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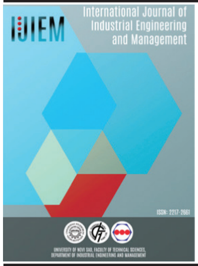

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Original research article

Relative Pairwise Ranking: A normalization-free ordinal ranking approach for multi-criteria decision-making

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ABSTRACT

In Multi-Criteria Decision-Making (MCDM) methods, selecting an appropriate data normalization technique is a complex process. An unsuitable normalization method may distort the intrinsic ranking of alternatives. To address this issue, this study proposes a normalization-free, ordinal pairwise ranking approach, referred to as Relative Pairwise Ranking (RPR). The method evaluates alternatives based on criterion-wise pairwise dominance and aggregates these outcomes using criterion weights, providing a scale-independent and interpretable ranking framework. The performance of the proposed approach is evaluated through illustrative examples and a real-world case study, supported by sensitivity and comparative analyses. The results indicate that RPR produces stable and consistent rankings across different weighting schemes and demonstrates robustness in the tested rank-reversal scenarios. These findings suggest that the proposed approach offers a practical alternative to normalization-based MCDM methods.

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1. Introduction

Multi-Criteria Decision Making (MCDM) has emerged as one of the most widespread methods that enables structured problem solving through the evaluation of criteria and the ranking of alternatives, thus contributing to more informed, reliable, and consistent decisions [1]. This approach is an effective technique frequently used in many fields such as management, engineering, and energy [2], [3] and provides a systematic process that results in rational, justifiable, and explainable decisions. Today, the field is becoming increasingly dynamic thanks to hundreds of

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MCDM methods and various algorithms developed by researchers [4]. Examples of recently proposed new MCDM methods include MUTRISS [5], CoCoFISo [6], RAWEC [7], RANCOM [8], ERUNS [9], CMR [10], etc. MCDM techniques can be classified into two broad categories: mathematical and human. Mathematical (objective evaluation) techniques depend on the criteria input into the decision matrix and information about them. The human approach depends on the choice of humans. Broadly, any evaluation process based on MCDM methods comprises four steps: (i) determination of the alternatives and criteria relating to a particular problem, (ii) computation of weights for each criterion, (iii) assessment of performance by each alternative under every criterion, and (iv) ranking of all alternatives based on their total performances on all criteria [11], [12].

In most MCDM methods, data normalization is a mandatory step [13]. Normalization converts criteria with different dimensions into a common dimensionless form [14]. However, the normalization method applied has a high impact on the reliability of the final ranking [15], [16]. Moreover, normalization methods that rely on minimum and maximum values are particularly sensitive to outliers. The presence of extreme values may compress the remaining data into a narrow range, thereby reducing discrimination power and potentially altering ranking outcomes. Many approaches have been developed over time to address this issue, and numerous studies have been conducted on the suitability of normalization techniques for MCDM methods [17]-[19]. Furthermore, the integration of MCDM methods that simultaneously utilize various normalization techniques, as exemplified by the MACONT approach [20] or the AROMAN technique [21], offers an alternative solution to the problem of addressing the normalization process. However, despite these considerations, the data normalization process has the potential to compromise the original truth of the information, thus affecting the evaluation of alternatives. However, normalization procedures may distort the original preference structure of alternatives, potentially leading to rank reversal [22]–[24] In this context, normalization can be interpreted as a transformation filter, where different normalization procedures may alter the relative distances between alternatives and lead to different ranking outcomes, even when based on the same raw data. These findings encourage the development of non-normalization approaches, such as the proposed Relative Pairwise Ranking (RPR) method, which preserves the inherent preference order through ordinal and binary dominance relationships.

Recent studies have extensively utilized MCDM methods to evaluate and rank complex environmental and climate-related systems. For instance, multi-temporal evaluations of CMIP6 climate models have demonstrated that ranking results are highly sensitive to the choice of normalization and aggregation techniques [25]. Similarly, performance assessments of climate models have emphasized the importance of multi-criteria model selection strategies by integrating hybrid machine learning and MCDM approaches [26]. Recent studies clearly demonstrate that MCDM results are highly sensitive to normalization procedures and methodological choices. For instance, Patel et al. [27] showed that different normalization techniques within the MOORA method can produce substantially different ranking outcomes in CMIP model selection. In addition, Kanji and Das [28] indicated that variations in model structure and criteria handling significantly influence the final rankings in MCDM-based groundwater assessment. Similarly, Das and Das [29] revealed that different methodological frameworks, including traditional, statistical, and MCDM-based approaches, lead to inconsistent prioritization results. Other studies have combined MCDM with statistical inference and machine learning to prioritize climate models, watersheds, and groundwater potential, further validating the widespread application of normalization-dependent MCDM frameworks in environmental decision-making [30]-[32]. Beyond environmental applications, fuzzy and interval-valued MCDM frameworks have recently been proposed to enhance robustness and reduce uncertainty in sustainability-focused decision problems such as electric vehicle adoption and renewable energy source selection [33]-[34]. Recent studies have increasingly focused on advanced fuzzy-based MCDM frameworks to address uncertainty in sustainability-related decision problems. For instance, a SWARA–ARAS approach under a confidence level-based interval-valued Fermatean fuzzy environment has been proposed for renewable energy selection [34]. Similarly, a confidence level-based interval-valued spherical fuzzy MEREC–VIKOR model has been developed to evaluate sustainable strategies for electric vehicle adoption [33]. In another study, interval-valued Fermatean fuzzy Dombi aggregation operators integrated with SWARA and PROMETHEE II methods have been applied to bio-medical waste management problems [35]. While these studies focus on application-oriented assessments, they collectively highlight the sensitivity of ranking results to normalization choices, revealing the need for ranking approaches that do not require normalization.

Various MCDM techniques that do not require data normalization have been developed, including SRP, FUCA, CURLI, and CARCACS. The SRP method evaluates alternatives using a collection of positive integers to create an "internal ranking" for each criterion [36], while the FUCA method ranks alternatives using real numbers, encompassing both positive integers and positive decimals, for each criterion [37]. However, both the FUCA and SRP methods are sensitive to criterion weights, and small changes can significantly affect the final ranking of alternatives [38]. Furthermore, the effectiveness of the SRP method is particularly enhanced in contexts with many alternatives and criteria [36]. Using only integers for internal ranking in the SRP methodology can lead to a "step effect" leading to inconsistencies when compared with results from other MCDM methodologies [39]. Conversely, the CURLI approach assesses each alternative by conducting pairwise comparisons with all remaining alternatives based on each criterion, employing the values -1, 0, and 1 throughout this procedure [40]. Such pairwise comparisons facilitate a more thorough evaluative process. Nevertheless, a notable drawback of this methodology is its failure to account for criterion weights, which are essential components in the assessment of alternatives [40]-[42]. CARCACS is a normalization-free MCDM method based on cumulative scores, but it relies on absolute performance values rather than relative rankings [43].

Recent studies using the CARCACS method have demonstrated the effectiveness of normalization-free MCDM in manufacturing decision problems such as polymer joining [44], milling cutter insert material selection [45] and cutting-process selection for thick metal plates [46]. These studies report robust rankings but also indicate that results may vary with changes in criteria or alternatives. In contrast, the proposed RPR method is based on weighted pairwise ordinal dominance, offering a distinct ranking perspective.

Existing ordinal MCDM methods remain insufficient for three main reasons: they (i) neglect criterion weights, (ii) rely on cardinal representations that may distort ordinal preference structures, or (iii) fail to provide a unified ordinal and scale-independent ranking framework. This highlights the need for a weighted, purely ordinal ranking framework. This study addresses this gap by proposing the RPR method, which integrates criterion weights into a purely ordinal, normalization-free pairwise ranking framework.

