2020, doi: 10.1016/j.omega.2020.102254.

[11] H. Taherdoost, "Data Collection Methods and Tools for Research; A Step-by-Step Guide to Choose Data Collection Technique for Academic and Business Research Projects,"

International Journal of Academic Research in Management (IJARM), vol. 10, no. 1, pp. 10–38, 2021.

[12] M. Mohammadi and J. Rezaei, "Ensemble ranking: Aggregation of rankings produced by different multi-criteria decision-making methods," *Omega (Westport)*, vol. 96, p. 102254, Oct. 2020, doi: 10.1016/j.omega.2020.102254.

[13] P. Lederer, D. Peters, and T. Wąs, "The Squared Kemeny Rule for Averaging Rankings," arXiv preprint arXiv:2404.08474, 2024. [Online]. Available: https://arxiv.org/abs/2404.08474.

[14] S. D. Dvoenko and D. O. Pshenichny, "Rank Aggregation Based on New Types of the Kemeny's Median," *Pattern Recognition and Image Analysis*, vol. 31, no. 2, pp. 185–196, Apr. 2021, doi: 10.1134/S1054661821020061.

[15] P. Zaraté and R. G. Rasoanaivo, "A rank aggregating method based on several multi-criteria methodologies 'minimum of ranks': a case study for student's room allocation," *International Journal of Decision Support Systems*, vol. 5, no. 1, pp. 75–101, 2024, doi: 10.1504/IJDSS.2024.10062705.

[16] W. H. Holliday, "A Simple Condorcet Voting Method for Final Four Elections," *Representation*, pp. 1–24, May 2025, doi: 10.1080/00344893.2025.2473397.

[17] T. Qin, X. Geng, and T.-Y. Liu, "A new probabilistic model for rank aggregation," in *Advances in Neural Information Processing Systems*, J. Lafferty, Ed. 2010, pp. 1–9.

[18] F. Franceschini and D. Maisano, "Design decisions: concordance of designers and effects of the Arrow's theorem on the collective preference ranking," *Research in Engineering Design*, vol. 30, no. 3, pp. 425–434, Jul. 2019, doi: 10.1007/s00163-019-00313-9.

[19] N. Boehmer, R. Bredereck, and D. Peters, "Rank Aggregation Using Scoring Rules," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 37, no. 5, pp. 5515–5523, Jun. 2023, doi: 10.1609/aaai.v37i5.25685.

[20] R. E. Hodgett, "Comparison of multi-criteria decision-making methods for equipment selection," *The International Journal of Advanced Manufacturing Technology*, vol. 85, no. 5–8, pp. 1145–1157, Jul. 2016, doi: 10.1007/s00170-015-7993-2.

[21] J. Więckowski and W. Sałabun, "Aggregating Multi-Criteria Decision Analysis results with a novel fuzzy ranking approach," in *2024 IEEE 63rd Conference on Decision and Control (CDC)*, IEEE, Dec. 2024, pp. 2958–2963. doi: 10.1109/CDC56724.2024.10886467.

[22] B. Bepari, B. Bairagi, H. S. Das, and G. Roymahapatra, "De-novo Approach in Rank Agglomeration in Multi Criteria Decision Making for Materials Selection," *ES General*, 2024, doi: 10.30919/esg1353.

[23] U. Grandi, A. Loreggia, F. Rossi, and V. Saraswat, "A Borda count for collective sentiment analysis," *Annals of Mathematics and Artificial Intelligence*, vol. 77, no. 3–4, pp. 281–302, Aug. 2016, doi: 10.1007/s10472-015-9488-0.

[24] S. Abacıoğlu, B. Ayan, and D. Pamucar, "The Race to Sustainability: Decoding Green University Rankings Through a Comparative Analysis (2018–2022)," *Innovative Higher Education*, vol. 50, no. 1, pp. 241–275, Feb. 2025, doi: 10.1007/s10755-024-09734-4.

[25] D. G. Saari, "Selecting a voting method: the case for the Borda count," *Constitutional Political Economy*, vol. 34, no. 3, pp. 357–366, Sep. 2023, doi: 10.1007/s10602-022-09380-y.

[26] J. Fraenkel and B. Grofman, "The Borda Count and its real-world alternatives: Comparing scoring rules in Nauru and Slovenia," *Australian Journal of Political Science*, vol. 49, no. 2, pp. 186–205, Apr. 2014, doi: 10.1080/10361146.2014.900530.

[27] Ö. Işık, A. Çalık, and M. Shabir, "A Consolidated MCDM Framework for Overall Performance Assessment of Listed Insurance Companies Based on Ranking Strategies," *Computational Economics*, vol. 65, no. 1, pp. 271–312, Jan. 2025, doi: 10.1007/s10614-024-10578-5.

