

COMPARING NOVEL MULTI-OBJECTIVE OPTIMIZATION METHODOLOGIES

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Abstract: Extracting bioactive compounds from botanicals is a pivotal undertaking within chemical sciences. This research undertakes a comparative analysis of three contemporary MCDM methodologies: IRPA, RAM, and DEPART. The comparative assessment of these three methods is conducted across three distinct botanical extraction scenarios: optimizing the extraction of Balloon Vine, Spinach, and Turkey Tail Mushroom. The DEPART method emerged as the most prominent performer, while the IRPA method ranked third.

KEYWORDS: Multi-objective optimization, MCDM, IRPA method, RAM method, DEPART method, botanical extraction

1 Introduction

Extraction is a fundamental process involving the use of a suitable solvent to solubilize target compounds from a raw botanical material, followed by the separation of the insoluble residue to yield an extract [1]. This crude extract can subsequently be processed into formulations for direct or indirect application in critical areas such as functional foods [2, 3], pharmaceuticals [4], flavorings [5], colorants [6], and cosmetics [7], among others. The primary objective of any extraction process is to maximize the yield of desired active compounds while minimizing the co-extraction of impurities into the solvent. The quality of the resulting extract, often assessed by its active compound content, is typically evaluated using chemical composition parameters (e.g., polyphenol, carotenoid, saponin content) or biological activity indicators (e.g., antioxidant, anti-inflammatory, antimicrobial capabilities). Current scientific evidence underscores the significant health benefits derived from natural products, coupled with growing concerns regarding the potential adverse effects of synthetic counterparts, leading to a surge in natural product consumption. This trend highlights the critical importance of optimizing extraction processes to obtain the highest quality extracts [8]. The quality of an extract is contingent upon the quality of the raw botanical material, the chosen extraction method, and the specific process parameters. Consequently, research in extraction processes typically focuses on several key areas: (1) investigating the impact of harvesting time, plant age, and pre-treatment conditions on the quality of the botanical material [9]; (2) exploring various extraction techniques such as maceration, percolation, ultrasound-assisted extraction, and supercritical fluid extraction [10 - 14]; or (3) studying the influence of process variables like particle size, extraction temperature, solvent-to-material ratio, extraction time, hydrodynamic conditions, and pre-wetting on extract quality to optimize extraction conditions [15 - 18].

The majority of studies falling under the third research direction (optimization studies) involve conducting experiments based on a predefined matrix. The data acquired from these experiments are then used to develop regression equations, which describe the relationships between input and output parameters. These regression equations subsequently serve as the foundation for optimizing the extraction process. This optimization approach is commonly known as Response Surface Methodology (RSM) [19-24]. For instance, RSM has been successfully applied to multi-objective optimization problems, such as determining the optimal ethanol concentration, extraction temperature, and extraction time to maximize total phenolic content and antioxidant activity during passion fruit and rambutan seed extraction [25]. In another study, RSM was utilized to identify optimal values for material-to-solvent ratio, stirring speed, and extraction time to achieve optimal total polyphenol content, total flavonoid content, and antioxidant capacity from *Rhamnus alaternus* leaves [26]. However, the application of RSM often encounters several limitations. Firstly, a sufficiently large number of experiments is a prerequisite for developing accurate regression equations; an insufficient number can compromise the precision of the model. Secondly, RSM necessitates that all input and output parameters be quantifiable to establish the regression relationships. Thirdly, users must possess a certain level of understanding of experimental design methodologies, which is not always straightforward for all experimental researchers. In practical extraction scenarios, the number of available experiments may be limited, and input/output parameters are not always quantitative; they can sometimes be qualitative, such as nutrient color, extraction appearance, ease/difficulty of the process, or operational safety, etc. Furthermore, extractions are not always conducted according to a rigid matrix but are often designed for specific situations, depending on the objective and practical feasibility in each case. Clearly, in such circumstances, employing RSM for extraction optimization becomes unfeasible. So, how can one identify the optimal method under these analogous conditions? The answer lies in utilizing Multi-Criteria Decision Making (MCDM) methods. MCDM is a technique for ranking alternatives based on multiple criteria, enabling the identification of high-ranking options among available choices and ultimately determining the optimal solution [27]. This technique has found widespread application across diverse fields including economics, education, construction, and food science [28], among others. Within chemistry in general, and extraction specifically, hundreds of studies have been published on the application of MCDM methods to solve multi-objective optimization problems [29]. However, the sheer number of MCDM methods currently available, each with distinct approaches, complicates the selection of an appropriate method for a given application. Different methods, when applied to the same problem, can yield varying results [30, 31]. This challenge necessitates comparing methods in specific contexts to identify the most suitable one [32, 33]. Beyond their ability to pinpoint the best alternative from a set of options, a method is often considered superior if the ranking of alternatives it generates remains more stable when criterion weights change across different scenarios [34, 35].

Three recently developed MCDM methods IRPA (2025) [36], RAM (2023) [37], and DEPART (2025) [38] exhibit significant differences in their problem-solving approaches. Detailed application of these three methods to optimization problems will be presented in Section 2 of this article. While RAM has been extensively applied to rank alternatives in various fields, such as ranking fire-resistant materials [39], mushroom cultivation strategies [40], financial health of banks [41], and logistics solutions [42], IRPA and DEPART are relatively new. Having only been recently discovered, there are currently no published studies utilizing these two methods for ranking alternatives in any field. This gap motivates the comparative study of these three methods in the present research. The context for this comparison is the field of botanical extraction, chosen as the research subject for the reasons previously discussed. Section 2 of this article will provide a summary of applying the IRPA,

RAM, and DEPART methods for ranking alternatives, as well as the tools used for their comparison. The problems posed for comparing these three methods, presented in Section 3, include ranking extraction alternatives for Balloon Vine, Spinach, and Turkey Tail Mushroom. Section 4 will delve into a detailed discussion comparing the IRPA, RAM, and DEPART methods for each of the aforementioned problems. The conclusions drawn from this research will be presented in the final section of the article.

2 METHODOLOGY

To apply Multi-Criteria Decision Making (MCDM) methods generally, a decision matrix must first be constructed. This matrix, represented by Equation (1), comprises m rows and n columns, where m denotes the number of alternatives and n represents the number of criteria characterizing each alternative. Let x_{ij} be the value of criterion j for alternative i , where j ranges from 1 to n , and i from 1 to m .

