STU SjF

Strojnícky časopis – Journal of MECHANICAL ENGINEERING,
VOL 76 (2026), NO 2, 18 – 45

COMPARING NOVEL MULTI-OBJECTIVE OPTIMIZATION METHODOLOGIES: A CASE STUDY IN BOTANICAL EXTRACTION PROCESSES

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Abstract: *Momordica charantia (M. charantia)*, *Polyscias fruticosa (P. fruticosa)*, and *Perilla frutescens (P. frutescens)* are three plant species widely utilized as traditional medicinal remedies in Vietnam. Extracting these plants to obtain beneficial phytochemicals is of significant importance. However, the yields of these target compounds vary considerably and, at times, show contrasting trends depending on the specific extraction alternative. Consequently, selecting the optimal extraction configuration requires a simultaneous evaluation of all compound concentrations, a task recognized as a multi-criteria decision-making (MCDM) problem. This study performs a comparative evaluation of three novel MCDM methodologies, namely the Integrative Reference Point Approach (IRPA), the Root Assessment Method (RAM), and the Deviation-Based Pairwise Assessment Ratio Technique (DEPART), in the context of extracting these three botanical species. The comparison of these approaches is based on two dimensions: first, their consistency in identifying the same optimal extraction alternative; and second, the stability of the alternative rankings when the significance (or weight) of the active compounds is altered. Regarding the first dimension, all three frameworks proved appropriate for application. Concerning the second dimension, the mean Spearman's rank correlation coefficient was employed to benchmark the methods under varying criteria weights. For the Momordica charantia extraction process, this coefficient reached 0.950, 0.989, and 0.983 for the IRPA, RAM, and DEPART techniques, respectively. In the case of Polyscias fruticosa extraction, the values were 0.983 for IRPA and 1.000 for both RAM and DEPART. For the Perilla frutescens extraction process, the metrics were 0.935, 0.982, and 0.971 for IRPA, RAM, and DEPART, respectively. Thus, from this perspective, the RAM approach demonstrated superior performance over the other two competitors. Establishing the priority order for employing the IRPA, RAM, and DEPART methods constitutes the primary contribution of this research. Furthermore, for each investigated plant species, this study successfully identifies the precise extraction parameter values required to achieve the optimal solution.

Keywords: MCDM, IRPA method, RAM method, DEPART method, botanical extraction

1 Introduction

By dissolving targeted botanical compounds in a suitable solvent and separating the remaining solid debris, the essential process of extraction generates a crude extract [1]. This substance is later adapted for diverse applications in vital fields, such as therapeutic agents [2], enriched foods [3-5], cosmetics [6], and both flavoring and coloring additives [7-9].

M. charantia, *P. fruticosa*, and *P. frutescens* have long integrated into the daily lives of the Vietnamese population as familiar and ubiquitous plant species. Owing to their robust growth characteristics and abundance of valuable nutrients, these herbs have been extensively utilized in traditional folk remedies passed down through generations. Specifically, *M. charantia* is frequently incorporated into prescriptions aimed at clearing body heat, detoxifying, and managing blood glucose levels in diabetic patients. *P. Fruticosa*, traditionally referred to as the "ginseng of the poor", serves as a potent tonic to replenish vital energy and blood circulation, while simultaneously relieving arthritic and bone pain. Meanwhile, *P. frutescens* is considered

DOI: 10.2478/scjme-2026-0019, Print ISSN 0039-2472, On-line ISSN 2450-5471
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an exceptionally effective therapeutic agent for treating common colds, alleviating coughs, and managing gout symptoms. Beyond their roles in traditional medicine, this botanical trio regularly features in the daily dietary habits of Vietnamese families. Possessing outstanding attributes such as distinctive flavor profiles that stimulate the palate, low toxicity profiles, and a rich composition of vitamins, minerals, and natural antioxidants, these plants serve concurrently as wholesome food sources and proactive kitchen-based healthcare solutions. Given their diverse pharmacological and nutritional virtues, investigating the extraction of bioactive compounds from *M. charantia*, *P. fruticosa*, and *P. frutescens* is a paramount scientific endeavor. This extraction process not only facilitates the optimization and comprehensive recovery of valuable active ingredients for integration into the pharmaceutical, cosmetic, and functional food sectors but also significantly elevates the intrinsic value of Vietnam's indigenous medicinal resources.

Extraction efficiency relies on extracting the maximum amount of key active agents while leaving behind as much inert debris as possible.

The fundamental goal of any extraction framework is to maximize the recovery of target bioactive constituents while strictly limiting the concurrent dissolution of unwanted ballast substances into the menstruum. Usually, an extract's quality depends on its concentration of active constituents, which is verified either by quantifying chemical groups (such as total saponins, carotenoids, or polyphenols) or by testing biological functions (such as antimicrobial, anti-inflammatory, or antioxidant activity). As modern research continues to demonstrate the health-promoting qualities of nature-derived substances and people become increasingly concerned about artificial substitutes, the market for natural products has boomed. This shift emphasizes the importance of fine-tuning extraction methodologies to produce high-quality extracts [10].

Structurally, the ultimate attributes of an extract depend on a triad of factors: the baseline quality of the plant biomass, the selected extraction technology, and the operational variables. Consequently, the academic literature in this domain generally branches into three primary trajectories: (1) assessing how harvesting schedules, plant maturity, and post-harvest conditioning dictate the integrity of the raw material [11]; (2) scrutinizing diverse isolation platforms, ranging from conventional maceration and percolation to advanced methods such as ultrasound-assisted or supercritical fluid extraction [12-16]; and (3) examining the interplay of physical variables (such as matrix particle size, thermal conditions, solvent-to-solid proportions, duration, fluid dynamics, and initial matrix wetting) to identify ideal processing conditions [17-20]. A significant portion of the literature dedicated to this third paradigm (process optimization) relies on conducting experimental runs according to a structured statistical matrix. The empirical datasets obtained from these trials are subsequently used to construct mathematical regression models that define the relationships between independent factors and dependent responses. These derived equations then serves as the computational basis for identifying optimal processing conditions, an approach universally recognized as Response Surface Methodology (RSM) [17, 19, 21-23]. To illustrate, RSM has been effectively deployed to resolve multi-response dilemmas, such as identifying the optimal combination of alcohol concentration, temperature, and processing duration to maximize the polyphenol yields and free-radical scavenging activity from rambutan seeds and passion fruit [19]. Similarly, this methodology has been used to establish the optimal material-to-solvent ratios, agitation speeds, and processing duration required to maximize flavonoid and polyphenol yields and antioxidant activity from *Rhamnus alaternus* foliage [23]. Nonetheless, the implementation of RSM is frequently constrained by inherent limitations. First, generating mathematically reliable regression equations requires a substantial number of experiments; limited datasets inevitably reduce model reliability. Second, RSM requires every input variable and output response to be

measurable and quantifiable to establish the mathematical relationships between them. Third, it requires a sophisticated understanding of experimental design theory, posing a steep learning curve for researchers relying primarily on empirical approaches. In real-world processing environments, however, the feasible number of experiments may be severely restricted, and variables often cannot be measure numerically. Instead, they may manifest as qualitative attributes, such as extract appearance, color intensity, operational complexity, or occupational safety hazards. Moreover, industrial or practical extraction processes frequently deviate from rigid experimental matrices, being tailored instead to dynamic scenarios governed by situational constraints and immediate feasibility. Under these conditions, applying RSM for optimization becomes mathematically unviable. To address the challenge of identifying optimal operational strategies when confronted with such non-quantifiable variables, Multi-Criteria Decision Making (MCDM) frameworks offer a robust alternative. MCDM provides a mathematical toolkit for evaluating and prioritizing competing alternatives across a range of diverse criteria, facilitating the identification of the best strategies from a pool of feasible options to ultimately establishing the optimal operational approach [24].