This article proposes a methodology based on the application of a methodological extension called RPR. The method proposed in this study also adopts a non-normalization-based approach. However, it differs from the SRP and FUCA methods by not using positive integers or real numbers in the internal ranking. Instead, an internal ranking process based on pairwise comparisons, as in CURLI, is adopted. Furthermore, the proposed method eliminates the fundamental limitation of CURLI by considering criteria weights. Although non-normalized MCDM methods such as CARCACS, SRP, FUCA, and CURLI exist in the literature, a pure decision framework that eliminates the effect of absolute performance values and relies solely on within-criteria rankings has not been sufficiently addressed in an integrated and weighted ordinal framework. This situation leads to the persistence of ranking instability and ranking reversal problems, especially in data of different scales. This study fills this gap with the RPR method.

In light of the identified research gaps, the main aim of this study is to develop a normalization-free, weighted ordinal ranking method based on pairwise dominance relationships. Specifically, the study seeks to address the following research question: how can stable, consistent, and scale-independent rankings be achieved without relying on data normalization while preserving the intrinsic preference structure of alternatives? To conclude, the proposed RPR method is introduced as a novel solution to overcome the limitations of existing MCDM approaches.

The main advantages and contributions of the proposed MCDM method are as follows:

- The proposed method avoids the potential distortions caused by normalization techniques, thereby preserving the original scale and meaning of the criteria values.
- By relying on direct pairwise assessments, the method provides a more intuitive and criterion-specific ranking of alternatives without requiring external reference points.
- This integration allows the method to flexibly combine the relative importance of criteria with the internal ranking outcomes, yielding a comprehensive evaluation of alternatives.
- The method involves straightforward pairwise comparisons and summation, making it computationally less demanding compared to normalization and distance-based approaches.
- The simplicity of calculations makes the method suitable for practical decision-making contexts where time and resources are limited.
- The method showed consistent rankings in the tested alternative-removal scenarios, indicating demonstrated ranking stability in the evaluated scenarios.

The remainder of the paper is organized as follows: Section 2 introduces the proposed RPR method in detail. Section 3 presents an evaluation of the method using three illustrative examples. Section 4 and 5 provide a sensitivity analysis along with a comparative assessment against other established MCDM techniques. Section 6 presents the results of the rank reversal test to verify the stability of the method. Finally, the paper concludes with a summary of key findings, practical implications, and potential directions for future research.

2. Proposed Method - Relative Pairwise Ranking

2.1 Theoretical Motivation and Background

Many conventional MCDM techniques rely on data normalization to handle criteria measured on different scales. However, it has been widely reported that different normalization procedures may lead to ranking instability, scale dependency, and rank reversal, thereby distorting the original preference structure of alternatives [22]-[24].

To mitigate these limitations, direct pairwise comparison has been adopted in decision analysis as a robust alternative, since it evaluates alternatives based on relative dominance relationships rather than absolute performance magnitudes. Such an ordinal decision perspective is inherently scale-independent and does not require data normalization [47], [48]. The proposed RPR method is grounded in ordinal decision theory and dominance-based aggregation principles. By transforming raw performance values into criterion-wise pairwise dominance relations, the method preserves essential preference information while eliminating normalization-induced distortions, leading to more stable and interpretable ranking results.

Many conventional MCDM techniques rely on normalization to address differing measurement scales. However, normalization may distort the original preference structure and cause ranking instability or rank reversal. To overcome these issues, the proposed RPR method adopts an ordinal perspective, focusing solely on the relative ordering of alternatives. RPR is based on direct pairwise comparisons within each criterion, as relative rankings are more robust and informative than absolute values, thereby eliminating scale dependency and normalization-related biases.

Since different normalization techniques interact differently with the original data scale and may yield inconsistent ranking results, direct pairwise comparison provides a more reliable and scale-independent alternative by preserving the original preference relations.

Normalization-based methods may introduce interdependence among alternatives and lead to ranking inconsistencies [22]–[24], whereas the proposed approach reduces such effects by avoiding normalization.

2.2 Mathematical Formulation of the RPR Method

The proposed method is called RPR and consists of the following steps: First, the m×n decision matrix X=[x_{ij}] given in Eq. (1) is created. Here, m is the number of alternatives, n is the number of criteria. The element x_{ij} represents the performance value of alternative A_i under criterion C_i, for i=1,…,m and j=1,…,n. The criteria weights are denoted by w_j, satisfying $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Algorithm 1. Relative Pairwise Ranking (RPR) Procedure

Input: Decision matrix X=[x_{ij}] and criterion weights w_j

Output: Overall scores S_i and ranking of alternatives

Step 1: For each criterion C_j, alternatives are compared pairwise. For any two alternatives A_i and A_k (i ≠ k), the pairwise dominance score $d_{ik}^{(j)}$ is determined based on whether the criterion is of benefit or cost type.

Step 2: For each alternative i and criterion j, the score f_{ij} is computed by aggregating the pairwise dominance values over all k ≠ i.

Step 3: The overall score S_i of each alternative is calculated using weighted aggregation, and alternatives are ranked in descending order of S_i.

Step 1: For each criterion C_j, alternatives are compared pairwise. Let A_i and A_k be two alternatives with $i \neq k$. Let B and C represent the benefit and cost criteria, respectively. The pairwise dominance score is defined as follows:

$$d_{ik}^{(j)} = \begin{cases} 1, & if \quad x_{ij} > x_{kj}, if \quad j \epsilon B \\ -1, & if \quad x_{ij} < x_{kj}, if \quad j \epsilon B \\ 1, & if \quad x_{ij} < x_{kj}, if \quad j \epsilon C \\ -1, & if \quad x_{ij} > x_{kj}, if \quad j \epsilon C \\ 0, & if \quad x_{ij} = x_{kj} \end{cases} \quad (2)$$

Eq. (2) formalizes the pairwise dominance relationship between alternatives under each criterion by assigning discrete scores of +1, 0, and −1. This formulation preserves only ordinal dominance information and ensures antisymmetry ($d_{ik}^{(j)} = -d_{ik}^{(j)}$) and boundedness of the comparison outcomes. The discrete set {-1,0,1} is adopted to encode pairwise dominance in a minimal and symmetric ordinal form, as commonly used in ordinal and outranking-based decision frameworks [49, 50]. Here, +1 denotes dominance, −1 inferiority, and 0 indifference. This trinary coding preserves ordinal information, avoids artificial cardinal distances, and ensures bound, scale-independent comparisons without normalization-induced distortions. While ignoring absolute performance differences is a deliberate modelling choice, it inherently involves a trade-off between ordinal robustness and the loss of magnitude information. A key limitation of RPR stems from its ordinal structure. By mapping cardinal values into trinary relations {−1, 0, +1}, the method applies a many-to-one transformation that reduces information content and eliminates magnitude differences. Consequently, marginal and large performance gaps are treated equally. For example, consider A1=100, A2=99, A3=10 and A1=100, A2=50, A3=49. In both cases, RPR produces identical rankings, despite substantially different gaps between A1 and A2.

In contrast, normalization-based methods (e.g., SAW, TOPSIS) preserve magnitude information through proportional scaling, allowing large differences to have stronger impact. Therefore, while RPR ensures scale-independence, it may be less informative when difference intensity is decision-relevant.

Step 2: The score of alternative A_i under criterion C_j is calculated as the sum of its pairwise dominance values:

$$f_{ij} = \sum_{k \neq i}^{m} d_{ik}^{(j)} \tag{3}$$

Eq. (3) aggregates the pairwise dominance scores for each alternative within a given criterion, resulting in a criterion-specific relative dominance score.