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

The IRPA method is employed to identify the optimal alternative from a set of available options through the following sequential steps [36]:

Step 1: Determine the Reference Point (RP) for each criterion using Equation (2). The value of rp_j can be the average value of the elements in the decision matrix, or it could be the minimum or maximum value of the criteria. The selection of rp_j values is contingent upon the decision-maker's preference.

$$RP = [rp_j]_{1n} = [rp_1 rp_2 \dots rp_n] \quad (2)$$

Step 2: Normalize the decision matrix according to Equation (3).

$$\begin{cases} N = [n_{ij}]_{m \times n} = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \\ n_{ij} = \frac{x_{ij}}{\sqrt{(\sum_{i=1}^m x_{ij}^2 + rp_j^2)}} \end{cases} \quad (3)$$

Step 3: Normalize the reference point matrix using Equation (4).

$$\begin{cases} NRP = [nrp_j]_{1n} = [nrp_1 nrp_2 \dots nrp_n] \\ nrp_j = \frac{rp_{ij}}{\sqrt{(\sum_{i=1}^m x_{ij}^2 + rp_j^2)}} \end{cases} \quad (4)$$

Step 4: Construct the Difference Matrix (DF) as per Equation (5).

$$\begin{cases} DF = [df_{ij}]_{m \times n} = \begin{bmatrix} df_{11} & \cdots & df_{1n} \\ \vdots & \ddots & \vdots \\ df_{m1} & \cdots & df_{mn} \end{bmatrix} \\ df_{ij} = n_{ij} - nrp_j \end{cases} \quad (5)$$

Step 5: Label "benefit" criteria (larger is better) with the letter 'B' and "cost" criteria (smaller is better) with the letter 'C'. Subsequently, construct the Positive Difference Matrix (DF^+) and Negative Difference Matrix (DF^-) using Equations (6) and (7), respectively.

$$\left\{ \begin{array}{l} DF^+ = [df_{ij}^+]_{m \times n} = \begin{bmatrix} df_{11}^+ & \cdots & df_{1n}^+ \\ \vdots & \ddots & \vdots \\ df_{m1}^+ & \cdots & df_{mn}^+ \end{bmatrix} \\ df_{ij}^+ = \begin{cases} \frac{df_{ij}}{nrp_j}, & df_{ij} > 0 \\ 0 & df_{ij} \leq 0 \end{cases} \quad \text{if } j \in B \\ df_{ij}^+ = \begin{cases} 0, & df_{ij} \geq 0 \\ \left| \frac{df_{ij}}{nrp_j} \right| & df_{ij} < 0 \end{cases} \quad \text{if } j \in C \end{array} \right. \quad (6)$$

$$\left\{ \begin{array}{l} DF^- = [df_{ij}^-]_{m \times n} = \begin{bmatrix} df_{11}^- & \cdots & df_{1n}^- \\ \vdots & \ddots & \vdots \\ df_{m1}^- & \cdots & df_{mn}^- \end{bmatrix} \\ df_{ij}^- = \begin{cases} \left| \frac{df_{ij}}{nrp_j} \right|, & df_{ij} < 0 \\ 0 & df_{ij} \geq 0 \end{cases} \quad \text{if } j \in B \\ df_{ij}^- = \begin{cases} 0, & df_{ij} \leq 0 \\ \frac{df_{ij}}{nrp_j} & df_{ij} > 0 \end{cases} \quad \text{if } j \in C \end{array} \right. \quad (7)$$

Step 6: Let w_j denote the weight of the j^{th} criterion. Calculate the Weighted Positive Difference Matrix (WDF^+) and Weighted Negative Difference Matrix (WDF^-) using Equations (8) and (9), respectively.

$$\left\{ \begin{array}{l} WDF^+ = [wdf_{ij}^+]_{m \times n} = \begin{bmatrix} wdf_{11}^+ & \cdots & wdf_{1n}^+ \\ \vdots & \ddots & \vdots \\ wdf_{m1}^+ & \cdots & wdf_{mn}^+ \end{bmatrix} \\ wdf_{ij}^+ = (w_j \times DF^+)^{(1-w_j)} \end{array} \right. \quad (8)$$

$$\left\{ \begin{array}{l} WDF^- = [wdf_{ij}^-]_{m \times n} = \begin{bmatrix} wdf_{11}^- & \cdots & wdf_{1n}^- \\ \vdots & \ddots & \vdots \\ wdf_{m1}^- & \cdots & wdf_{mn}^- \end{bmatrix} \\ wdf_{ij}^- = (w_j \times DF^-)^{(1-w_j)} \end{array} \right. \quad (9)$$

Step 7: Compute the Positive Distance Matrix (PD) and Negative Distance Matrix (ND) based on Equations (10) and (11), respectively.

$$\left\{ \begin{array}{l} PD = [pd_i]_{m1} = \begin{bmatrix} pd_1 \\ pd_2 \\ \vdots \\ pd_m \end{bmatrix} \\ pd_i = \sum_{j=1}^n wdf_{ij}^+ \end{array} \right. \quad (10)$$

$$\left\{ \begin{array}{l} ND = [nd_i]_{m1} = \begin{bmatrix} nd_1 \\ nd_2 \\ \vdots \\ nd_m \end{bmatrix} \\ nd_i = \sum_{j=1}^n wdf_{ij}^- \end{array} \right. \quad (11)$$

Step 8: Calculate the score for each alternative using Equation (12). The alternative with the highest score is identified as the optimal solution, and vice-versa.

$$\left\{ \begin{array}{l} RV = [rv_i]_{m1} = \begin{bmatrix} rv_1 \\ rv_2 \\ \vdots \\ rv_m \end{bmatrix} \\ rv_i = \frac{pd_i - nd_i}{2} \end{array} \right. \quad (12)$$

The RAM method is applied to determine the optimal alternative from a set of available options through the following structured steps [37]:

Step 1: Normalize the raw data using Equation (13).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (13)$$

Step 2: Calculate the weighted normalized values for each criterion as shown in Equation (14).

$$y_{ij} = w_j \cdot r_{ij} \quad (14)$$

Step 3: Compute the total weighted normalized scores for each alternative using Equations (15) and (16).

$$S_{+i} = \sum_{j=1}^n y_{+ij} \quad \text{if } j \in B \quad (15)$$

$$S_{-i} = \sum_{j=1}^n y_{-ij} \quad \text{if } j \in C \quad (16)$$

Step 4: Calculate the final score for each alternative according to Equation (17). The alternative possessing the highest score is identified as the optimal solution, and conversely.