Consequently, this analytical approach has gained substantial traction across a broad spectrum of disciplines, including economics, pedagogy, civil engineering, and food science. In the field of chemistry, particularly in extraction technologies, the literature features hundreds of publications leveraging MCDM frameworks to address complex, multi-objective optimization problems [25]. Nonetheless, the vast array of existing MCDM algorithms, each operating on fundamentally different mathematical principles, creates a major challenge when selecting the most appropriate tool for a particular case study [26, 27]. Indeed, applying different techniques to an identical dataset can generate conflicting rankings [28]. This discrepancy underscores the critical need for comparative assessments under specific operational conditions to identify the most reliable methodology [29, 30]. Furthermore, although the primary goal is to identify the single best option from a pool of alternatives, an MCDM technique is generally considered superior if its resulting rankings exhibit high stability and robustness when criteria weights are varied across different simulated scenarios [31, 32].

Three recently developed MCDM methodologies, namely IRPA (2025) [33], RAM (2023) [34], and DEPART (2025) [35], exhibit pronounced pronounced differences in their underlying problem-solving paradigms. A comprehensive breakdown of the implementation of these three techniques in optimization problems is provided in Section 2 of this article. While RAM has already been extensively applied to rank alternatives across diverse domains, such as evaluating the financial health of banks [36], flame-retardant materials [37], logistics systems [38], and agricultural sectors [39]), IRPA and DEPART remain relatively new frameworks, with very few empirical applications reported in the literature [40]. Furthermore, the conceptual mechanisms governing alternative prioritization inherently differ among these three approaches. The IRPA framework ranks alternatives based on a nonlinear comprehensive satisfaction score aggregated from both positive and negative deviation distances relative to a set of target reference points, with the alternative yielding the highest overall satisfaction score assigned the top priority [33]. The RAM approach prioritizes options using a composite index derived through a radical (root-based) function, in which a larger composite value indicates a higher rank; this specific formulation enforces a strict preference for alternatives that maintain balanced performance across benefit criteria, ensuring that cost criteria cannot excessively compensate for deficiencies in benefit metrics [34]. Concurrently, the DEPART method evaluates and ranks candidates according to a total score computed by averaging integrated pairwise deviation ratios across alternatives, with higher scores indicating greater preference [35]. The novelty of both IRPA and DEPART, coupled with the structurally distinct algorithmic

features of the three methodologies, reveals a research gap that motivates the comparative analysis conducted in the present study.

The setting chosen for this comparative exploration is the domain of botanical extraction, a topic selected for the reasons established earlier. This research is driven by two primary objectives: first, to identify the most suitable decision-making framework for optimization within the extraction processes of the three aforementioned plant species; and second, to determine the optimal extraction configuration for each specific plant. To this end, Section 2 of this paper provides a concise summary of the procedures for implementing the IRPA, RAM, and DEPART frameworks for alternative prioritization, alongside the analytical instruments used for benchmarking them. Section 3 describes the experimental extraction protocols and datasets for the plants under study, while also explaining the need to employ alternative ranking methodologies to identify the optimal extraction parameters for *M. charantia*, *P.fruticosa*, and *P. frutescens*. Section 4 presents the comparative findings of the IRPA, RAM, and DEPART techniques for each investigated problem. Finally, the overarching insights and conclusions derived from this investigation are summarized in the final section of the paper.

2 METHOD

To apply MCDM methods, 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*.

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

The IRPA method is employed to identify the optimal alternative from a set of available options through the following sequential steps [33]:

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 can be the minimum or maximum value of the criteria. The selection of rp_j values depends on the decision-maker's preference. In the subsequent applications presented in the following sections of this paper, r_{pj} is set equal to the mean value of the elements in the decision matrix [33].

$$RP = \left[rp_j\right]_{1n} = [rp_1 rp_2 \ldots rp_n] \tag{2}$$

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

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

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

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

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

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

Step 5: Label benefit criteria (larger is better) with the letter 'B' and cost criteria (smaller is better) with the letter 'C'. For the extraction processes of botanical species such as *P. fruticosa*, *M. charantia*, and *P. frutescens* aimed at producing traditional folk medicines, benefit criteria (B-type) encompass advantageous parameters, including total polyphenol content, total saponin content, and antioxidant activity, among others. Conversely, cost criteria (C-type) comprise parameters such as extraction expenditure, tannin content (which causes astringency), moisture content (which induces mold growth), residual solvents, and heavy metal residues. Subsequently, construct the Positive Difference Matrix (DF^+) using Equation (6).

$$DF^+ = [df_{ij}^+]_{mxn} = \begin{bmatrix} df_{11}^+ & \cdots & df_{11n}^+ \\ \vdots & \ddots & \vdots \\ df_{m1}^+ & \cdots & df_{mn}^+ \end{bmatrix} \quad (6)$$

In Eq. (6):

$$df_{ij}^+ = \begin{cases} \dfrac{df_{ij}}{nrp_j}, & df_{ij} > 0 \\ 0 & df_{ij} \le 0 \end{cases} \quad if \quad j \in B \quad (7)$$

$$df_{ij}^+ = \begin{cases} 0, & df_{ij} \ge 0 \\ \left|\dfrac{df_{ij}}{nrp_j}\right| & df_{ij} < 0 \end{cases} \quad if \quad j \in C \quad (8)$$

And, construct the Negative Difference Matrix (DF^-) using Equation (9).

$$DF^- = [df_{ij}^-]_{mxn} = \begin{bmatrix} df_{11}^- & \cdots & df_{11n}^- \\ \vdots & \ddots & \vdots \\ df_{m1}^- & \cdots & df_{mn}^- \end{bmatrix} \quad (9)$$

In Eq. (9):

$$df_{ij}^- = \begin{cases} \left|\dfrac{df_{ij}}{nrp_j}\right|, & df_{ij} < 0 \\ 0 & df_{ij} \ge 0 \end{cases} \quad if \quad j \in B \quad (10)$$

$$df_{ij}^- = \begin{cases} 0, & df_{ij} \le 0 \\ \dfrac{df_{ij}}{nrp_j} & df_{ij} > 0 \end{cases} \quad if \quad j \in C \quad (11)$$

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 (12) and (13), respectively.

$$\begin{cases} WDF^{+} = \left[wdf_{ij}^{+}\right]_{mxn} = \begin{bmatrix} wdf_{11}^{+} & \cdots & wdf_{11n}^{+} \\ \vdots & \ddots & \vdots \\ wdf_{m1}^{+} & \cdots & wdf_{mn}^{+} \end{bmatrix} \\ wdf_{ij}^{+} = \left(w_j \times DF^{+}\right)^{(1-w_j)} \end{cases} \tag{12}$$

$$\begin{cases} WDF^{-} = \left[wdf_{ij}^{-}\right]_{mxn} = \begin{bmatrix} wdf_{11}^{-} & \cdots & wdf_{11n}^{-} \\ \vdots & \ddots & \vdots \\ wdf_{m1}^{-} & \cdots & wdf_{mn}^{-} \end{bmatrix} \\ wdf_{ij}^{-} = \left(w_j \times DF^{-}\right)^{(1-w_j)} \end{cases} \tag{13}$$

Step 7: Compute the Positive Distance Matrix (PD) and Negative Distance Matrix (ND) based on Equations (14) and (15), respectively.

$$\begin{cases} PD = [pd_i]_{m1} = \begin{bmatrix} pd_1 \\ pd_2 \\ \vdots \\ pd_m \end{bmatrix} \\ pd_i = \sum_{j=1}^{n} wdf_{ij}^{+} \end{cases} \tag{14}$$

$$\begin{cases} ND = [nd_i]_{m1} = \begin{bmatrix} nd_1 \\ nd_2 \\ \vdots \\ nd_m \end{bmatrix} \\ nd_i = \sum_{j=1}^{n} wdf_{ij}^{-} \end{cases} \tag{15}$$

$$\begin{cases} RV = [rv_i]_{m1} = \begin{bmatrix} rv_1 \\ rv_2 \\ \vdots \\ rv_m \end{bmatrix} \\ rv_i = \dfrac{pd_i - nd_i}{2} \end{cases} \tag{16}$$

From a practical decision-making perspective in botanical extraction, the Positive Difference Matrix and Negative Difference Matrix have distinct physical and economic implications for actual extraction yields. The Positive Difference Matrix represents scenarios in which an alternative achieves superior performance relative to the average reference point; elevated values within this matrix signify a high capacity for bioactive compound accumulation and cost optimization through the efficient utilization of raw materials. Conversely, the Negative Difference Matrix captures the performance deficits of the alternatives compared with the benchmark level. For operations managers, a high magnitude of negative values serves as a critical risk indicator, signaling suboptimal extraction conditions, solvent wastage, or inadequate active ingredient recovery. Distinguishing between these two matrices enables decision-makers to balance profitability maximization (positive differences) against the mitigation of low-efficiency operational risks (negative differences), thereby ensuring that the extraction process achieves optimal economic viability.

