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COMPARISON OF KEY WEIGHTING METHODS IN MULTI-CRITERIA DECISION ANALYSIS

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Purpose: The paper aims to conduct a structured comparison of key weighting methods used in Multi-Criteria Decision Analysis (MCDA)
Design/methodology/approach: The study provides a qualitative assessment of eight selected weighting methods, categorized as subjective (AHP, SMART/SWING, Direct Rating, BWM), objective (Entropy, CRITIC, PCA), and hybrid (Fuzzy AHP + Entropy). A set of seven evaluation criteria is proposed: ease of use, data requirements, transparency, resistance to subjectivity, group applicability, compliance with decision theory, and stability of results. A comparative matrix was developed using a structured Likert-scale-based scoring system.
Findings: No single method proved to be universally superior across all evaluation dimensions. Subjective methods offer greater intuitiveness and simplicity, while objective methods provide better stability and theoretical soundness. Hybrid methods present a balanced compromise but may suffer from computational complexity. The Best-Worst Method (BWM) and hybrid approaches achieved the highest overall scores.
Research limitations/implications: The evaluation is based on the author's subjective judgment and literature review. The scoring reflects synthesized knowledge rather than empirical testing. Future research could include sensitivity analyses or the application of fuzzy/probabilistic evaluation to account for uncertainty.
Practical implications: The study provides decision-makers with contextual recommendations for selecting appropriate weighting techniques depending on the nature of the decision environment, the availability of data, and the level of stakeholder involvement.
Originality/value: This paper offers a unique synthesis and structured comparison of key weighting methods within the MCDA framework, combining theoretical classification with a multi-criteria quality assessment matrix. It contributes to both academic research and practical guidance for analysts and policy-makers.
Keywords: criteria weighting, multi-criteria decision analysis, subjective and objective methods, hybrid weighting, comparative evaluation.
Category of the paper: Research paper.

1. Introduction

Contemporary decision-making challenges in management, engineering, public policy, and environmental analysis (Belton, Stewart, 2002) increasingly require the use of multi-criteria evaluation approaches. In such contexts, Multi-Criteria Decision Analysis (MCDA) has gained particular importance, as it enables a structured decision-making process that accounts for multiple, often conflicting, aspects (Cinelli et al., 2020). One of the key components of this process is the determination of criteria weights, which reflect the relative importance of individual factors influencing the selection of alternatives.

Numerous weighting approaches have emerged in both the literature and practice, differing in terms of the source of information (e.g., empirical data vs. decision-maker preferences), methodological complexity, interpretability, and robustness to error (Cinelli et al., 2020; Mardani et al., 2015). These methods are commonly classified into three categories: subjective, objective, and hybrid. Each of these categories offers specific advantages and limitations, and their use may lead to significantly different outcomes in MCDA. Therefore, the selection of an appropriate weighting method is a critical stage in the entire decision-making process.

The aim of this paper is to evaluate and compare selected weighting methods applied in the MCDA context. Eight representative methods from the three major categories were analyzed:

- Subjective methods: AHP (Saaty, 1987), SMART/SWING (Edwards and Barron, 1994), Direct Rating (French, 1986), BWM (Rezaei, 2015),
- Objective methods: Entropy (Mukhametzyanov, 2021), CRITIC (Diakoulaki et al., 1995), PCA (Jolliffe, 2002),
- Hybrid method: Fuzzy AHP combined with Entropy (Kahraman et al., 2003).

In contrast to many previous studies (Agar et al., 2023; Agarski et al., 2019; Dereli, Tercan, 2021; Esmaili, Karipour, 2024; Khan, Purohit, 2024; Mahmoodi et al., 2023; Németh et al., 2019), this paper does not rely solely on illustrative decision-making datasets. Instead, it focuses on a qualitative comparison of methods using a multi-criteria evaluation framework based on an author-developed comparison matrix. Seven evaluation criteria were applied: ease of use, data requirements, transparency, resistance to subjectivity, group applicability, theoretical soundness, and stability of results.

This paper offers a novel synthesis by comparing eight widely used weighting methods within a unified multi-criteria evaluation framework, which has not yet been systematically addressed in prior literature.

The structure of the article includes a theoretical background, classification of weighting methods, justification of evaluation criteria, description of the analyzed techniques, construction and interpretation of the comparison matrix, and a discussion of the findings. The paper concludes with final remarks and recommendations.