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \quad (17)$$

The DEPART method is applied to identify the optimal alternative from a given set of options by following this sequence of steps [38]:

Step 1: Normalize the raw data using Equation (18).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m (x_{ij})^2}} \quad (18)$$

Step 2: Calculate the positive and negative deviations for each criterion using Equations (19) and (20), respectively.

$$dv_{ij}^+ = |x'_{ij} - t_j^+| \quad (19)$$

$$dv_{ij}^- = |x'_{ij} - t_j^-| \quad (20)$$

Where

$$t_j^+ = \begin{cases} \max_i x'_{ij} & \text{if } j \in B \\ \min_i x'_{ij} & \text{if } j \in C \end{cases} \quad (21)$$

$$t_j^- = \begin{cases} \min_i x'_{ij} & \text{if } j \in B \\ \max_i x'_{ij} & \text{if } j \in C \end{cases} \quad (22)$$

Step 3: Construct the pairwise positive ratio matrix (E^+) and the pairwise negative ratio matrix (E^-) using Equations (23) and (24), respectively.

$$e_{kl}^+ = \sum_{j=1}^n w_j \left(\frac{dv_{lj}^+ + md^+}{dv_{kj}^+ + md^+} \right) \quad k, l \in \{1, 2, \dots, m\} \quad (23)$$

$$e_{kl}^- = \sum_{j=1}^n w_j \left(\frac{dv_{kj}^- + md^-}{dv_{lj}^- + md^-} \right) \quad k, l \in \{1, 2, \dots, m\} \quad (24)$$

Where

$$md^+ = \max(dv_{ij}^+) \quad (25)$$

$$md^- = \max(dv_{ij}^-) \quad (26)$$

If $k = l$ then $e_{kl}^+ = e_{kl}^- = 1$

Step 4: Aggregate the E^+ and E^- matrices (determined in Step 3) based on a user-defined coefficient η using Equation (27).

$$e_{kl} = \eta e_{kl}^+ + (1 - \eta) e_{kl}^-, \quad k, l \in \{1, 2, \dots, m\} \quad (27)$$

Step 5: Compute the total deviation ratio for each alternative using Equation (28).

$$e_l^s = \sum_{k=1}^m e_{kl}, \quad l \in \{1, 2, \dots, m\} \quad (28)$$

Step 6: Calculate the score for each alternative using Equation (29). The alternative with the highest score is ranked first, while the alternative with the lowest score is ranked m^{th} .

$$S_i = \frac{1}{n} \left(\sum_{l=1}^n \frac{e_{il}}{e_l^s} \right) \quad (29)$$

To facilitate a comparative analysis among the IRPA, RAM, and DEPART methodologies, Spearman's rank correlation coefficient was employed. This coefficient serves as an indicator of the concordance in the ranking of alternatives when a specific ranking method is applied under varying criterion weight scenarios. The coefficient is calculated using Equation (30), where D_i represents the difference in rank for alternative i as the criterion weights are altered [43, 44].

$$S = 1 - \frac{6 \sum_{i=1}^m D_i^2}{m(m^2 - 1)} \quad (30)$$

3 METHODOLOGY

The primary objective of this investigation is to conduct a comparative analysis of the IRPA, RAM, and DEPART methodologies within the context of botanical extraction processes. To achieve this, data pertaining to extraction solutions were drawn from recently published literature. To ensure the objectivity of the comparison, this study purposefully selected datasets from extraction processes exhibiting diverse characteristics, including variations in the type of plant extracted, the number of extraction alternatives in each case, and the number of criteria used to evaluate these alternatives. Details of the three distinct case studies are summarized below:

Case 1: Balloon Vine extraction

This case consolidates data for six distinct extraction alternatives for Balloon Vine (*Cardiospermum Halicacabum L.*), designated A1 through A6. Each alternative was implemented by varying the solvent concentration and evaluated across three specific criteria: total polyphenol content (mg GAE/g DW), denoted as C1; total saponin content (mg OAE/g DW), denoted as C2; and antioxidant activity (mmol TE/g DW), denoted as C3. All three criteria are of the "benefit" type, meaning higher values are desirable. The data for these six alternatives are summarized in Table 1 [45].

Table 1. Extraction alternatives for Balloon Vine

Alt.	C1	C2	C3
	Total polyphenol content (mg GAE/g CK)	Total saponin content (mg OAE/g CK)	Antioxidant activity (mmol TE/g CK)
A1	7.688	106.2	0.014
A2	9.418	111.2	0.029
A3	11.035	140.2	0.054
A4	13.957	187.2	0.022
A5	12.142	164.2	0.054
A6	19.716	96.2	0.039

Analysis of the data in Table 1 reveals that C1 exhibits its maximum value of 19.716 mg GAE/g DW for alternative A6, C2 reaches its maximum of 187.2 for alternative A4, while C3 peaks at 0.054 for both alternatives A3 and A5. Evidently, no single alternative simultaneously achieves the maximum value across all three criteria. Identifying the optimal alternative among the six implemented options necessitates a simultaneous consideration of all three criteria, thus constituting an MCDM task. The comparative evaluation of the IRPA, RAM, and DEPART methods will be performed during the execution of this task.

Case 2: Spinach Extraction

This case involves a dataset comprising nine extraction alternatives for Spinach (*Spinacia oleracea*), labeled A1 through A9. Similar to Case 1, each alternative was developed by adjusting the solvent concentration. Each alternative was characterized by four criteria: Chlorophyll *a* content ($\mu\text{g/g}$ FW), Chlorophyll *b* content ($\mu\text{g/g}$ FW), polyphenol content (mg GAE/g FW), and antioxidant activity (mg TE/g FW), designated as C1 through C4, respectively. All four of these criteria are also "benefit" criteria, where higher values are desired. The data for these nine spinach extraction processes are consolidated in Table 2 [46].