The RAM method is applied to determine the optimal alternative from a set of available options through the following structured steps [34]:

Step 1: Normalize the raw data using Equation (17).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{17}$$

Step 2: Calculate the weighted normalized values for each criterion as shown in Equation (18).

$$y_{ij} = w_j \cdot r_{ij} \tag{18}$$

Step 3: Compute the total weighted normalized scores for each alternative using Equations (19) and (20).

Where y_{+ij} is the weighted normalized value at the i^{th} alternative of the j^{th} benefit (the-larger-the-better) criterion, and y_{-ij} is the weighted normalized value at the i^{th} alternative of the j^{th} cost (the-smaller-the-better) criterion.

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad if \quad j \in B \tag{19}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad if \quad j \in C \tag{20}$$

Step 4: Calculate the final score for each alternative according to Equation (21). The alternative possessing the highest score is identified as the optimal solution, and conversely.

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \tag{21}$$

The DEPART method is applied to identify the optimal alternative from a given set of options by following this sequence of steps [35]:

Step 1: Normalize the raw data using Equation (22).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \left(x_{ij}\right)^2}} \tag{22}$$

Step 2: Calculate the positive and negative deviations for each criterion using Equations (23) and (24), respectively.

$$dv_{ij}^{+} = \left| x'_{ij} - t_j^{+} \right| \tag{23}$$

$$dv_{ij}^{-} = \left| x'_{ij} - t_j^{-} \right| \tag{24}$$

Where

$$t_j^{+} = \begin{cases} max_i x'_{ij} & if \quad j \in B \\ min_i x'_{ij} & if \quad j \in C \end{cases} \tag{25}$$

$$t_j^{-} = \begin{cases} min_i x'_{ij} & if \quad j \in B \\ max_i x'_{ij} & if \quad j \in C \end{cases} \tag{26}$$

Step 3: Construct the pairwise positive ratio matrix (E^{+}) and the pairwise negative ratio matrix (E^{-}) using Equations (27) and (28), respectively.

$$e_{kl}^{+} = \sum_{j=1}^{n} w_j \left(\frac{dv_{lj}^{+} + md^{+}}{dv_{kj}^{+} + md^{+}} \right) \quad k, l \in \{1,2, \ldots, m\} \tag{27}$$

$$e_{kl}^{-} = \sum_{j=1}^{n} w_j \left(\frac{dv_{kj}^{-} + md^{-}}{dv_{lj}^{-} + md^{-}} \right) \quad k, l \in \{1,2, \ldots., m\} \tag{28}$$

Where

$$md^{+} = max\left(dv_{ij}^{+}\right) \tag{29}$$

$$md^{-} = max\left(dv_{ij}^{-}\right) \tag{30}$$

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

Step 4: Aggregate the E^+ and E^- matrices (determined in Step 3) using Equation (31) and a user-defined coefficient η. The coefficient η adjusts the level of emphasis on positive or negative deviation ratios, with its value ranging from 0 to 1. In the applications presented in this study, η is set to 0.5 to ensure structural balance and neutrality, thereby assigning equal weight to both the positive deviation ratio (E^+) and the negative deviation ratio (E^-). This configuration enables an objective evaluation within the model, simulatneously recognizing efforts to maximize the distance from the anti-ideal point and promoting convergence toward the ideal solution, without introducing subjective bias. Furthermore, this specific value is consistent with the configuration originally implemented in the literature proposing this methodology [34].

$$e_{kl} = \eta e_{kl}^{+} + (1 - \eta) e_{kl}^{-}, \quad k, l \in \{1,2, \ldots., m\} \tag{31}$$

Step 5: Compute the total deviation ratio for each alternative using Equation (32).

$$e_l^s = \sum_{k=1}^{m} e_{kl}, \quad l \in \{1,2, \ldots., m\} \tag{32}$$

Step 6: Calculate the score for each alternative using Equation (33). The alternative with the highest score is ranked first, while the alternative with the lowest score is ranked m^{th}.

$$S_i = \frac{1}{n} \left(\sum_{l=1}^{n} \frac{e_{il}}{e_l^s} \right) \tag{33}$$

Based on the procedural steps of the IRPA, RAM, and DEPART methodologies detailed above, Table 1 synthesizes and compares the computational complexity of these three approaches.

Table 1. Comparison of computational complexity

Method	Main Computational Steps	Computational Complexity	Overall Complexity
IRPA	Step 1: Normalize the decision matrix	Bilinear time	Bilinear time
	Step 2: Calculate the deviation matrix from reference points	Bilinear time	
	Step 3: Calculate the non-linear satisfaction function for alternatives	Bilinear time	
	Step 4: Compute the integrated utility scores	Bilinear time	
RAM	Step 1: Normalize the decision matrix	Bilinear time	Bilinear time
	Step 2: Calculate the weighted sums for benefit and cost criteria	Bilinear time	

	Step 3: Determine the radical overall index (RI_i)	Linear time in terms of alternatives	
DEPART	Step 1: Normalize the decision matrix	Bilinear time	Quadratic time in alternatives and linear in criteria
	Step 2: Determine the positive and negative deviation matrices	Bilinear time	
	Step 3: Construct the pairwise deviation ratio matrix between alternatives	Quadratic time in alternatives and linear in criteria	
	Step 4: Compute the final evaluation scores (Si)	Quadratic time in terms of alternatives	
Note: *"Linear"* means proportional to the number of alternatives or criteria; *"Bilinear"* means proportional to the product of both; *"Quadratic"* means proportional to the square of the number of alternatives.			

As shown in Table 1, both IRPA and RAM exhibit high computational efficiency, operating within a bilinear time complexity relative to the seze of the decision matrix. Conversely, the DEPART framework requires a higher overarall computational workload due to its inherent pairwise comparison mechanism, which results in a quadratic execution time with respect to the number of alternatives. Nevertheless, considering the scale of practical empirical applications, all three methodologies are computationally lightweight and can be readily executed on standard computing systems.

To facilitate a rigorous comparative analysis of the IRPA, RAM, and DEPART frameworks, it is imperative to evaluate the stability of the alternative rankings generated by these techniques under variations in criteria weights [41, 42]. Ranking stability can be quantified using metrics such as Spearman's rank correlation coefficient (S), the Rank Similarity (RS) coefficient, or the Weighted Spearman's Rank Correlation (WSRE) coefficient [43]. While the RS and WSRE formulations inherently assign greater importance to top-ranked alternatives while reducing the emphasis on lower-ranked alternatives, the standard Spearman coefficient treats all rank positions equally [44, 45]. Consequently, the present study employs the Spearman coefficient calculating using Equation (34), where D_i denotes the rank difference for the i^{th} alternative resulting from changes in the criteria weights [46].

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2-1)} \tag{34}$$

When tied ranks occur among alternatives under the same criteria weight configuration, the standard Spearman correlation formulation must be adjusted to maintain mathematical rigor. Specifically, these tied observations are assigned midrank (the average of the rank positions they would otherwise occupy). To account for these ties accurately, the corrected Spearman's rank correlation coefficient can be calculated using the methodology described in the literature [47].