2. Classification of weighting methods and evaluation principles

The determination of criteria weights in MCDA is a crucial process that defines the structure of preferences and significantly influences the final outcome of the decision analysis. Depending on the decision-making context, the availability of data, the competence of decision-makers, and the requirements for transparency and repeatability, the choice of an appropriate weighting method can have a substantial impact on the accuracy and practical usefulness of the solution.

This study focuses on the qualitative evaluation of selected weighting methods, namely AHP, SMART/SWING, Direct Rating, BWM, Entropy, CRITIC, PCA, and Fuzzy AHP combined with Entropy. The goal of this evaluation is not to identify a single universally "best" method, but rather to provide a foundation for an informed selection of a method tailored to the specific context.

2.1. Classification of weighting methods

In the literature, weighting methods are typically classified according to the source of information used to determine the weights. Most commonly, three main categories are distinguished.

2.1.1. Subjective methods

Weights are determined based on the preferences, judgments, or intuition of the decision-maker. These methods are characterized by their simplicity and directness but may be prone to cognitive biases, inconsistencies, and a lack of objectivity. Selected methods include: Analytic Hierarchy Process (AHP), SMART / SWING, Direct Rating, and Best-Worst Method (BWM).

2.1.2. Objective methods

Weights are derived from empirical data, without the direct involvement of the decision-maker's judgments. These methods are typically based on the analysis of data structure, variability, and correlations between criteria. Their main advantages include high repeatability and independence from subjective assessments. The considered methods are: Entropy (Shannon Entropy Method), CRITIC (CRiteria Importance Through Intercriteria Correlation), and Principal Component Analysis (PCA).

2.1.3. Hybrid methods

These methods combine elements of both subjective and objective approaches, incorporating, for example, empirical data as well as the preferences of the decision-maker. They are particularly useful in situations where decisions must account for uncertainty or imperfect information. One method considered in this study is Fuzzy AHP combined with Entropy. It should be noted, however, that the range of hybrid methods and their potential applications is very broad.

2.2. Scope of comparison and evaluation approach

The analyzed methods were compared based on qualitative evaluation criteria including ease of application, resistance to errors and uncertainty, data requirements, and compliance with decision theory. To ensure consistency and comparability, each method was rated using a standardized 0-5 Likert scale. In this scale, a score of 0 indicated no compliance with a given criterion, while higher values represented increasing levels of adequacy—ranging from very poor (1) to very good compliance (5).

2.3. Comparative criteria for weighting methods – description and justification

*2.3.1. Ease of use (**EU**)*

This criterion refers to the level of difficulty involved in applying the method—both in terms of computational complexity and cognitive demand for the decision-maker or analyst. In situations with limited time and expertise (e.g., public consultations or fast-paced operational decisions), the simplicity of a method becomes a key factor (Edwards, Barron, 1994; Goodwin, Wright, 2014; Vaidya, Kumar, 2006).

*2.3.2. Data requirements (**DR**)*

This criterion indicates whether a method can be applied when quantitative data are limited or when only qualitative data are available. In many real-world cases, numerical data are not accessible, which makes information-light methods preferable (Cinelli et al., 2020; Mardani et al., 2015).

*2.3.3. Transparency (**TR**)*

This criterion refers to the comprehensibility of the method's underlying logic and the ease with which its results can be interpreted by non-experts. Decision outcomes should be communicable and acceptable—methods that function as "black boxes" tend to reduce stakeholders' trust (Agar et al., 2023; Bączkiewicz, Wątróbski, 2022; Li et al., 2024).

*2.3.4. Resistance to subjectivity (**RS**)*

This criterion indicates the extent to which a method minimizes the influence of subjective judgments, cognitive biases, and inconsistencies on the part of decision-makers. Reducing arbitrariness improves the repeatability and objectivity of the results (Jia et al., 1998; Krishnan et al., 2021; Pamucar, Ecer, 2020).

*2.3.5. Group Applicability (**GA**)*

This criterion evaluates the method's ability to function in group decision-making settings, such as workshops, consultations, or team-based environments. In practice, decisions are often made collectively, so the method should support the aggregation of multiple opinions (De Feo, De Gisi, 2010; Mahmoodi et al., 2023; Vavrek, 2019).

*2.3.6. Compliance with decision theory (**CT**)*

This criterion refers to the extent to which a method is grounded in established foundations of decision theory, information theory, or preference theory. A method aligned with formal theoretical principles enhances the credibility and scientific rigor of the analysis (Dytianquin et al., 2023; Saaty, 1987; Zhu et al., 2020).