Table 2. Extraction alternatives for Spinach

Alt.	C1	C2	C3	C4
	Chlorophyll <i>a</i> content ($\mu\text{g/g}$ CT)	Chlorophyll <i>b</i> content ($\mu\text{g/g}$ CT)	Polyphenol content (mg GAE/g CT)	Antioxidant activity (mg TE/g CT)
A1	40.898	9.535	1.918	0.195
A2	32.911	18.481	1.282	0.06
A3	13.791	7.011	1.269	0
A4	27.308	8.788	1.659	0.064
A5	39.325	27.159	1.53	0.132
A6	30.186	78.444	1.791	0.368
A7	5.488	0	1.037	0.1
A8	8.668	1.544	1.155	0.234
A9	78.447	2.243	1.443	0.062

Table 3. Extraction alternatives for Turkey Tail Mushroom

Alt.	C1	C2	C3	C4	C5	C6
	Yield (%)	Powder moisture content (%)	Reduction in antioxidant activity (%)	Reduction in TPC (%)	Reduction in TFC (%)	Reduction in TTC (%)
A1	28.87	3.72	9.69	4.09	2.61	1.1
A2	50.37	3.32	11.3	5.41	3.29	1.83
A3	29.78	3.98	9.92	4.87	2.83	1.25
A4	58.06	2.28	9.43	4.49	2.42	1.02
A5	56.72	2.56	13.49	8.51	5.49	2.74
A6	57.89	2.29	9.96	4.37	2.89	1.43
A7	49.06	3.89	10.46	5.42	3.06	2.46
A8	46.81	3.02	11.35	6.29	3.35	2.26
A9	39.45	3.79	9.98	4.9	2.98	1.58
A10	57.82	3.05	11.37	6.27	3.86	2.35
A11	59.26	2.47	9.53	4.76	2.35	1.24
A12	29.76	3.82	10.17	5.05	2.81	2.01
A13	54.58	2.95	14.32	8.32	5.87	3.43
A14	31.41	3.52	10.02	5.02	3.11	0.94
A15	42.13	3.67	13.21	8.21	5.19	2.99

From the data presented in Table 2, it is observed that C1 reaches its maximum value of 78.447 $\mu\text{g/g}$ FW with alternative A9, C2 peaks at 78.444 $\mu\text{g/g}$ FW for alternative A6, C3 is maximized at 1.918 mg GAE/g FW for alternative A1, and C4 achieves its highest value of 0.368 mg TE/g FW for alternative A6. Therefore, to determine the optimal alternative among

the options tested, the application of MCDM methods is essential. The IRPA, RAM, and DEPART methods will again be employed for this specific task.

Case 3: Turkey Tail Mushroom Extraction

Table 3 compiles data for fifteen extraction alternatives for Turkey Tail Mushroom (*Trametes versicolor*), labeled A1 through A15, as described in [47]. Each alternative was executed by varying the drying temperature, carrier material content, and feed rate. Six criteria were utilized to evaluate each alternative: yield (%), powder moisture content (%), reduction in antioxidant activity (%), reduction in TPC (%), reduction in TFC (%), and reduction in TTC (%), denoted as C1 through C6, respectively. Among these, only C1 is a "benefit" criterion (higher values desired), while the remaining criteria (C2-C6) are "cost" criteria (lower values desired).

Based on the data in Table 3, it is evident that alternative A11 demonstrates the highest C1 and the lowest C5 compared to all other alternatives. Alternative A4 exhibits the lowest values for both C2 and C3 among all alternatives. Criterion C6 shows its minimum value with alternative A14. This again signifies that to determine the optimal alternative among the investigated options, the application of MCDM methods is necessary. Once more, the IRPA, RAM, and DEPART methods will be deployed for this objective.

4 RESULTS AND DISCUSSION

4.1 Case 1: Balloon Vine extraction

To ensure an objective comparison among the IRPA, RAM, and DEPART methods, the assessment was conducted under various sets of criterion weights. Accordingly, four distinct scenarios were created. In the initial scenario (Set 1), the weights of all criteria were set equally, meaning each criterion had a weight of 1/3. In each of the subsequent scenarios, one criterion was assigned a weight double that of the others. For example, in Scenario 2 (Set 2), the weight for criterion C1 was set to 0.5, while the remaining two criteria each had a weight of 0.25. Table 4 summarizes the criterion weights for these four different scenarios, corresponding to weight sets 1 through 4.

Table 4. Criterion weights for case 1 across different scenarios

Alt.	C1	C2	C3
set 1	1/3	1/3	1/3
set 2	0.5	0.25	0.25
set 3	0.25	0.5	0.25
set 4	0.25	0.25	0.5

The decision matrix for this case is precisely the data compiled in Table 1, which outlines the different extraction alternatives.

The IRPA method was applied to rank the alternatives using Equations (2) through (12). The RAM method was used for ranking with Equations (13) through (17). Finally, the DEPART method was employed for ranking using Equations (18) through (29). Tables 5 through 8 present the summarized rankings of the alternatives as determined by the IRPA, RAM, and DEPART methods, corresponding to the four distinct weight sets.

Table 5. Alternative rankings for case 1 using weight set 1

Alt.	IRPA	RAM	DEPART
A1	6	6	6
A2	5	5	5
A3	2	2	3
A4	4	4	4
A5	1	1	1
A6	3	3	2

Table 6. Alternative rankings for case 1 using weight set 2

Alt.	IRPA	RAM	DEPART
A1	6	6	6
A2	5	5	5
A3	4	3	4
A4	2	4	3
A5	3	2	2
A6	1	1	1

Table 7. Alternative rankings for case 1 using weight set 3

Alt.	IRPA	RAM	DEPART
A1	6	6	6
A2	5	5	5
A3	3	3	3
A4	2	2	2
A5	1	1	1
A6	4	4	4

Table 8. Alternative rankings for case 1 using weight set 4

Alt.	IRPA	RAM	DEPART
A1	6	6	6
A2	5	5	5
A3	2	2	2
A4	4	4	4
A5	1	1	1
A6	3	3	3

From the data presented in Tables 5 through 8, the Spearman's rank correlation coefficient between the various MCDM methods was calculated using Equation (30), as summarized in Table 9. Similarly, the Spearman's coefficients reflecting the consistency of rankings across different weighting scenarios for each individual MCDM method were also computed and compiled in Table 10.