3 CASE STUDIES FOR COMPARING IRPA, RAM, AND DEPART METHODS

3.1 Plant Extraction Experiment

Plant extracts, or crude extracts, are the end products obtained from various botanical extraction processes. They serve as a rich reservoir of natural bioactive agents containing secondary metabolites (such as polyphenols, glycosides, alkaloids, terpenoids, sterols, and saponins) with significant potential for applications in pharmaceuticals, cosmetics, and food technology. Among these chemical classes, the primary biological properties of interest include antioxidant, antimicrobial, anticancer, and antiviral activities.

Extraction is a process that employs solvents to isolate solutes from plant tissues through dissolution and diffusion mechanisms. Beyond the extraction yield, the profile of bioactive compounds in the resulting extract is a critical determinant of final product quality. The choice of extraction methodology and its operating parameters are pivotal factors governing the success of the isolation process [48, 49]. Ultrasound-assisted extraction (UAE) is a modern technique in which the process is driven by high-frequency acoustic waves (20–100 kHz). This acoustic energy enhances solvent penetration and disrupts plant cell walls, thereby facilitating mass transfer [50, 51].

A myriad of parameters influence the solid-solvent interactions during extraction, including ultrasonic power, solvent type, temperature, duration, and the solid-to-solvent ratio [52]. Among these, solvent selection, temperature, and extraction time typically receive the most attention. When selecting a solvent, careful consideration must be given to how its polarity, viscosity, and surface tension interact with the target compound classes in the matrix. Elevated temperatures accelerate compound diffusion, alter the surface tension and viscosity of the solvent, and increase solute solubility; however, they can also adversely affect thermally sensitive constituents. Conversely, a short extraction period may fail to fully recover chemical constituents from the matrix, whereas prolonged exposure can induce oxidation and degradation of promising compounds, particularly under high-temperature, high-pressure, ultrasonic, or microwave-assisted conditions. Consequently, systematically investigating and optimizing these variables during experimental design is imperative to maximize extraction efficiency while preserving the stability and potency of the target compounds [53–56].

In this report, extraction experiments were performed on three botanical matrices: *M. charantia*, *P. fruticosa*, and *P.a frutescens*. *M. charantia* is a widely distributed species in tropical regions. Its fruits are consumed as a daily vegetable and have long been used in traditional medicine to support diabetes management. The primary chemical profile of its fruit comprises phenolic compounds (e.g., catechin, epicatechin), carotenoids (e.g., lutein, α-and β-carotene), saponins (triterpenoid glycosides), phytosterols (e.g., decortinone, clerosterol), and alkaloids. Pharmacological investigations indicate that this species exhibits prominent antioxidant, antidiabetic, antimicrobial, and anthelmintic activities [57, 58]. Similarly, *P. fruticosa* is employed as a medicinal plant with diverse pharmacological benefits, including antidepressant, antistress, memory-enhancing, antioxidant, hypoglycemic, hepatoprotective, hypolipidemic, antifungal, and antibacterial properties. Furthermore, *P. fruticosa* leaves are rich in bioactive agents such as phenolics, flavonoids, and saponins, which contribute to these multifaceted biological activities [59, 60]. *P. frutescens*,which belongs to the Lamiaceae family, is an annual herb extensively cultivated in tropical countries, including Vietnam, where it serves as both a culinary spice and a medicinal herb. Comprehensive phytochemical studies have identified key bioactive constituents of *P. frutescens*, including volatile oils (perillaldehyde, limonene), flavonoids (apigenin, luteolin), phenolic acids (rosmarinic acid, caffeic acid), and triterpenoids [61].

For the extraction of these species, three widely recognized input parameters influencing the process were selected for evaluation: temperature, extraction time, and the solvent system, which employed a versatile and safe green solvent system of ethanol–water at varying concentrations. The corresponding output responses used to assess extract quality included bioactive compound content and biological activity. The specific quantitative targets evaluated in this study were selected based on the known phytochemical profiles of each species: *total polyphenol content* (TPC) and *total saponin content* (TSC) were monitored for *M. charantia* and *P. fruticosa*, whereas TPC and *total flavonoid content* (TFC) were determined for *P. frutescens*. Regarding biological efficacy, the antioxidant activity of the extracts was selected for characterization across all species due to its widespread occurrence and extensively studied

role in mitigating oxidative stress, a fundamental driver in chronic pathologies such as cardiovascular disorders, neurodegenerative diseases, and malignancies.

The Taguchi orthogonal array was selected for *M. charantia* and *P. fruticosa*. The extraction parameters were established as follows:

Solvent: Ethanol–water mixtures at ratios of 50:50, 70:30, and 96:4 (v/v), corresponding to ethanol concentrations of 50°, 70°, and 96°, respectively.

Extraction temperature: Evaluated at three levels - 40, 50, and 60 °C.

Extraction time: Investigated across three durations - 15, 20, and 25 minutes.

For *P. frutescens*, the Box-Behnken design (BBD) was adopted. The corresponding extraction parameters were set as follows:

Solvent: Ethanol–water mixtures at ratios of 30:70, 50:50, and 70:30 (v/v), corresponding to ethanol concentrations of 30°, 50°, and 70°, respectively.

Extraction temperature: Evaluated at three levels - 40, 55, and 70 °C.

Extraction time: Investigated across three durations - 30, 60, and 90 minutes.



a) *b)* *c)*

a) Genesys 10S UV-Vis spectrophotometer; b) Elmasonic S 300 H ultrasonic cleaner; c) Hermle Z 206 A centrifuge

Fig. 1 Experimental instrumentation

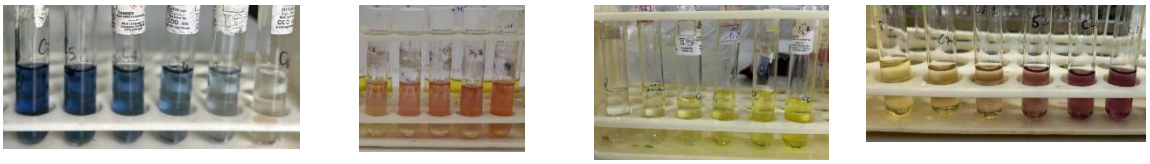
The diffences in the input parameter ranges among the experiments were governed by the distinct characteristics of the raw materials utilized. The matrices for *M. charantia* and *P. fruticosa* consisted exclusively of fruits or leaves, ensuring a homogenous raw material composition. In contrast, the entire above-ground biomass of *P. frutescens* (including stems, leaves, twigs, flowers, fruits, and seeds) was used. Because the extraction kinetics of constituents from leaves differ substantially from those of woody stems and twigs, the processing parameters were adapted to ensure exhaustive extraction of the analytical samples. The specific boundary values for the input variables were determined based on preliminary screening assays, tailored to target compounds ranging from moderately polar to highly polar.

The instrumentation used for sample processing included an Elmasonic S 300 H ultrasonic bath and a Hermle Z 206 A centrifuge. Quantitative analysis of the bioactive components and antioxidant assays were performed using a Genesys 10S UV-Vis spectrophotometer. Figure 1 illustrates the laboratory equipment utilized in these experiments.

Botanical samples were collected from the botanical garden, thoroughly washed with water, and dried in an oven at 50 °C until a constant weight was achieved (maintaining a moisture content below 10%). Subsequently, the dried materials were pulverized into a fine powder. These medicinal plant powders were kept in hermetically sealed bags and stored in a cool, dry environment for subsequent experimental trials. In each 50 mL Falcon tube, 2 g of dried powdered plant material was mixed with 40 mL of the corresponding solvent. The tubes containing the extraction mixtures were then subjected to ultrasound-assisted extraction under the specific conditions difined by the experimental design matrix. Following extraction, the mixtures were centrifuged at 6,000 rpm for 15 min and subsequently filtered to obtain the clear

extracts. All resulting extracts were refrigerated prior to the determination of their phytochemical contents and antioxidant capacity.