Step 3: Let w_j denote the weight of criterion C_j, where $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$

j. The overall score S_i of alternative A_i is calculated using Eq. (4). The alternatives are then ranked in descending order based on their overall scores S_i. Since the weights are non-negative and the aggregation is additive, the overall score preserves the ordinal dominance structure induced by Eq. (3).

$$S_i = \sum_{j=1}^{n} w_j \cdot f_{ij} \tag{4}$$

Eq. (4) combines these dominance scores using weighted additive aggregation, which represents an ordinal adaptation of the classical additive utility model. As a direct consequence of this formulation, improving an alternative in any benefit criterion (or reducing one in a cost criterion) can only increase or maintain the pairwise superiority scores. Since the final summation in Eq. (4) is monotonic with respect to these superiority values, the proposed RPR method ensures ordinal monotonicity.

From a computational perspective, RPR relies on pairwise comparisons, resulting in $O(m^2n)$complexity, whereas methods such as SAW and TOPSIS operate with $O(mn)$. This indicates higher computational growth with increasing alternatives. However, the cost remains manageable for moderate-sized problems, and scalability for larger datasets can be improved through parallelization or pre-screening of alternatives.

To illustrate the proposed method, a small case study is presented in this section. The purpose of this illustrative example is to explain the mechanics of the proposed method. The applicability of the RPR method to different data types will be demonstrated in Section 3 through comprehensive illustrative examples and sensitivity analyses. Table 1 summarizes the data for four alternatives (A1–A4) to be ranked. Each alternative is characterized by three criteria (C1–C3). While C1 and C2 are beneficial criteria, C3 represents a cost criterion. In this table, the maximum value for C1 is 5 (obtained by A3), the maximum value for C2 is 19 (obtained by A2), and the minimum value for C3 is 0.9 (obtained by A4). None of the alternatives provides the best value across all criteria. The task, therefore, is to rank the alternatives from A1 to A4.

Table 1. Hypothetical dataset used for illustrating the RPR procedure

Alt.	$C1$	$C2$	$C3$
A1	3.5	17	1.2
A2	3	19	1.5
A3	5	16	1.7
A4	4	18	0.9

Using Eq. (2), the alternatives were scored for each criterion (C1-C3), resulting in the matrices shown in Tables 2 through 4.

For example, for type B criterion C1: A1=3.5 and A2=3

$$d_{12}^{1} = +1, d_{21}^{1} = -1$$

For type C criterion C3; A1=1.2 and A2=1.5

$$d_{12}^{3} = +1, d_{21}^{3} = -1$$

Table 2. Scoring matrix for criterion *C1*

Alt.	d_{ik}^{1}			
A1	0	1	-1	-1
A2	-1	0	-1	-1
A3	1	1	0	1
A4	1	1	-1	0

Table 3. Scoring matrix for criterion *C2*

Alt.	d_{ik}^{2}			
A1	0	-1	1	-1
A2	1	0	1	1
A3	-1	-1	0	-1
A4	1	-1	1	0

Table 4. Scoring matrix for criterion *C3*

Alt.	d_{ik}^{3}			
A1	0	1	1	-1
A2	-1	0	1	-1
A3	-1	-1	0	-1
A4	1	1	1	0

Then, Eq. (3) is applied to calculate the score of each alternative for each criterion. For criterion C1 (Table 2), the scores are calculated as:

Score of ***A1*** is $f_{11} = 0 + 1 + (-1) + (-1) = -1$.

Score of ***A2*** is $f_{21} = -1 + 0 + (-1) + (-1) = -3$.

Score of ***A3*** is $f_{31} = 1 + 1 + 0 + 1 = 3$.

Score of ***A4*** is $f_{41} = 1 + 1 + (-1) + 0 = 1$.

It is observed that $\mathbf{f_{31}} > \mathbf{f_{41}} > \mathbf{f_{11}} > \mathbf{f_{21}}$, so the ranking according to criterion *C1* is *A3* > *A4* > *A1* > *A2*. This ranking is also correct when compared to the *C1* data in Table 1.

For criterion ***C2*** (Table 3):

Score of ***A1*** is $f_{12} = 0 + (-1) + 1 + (-1) = -1$.

Score of ***A2*** is $f_{22} = 1 + 0 + 1 + 1 = 3$.

Score of ***A3*** is $f_{32} = -1 + (-1) + 0 + (-1) = -3$.

Score of ***A4*** is $f_{42} = 1 + (-1) + 1 + 0 = 1$.

It is observed that $f_{22} > f_{42} > f_{12} > f_{32}$, so the ranking according to criterion ***C2*** is ***A2*** > ***A4*** > ***A1*** > ***A3***. This ranking is also correct when compared to the ***C2*** data in Table 1.

For criterion ***C3*** (Table 4):

Score of ***A1*** is $f_{13} = 0 + 1 + 1 + (-1) = 1$.

Score of ***A2*** is $f_{23} = -1 + 0 + 1 + (-1) = -1$.

Score of ***A3*** is $f_{33} = -1 + (-1) + 0 + (-1) = -3$.

Score of ***A4*** is $f_{43} = 1 + 1 + 1 + 0 = 3$.

It is observed that $f_{43} > f_{13} > f_{23} > f_{33}$, so the ranking is ***A4*** > ***A1*** > ***A2*** > ***A3***. This ranking is also correct when compared to the ***C3*** data in Table 1.

Let w_1, w_2, and w_3 be the respective weights of criteria ***C1***, ***C2***, and ***C3***. Using Eq. (4), the overall scores for the alternatives are calculated as follows:

S1 $= w_1 \times f_{11} + w_2 \times f_{12} + w_3 \times f_{13} = w_1 \times (-1) + w_2 \times (-1) + w_3 \times 1 = -w_1 - w_2 + w_3$.

S2 $= w_1 \times f_{21} + w_2 \times f_{22} + w_3 \times f_{23} = w_1 \times (-3) + w_2 \times 3 + w_3 \times (-1) = -3w_1 + 3w_2 - w_3$.

S3 $= w_1 \times f_{31} + w_2 \times f_{32} + w_3 \times f_{33} = w_1 \times 3 + w_2 \times (-3) + w_3 \times (-3) = 3w_1 - 3w_2 - 3w_3$.

S4 $= w_1 \times f_{41} + w_2 \times f_{42} + w_3 \times f_{43} = w_1 \times 1 + w_2 \times 1 + w_3 \times 3 = w_1 + w_2 + 3w_3$.

By assigning specific values to $w1$, $w2$, and $w3$, concrete numerical scores can be obtained for *S1*, *S2*, *S3*, and *S4*; these scores will subsequently determine the final ranking of the alternatives A1-A4.

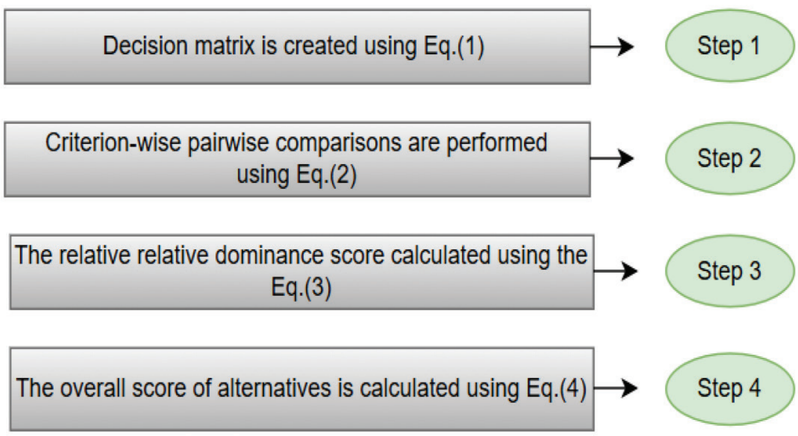

Figure 1. Flowchart of the proposed RPR method

2.3 Distinction from Copeland and Related Methods

Although RPR is based on pairwise comparisons and is conceptually related to outranking approaches, it is mathematically different from Copeland-type ranking. In RPR, the overall score is computed as

$$\sum_{k\neq i}\sum_{j=1}^{n} w_j d_{ik}^{(j)} \tag{5}$$

where $d_{ik}^{(j)} \varepsilon \{-1,0,1\}$ represents criterion-wise dominance.