Table 9. Spearman's coefficients between methods for case 1

Method	Set 1		Set 2		Set 3		Set 4	
	RAM	DEPART	RAM	DEPART	RAM	DEPART	RAM	DEPART
IRPA	1	0.943	0.829	0.943	1	1	1	1
RAM		0.943		0.943		1		1

Table 10. Spearman's coefficients between weighting scenarios for case 1

Set	IRPA			RAM			DEPART		
	set 2	set 3	set 4	set 2	set 3	set 4	set 2	set 3	set 4
set 1	0.543	0.829	1.000	0.829	0.829	1.000	0.886	0.771	0.943
set 2		0.600	0.543		0.600	0.829		0.657	0.714
set 3			0.829			0.829			0.829
Average	0.724			0.819			0.800		

Analysis of the data in Table 9 reveals a consistently high Spearman's coefficient between any two of the methods, with the lowest value observed at 0.829, occurring between the IRPA and RAM methods when criterion weights were assigned according to Scenario 2 (Set 2). This finding strongly suggests a high degree of consistency in the rankings of the alternatives when evaluated by these three methods. A re-examination of the raw ranking data in Tables 5 through 8 further supports this observation. Notably, across all tested weighting scenarios, the application of IRPA, RAM, and DEPART consistently identified the same optimal alternative among the six under investigation. This outcome provides compelling evidence that all three methods are suitable for use in this particular case study.

When assessing the ranking consistency of alternatives as criterion weights are varied (Table 10), it is evident that the average Spearman's coefficient among the different weight sets is highest when the RAM method is employed for ranking alternatives, and lowest when the IRPA method is utilized. This result indicates that while all three methods IRPA, RAM, and DEPART demonstrate substantial consistency in alternative rankings, the RAM method exhibits superior robustness when considering shifts in criterion weights. However, it is crucial to acknowledge that these findings are derived solely from the current case study; therefore, additional case studies are necessary to ensure the utmost objectivity in drawing broader conclusions.

4.2 Case 2: Spinach extraction

In this case study, the criterion weights were generated across five distinct scenarios, as detailed in Table 11. In Scenario 1, each criterion was assigned an equal weight of 0.25. For the remaining scenarios, one criterion received a weight twice that of each of the others. For example, in Scenario 2 (Set 2), criterion C1 was weighted at 0.4, while the remaining criteria each received a weight of 0.2. The ranking of alternatives using the IRPA, RAM, and DEPART methods was performed for each different weight set, with the results illustrated in Figures 1 through 5.

Table 11. Criterion weights for case 2 across different scenarios

Alt.	C1	C2	C3	C4
set 1	0.25	0.25	0.25	0.25
set 2	0.4	0.2	0.2	0.2
set 3	0.2	0.4	0.2	0.2
set 4	0.2	0.2	0.4	0.2
set 5	0.2	0.2	0.2	0.4