TPC was quantified using the Folin-Ciocalteu method, employing gallic acid as the reference standard. The results were were expressed as milligrams of gallic acid equivalents per gram of dry weight (mg GAE/g DW) [62]. TFC was determined through the aluminium chloride colorimetric assay [78], using quercetin as the reference standard. The results were expressed as milligrams of quercetin equivalents per gram of dry weight (mg QE/g DW). TSC in the extracts was quantified according to the protocol described by Hadidi et al. [63], using oleanolic acid as the reference standard. The TSC results were expressed as milligrams of oleanolic acid equivalents per gram of dry weight (mg OAE/g DW). Meanwhile, the antioxidant activity was evaluated via the DPPH (2,2-diphenyl-1-picrylhydrazyl) radical scavenging assay following the procedure reported by Gulcin et al. [64], with Trolox as the reference standard. These outcomes were expressed as milligrams of Trolox equivalents per gram of dry weight (mg TE/g DW). Every experimental measurement was performed in triplicate. The calibration curves used to quantify these bioactive compounds and antioxidant activity are illustrated in Figure 2.



a) *b)* *c)* *d)*

a) Calibration curve for TPC determination; b) Calibration curve for TSC determination; c) Calibration curve for TFC determination; d) Calibration curve for DPPH radical scavenging antioxidant activity

Fig. 2 Calibration curves for the quantification of bioactive constituents and antioxidant activity

3.2 Case 1: Extraction of *M. charantia*

Table 2 encapsulates the nine extraction configurations investigated for *M. charantia*, which are designated as A1 through A9, respectively.

Table 2. Extraction alternatives for *M. charantia*

Alt.	Temperature (oC)	Duration (min)	Concentration (%)	C1	C2	C3
				Total polyphenol content (mg GAE/g CK)	Total saponin content (mg OAE/g CK)	Antioxidant activity (mmol TE/g CK)
A1	40	15	50	74.17	6.916	2.281
A2	40	20	70	102	5.452	2.368
A3	40	25	96	115.94	3.557	2.367
A4	50	15	70	89.303	8.811	2.412
A5	50	20	96	108.7	8.261	2.098
A6	50	25	50	97.47	4.539	1.448
A7	60	15	96	73.037	9.288	1.876
A8	60	20	50	82.703	6.099	2.102
A9	60	25	70	97.37	5.543	1.543

As shown in Table 2, C1 attains its maximum value of 115.94 mg GAE/g DW under alternative A3, C2 reaches its maximum value of 9.288 under alternative A7, whereas C3 achieves its highest value of 2.412 under alternative A4. Consequently, it is evident that no

single alternative achieves the maximum values for all three criteria simultaneously. Identifying the optimal configuration among the nine investigated alternatives therefore requires a simultaneous evaluation of the trade-offs among all three criteria, a task defined as an MCDM problem. A comparative assessment of the three methodologies, IRPA, RAM, and DEPART, will be systematically conducted to address this optimization problem.

3.3 Case 2: Extraction of *P. fruticosa*

This scenario concerns the dataset comprising nine extraction configurations for the *P.s fruticosa* species, sequentially labeled from A1 through A9 and compiled in Table 3.

Table 3. Extraction alternatives for *Polyscias fruticosa*

Alt.	Temperature (oC)	Duration (min)	Concentration (%)	C1	C2	C3
				Total polyphenol content (mg GAE/g CK)	Total saponin content (mg OAE/g CK)	Antioxidant activity (mmol TE/g CK)
A1	40	15	50	99.003	9.617	2.214
A2	40	20	70	79.537	6.570	2.355
A3	40	25	96	71.870	5.294	2.438
A4	50	15	70	88.503	8.176	2.253
A5	50	20	96	85.403	8.743	2.370
A6	50	25	50	79.237	4.840	2.180
A7	60	15	96	86.303	8.250	2.287
A8	60	20	50	80.370	7.983	2.347
A9	60	25	70	59.770	5.231	2.161

According to the empirical data presented in Table 2, C1 reaches its maximum value of 99.003 (µg/g DW) under alternative A1, C2 similarly reaches its maximun value of 9.617 (µg/g DW) under the same alternative (A1), whereas C3 attains its highest value of 2.438 (mg GAE/g DW) under alternative A3. Accordingly, identifying the optimal solution from the investigated set of alternatives requires the application of MCDM methodologies. Consequently, the IRPA, RAM, and DEPART frameworks will once again be employed to address this decision-making task.

3.4 Case 3: Extraction of *P. frutescens*

This case study involves the dataset of fifteen extraction configurations for *P. frutescens*, designated A1 to A15 and summarized in Table 4. Based on the data presented in Table 3, the highest value for C1, quantified at 77.252 (µg/g DW), is associated with alternative A8; C2 reaches its maximum value of 22.4855 (µg/g DW) under alternative A15; whereas C3 attains its highest value of 0.083 (mg GAE/g DW) under alternative A3. Consequently, identifying the most favorable configuration among the investigated alternatives requires the application of MCDM techniques. To address this optimization problem, the IRPA, RAM, and DEPART approaches will be utilized once more time.

To ensure the objectivity of the comparative results obtained using the IRPA, RAM, and DEPART methodologies, it is essential to benchmark these frameworks under different criteria weight configurations. Rather than employing large-scale random simulation models such as Monte Carlo simulations, which require extensive iterative datasets and substantial computational resources, we constructed targeted, deterministic weight scenarios as presented in Table 5.

Table 4. Extraction alternatives for *P. frutescens*

Alt.	Temperature (oC)	Duration (min)	Concentration (%)	C1	C2	C3
				Total polyphenols content (TPC)	Total flavonoids content (TFC)	Antioxidant activity
A1	70	50	30	76.1463	14.6436	0.0756
A2	40	30	60	62.4878	11.5884	0.0765
A3	40	70	60	37.8049	7.4131	0.0830
A4	55	70	90	61.2520	10.0665	0.0808
A5	55	50	60	59.9512	11.6741	0.0793
A6	55	30	90	76.1138	14.4570	0.0783
A7	55	50	60	71.3171	15.3179	0.0791
A8	70	30	60	77.2520	13.0874	0.0770
A9	55	70	30	52.5366	9.7389	0.0810
A10	70	70	60	69.7724	14.6570	0.0805
A11	55	30	30	65.7724	9.9484	0.0769
A12	40	50	90	55.4797	9.8760	0.0808
A13	55	50	60	63.3171	13.7103	0.0795
A14	40	50	30	56.2276	7.9979	0.0777
A15	70	50	90	71.7724	22.4855	0.0813

Table 5. Criteria weight configurations across different scenarios

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

Accordingly, four distinct weight profiles were established. In the first profile (Set 1), an equal weight are assigned to all criteria, with each receiving a weight of 1/3. In each of the remaining configurations, one criterion is systematically prioritized by assigning it a weight twice as large as that of each of the other two criteria. For instance, in the second profile (Set 2), criterion C1 is assigned a weight of 1/2, while each of the remaining two criteria receives a weight of 1/4. Since all three case studies involve exactly three evaluation criteria, the weight adjustments in all cases strictly follow these four predefined scenarios.

4 RESULTS AND DISCUSSION

4.1 Case 1: Extraction of *M.charantia*

The decision matrix for this case study consists of the data presented in Table 1, which lists the different extraction alternatives.

The IRPA method was applied to rank the alternatives using Equations (2) through (16). The RAM method was used to rank the alternatives using Equations (17) through (21), while the DEPART method was employed for ranking using Equations (22) through (33). Tables 6-9 summarize the rankings of the alternatives obtained using the IRPA, RAM, and DEPART methods under the four distinct weight sets.

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

Alt.	IRPA	RAM	DEPART
A1	5	5	6
A2	3	4	4
A3	4	6	5
A4	2	1	1
A5	1	2	2
A6	9	9	9
A7	6	3	3
A8	7	7	7
A9	8	8	8

Table 7. Alternative rankings for case 1 using weight set 2

Alt.	IRPA	RAM	DEPART
A1	8	6	6
A2	3	4	4
A3	2	3	3
A4	4	2	2
A5	1	1	1
A6	6	9	9
A7	7	5	5
A8	9	7	8
A9	5	8	7

Based on the empirical data presented in Tables 6-9, the rankings of the alternatives for *M. charantia* extraction do not fully converge across the three distinct methods (IRPA, RAM, and DEPART) under any of the criteria weight scenarios. Furthermore, even within a single decision-making framework, ralative rankings of the alternatives vary slightly across the different criteria weight configurations. This observation is perfectly aligned with findings reported in the existing MCDM literature [65, 66]. Nevertheless, the rank differences among the candidate alternatives remain relatively small, regardless of the MCDM method or weight profile applied.