[28] Z. Qiu, M. G. Dosskey, and Y. Kang, "Choosing between alternative placement strategies for conservation buffers using Borda count," *Landscape and Urban Planning*, vol. 153, pp. 66–73, Sep. 2016, doi: 10.1016/j.landurbplan.2016.03.012.

[29] Z. Kılıç and A. İ. Şimşek, "Utilizing Multi-Criteria Decision-Making Techniques in the Selection of Electric Vehicles: An Analysis for the Turkish Electric Vehicle Market," *Fırat Üniversitesi Uluslararası İktisadi ve İdari Bilimler Dergisi*, vol. 8, no. 2, pp. 107–130, Dec. 2024, doi: 10.61524/fuuiibfdergi.1574901.

[30] S. Karakaş Geyik, M. Satman, and G. Kalyoncu, "G20 Ülkelerinin Covid-19 Pandemisi ile Mücadele Performanslarının Çok Kriterli Karar Verme Yöntemleri ile Değerlendirilmesi," *Ekoist: Journal of Econometrics and Statistics*, vol. 0, no. 37, pp. 27–52, Dec. 2022, doi: 10.26650/ekoist.2022.37.1161945.

[31] H. Naderi, H. Shahosseini, and A. Jafari, "Evaluation MCDM Multi-disjoint Paths Selection Algorithms Using Fuzzy-Copeland Ranking Method," *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 5, no. 1, Apr. 2022, doi: 10.17762/ijcnis.v5i1.288.

[32] N. Ersoy and S. Taslak, "Comparative Analysis of MCDM Methods for the Assessment of Corporate Sustainability Performance in Energy Sector," *Ege Akademik Bakis (Ege Academic Review)*, Aug. 2022, doi: 10.21121/eab.986122.

[33] F. Aydin and B. Gümüş, "Comparative analysis of multi-criteria decision making methods for the assessment of optimal SVC location," *Bulletin of the Polish Academy of Sciences Technical Sciences*, pp. 140555–140555, Feb. 2022, doi: 10.24425/bpasts.2022.140555.

[34] M. Moghimi and M. Taghizadeh Yazdi, "Applying Multi-Criteria Decision-Making (MCDM) Methods for Economic Ranking of Tehran-22 Districts to Establish Financial and Commercial Centers (Case: City of Tehran)," *Journal of Urban Economics and Management*, vol. 5, no. 20, pp. 39–51, Dec. 2017, doi: 10.29252/iueam.5.20.39.

[35] J. R. Kiger and D. J. Annibale, "A new method for group decision making and its application in medical trainee selection," *Medical Education*, vol. 50, no. 10, pp. 1045–1053, Oct. 2016, doi: 10.1111/medu.13112.

[36] A. Bączkiewicz, B. Kizielewicz, A. Shekhovtsov, J. Wątróbski, and W. Sałabun, "Methodical Aspects of MCDM Based E-Commerce Recommender System," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 16, no. 6, pp. 2192–2229, Sep. 2021, doi: 10.3390/jtaer16060122.

[37] C. Kuhlman and E. Rundensteiner, "Rank aggregation algorithms for fair consensus," *Proceedings of the VLDB Endowment*, vol. 13, no. 12, pp. 2706–2719, Aug. 2020, doi: 10.14778/3407790.3407855.

[38] R. Kumar and D. Pamucar, "A Comprehensive and Systematic Review of Multi-Criteria Decision-Making (MCDM) Methods to Solve Decision-Making Problems: Two Decades from 2004 to 2024," *Spectrum of Decision Making and Applications*, vol. 2, no. 1, pp. 178–197, Jan. 2025, doi: 10.31181/sdmap21202524.

[39] A. Biswas, K. H. Gazi, P. Bhaduri, and S. P. Mondal, "Site Selection for Girls Hostel in a University Campus by MCDM based Strategy," *Spectrum of Decision Making and Applications*, vol. 2, no. 1, pp. 68–93, Jan. 2025, doi: 10.31181/sdmap21202511.

[40] A. Shahid, S. Ashraf, and M. S. Chohan, "Complex Fuzzy MARCOS and WASPAS Approaches with Z-Numbers for Augmented Reality Decision Making," *Spectrum of Operational Research*, vol. 3, no. 1, pp. 40–62, Mar. 2026, doi: 10.31181/sor31202637.

[41] R. Gul, "An Extension of VIKOR Approach for MCDM Using Bipolar Fuzzy Preference δ-Covering Based Bipolar Fuzzy Rough Set Model," *Spectrum of Operational Research*, vol. 2, no. 1, pp. 72–91, Jan. 2025, doi: 10.31181/sor21202511.

[42] S. Petchimuthu, B. Palpandi, K. Rajakumar, and F. Banu M, "Sustainable Urban Development: q-Rung Orthopair Fuzzy MCDM withGeneralized Power Prioritized Yager Aggregation," *Spectrum of Operational Research*, vol. 3, no. 1, pp. 275–309, Jun. 2026, doi: 10.31181/sor31202649.