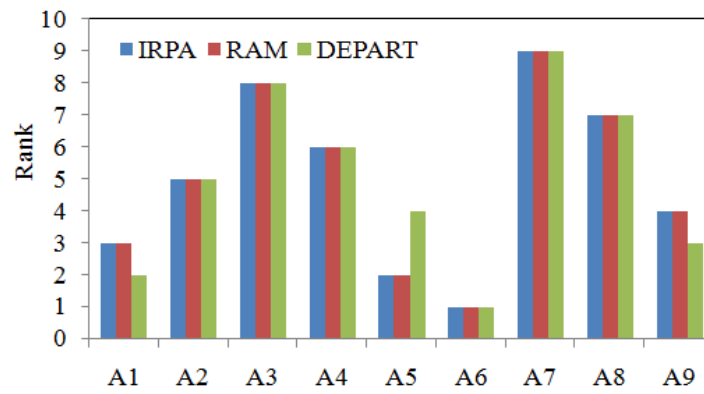


Fig. 1 Alternative rankings for case 2 using weight set 1

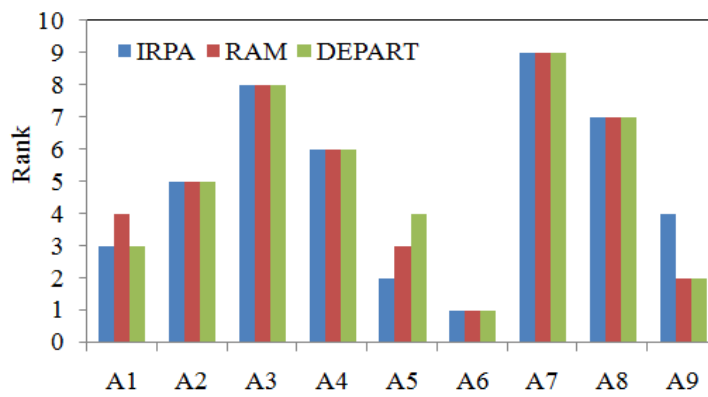


Fig. 2 Alternative rankings for case 2 using weight set 2

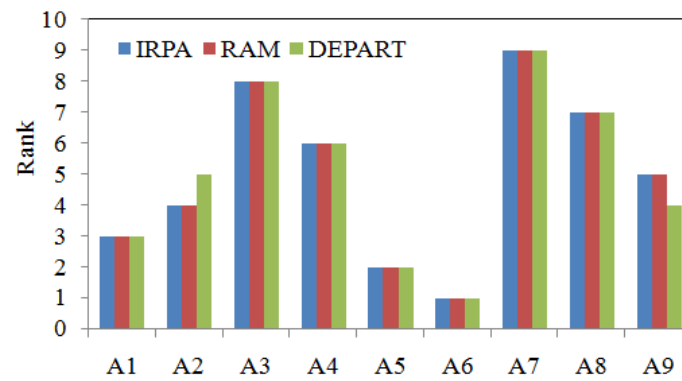


Fig. 3 Alternative rankings for case 2 using weight set 3

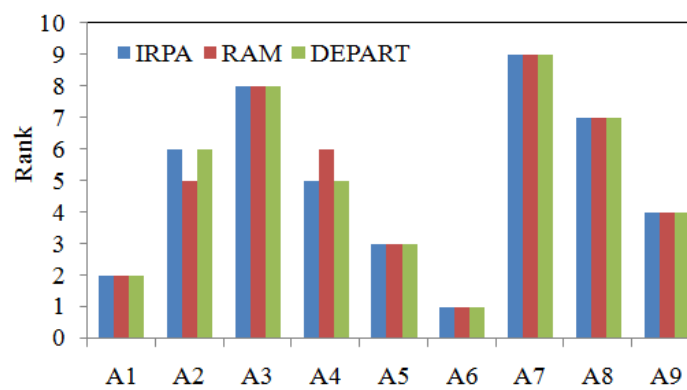


Fig. 4 Alternative rankings for case 2 using weight set 4

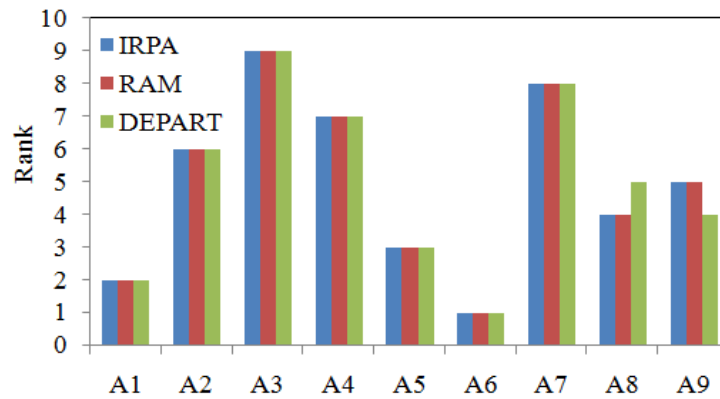


Fig. 5 Alternative rankings for case 2 using weight set 5

Observation of Figures 1 through 5 reveals a high degree of concordance in the alternative rankings produced by the IRPA, RAM, and DEPART methods. Notably, across all five distinct weighting scenarios (from Set 1 to Set 5), alternative A6 was consistently identified as the optimal solution, regardless of which ranking method was employed. The Spearman's rank correlation coefficients between the methods were also calculated and summarized in Table 12. These coefficients exhibit very high values, with the lowest being 0.983. This further strengthens the assertion that the alternative rankings demonstrate significant agreement when derived using the IRPA, RAM, and DEPART methods. In other words, all three methods proved suitable for application in this particular case.

Table 12. Spearman's coefficients between methods for case 2

Scenario	Method	IRPA	RAM
Set 1	RAM	1.000	-
	DEPART	0.950	0.950
Set 2	RAM	0.950	-
	DEPART	0.933	0.983
Set 3	RAM	1.000	-
	DEPART	0.983	0.983
Set 4	RAM	0.983	-
	DEPART	1.000	0.983
Set 5	RAM	1.000	-
	DEPART	0.983	0.983

Table 13 aggregates the Spearman's coefficients between different weighting scenarios for each ranking method. In this specific case, it is evident that when criterion weights are varied, employing the DEPART method for ranking alternatives ensures the highest stability in the alternative rankings. The IRPA method ranked second in terms of stability, while the RAM method ranked third.

Thus, in this case study, although all three methods IRPA, RAM, and DEPART were validated as suitable for use, the DEPART method ensured greater stability in the alternative rankings compared to the other two methods.

Interestingly, in Case 1, the RAM method yielded the highest stability in alternative rankings, whereas in Case 2, the RAM method resulted in the lowest stability. This discrepancy indicates that a definitive conclusion regarding the comparative performance of the IRPA, RAM, and DEPART methods cannot yet be drawn. Instead, implementing at least one additional case study is imperative.

Table 13. Spearman's coefficients between weighting scenarios for case 2

Method	Scenario	Set 2	Set 3	Set 4	Set 5	Average
IRPA	Set 1	1.000	0.983	0.967	0.867	0.928
	Set 2		0.983	0.967	0.867	
	Set 3			0.933	0.850	
	Set 4				0.867	
RAM	Set 1	0.950	0.983	0.983	0.867	0.910
	Set 2		0.900	0.933	0.783	
	Set 3			0.967	0.850	
	Set 4				0.883	
DEPART	Set 1	0.983	0.950	0.967	0.917	0.937
	Set 2		0.933	0.933	0.883	
	Set 3			0.967	0.917	
	Set 4				0.917	

4.3 Case 3: Turkey Tail Mushroom extraction

For this final case, seven distinct scenarios for criterion weights were generated, as detailed in Table 14. In the first scenario (Set 1), all criteria were assigned equal weights, i.e., $1/6$ each. In each of the subsequent scenarios, one specific criterion received a weight twice that of the remaining criteria. For instance, in Set 2, criterion C1 was weighted at $2/7$, while the other five criteria each received a weight of $1/7$.

Table 14. Criterion weights for case 3 across different scenarios

Alt.	C1	C2	C3	C4	C5	C6
set 1	$1/6$	$1/6$	$1/6$	$1/6$	$1/6$	$1/6$
set 2	$2/7$	$1/7$	$1/7$	$1/7$	$1/7$	$1/7$
set 3	$1/7$	$2/7$	$1/7$	$1/7$	$1/7$	$1/7$
set 4	$1/7$	$1/7$	$2/7$	$1/7$	$1/7$	$1/7$
set 5	$1/7$	$1/7$	$1/7$	$2/7$	$1/7$	$1/7$
set 6	$1/7$	$1/7$	$1/7$	$1/7$	$2/7$	$1/7$
set 7	$1/7$	$1/7$	$1/7$	$1/7$	$1/7$	$2/7$

Figures 6 through 12 illustrate the alternative rankings generated by the different methods for each of the seven distinct weight sets.