For example, under scenario S1 (Table 6), alternative A4 ranks first using both RAM and DEPART frameworks but second using IRPA method. Conversely, alternative A5 ranks first rank using the IRPA method but second using both RAM and DEPART. Similarly, alternative A2 is ranked first by IRPA but fourth using RAM and DEPART. Notably, three alternatives (A8, A9, and A6) consistently occupy the 7th, 8th, and 9th positions, respectively, across all three frameworks. Under scenario S2 (Table 7), alternative A5 consistently ranks first across the IRPA, RAM, and DEPART frameworks. Meanwhile, alternative A3 ranks second using IRPA but fourth using both RAM and DEPART, while alternative A1 ranks 6th rank using RAM and DEPART but 8th using IRPA.

An examination of scenarios S3 (Table 8) and S4 (Table 9) further confirms that the alternative rankings remain highly stable across the different configurations. It is also noteworthy that across all four assessment matrices (Tables 6-9), A4 and A5 frequently occupy the top two positions, whereas A6, A8, and A9 consistently occupy the bottom three positions. These findings fundamentally indicate that the IRPA, RAM, and DEPART methodologies are all highly appropriate for identifying favorable extraction conditions for *M. charantia* extraction. Among the nine candidates investigated, A4 and A5 emerge as the recommended extraction alternatives. Specifically, to maximize total polyphenol content, total saponin

content, and antioxidant activity during *M. charantia* extraction, the three process parameters, temperature, time, and solvent concentration, should be set to either 50°C, 20 minutes, and 96%, or 50°C, 25 minutes, and 50%, respectively.

Table 8. Alternative rankings for case 1 using weight set 3

Alt.	IRPA	RAM	DEPART
A1	4	4	4
A2	5	5	5
A3	7	8	7
A4	1	1	1
A5	2	2	2
A6	9	9	9
A7	3	3	3
A8	6	6	6
A9	8	7	8

Table 9. Alternative rankings for case 1 using weight set 4

Alt.	IRPA	RAM	DEPART
A1	5	5	6
A2	3	3	3
A3	4	4	4
A4	1	1	1
A5	2	2	2
A6	9	9	9
A7	7	6	5
A8	6	7	7
A9	8	8	8

To provide a more robust and objective comparison of the IRPA, RAM, and DEPART techniques, the ranking stability of the alternatives generated by these three frameworks was assessed across the different weight profiles. Using the data presented in Tables 6-9, Spearman's rank correlation coefficient between the pairs of MCDM methods were calculated using Equation (34), and the results are summarized in Table 10. Similarly, the Spearman's rank correlation coefficients measuring the consistency of the rankings obtained by each individual MCDM method across the different weighting scenarios were alculated and are presented in Table 11.

Table 10. 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	0.867	0.883	0.700	0.767	0.983	1.000	0.983	0.950
RAM		0.983		0.983		0.983		0.983

According to the empirical data in Table 10, the Spearman correlation coefficients between pair of methodologies are relatively high, with the minimum value of 0.700 observed between the IRPA and RAM frameworks under the Set 2 weight scenario. This results indicates a substantial degree of agreemen among the rankings generated by the three frameworks. This high consistency is further supported by the ranking matrices in Tables 6-9 and the preceding analysis. Regarding ranking stability under variations in criteria weights (Table 11), the mean Spearman correlation coefficient is highest for the RAM and lowest for the IRPA framework.

Table 11. 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	0.925	0.992	1.000	0.992	0.992	1.000	1.000	0.967	1.000
Set 2		0.867	0.925		0.967	0.992		0.967	1.000
Set 3			0.992			0.992			0.967
Average	0.950			0.989			0.983		

This behavior may be related to mathematical formulations of the methods. When the criteria weights change across the four distinct scenarios (Set 1 to Set 4), the RAM methodology exhibits greater ranking stability, as indicated by its higher mean Spearman correlation co efficiency. The linear sum normalization technique implemented in Equation (13) preserves the original proportional relationships among the alternatives. Consequently, when the weight configurations change substantially, such as when polyphenol content (C1) is emphasized in Set 2 or antioxidant activity (C3) is given greater weight in Set 4, the root-based formulation of RAM in Equation (17) may moderate fluctuations in the composite utility scores. This effect may help preserve the relatives positions of the alternatives. rmly maintain their relative positions. These findings indicate that, although IRPA, RAM, and DEPART all demonstrate a high degree of ranking consistency, a more detailed examination of sensitivity to criteria weights identifies RAM as the most stable of the three methods in this case study. Nevertheless, because this conclusion is based on a single case study, further evaluation using additional empirical cases is necessary to assess the generalizability of these findings.

4.2 Case 2: Extraction of *P. fruticosa*

Using the dataset for *P. fruticosa* extraction configurations presented in Table 2, the rankings of the extraction alternatives were determined using the IRPA, RAM, and DEPART methods under four distinct criteria weight scenarios. The ranking results are illustrated in Figures 3-6.



Fig. 3 Alternative rankings for case 2 using weight set 1

An examination of these figures reveals a high degree of agreement among the rankings generated by the three methods in this case study. For example, as shown in Figure 3, all three methods consistently rank alternative A1 first, A2 6th, A3 7th, A5 second, A6 8th, A8 5th, and A9 9th. The remaining two alternatives, A4 and A7, also exhibit a high degree of ranking stability. Specifically, A4 ranks 4th using both IRPA and DEPART but third using RAM. Conversely, A7 ranks third using IRPA and DEPART but 4th using RAM. Similarly, Figure 4 shows that alternatives A1, A2, A4, A5, A7, A8, and A9 occupy identical positions across all three methods. Meanwhile, alternative A3 ranks 8th using both IRPA and RAM but 7th using DEPART. Alternative A6 ranks 8th using DEPART, whereas the other two methods place it 7th. Notably, in Figure 5, the rankings of all alternatives are identical across the three methods.