*2.3.7. Stability of results (**ST**)*

This criterion measures the method's resistance to small changes in input data or decision-maker evaluations. Stability increases confidence in the results and enhances their repeatability (Du et al., 2019; Esangbedo et al., 2024; Vagiona, 2025).

3. Characteristics of selected weighting methods

This section presents eight selected weighting methods representing the three main categories of approaches: subjective, objective, and hybrid. The selection of methods was based on their popularity in the literature, widespread use in MCDA applications, and conceptual diversity. Each method has its unique characteristics, advantages, and limitations, which are described in detail below.

3.1. Subjective methods

3.1.1. AHP (Analytic Hierarchy Process) (Saaty, 1987)

The AHP method, developed by Thomas Saaty, is based on a hierarchical structure of the decision problem and pairwise comparisons of criteria made by the decision-maker. Each pair of criteria is evaluated in terms of their relative importance, and the weights are derived accordingly.

AHP is one of the most well-known MCDA methods. Its main strengths lie in its systematic approach and the ability to assess the consistency of the responses. However, a notable drawback is the rapidly increasing number of comparisons required as the number of criteria grows, which can lead to decision-maker fatigue and inconsistent judgments. Nevertheless, AHP remains a widely used and popular method.

3.1.2. SMART/SWING (Edwards, Barron, 1994)

The SMART and SWING methods belong to the category of point allocation techniques. They involve assigning a numerical score to each criterion to reflect its importance. In the SWING method, the decision-maker considers which criterion should be "activated" first in a hypothetical scenario where all criteria initially hold the lowest possible level.

These methods are very simple, fast, and intuitive. Due to their transparency, they are widely used in expert evaluations, public consultations, and educational settings. Their main drawback is the lack of mechanisms to verify the consistency of judgments and a strong dependence on the subjective beliefs of the decision-makers.

3.1.3. Direct Rating

Direct Rating is the simplest approach to determining weights. It involves directly assigning a weight to each criterion without the need for pairwise comparisons or intermediary evaluations. This method often uses percentage or rating scales, such as 0-10 or 0-100.

The main advantage of Direct Rating is its simplicity and speed of application—it requires no specialized knowledge or tools. It is particularly useful in situations where quick results are needed or where the analysis is limited in scope. However, its greatest limitation lies in its high degree of subjectivity and the absence of any mechanisms to control the quality or consistency of the assessments.

3.1.4. BWM (Best-Worst Method) (Rezaei, 2015)

The Best-Worst Method (BWM) is based on the decision-maker's selection of the best (most important) and worst (least important) criteria from the set under consideration. The decision-maker then evaluates all remaining criteria relative to these two reference points. The final weights are derived from these assessments.

BWM requires fewer evaluations than AHP and offers better control over the consistency and intensity of preferences. The method is gaining popularity due to its simple decision structure and suitability for both individual and group analyses. However, in its more advanced form, it may require familiarity with optimization tools.

3.2. Objective methods

3.2.1. Entropy (Shannon Entropy Method)

The entropy method is based on analyzing the variability of data in the decision matrix. The greater the variation in the values of a given criterion across alternatives, the higher its informational value—and consequently, its assigned weight.

This is a fully objective approach that does not require any expert judgments. It performs well when numerical and complete data are available, and the goal is to eliminate the influence of decision-maker preferences. However, its main limitation is that it considers only the statistical properties of the criteria, without accounting for their decision-making relevance.

3.2.2. CRITIC (CRiteria Importance Through Intercriteria Correlation) (Diakoulaki et al., 1995)

The CRITIC method takes into account both the variability of criterion values (i.e., their informational strength) and the interrelationships between them (e.g., correlations). A criterion that shows high variability and low correlation with others is considered more important.

Compared to the entropy method, CRITIC offers a more refined approach, as it accounts for interdependencies between criteria, thereby enhancing the relevance of the weighting results. However, the method requires a complete numerical data matrix and the calculation of inter-criterion correlations, which may present a barrier in certain applications.

3.2.3. PCA (Principal Component Analysis) (Jolliffe, 2002)

Principal Component Analysis (PCA) is a statistical method used for data dimensionality reduction and for identifying patterns of dependence. In the context of weighting, it can be applied to determine the contribution of each criterion to the overall variance in the dataset—and thus to assign corresponding weights.