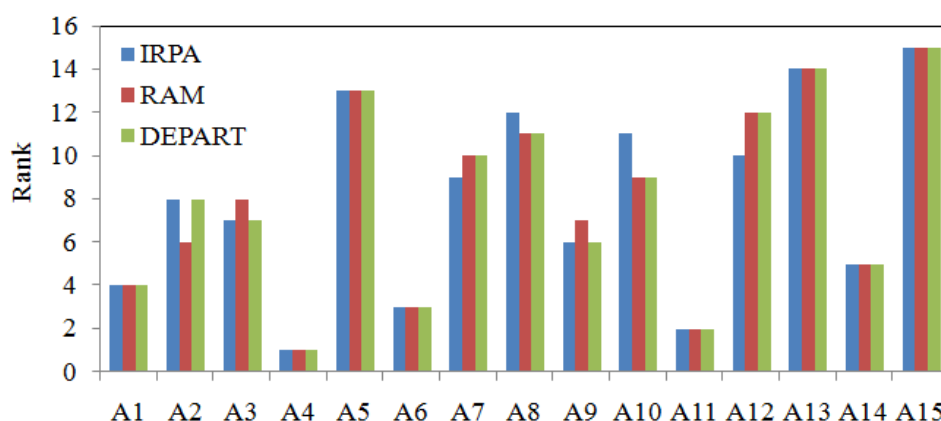


Fig. 6 Alternative rankings for case 3 using weight set 1

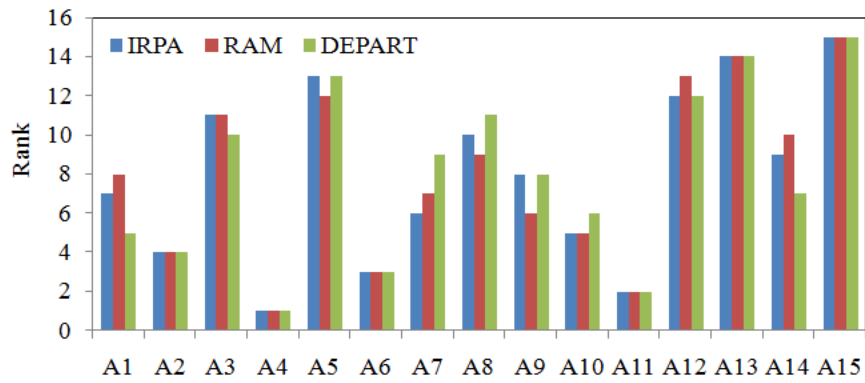


Fig. 7 Alternative rankings for case 3 using weight set 2

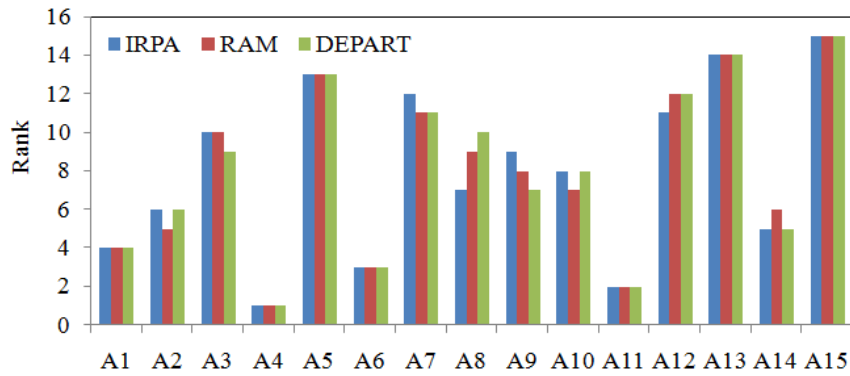


Fig. 8 Alternative rankings for case 3 using weight set 3

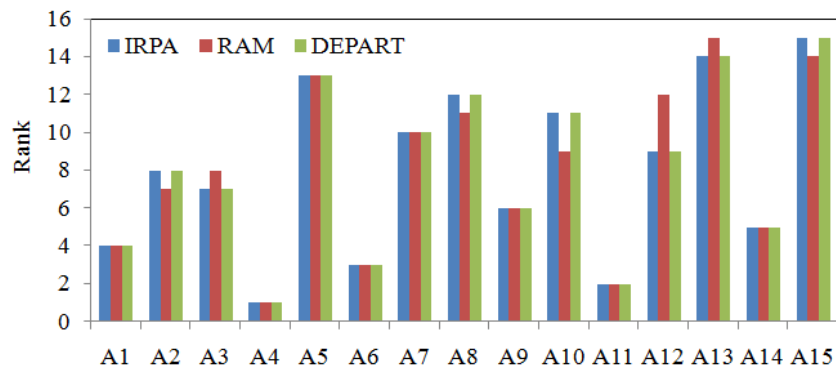


Fig. 9 Alternative rankings for case 3 using weight set 4

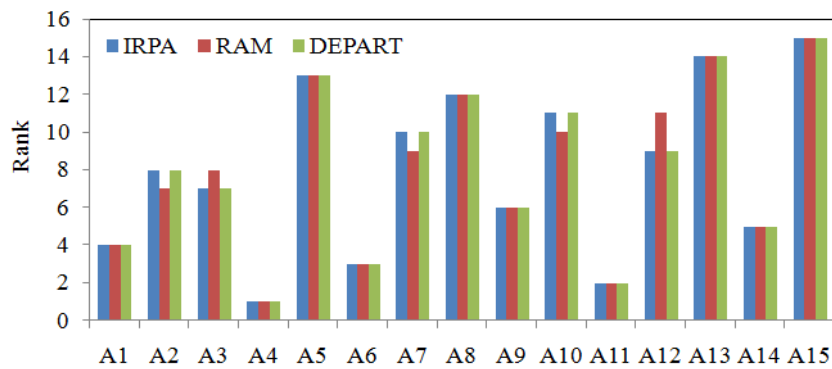


Fig. 10 Alternative rankings for case 3 using weight set 5

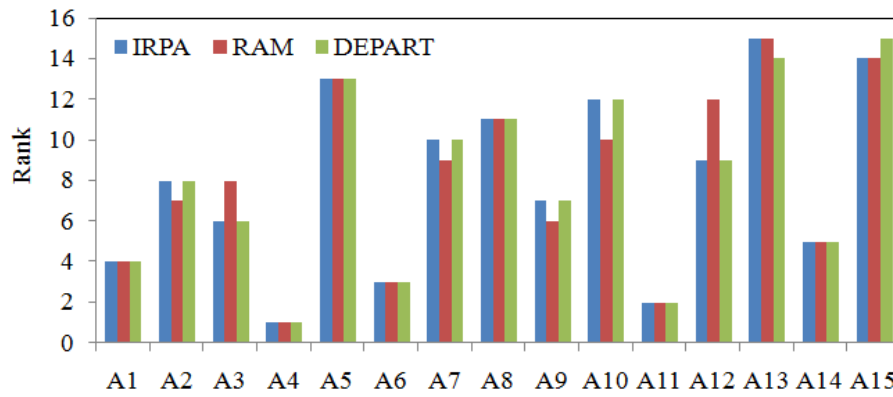


Fig. 11 Alternative rankings for case 3 using weight set 6

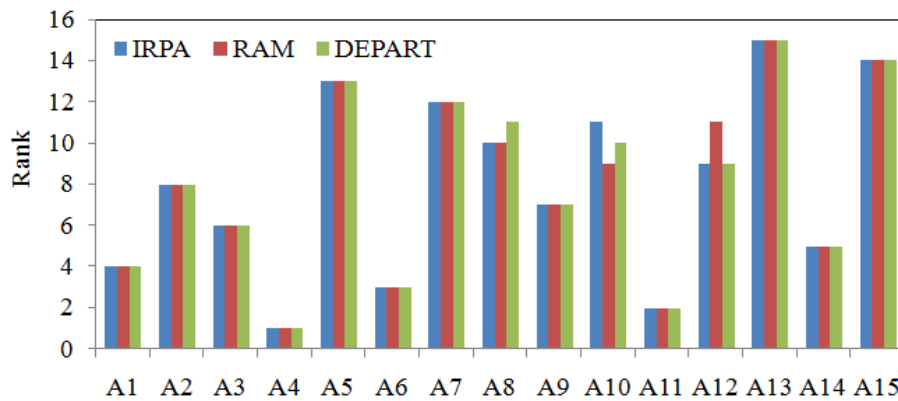


Fig. 12 Alternative rankings for case 3 using weight set 7

Upon observing Figures 7 through 12, it is evident that for each set of criterion weights, the rankings of alternatives consistently show a high degree of agreement across the IRPA, RAM, and DEPART methods. Notably, in all implemented scenarios, all three methods IRPA, RAM, and DEPART unanimously identified A4 as the optimal alternative among the 15 investigated options. This strongly suggests that all three methods are validated as suitable for use in this particular case. The Spearman's coefficients between the methods, summarized in Table 15, are also remarkably high, further reinforcing the notion of high consistency in the alternative rankings produced by the three utilized methods.

Table 15. Spearman's coefficients between methods for case 3

Scenario	Method	IRPA	RAM
Set 1	RAM	0.971	-
	DEPART	0.982	0.989
Set 2	RAM	0.982	-
	DEPART	0.964	0.939
Set 3	RAM	0.982	-
	DEPART	0.971	0.989
Set 4	RAM	0.968	-
	DEPART	1.000	0.968
Set 5	RAM	0.986	-
	DEPART	1.000	0.986
Set 6	RAM	0.964	-
	DEPART	0.996	0.961
Set 7	RAM	0.986	-
	DEPART	0.996	0.989

The Spearman's coefficients between the different weight sets for the IRPA, RAM, and DEPART methods are compiled in Tables 16, 17, and 18, respectively. According to the data in these three tables, when criterion weights vary, employing the DEPART method for ranking alternatives ensures the highest stability in alternative rankings, followed by the RAM method, and lastly the IRPA method.

Table 16. Spearman's coefficients between weighting scenarios for case 3 (IRPA method)

	set 2	set 3	set 4	set 5	set 6	set 7
set 1	0.796	0.882	0.996	0.996	0.986	0.968
set 2		0.846	0.775	0.775	0.743	0.732
set 3			0.886	0.886	0.882	0.914
set 4				1.000	0.989	0.979
set 5					0.989	0.979
set 6						0.989
Average	0.904					

Table 17. Spearman's coefficients between weighting scenarios for case 3 (RAM method)

	set 2	set 3	set 4	set 5	set 6	set 7
set 1	0.846	0.971	0.993	0.989	0.989	0.971
set 2		0.893	0.836	0.818	0.829	0.764
set 3			0.957	0.936	0.943	0.936
set 4				0.989	0.996	0.979
set 5					0.993	0.961
set 6						0.968
Average	0.931					

Table 18. Spearman's coefficients between weighting scenarios for case 3 (DEPART method)

	set 2	set 3	set 4	set 5	set 6	set 7
set 1	0.921	0.979	0.975	0.975	0.964	0.968