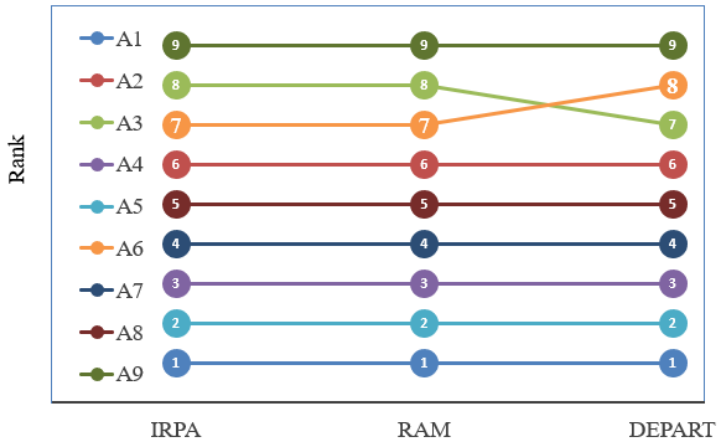


Fig. 4 Alternative rankings for case 2 using weight set 2

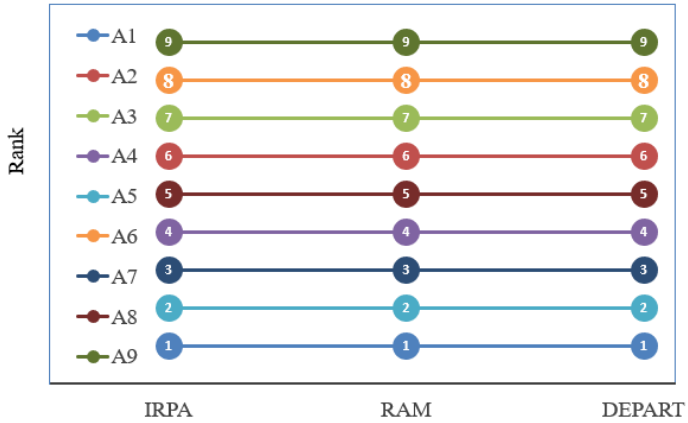


Fig. 5 Alternative rankings for case 2 using weight set 3

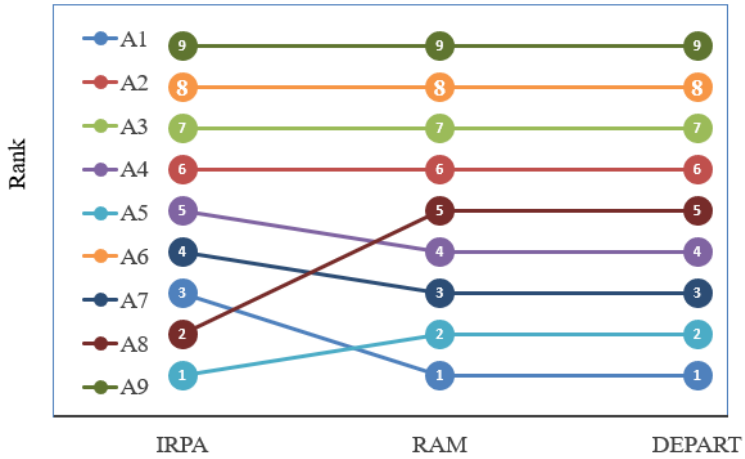


Fig. 6 Alternative rankings for case 2 using weight set 4

Figure 6 likewise demonstrates a high degree of agreement among the rankings generated by the different approaches.

Importantly, across all four figures (Figures 3-6), alternative A1 is identified as the optimal alternative in nearly every scenario. This suggests that, for *P. fruticosa* extraction, the three process parameters, temperature, time, and solvent concentration, should be set to 40°C, 15 min, and 50%, respectively, to maximize total polyphenol content, total saponin content, and antioxidant activity. Conversely, alternative A9 is consistently identified as the least preferred option across all evaluations. These findings indicate that the IRPA, RAM, and DEPART

methods are all suitable for identifying optimal extraction conditions for *P. fruticosa*. Among the nine configurations investigated, A1 is the most recommended alternative, whereas A9 is the least preferred. To provide a more robust and objective basis for comparing the three methods, it is necessary to quantify the stability of the alternative rankings under different criteria weight scenarios.

Accordingly, the Spearman correlation coefficients between the methods were calculated, and the results are presented in Table 12. The results indicate that the Spearman correlation coefficients are high for all pairs of methods, with a minimum value of 0.867. This finding further supports the conclusion that the rankings generated by IRPA, RAM, and DEPART exhibit a high degree of agreement. In other words, all three methods demonstrate strong applicability and compatibility in this empirical case study.

Table 13 presents the Spearman correlation coefficients calculated across the different weight profiles for each ranking method. In this case study, both DEPART and RAM maintain identical rankings of the alternatives under changes in criteria weights, with Spearman coefficients of 1.000. The complete ranking stability observed for RAM may be attributed to the pronounced differentiation within the *P. fruticosa* extraction decision matrix, in which alternative A1 performs particularly well with respect to criteria C1 and C2. The mathematical formulation of RAM favors alternatives that exhibit balanced performance across beneficial criteria while limiting excessive compensation effects. Consequently, as the criteria weights change, the root-based function may help preserve the relative positions of the alternatives, resulting in identical rankings across all weight scenarios.

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

Method	Set 1		Set 2		Set 3		Set 4	
	RAM	DEPART	RAM	DEPART	RAM	DEPART	RAM	DEPART
IRPA	0.983	1.000	1.000	0.983	1.000	1.000	0.867	0.867
RAM		0.983		0.983		1.000		1.000

Similarly, the DEPART method maintains consistent rankings of the candidate alternatives under variations in criteria weights. This stability is related to the method's use of pairwise deviation ratios between alternatives for each criterion. In the dataset for Case 2, alternative A1 exhibits superior performance and a substantial differentiation margin relative to the other alternatives. This margin may help prevent changes in criteria weights from reversing the relative pairwise deviation ratios, thereby preserving the overall ranking structure. In summary, for this case study, the RAM and DEPART methods demonstrate slightly greater ranking stability than IRPA. Specifically, the mean Spearman correlation coefficient across the weight profiles is 0.983 for IRPA and 1.000 for both RAM and DEPART methodologies.

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

	IRPA			RAM			DEPART		
	set 2	set 3	set 4	set 2	set 3	set 4	set 2	set 3	set 4
set 1	1.000	1.000	0.967	1	1	1	1	1	1
set 2		1.000	0.967		1	1		1	1
set 3			0.967			1			1
Average	0.983			1.000			1.000		

4.3 Case 3: Extraction of *P. frutescens*

Using the empirical dataset of *P. frutescens* extraction configurations presented in Table 3, the candidate alternatives were ranked using the IRPA, RAM, and DEPART methods. Figures

7–10 illustrate the resulting rankings of the *P. frutescens* extraction configurations under the four predefined criteria weight scenarios.

An examination of Figures 7-10 indicates that the alternative rankings in this case study remain highly stable across the three multi-criteria evaluation methods and the four criteria weight configurations. For example, as shown in Figure 7, the rankings of alternatives A2 (9th), A3 (15th), A5 (8th), A8 (6th), A9 (13th), A12 (12th), A13 (7th), A14 (14th), and A15 (first) remain unchanged across the IRPA, RAM, and DEPART methods. The rankings of the remaining alternatives exhibit only minor variations across the three methods. For instance, alternative A1 ranks 5th using IRPA but 4th using both RAM and DEPART.

Similarly, alternative A4 ranks 10th using IRPA and DEPART but 11th using the RAM framework.