In contrast, the Copeland method first aggregates pairwise comparisons into a single outcome

$$sgn\sum\nolimits_{j=1}^{n} w_j d_{ik}^{(j)} \tag{6}$$

where sgn(·) denotes the sign function, returning +1, 0, or −1 depending on whether the argument is positive, zero, or negative. The Copeland method then counts wins and losses. Unlike Copeland-type ranking, which reduces each pairwise comparison to a binary win–loss outcome, RPR directly aggregates weighted criterion-wise dominance values, thereby preserving the internal intensity of multi-criteria support within each pairwise relation.

Moreover, CURLI can be interpreted as a special unweighted case of RPR, while ELECTRE and PROMETHEE rely on concordance–discordance or preference-flow structures. In addition, CARCACS differs fundamentally as it is based on cumulative cardinal values rather than purely ordinal relations.

The main differences between RPR and related methods are summarized in Table 5.

3. Evaluation of the Proposed Method

The first two examples presented in this section are based on hypothetical datasets intentionally created to evaluate the behavior of the proposed RPR method under different decision-making conditions. The third example consists of real-life data to demonstrate the applicability and performance of the method in a real decision-making problem. The use of synthetic datasets in the first two examples was intentional to provide controlled evaluation environments where the ordinal behavior of the proposed method could be transparently examined under different dominance structures and weighting conditions. Such controlled synthetic scenarios are commonly used in methodological MCDM studies to isolate the effects of ranking logic from domain-specific noise. The values are constructed to reflect varying numbers of alternatives, different types of criteria (benefit and cost), and heterogeneous performance models, allowing for a controlled and transparent methodological evaluation. The criterion weights were determined using the CRITIC method, an objective technique designed to prevent subjective bias and ensure that the evaluation of the proposed RPR method is not influenced by expert opinion.

3.1 Illustrative Example 1

This example involves ranking seven alternatives, labeled A1 to A7. This dataset is synthetically generated. Each alternative is characterized by five criteria, C1 to C5, all of which are beneficial criteria. The data are summarized in Table 6, and the weights determined by the CRITIC method are presented in the last row.

Using Eq. (2), the scores of each alternative for each criterion were calculated and are summarized in Tables 7 through 11.

Table 5. Key differences between RPR and related methods

Method	Pairwise comparison	Uses weights	Uses magnitude information	Key distinction from RPR
RPR	Yes	Yes	No	Weighted ordinal pairwise aggregation
Copeland	Yes	No	No	Counts wins/losses only, ignoring dominance intensity
CURLI	Yes	No	No	Unweighted special case of RPR
PROMETHEE / ELECTRE	Yes	Yes	Yes	Uses preference functions, thresholds, and concordance–discordance logic
CARCACS	No	Yes	Yes	Based on cumulative cardinal performance values

Table 6. Data for example 1

Alt.	$C1$	$C2$	$C3$	$C4$	$C5$
A1	12	4.5	45.6	102	1.12
A2	14	4.6	46.7	104	1.06
A3	13	4.4	48	102	1.2
A4	15	5	44.3	100	1.08
A5	15	4.8	42.9	99.6	0.98
A6	16	4.7	39.5	98.7	0.94
A7	12	4.5	47.5	100.4	1.01
w_i	0.2195	0.2320	0.1880	0.1806	0.1799

Table 7. RPR scores for criterion ***C1***

Alt.				RPR_{i1}			
A1	0	-1	-1	-1	-1	-1	0
A2	1	0	1	-1	-1	-1	1
A3	1	-1	0	-1	-1	-1	1
A4	1	1	1	0	0	-1	1
A5	1	1	1	0	0	-1	1
A6	1	1	1	1	1	0	1
A7	0	-1	-1	-1	-1	-1	0

Table 8. RPR scores for criterion ***C2***

Alt.				RPR_{i2}			
A1	0	-1	1	-1	-1	-1	0
A2	1	0	1	-1	-1	-1	1
A3	-1	-1	0	-1	-1	-1	-1
A4	1	1	1	0	1	1	1
A5	1	1	1	-1	0	1	1
A6	1	1	1	-1	-1	0	1
A7	0	-1	1	-1	-1	-1	0

Table 9. RPR scores for criterion ***C3***

Alt.				RPR_{i3}			
A1	0	-1	-1	1	1	1	-1
A2	1	0	-1	1	1	1	-1
A3	1	1	0	1	1	1	1
A4	-1	-1	-1	0	1	1	-1
A5	-1	-1	-1	-1	0	1	-1
A6	-1	-1	-1	-1	-1	0	-1
A7	1	1	-1	1	1	1	0

Table 10. RPR scores for criterion ***C4***

Alt.				RPR_{i4}			
A1	0	-1	0	1	1	1	1
A2	1	0	1	1	1	1	1
A3	0	-1	0	1	1	1	1
A4	-1	-1	-1	0	1	1	-1
A5	-1	-1	-1	-1	0	1	-1
A6	-1	-1	-1	-1	-1	0	-1
A7	-1	-1	-1	1	1	1	0

Table 11. RPR scores for criterion ***C5***

Alt.	RPR$_{i5}$						
A1	0	1	-1	1	1	1	1
A2	-1	0	-1	-1	1	1	1
A3	1	1	0	1	1	1	1
A4	-1	1	-1	0	1	1	1
A5	-1	-1	-1	-1	0	1	-1
A6	-1	-1	-1	-1	-1	0	-1
A7	-1	-1	-1	-1	1	1	0

Then, Eq. (3) was applied to calculate the fi score of each alternative for each criterion and the results were compiled in Table 12.

Step 3 was completed using the criteria weights determined by the CRITIC method and the overall score Si was calculated via Eq. (4) and the results are presented in Table 13.

According to the results in Table 13, A4 emerged as the best alternative in the ranking using the RPR method. A2 and A3 were ranked higher, while A7 and especially A6 were the lowest performing alternatives due to their negative scores. The overall ranking was obtained as follows: A4>A2>A3>A1>A5>A7>A6.

Table 12. f$_i$ scores of each alternative in example 1

Alt.	$C1$	$C2$	$C3$	$C4$	$C5$
	f$_{i1}$	f$_{i2}$	f$_{i3}$	f$_{i4}$	f$_{i5}$
A1	-5	-3	0	3	4
A2	0	0	2	6	0
A3	-2	-6	6	3	6
A4	3	6	-2	-2	2
A5	3	4	-4	-4	-4
A6	6	2	-6	-6	-6
A7	-5	-3	4	0	-2

Table 13. Alternative rankings obtained by the RPR method

Alt.	Weighted decision matrix						
	$C1$	$C2$	$C3$	$C4$	$C5$	S$_i$	Rank
A1	-1.0973	-0.6960	0.0000	0.5419	0.7195	-0.532	4
A2	0.0000	0.0000	0.3760	1.0838	0.0000	1.460	2
A3	-0.4389	-1.3921	1.1281	0.5419	1.0793	0.918	3
A4	0.6584	1.3921	-0.3760	-0.3613	0.3598	1.673	1
A5	0.6584	0.9280	-0.7521	-0.7225	-0.7195	-0.608	5
A6	1.3167	0.4640	-1.1281	-1.0838	-1.0793	-1.510	7
A7	-1.0973	-0.6960	0.7521	0.0000	-0.3598	-1.401	6

3.2 Illustrative Example 2

In this section, an example consisting of nine alternatives (A1–A9) and six criteria (C1–C6), all of which are cost-oriented is presented to demonstrate the effectiveness of the proposed method. This dataset is synthetically generated. The data are summarized in Table 14, with the weights determined by the CRITIC method presented in the last row.