PCA is primarily used in the development of composite indicators (e.g., sustainability indices) and in situations where the goal is to automatically identify the most influential variables. Its advantages include high objectivity and resistance to redundancy. However, its limitations involve low transparency and difficulty in interpreting the results for individuals without statistical expertise.

3.2.4. Hybrid method: Fuzzy AHP + Entropy (Kahraman et al., 2003)

The hybrid method combines the subjective approach (Fuzzy AHP) with the objective one (Entropy). In Fuzzy AHP, expert preferences are expressed not through precise numerical values but using fuzzy numbers, which allows for the incorporation of uncertainty and vagueness in the assessments. The resulting weights are then complemented with information derived from the entropy analysis of the data matrix.

The advantage of this method lies in its flexibility—it enables the consideration of uncertainty while still relying on real data. It is particularly useful in risk assessments, quality evaluations, and situations involving incomplete or imprecise data. Its main drawbacks are its high computational complexity and the need for advanced interpretation of results.

4. Methods

The methodological approach adopted in this study is based on a structured literature review combined with a comparative evaluation framework developed by the author. The primary objective was to assess and contrast selected weighting methods used in Multi-Criteria Decision Analysis (MCDA) based on a set of predefined qualitative criteria.

4.1. Selection of weighting methods

The selection of the eight weighting methods included in this study was guided by three criteria: (1) frequency of use in academic and applied MCDA literature, (2) conceptual and methodological diversity (subjective, objective, and hybrid approaches), and (3) relevance to decision-making problems in management, engineering, and policy contexts. The final set consists of four subjective methods (AHP, SMART/SWING, Direct Rating, BWM), three objective methods (Entropy, CRITIC, PCA), and one hybrid method (Fuzzy AHP combined with Entropy).

4.2. Literature sources and scope

The literature review supporting the evaluation was conducted using academic databases such as Scopus, Web of Science, and Google Scholar. The search focused on peer-reviewed journal articles, review papers, and methodological studies published primarily between 2000 and 2024. Keywords included: criteria weighting, MCDA methods, subjective weighting, objective weighting, hybrid MCDA, and the names of specific methods (e.g., "Entropy method", "BWM", "Fuzzy AHP"). Publications in English were prioritized due to their international relevance and broader citation base.

Inclusion criteria required that sources describe, apply, or compare MCDA weighting methods in a documented decision context. Methodological syntheses and comparative reviews were particularly emphasized. Gray literature, conference abstracts, and non-peer-reviewed content were excluded to ensure quality.

4.3. Evaluation framework

The comparative evaluation was carried out using a multi-criteria framework composed of seven qualitative criteria: ease of use, data requirements, transparency, resistance to subjectivity, group applicability, compliance with decision theory, and stability of results. These criteria were selected based on their recurrence in existing literature (e.g., Cinelli et al., 2020; Mardani et al., 2015; De Feo, De Gisi, 2010) and their practical relevance in decision-making contexts.

Each method was rated on a 0-5 Likert scale, where: 0 – does not meet the criterion at all, 1 – very poor compliance, 2 – poor, 3 – moderate, 4 – good, 5 – very good or fully compliant.

Scores were assigned based on a synthesis of findings from the reviewed literature, complemented by the author's academic experience and prior applications of the methods. While the evaluation follows a structured approach, it remains qualitative in nature and should be interpreted as a reasoned support tool rather than a definitive ranking.

Future research may benefit from validating the ratings through expert elicitation, fuzzy logic, or probabilistic methods to better address uncertainty in comparative assessments.

5. Results

The evaluation of weighting methods in this study is qualitative in nature and based on a review of relevant literature. Although a numerical scale (0-5) was adopted, it is important to emphasize that the assigned values reflect synthesized conclusions from comparisons available in academic sources as well as the authors' research experience. The assessments were conducted in a structured manner; however, they involve a certain degree of subjectivity and uncertainty, which is typical for review-based studies. These values should be regarded as a starting point for further analysis rather than absolute measures of method quality. The summarized results are presented in Table 1.

Table 1.
Qualitative evaluation of selected criteria weighting methods in MCDA

Method	EU	DR	TR	RS	GA	CT	ST
AHP	5	3	3	1	4	5	4
SMART_SWING	5	5	5	1	4	4	3
Direct_Rating	5	5	5	1	5	2	2
BWM	4	5	4	2	5	5	5
Entropy	4	1	2	5	2	5	5
CRITIC	3	1	3	5	2	5	5
PCA	3	1	2	5	3	5	5
Fuzzy_AHP_Entropy	2	2	2	4	4	5	5

EU – ease of use, DR – data requirements, TR – transparency, RS – resistance to subjectivity, GA – group applicability, CT – compliance with decision theory, ST – stability of results.