set 2		0.964	0.875	0.875	0.850	0.868
set 3			0.943	0.943	0.929	0.946
set 4				1.000	0.993	0.982
set 5					0.993	0.982
set 6						0.982
Average	0.948					

Therefore, in this specific case, all three methods IRPA, RAM, and DEPART were again determined to be suitable for application. However, a more detailed examination reveals that the DEPART method demonstrates a superior advantage over the other two methods.

Across all three case studies conducted, it is evident that all three methods IRPA, RAM, and DEPART are suitable for use in botanical extraction optimization. This represents the first significant discovery of this research, as, to date, none of these three methods have been previously applied to rank botanical extraction alternatives. The comparative analysis of these three methods across the three cases yielded inconsistent results concerning their stability under varying criterion weights, as summarized in Table 18. Specifically, when criterion weights changed in Case 1, the RAM method ensured the highest stability in alternative rankings, with DEPART ranking second and IRPA third. In Case 2, the DEPART method

ranked first in stability, followed by IRPA in second and RAM in third. For Case 3, the DEPART method again provided the highest stability in alternative rankings, with RAM ranking second and IRPA third.

Table 19. Summary of method rankings by stability

Method	Case 1	Case 2	Case 3	Average
IRPA	3	2	3	2.67
RAM	1	3	2	2
DEPART	2	1	1	1.33

Although no single method (IRPA, RAM, or DEPART) consistently maintained the top position for ensuring ranking stability across all three case studies, it is noteworthy that the DEPART method ranked first in two cases (Cases 2 and 3) and second in Case 1. In contrast, the IRPA method ranked third in two cases (Cases 1 and 3) and second in Case 2. The average rank value for each method across all cases was also calculated and presented in the last column of Table 19. This aggregated data further suggests that the DEPART method demonstrates overall superiority to the RAM method, with the IRPA method appearing to be the least robust among the three.

CONCLUSION

This study undertook a comparative analysis of three recently developed multi-objective optimization methods: IRPA (2025), RAM (2023), and DEPART (2025), specifically in the context of ranking botanical extraction alternatives. Two key findings emerged from this investigation:

- All three methods – IRPA, RAM, and DEPART – were validated as suitable for ranking alternatives to identify optimal solutions in botanical extraction processes.
- When the weights of the evaluation criteria varied, the DEPART method consistently ensured higher stability in the ranking of alternatives compared to the other two methods. This implies that, when choosing among these three methodologies, DEPART should be prioritized for its superior robustness in ranking consistency.

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