Table 15 shows the ranking of nine alternatives (A1–A9) using the RPR method. Each alternative was evaluated based on five criteria (C1–C5), and a weighted decision matrix was created. Considering the Si values, A1, with the highest total score, ranks first, while A5 and A2 are second and third, respectively. A7, with the lowest Si value, ranks ninth, and A3 and A6 are eighth and seventh, respectively.

Table 14. Data for example 2

Alt.	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$
A1	1.72	205	45.5	5.6	1.06	3.1
A2	1.45	198	47	5.8	1.06	3.6
A3	1.98	210	47	6.2	1.03	4.1
A4	1.82	212	45	6	1.1	3.2
A5	1.33	200	45.6	6	0.98	4
A6	1.74	203	49	6.4	1.1	3.5
A7	1.59	199	48	6.9	1.04	4.3
A8	2.07	206	47.5	7	0.92	2.2
A9	2.12	209	44.3	7.2	0.78	4
w_i	0.1445	0.1484	0.1671	0.1455	0.2004	0.1941

Table 15. Alternative rankings obtained by the RPR method

	Weighted decision matrix							
Alt.	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	Si	Rank
A1	0.2891	0.2968	0.6683	1.1638	-0.6012	1.1645	2.981	1
A2	0.8673	1.1872	-0.1671	0.8728	-1.4029	0.0000	1.357	3
A3	-0.5782	-0.8904	-0.1671	0.0000	0.4008	-1.1645	-2.399	8
A4	-0.2891	-1.1872	1.0025	0.4364	-1.4029	0.3882	-1.052	6
A5	1.1564	0.2968	0.6683	0.4364	0.8016	-0.5822	2.777	2
A6	0.0000	0.5936	-1.3367	-0.2909	-0.2004	0.0000	-1.234	7
A7	-0.8673	0.8904	-1.0025	-0.5819	0.0000	-1.5526	-3.114	9
A8	-0.8673	-0.2968	-0.6683	-0.8728	1.2025	1.5526	0.050	4
A9	-1.1564	-0.5936	1.3367	-1.1638	1.6033	-0.5822	-0.556	5

3.3 Illustrative Example 3

This section focuses on the ranking of twelve distinct cutting tool materials (A1-A12). Each alternative was evaluated using seven criteria (C1-C7). Among these criteria, only C4 was defined as a cost criterion, while all other criteria were classified as benefit criterion. The relevant data are summarized in Table 16 [51]. The last row of the table contains the weights determined by the CRITIC method.

According to Table 17, the highest-performing alternative is A2 (Si=5.520), followed by A8 (Si=2.960). The lowest-performing alternative is A7 (Si=-5.042).

Table 16. Cutting tool materials [51]

No.	H (GPa) ($C1$)	E (GPa) ($C2$)	We (%) ($C3$)	μ ($C4$)	Lc (N) ($C5$)	H/E ($C6$)	H^3/E^2 ($C7$)
A1 (TiBN)	34	380	60	0.6	30	0.089	0.272
A2 (TiBN)	31	380	59	0.49	50	0.082	0.206
A3 (TiBN)	20	280	49	0.45	41	0.071	0.102
A4 (TiBN)	23	300	46	0.45	46	0.077	0.135
A5 (TiBN)	19	270	45	0.45	46	0.7	0.094
A6 (TiCrBN)	30	370	53	0.52	22	0.081	0.197
A7 (TiSiBN)	19	270	43	0.51	47	0.07	0.094
A8 (TiSiBN	25	340	47	0.45	90	0.074	0.135
A9 (TiSiBN)	17	280	40	0.5	67	0.061	0.063
A10 (TiAlSiBN)	23	300	48	0.52	54	0.077	0.135
A11 (TiAlSiBN)	20	260	46	0.43	37	0.077	0.118
A12(TiAlSiBN)	19	280	44	0.45	41	0.068	0.087
w_i	0.0891	0.0950	0.0943	0.1886	0.2138	0.2284	0.0909

Table 17. Alternative rankings obtained by the RPR method

	Weighted decision matrix								
	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	S_i	Rank
A1	0.980	0.950	1.037	-2.074	-1.924	2.056	1.000	2.025	3
A2	0.802	0.950	0.849	-0.566	1.069	1.599	0.818	5.520	1
A3	-0.178	-0.285	0.472	0.943	-0.855	-1.142	-0.273	-1.319	9
A4	0.178	0.190	-0.189	0.943	0.000	0.228	0.273	1.623	4
A5	-0.623	-0.760	-0.472	0.943	0.000	2.513	-0.727	0.873	6
A6	0.623	0.665	0.660	-1.886	-2.351	1.142	0.636	-0.510	8
A7	-0.623	-0.760	-0.849	-0.943	0.641	-1.599	-0.909	-5.042	12
A8	0.445	0.475	0.094	0.189	2.351	-0.685	0.091	2.960	2
A9	-0.980	-0.285	-1.037	-0.566	1.924	-2.513	-1.000	-4.456	11
A10	0.178	0.190	0.283	-1.508	1.496	0.228	0.273	1.140	5
A11	-0.178	-0.855	-0.189	2.074	-1.496	0.228	-0.091	-0.506	7
A12	-0.623	-0.285	-0.660	0.943	-0.855	-2.056	-0.818	-4.355	10

4. Sensitivity Analysis

4.1 Robustness Check Using Alternative Weighting Techniques

To evaluate the robustness and reliability of the proposed RPR method, a comprehensive sensitivity analysis was conducted based on different weighting techniques, namely EW, LOPCOW, SD, SPC, WENSLO and CRITIC. These methods represent different weighting approaches in terms of uniform importance, data distribution, information contrast, logarithmic ratio, and correlation-based structures. The choice allows for the consideration of a wide range of objective weighting perspectives. The purpose of this analysis is to evaluate the stability of the RPR rankings under varying criteria importance assignments. To achieve this, the rankings generated by RPR with each weighting method were compared, and correlation coefficients were calculated. The results obtained based on each illustrative example are presented in Figures 2-4, respectively.