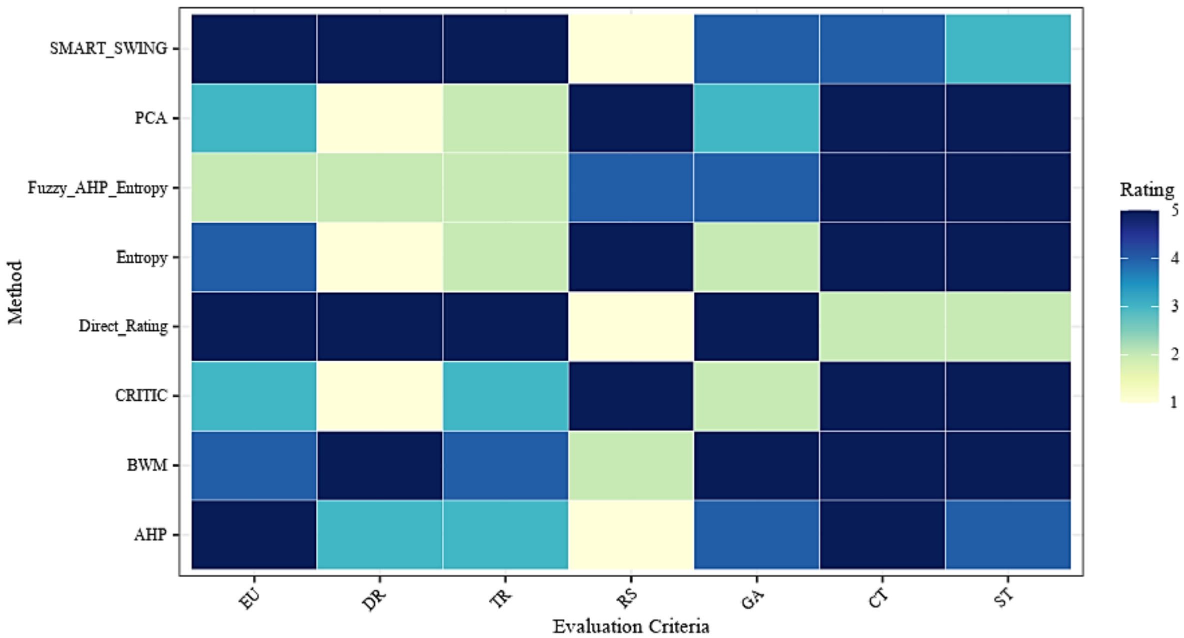
Source: Based on the author's own analysis.

Justification of the evaluations assigned to each method with respect to the considered criteria is grounded in a synthesis of findings from key literature sources (Agar et al., 2023; Agarski et al., 2019; De Araújo et al., 2022; De Feo, De Gisi, 2010; Du et al., 2019; Dytianquin et al., 2023; Ecer, 2024; Mahmoodi et al., 2023; Mukhametzyanov, 2021; Németh et al., 2019; Pliego-Martínez et al., 2024; Vagiona, 2025; Wolny, 2015; Wu et al., 2022; Zhu et al., 2020):

- AHP (EU: 5 – widely recognized as intuitive, DR: 3 – requires pairwise comparisons but not a complete data matrix, TR: 3 – moderate transparency for non-experts, depending on the number of criteria, RS: 1 – highly dependent on the preferences and inconsistencies of the decision-maker, GA: 4 – well-suited for group aggregation, CT: 5 – strong axiomatic foundation, ST: 4 – moderately stable but sensitive to inconsistency),
- SMART/SWING (EU: 5 – exceptionally simple and transparent methods, DR: 5 – require only basic input data, TR: 5 – highly understandable for non-experts, RS: 1 – evaluations are entirely subjective, GA: 4 – easy to apply in group settings, CT: 4 – consistent with utility theory, ST: 3 – sensitive to changes in point-based ratings),
- Direct Rating (EU: 5 – the fastest and easiest form of weight assessment, DR: 5 – no need for complex data, TR: 5 – fully transparent and easy to interpret, RS: 1 – no control over subjectivity, GA: 5 – particularly useful in consultations and social research, CT: 2 – lacks formal theoretical foundations, ST: 2 – high risk of result variability),