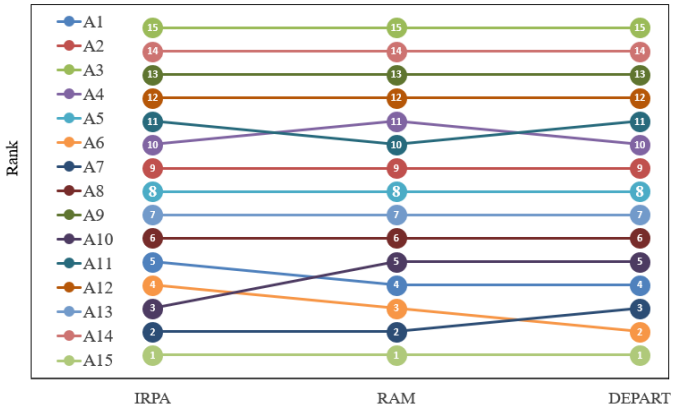


Fig. 7 Alternative rankings for case 3 using weight set 1

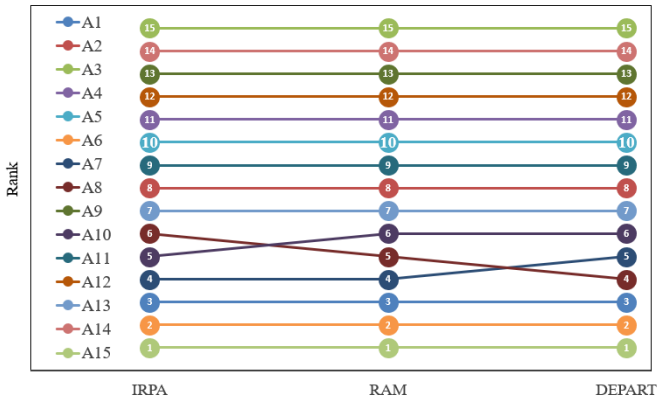


Fig. 8 Alternative rankings for case 3 using weight set 2

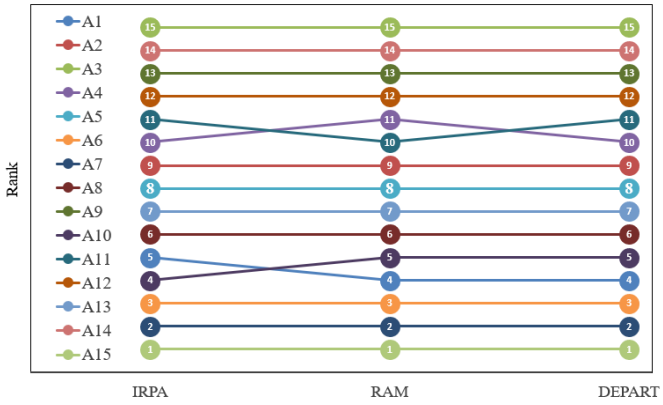


Fig. 9 Alternative rankings for case 3 using weight set 3

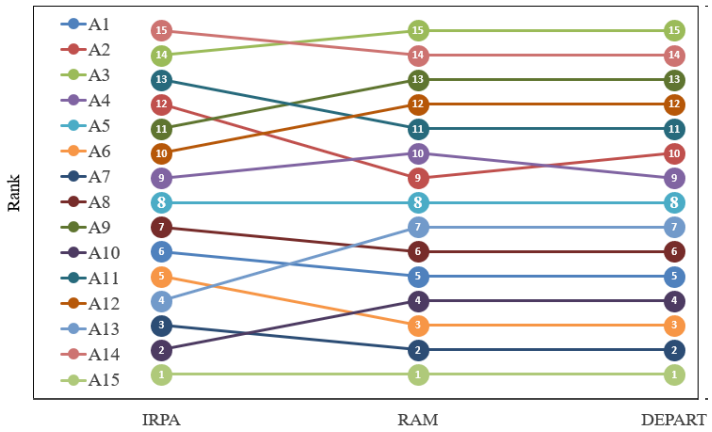


Fig. 10 Alternative rankings for case 3 using weight set 4

Under the second weight profile (Figure 8), the rankings of twelve alternatives, A1, A2, A3, A4, A5, A6, A9, A11, A12, A13, A14, and A15, are identical across the IRPA, RAM, and DEPART methods. The rankings of the remaining three alternatives (A7, A8, and A10) exhibit only minor deviations. Specifically, A7 ranks 4th using IRPA and RAM but 5th using DEPART method. Alternative A8 ranks 6th, 5th, and 4th using IRPA, RAM, and DEPART, respectively, while A10 ranks 5th using IRPA and 6th using both RAM and DEPART frameworks. An examination of Figures 9 and 10 further supports these observations, indicating that the rankings of all fifteen alternatives remain highly stable across the evaluated scenarios. Notably, all four figures (Figures 7-10) consistently place A15 first, A14 14th, and A3 15th.

These empirical results demonstrate a high degree of agreement among the alternative rankings and identify A15 as the optimal extraction configuration for *P. frutescens*, while A14 and A3 are the two least preferred alternatives. To maximize total polyphenol content, total saponin content, and antioxidant activity, the three extraction parameters, temperature, time, and solvent concentration, should be set to 70°C, 50 min, and 90%, respectively.

The Spearman correlation coefficients between the different methods were subsequently calculated, and the results are presented in Table 14. The coefficients are high for all pairs of methods, with a minimum value of 0.921. This result further supports the conclusion that the rankings generated by IRPA, RAM, and DEPART exhibit a high degree of agreement. Thus, all three methods demonstrate strong applicability and compatibility in this empirical case study.

Table 15 presents the Spearman correlation coefficients calculated across the different weight profiles for each ranking method. In this case study, the mean Spearman coefficient across the weight configurations is 0.935 for IRPA, 0.982 for RAM, and 0.971 for DEPART method. Therefore, although all three methods demonstrate a high degree of ranking stability under variations in criteria weights, a more detailed comparison identifies RAM as the most stable method, followed by DEPART and IRPA. The superior performance of RAM in this case may be related to its mathematical formulation, which calculates composite scores using root-based proportions across the criteria and may help reduce the likelihood of rank reversal.

Table 14 Spearman's coefficients between weighting scenarios for case 3

Method	Set 1		Set 2		Set 3		Set 4	
	RAM	DEPART	RAM	DEPART	RAM	DEPART	RAM	DEPART
IRPA	0.986	0.982	0.996	0.989	0.993	0.996	0.921	0.932

RAM		0.993		0.996		0.996		0.996

Table 15 Spearman's coefficients between weighting scenarios for case 3

	IRPA			RAM			DEPART		
	set 2	set 3	set 4	set 2	set 3	set 4	set 2	set 3	set 4
set 1	0.954	0.996	0.932	0.975	1.000	0.993	0.964	0.996	0.989
set 2		0.964	0.843		0.975	0.957		0.954	0.932
set 3			0.921			0.993			0.993
Average	0.935			0.982			0.971		

The three case studies presented above, *M. charantia* extraction (Case 1), *P. fruticosa* extraction (Case 2), and *P. frutescens* extraction (Case 3), provide an empirical assessment of the robustness of the three methods. Although the number of candidate alternatives differs across the cases, with nine configurations evaluated in each of the first two cases and fifteen in the third, IRPA, RAM, and DEPART consistently demonstrate their applicability to the problems considered.

A comprehensive comparison of the three methods across the case studies was also conducted. In terms of ranking stability under variations in criteria weights, RAM ranks first, followed by DEPART and IRPA in Case 1. In Case 2, both RAM and DEPART maintain identical rankings across the weight scenarios, with Spearman coefficients of 1.000, whereas IRPA exhibits slightly lower stability, with a coefficient of 0.983. In Case 3, RAM again demonstrates the highest ranking stability, followed by DEPART and IRPA. Taken together, these findings indicate that all three methods provide highly consistent rankings, with the overall ranking stability following the order RAM > DEPART > IRPA.

Furthermore, an assessment of the computational complexity of the respective algorithms indicates that RAM is less computationally demanding and more straightforward to implement than DEPART. Given its computational simplicity and strong ranking stability under variations in criteria weights, RAM is recommended as the preferred method among the three approaches investigated in this study. This practical advantage may be particularly beneficial to laboratory practitioners and researchers with limited backgrounds in mathematical optimization.

CONCLUSION

This study investigates the application of multi-criteria decision-making (MCDM) methods in chemical extraction. Three MCDM frameworks, namely IRPA, RAM, and DEPART, were evaluated and systematically applied to the extraction processes of three botanical species: *M. charantia*, *P.s fruticosa*, and *P.frutescens*. The key findings of this research are summarized as follows:

- ✓ All three frameworks (IRPA, RAM, and DEPART) demonstrate their suitability and effectiveness for ranking alternative configurations and identifying optimal operating conditions for extraction processes.
- ✓ Regarding ranking stability under variations in criteria weights, RAM exhibits the best performance, followed by DEPART and IRPA. In terms of algorithmic complexity,

RAM is also more straightforward and computationally efficient than DEPART. Therefore, among the three methods evaluated, RAM emerges as the preferred approach.

- ✓ To simultaneously optimize total polyphenol content (TPC), total saponin content (TSC), and antioxidant activity, the following optimal operating parameters, temperature, extraction time, and solvent concentration, are recommended: For *M. charantia*: either 50°C, 20 minutes, and 96%, or 50°C, 25 minutes, and 50%, respectively; for *P. fruticosa* : 40°C, 15 minutes, and 50%, respectively. And for *P. frutescens*: 70°C, 50 minutes, and 90%, respectively.
- ✓ Although this study focuses on TPC, TSC, and antioxidant activity, which are all criteria for which higher values are preferred, future research should incorporate extraction costs and other important indicators, such as total flavonoid content (TFC), impurity levels, heavy metal concentrations, extraction yield, and residual solvent levels, to establish a more comprehensive optimization framework. Furthermore, the criteria weight profiles in this study were established using predefined deterministic scenarios. Therefore, incorporating expert judgments to determine empirically grounded criteria weights represents an important direction for future research, potentially improving the practical relevance and scientific rigor of extraction optimization.

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