In the sensitivity analysis of the proposed RPR method, quite high correlations were obtained among the six different criterion weighting techniques used. An examination of Figures 2-4 reveals that in Example 1, quite strong correlations were found between the EA, SD, and WENSLO methods, while the SPC method achieved lower values compared to the other methods. In Example 2, the correlations were generally more homogeneous, and the EA, SD, and SPC methods exhibited perfect or nearly perfect corre-

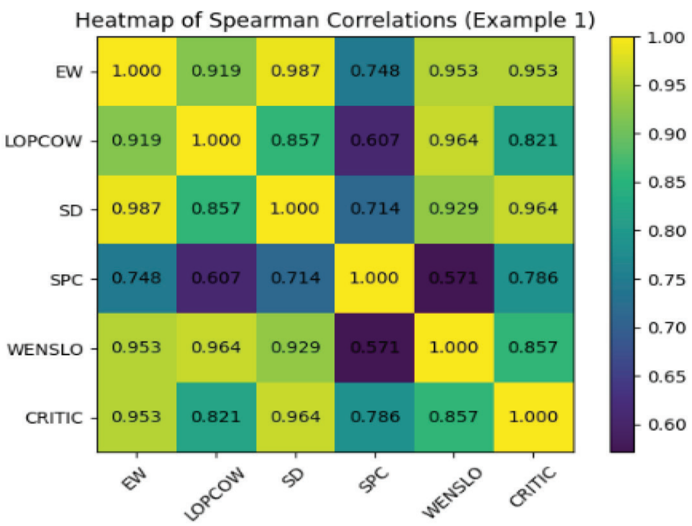

Figure 2. Correlation of RPR scores using different weighting techniques (example 1)

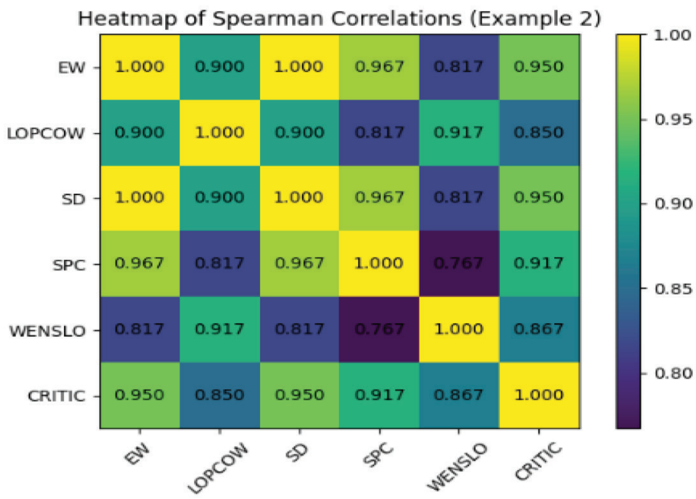

Figure 3. Correlation of RPR scores using different weighting techniques (example 2)

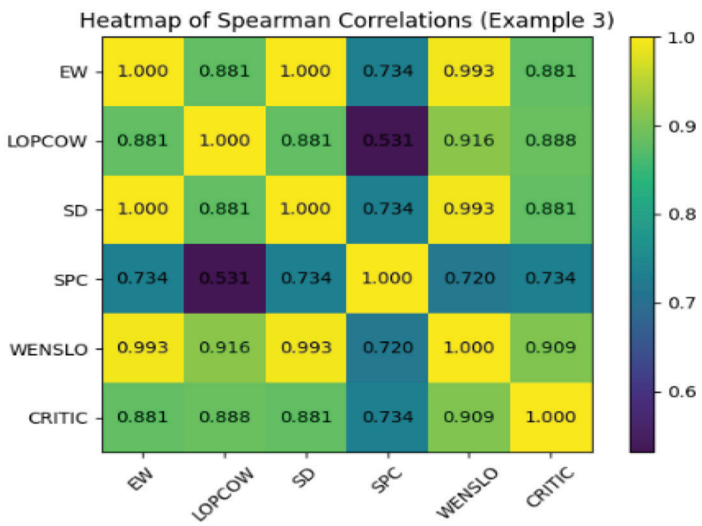

Figure 4. Correlation of RPR scores using different weighting techniques (example 3)

lations, reinforcing the reliability of the method. In Example 3, high correlation values were observed between the EA, SD, and WENSLO methods, but the SPC method also exhibited relatively lower agreement in this example. Overall, the findings of the three case studies indicate that the proposed RPR method yielded consistent and stable results under different criterion weighting techniques, with only the SPC method partially distinguishing itself from the others.

4.2 Impact of Variations in the Most Influential Criterion's Weight

In this section, the impact of changes in the weight of the most prominent criterion is analyzed using Eq. (5) [52]. For this purpose, 20 different scenarios were created for each example, and the results are presented in Figure 7.

$$w_{m\gamma} = (1 - w_{m\pi}).\frac{w_\gamma}{(1-w_m)} \quad (7)$$

Where m represents any criterion, $w_{m\gamma}$ denotes the modified value of $w_{m\pi}$ indicates the reduced value of the best criterion, w_γ refers to the original value of m, and w_m represents the original value of the best criterion [52].

For Case 1, the criterion weights obtained using the CRITIC method are as follows (Table 5): ω=(0.2195,0.2320,0.1880,0.1806,0.1799). The weight of the most important criterion (C_2 (ω^2=0.2320)) has been reduced by 1%: $w_{m\pi}$=0.2320×0.99=0.2297 and other criterion weights were rescaled using Eq. (7):

$$w_1^{new} = (1 - 0.2297)\frac{0.2195}{(1 - 0.2320)} = 0.2202$$

The same process is applied to all other criteria, and Scenario 1 is obtained as follows.
ωnew=(0.2202,0.2297,0.1886,0.1811,0.1804)

Figure 5 illustrates the ranking results obtained using the RPR method under varying criterion weight scenarios. For each of the three examples, the most influential criterion identified through the CRITIC method was systematically reduced across 20 scenarios, allowing an assessment of the method's sensitivity to changes in criterion importance. The results indicate that, while the absolute rankings of the options experience slight modifications when there is a decrease in the weight allocated to the primary criterion, the fundamental ranking structures maintain a significant level of consistency. This suggests that the RPR methodology demonstrates robustness against small shifts in criterion weighting, thereby facilitating a dependable prioritization of options despite differing input assumptions. Additionally, the gradual improvement of the radar plots highlights the collective impact of weight modifications, offering a clear visual representation of how the comparative positions of the alternatives respond to changes in criterion focus.

5. Comparative Analysis

The robustness and validity of the RPR were tested through comparative analysis with various MCDM methods; the aim was to assess the consistency of the RPR rankings under different methodological approaches. A similar validation strategy based on comparative analysis was adopted by Kumari and Acherjee38 for the CARCACS framework; the effectiveness of the proposed method was validated by comparing it with existing decision-making techniques. The methods SAW, WASPAS, PIV, RAM, and RAWEC were selected to provide both classical and recently developed MCDM approaches. While SAW and WASPAS are traditional and widely used, PIV, RAM, and RAWEC represent relatively new methods, enabling a comprehensive and balanced sensitivity analysis. All the results obtained are presented in Tables 18-20, respectively.

Tables 18-20 show that the proposed RPR method exhibits quite strong correlations with other MCDM methods. In Table 4, the correlation coefficients between RPR and the SAW, PIV, RAM, RAWEC, and WASPAS methods are at 0.8214, indicating a strong and stable relationship between the methods. In Table 19, the correlations range from 0.8333 to 0.8500,

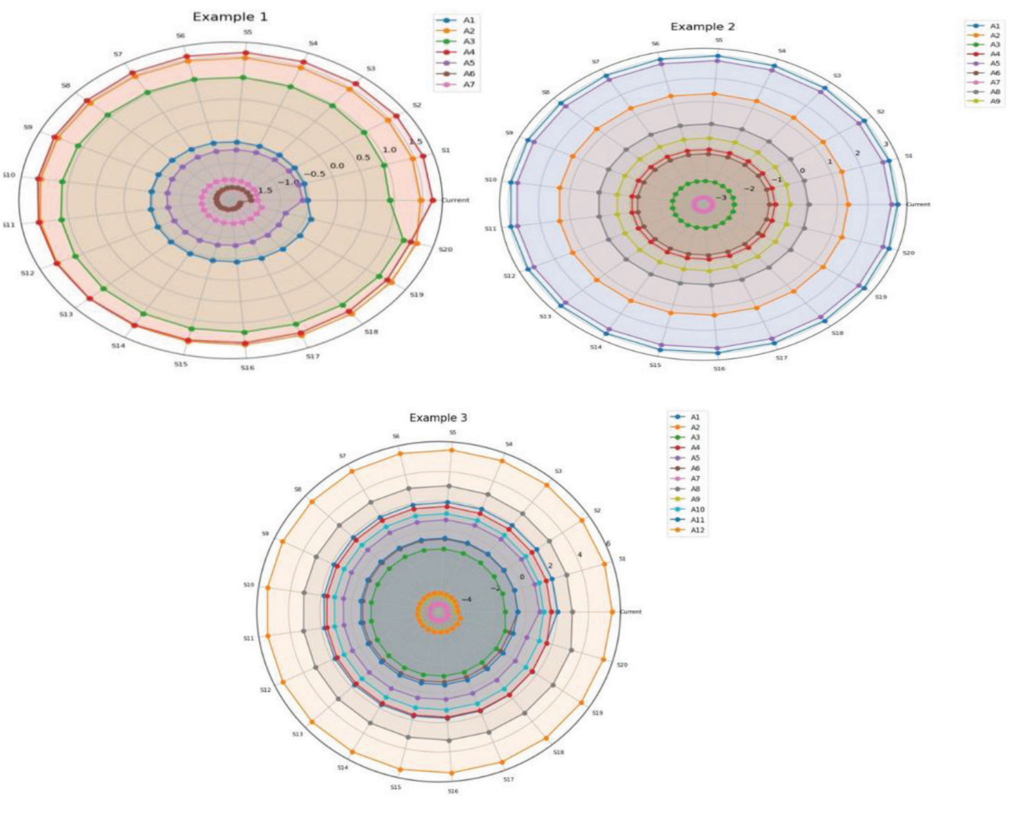

Figure 5. Ranking results under different criterion weight scenarios

Table 18. Correlation of RPR Scores with Alternative Ranking Methods (Example 1)

	RPR		SAW		PIV		RAM		RAWEC		WASPAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A1	-0.5319	4	0.8971	6	0.0435	6	1.4628	6	-0.2254	6	0.8950	6
A2	1.4598	2	0.9279	2	0.0305	2	1.4645	2	0.1623	2	0.9273	2
A3	0.9183	3	0.9275	3	0.0305	3	1.4645	3	0.1346	3	0.9259	3
A4	1.6729	1	0.9469	1	0.0222	1	1.4656	1	0.3781	1	0.9465	1
A5	-0.6077	5	0.9164	4	0.0349	4	1.4640	4	0.0205	4	0.9156	4
A6	-1.5105	7	0.9046	5	0.0394	5	1.4634	5	-0.1558	5	0.9027	5
A7	-1.4010	6	0.8852	7	0.0487	7	1.4622	7	-0.3735	7	0.8830	7
			SAW		PIV		RAM		RAWEC		WASPAS	
	RPR		0.8214*		0.8214*		0.8214*		0.8214*		0.8214*	
	τ		0.7143		0.7143		0.7143		0.7143		0.7143	

Note: Correlation coefficients are significant at 0.05 level (two-tailed)

Table 19. Correlation of RPR Scores with Alternative Ranking Methods (Example 2)

	RPR		SAW		PIV		RAM		RAWEC		WASPAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A1	2.9813	1	0.8485	3	0.0483	2	1.3896	2	-0.0472	3	1.6881	3
A2	1.3574	3	0.8450	4	0.0516	4	1.3893	4	-0.0897	4	1.6765	4
A3	-2.3994	8	0.7818	9	0.0789	9	1.3873	9	-0.5701	9	1.5471	9
A4	-1.0521	6	0.8200	5	0.0596	5	1.3887	5	-0.2500	5	1.6308	5
A5	2.7773	2	0.8558	2	0.0506	3	1.3894	3	-0.0384	2	1.6926	2
A6	-1.2344	7	0.7977	7	0.0685	6	1.3881	6	-0.4109	7	1.5860	7
A7	-3.1139	9	0.7904	8	0.0764	8	1.3875	8	-0.5230	8	1.5630	8
A8	0.0499	4	0.8717	1	0.0457	1	1.3898	1	0.0589	1	1.7350	1
A9	-0.5560	5	0.8187	6	0.0685	7	1.3881	7	-0.3368	6	1.6148	6
			SAW		PIV		RAM		RAWEC		WASPAS	
	RPR		0.8500*		0.8333*		0.8333*		0.8500*		0.8500*	
	τ		0.6111		0.5556		0.5556		0.6111		0.6111	

Note: Correlation coefficients are significant at 0.05 level (two-tailed)

Table 20. Correlation of RPR Scores with Alternative Ranking Methods (Example 3)

	RPR		SAW		PIV		RAM		RAWEC		WASPAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A1	2.0249	3	0.6047	4	0.2801	4	1.4337	4	-0.1295	4	0.5341	4
A2	5.5205	1	0.6488	3	0.2610	3	1.4352	3	0.0346	3	0.5789	3
A3	-1.3186	9	0.5342	9	0.3155	9	1.4291	9	-0.3004	8	0.4737	8
A4	1.6233	4	0.5672	5	0.2984	6	1.4311	6	-0.1767	5	0.5078	6
A5	0.8734	6	0.7373	1	0.1217	1	1.4614	1	0.2310	1	0.7175	1
A6	-0.5099	8	0.5548	7	0.3058	7	1.4306	7	-0.3122	9	0.4839	7
A7	-5.0416	12	0.5097	12	0.3219	11	1.4287	11	-0.3790	11	0.4563	12
A8	2.9601	2	0.6876	2	0.2393	2	1.4372	2	0.0737	2	0.6057	2
A9	-4.4565	11	0.5397	8	0.3075	8	1.4300	8	-0.4338	12	0.4709	10
A10	1.1400	5	0.5651	6	0.2953	5	1.4316	5	-0.1846	6	0.5092	5
A11	-0.5064	7	0.5307	10	0.3169	10	1.4291	10	-0.2949	7	0.4730	9
A12	-4.3547	10	0.5177	11	0.3229	12	1.4283	12	-0.3744	10	0.4576	11
			SAW		PIV		RAM		RAWEC		WASPAS	
	RPR		0.8182*		0.7972*		0.7972*		0.8741*		0.8531*	
	τ		0.6667		0.6061		0.6061		0.7576		0.6970	

Note: Correlation coefficients are significant at 0.05 level (two-tailed) demonstrating that RPR can produce consistent results with different methods. In Table 20, although the correlation values vary slightly, they remain between 0.7972 and 0.8741, demonstrating particularly high levels of agreement with RAWEC and WASPAS. Overall, all three tables demonstrate that the RPR method is reliable, applicable, and provides consistent results compared to methods in literature. The bottom row of Tables 18-20 presents the Kendal Tau coefficients (τ) between RPR and other MCDM methods. Overall, Kendall's τ coefficients show a moderate to strong fit, indicating that the rankings produced by RPR are largely consistent with the rankings of established MCDM methods while also allowing for reasonable pairwise differences.

The findings obtained from the comparative and sensitivity analyses indicate that the proposed RPR framework behaves consistently with several established MCDM techniques while avoiding explicit normalization procedures. This observation is particularly important because previous studies have shown that normalization choices may substantially alter ranking outcomes and introduce instability into decision processes [13]-[16]. In contrast to normalization-dependent approaches, RPR preserves ordinal dominance relationships directly through pairwise comparisons. However, unlike cardinal cumulative methods such as CARCACS, the proposed framework intentionally sacrifices magnitude information in favor of ordinal robustness and scale independence. Therefore, the method may be particularly suitable for heterogeneous decision environments where preserving relative preference structure is more important than modelling absolute performance intensity.

6. Rank Reversal Test

One of the most important ways to test methodological reliability in MCDM methods is through rank reversal testing. In decision-making problems, rank reversal can occur when changes in the set of alternatives occur, especially when dynamic and time-dependent conditions are involved [53]. In this study, the proposed RPR method was subjected to a ranking reversal test. Since the proposed RPR method aims to eliminate normalization-induced distortions, it is necessary to examine its behavior under reverse ordering conditions. In this context, a reverse ordering test is applied to verify whether the ordering stability is maintained when the decision set changes. At each iteration, the lowest-performing alternative in the decision set was removed and the remaining alternatives were reranked. This process was repeated until only two alternatives remained. This evaluated the stability of the RPR method across different alternative sets. The results are presented in Table 21.

The results of the rank reversal test using three separate samples reveal that the RPR method exhibits a stable ranking structure under sequential deletion of the lowest-ranked alternatives. As presented in Table 21, the relative positions of the remaining alternatives were preserved in the tested cases. These findings provide empirical evidence of ranking stability for the considered deletion scenarios. However, this result should not be interpreted as a general proof of rank-reversal immunity for all possible modifications of the alternative set. The stability in Table 21 stems from RPR's ordinal, pairwise structure, where criterion-wise comparisons between two alternatives do not require normalization against the full dataset. However, since final scores depend on the available alternatives, these results indicate empirical robustness in the tested cases, not a universal guarantee against rank reversal under all additions or removals.

The findings from the comparative, sensitivity, and rank reversal analyses offer several important insights into the proposed RPR method. First, the strong agreement between RPR and established MCDM techniques suggests that reliable rankings can be achieved without normalization, which is often a major source of instability in conventional methods. Second, the limited ranking changes under different weighting scenarios indicate that RPR is less sensitive to weight fluctuations, increasing its practical reliability. Third, the preservation of rankings after alternative removal implies that the method is suitable for dynamic decision environments where candidate options may change over time. These results demonstrate that RPR is not only computationally simple, but also a robust and practical alternative for heterogeneous decision problems.

7. Conclusions

MCDM methods are widely used to evaluate alternatives involving multiple and often conflicting criteria in complex decision-making environments [54]. In this study, a normalization-free ordinal pairwise ranking approach, RPR, which does not require data normalization, is proposed. The RPR method directly ranks alternatives under each criterion, thereby preventing inconsistencies that may

Table 21. Results of the Rank Reversal Test for the Proposed RPR Method

Example 1	
Current ranking	A4>A2>A3>A1>A5>A7>A6
Exclusion of A6	A4>A2>A3>A1>A5>A7
Exclusion of A6, A7	A4>A2>A3>A1>A5
Exclusion of A6, A7, A5	A4>A2>A3>A1
Exclusion of A6, A7, A5, A1	A4>A2>A3
Exclusion of A6, A7, A5, A1, A3	A4>A2
Exclusion of A6, A7, A5, A1, A3, A2	A4
Example 2	
Current ranking	A1>A5>A2>A8>A9>A4>A6>A3>A7
Exclusion of A7	A1>A5>A2>A8>A9>A4>A6>A3
Exclusion of A7, A3	A1>A5>A2>A8>A9>A4>A6
Exclusion of A7, A3, A6	A1>A5>A2>A8>A9>A4
Exclusion of A7, A3, A6, A4	A1>A5>A2>A8>A9
Exclusion of A7, A3, A6, A4, A9	A1>A5>A2>A8
Exclusion of A7, A3, A6, A4, A9, A8	A1>A5>A2
Exclusion of A7, A3, A6, A4, A9, A8, A2	A1>A5
Exclusion of A7, A3, A6, A4, A9, A8, A2, A5	A1
Example 3	
Current ranking	A2>A8>A1>A4>A10>A5>A11>A6>A3>A12>A9>A7
Exclusion of A7	A2>A8>A1>A4>A10>A5>A11>A6>A3>A12>A9
Exclusion of A7, A9	A2>A8>A1>A4>A10>A5>A11>A6>A3>A12
Exclusion of A7, A9, A12	A2>A8>A1>A4>A10>A5>A11>A6>A3
Exclusion of A7, A9, A12, A3	A2>A8>A1>A4>A10>A5>A11>A6
Exclusion of A7, A9, A12, A3, A6	A2>A8>A1>A4>A10>A5>A11
Exclusion of A7, A9, A12, A3, A6, A11	A2>A8>A1>A4>A10>A5
Exclusion of A7, A9, A12, A3, A6, A11, A5	A2>A8>A1>A4>A10
Exclusion of A7, A9, A12, A3, A6, A11, A5, A10	A2>A8>A1>A4
Exclusion of A7, A9, A12, A3, A6, A11, A5, A10, A4	A2>A8>A1
Exclusion of A7, A9, A12, A3, A6, A11, A5, A10, A4, A1	A2>A8
Exclusion of A7, A9, A12, A3, A6, A11, A5, A10, A4, A1, A8	A2

arise from the normalization process. The applicability and robustness of the proposed method have been validated through three illustrative case studies representing different decision-making scenarios. These examples demonstrate that RPR can generate reliable and consistent rankings under a variety of conditions.

Sensitivity analysis findings further indicate that the method largely preserves the ranking of alternatives under different conditions, providing decision-makers with a reliable tool. Moreover, by maintaining ranking consistency, the RPR method demonstrated robust ranking stability in the rank-reversal scenarios examined in this study. The results show that RPR makes a valuable contribution to MCDM studies from both theoretical and practical perspectives. Thus, the contributions of this study can be summarized as follows: i) A proposed approach has been developed in MCDM literature that eliminates the need for data normalization. The proposed RPR method simplifies calculations and reduces potential biases by evaluating alternatives based on criterion-based rankings. ii) The RPR method has been extensively tested under different weighting techniques (EW, LOPCOW, SD, SPC, WENSLO, CRITIC), and the results indicate a high level of stability. This demonstrates the robustness and reliability of the method. The study offers an alternative that overcomes the limitations of existing MCDM methods through both methodological innovation and stability and consistency tests.

Despite its advantages, the RPR method has practical limitations. Its pairwise structure leads to quadratic computational growth with the number of alternatives, and non-discriminatory criteria (all ties) do not influence the final ranking. The evaluation of the proposed RPR method is limited to three examples created using synthetically generated datasets. While these examples are sufficient to demonstrate the conceptual validity and computational behavior of the proposed approach, the findings are limited by the datasets and decision-making environments considered. Therefore, the generalizability of the results can be increased in future research by applying the proposed method to a wider range of datasets and real-world decision-making problems.

From a practical perspective, the proposed approach is particularly suitable for decision-making problems where normalization may distort the original data structure or where reliable cardinal information is not available. In such cases, decision-makers can benefit from a scale-independent and robust ranking framework based solely on relative comparisons. This makes the method applicable to areas such as supplier selection, material evaluation, and multi-criteria screening problems, where consistent ranking is often more critical than precise magnitude differences.

Future research should investigate the applicability of the RPR method in decision-making scenarios involving fuzzy numbers or qualitative factors, as this would allow for a more comprehensive assessment of its effectiveness. Another promising direction is a systematic comparison of RPR with established methods such as FUCA and SRP across diverse contexts, which would provide deeper insights into its relative advantages and limitations. In addition, extending the comparative analysis to widely used MCDM methods such as TOPSIS, VIKOR, PROMETHEE, and AHP remains an important direction for future research.

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