- BWM (EU: 4 – simpler than AHP but requires optimization, DR: 5 – can be applied without numerical data, TR: 4 – logical structure and limited number of judgments, RS: 2 – partially reduces subjectivity, GA: 5 – easy to aggregate in group settings, CT: 5 – strong theoretical foundation, ST: 5 – highly repeatable and stable results),
- Entropy (EU: 4 – requires only basic statistical knowledge, DR: 1 – demands a complete and fully populated numerical matrix, TR: 2 – low understandability for non-technical users, RS: 5 – fully objective, GA: 2 – limited applicability in group settings, CT: 5 – fully aligned with information theory, ST: 5 – high stability and repeatability),
- CRITIC (EU: 3 – somewhat more complex to apply, DR: 1 – requires numerical data and correlation analysis, TR: 2 – moderate transparency for general users, RS: 5 – strong resistance to subjectivity, GA: 2 – limited suitability for group use, CT: 5 – robust statistical foundation, ST: 5 – high resistance to variability),
- PCA (EU: 3 – requires statistical knowledge, DR: 1 – a complete matrix and data normalization are necessary, TR: 2 – difficult to interpret without analytical background, RS: 5 – highly objective, GA: 3 – applicable in group settings but requires adaptation, CT: 5 – strong theoretical foundation, ST: 5 – high result stability),
- Fuzzy AHP + Entropy (EU: 2 – complex concept of fuzzy numbers, DR: 2 – moderate data requirements (depending on the version), TR: 2 – low transparency due to methodological complexity, RS: 4 – high flexibility and partial objectivity, GA: 4 – suitable for group use but requires facilitation, CT: 5 – strong theoretical integration of data and preferences, ST: 5 – robust and stable outcomes).

Figure 1 presents a synthetic overview of the results in the form of a heatmap.



EU – ease of use, DR – data requirements, TR – transparency, RS – resistance to subjectivity, GA – group applicability, CT – compliance with decision theory, ST – stability of results.

Figure 1. Heatmap of weighting method ratings.

Source: Own study.

The heatmap presents a comparative evaluation of eight weighting methods used in Multi-Criteria Decision Analysis (MCDA) with respect to seven qualitative criteria: ease of use, data requirements, transparency, resistance to subjectivity, group applicability, compliance with decision theory, and result stability. Each method was assessed using a 0-5 Likert scale, and the scores are visually encoded through a color gradient, where darker shades indicate higher ratings. The visual analysis reveals that subjective methods, such as AHP and SMART/SWING, score highly in terms of intuitiveness and theoretical grounding but exhibit lower resistance to subjectivity. Objective methods, including Entropy and CRITIC, demonstrate strong resistance to bias and low data requirements but are generally less transparent. Hybrid approaches, such as Fuzzy AHP + Entropy, offer high result stability but tend to be more complex and less interpretable. No single method outperforms others across all dimensions, highlighting the importance of selecting a weighting technique in alignment with the specific decision-making context.

6. Discussion

6.1. Summary of the qualitative evaluation

The conducted evaluation of weighting methods revealed that no single approach consistently achieves the highest scores across all considered criteria. Each technique displays a distinct profile of strengths and weaknesses, indicating that the selection of an appropriate method should be context-dependent rather than standardized.

According to the analysis:

- Subjective methods (AHP, SMART/SWING, Direct Rating, BWM) offer high simplicity, transparency, and ease of use, but their results are more susceptible to cognitive biases and lower stability. BWM is an exception—it combines high accuracy and clarity with better resistance to subjectivity.
- Objective methods (Entropy, CRITIC, PCA) score highest in terms of resistance to subjectivity, theoretical soundness, and result stability. However, they are more difficult to implement and require complete numerical datasets.
- The hybrid method (Fuzzy AHP + Entropy) received high marks for flexibility, integration of information sources, and stability, although its complexity and lower transparency may limit its practical applicability.

In summary, the evaluation confirms that the choice of a weighting method should be tailored to the specific decision-making context, as each approach involves trade-offs between usability, robustness, and methodological rigor. The observed differences underscore the need for informed selection rather than reliance on a universally optimal technique.

6.2. Contextual method selection – recommendations

Based on the multi-criteria evaluation, it is possible to identify preferred methods for various decision-making scenarios, as presented in Table 2.

Table 2.
Recommended weighting methods depending on decision-making context

Decision-making context	Recommended methods	Justification
Group decision-making	AHP, BWM, SMART/SWING	High transparency and ability to aggregate preferences
Lack of numerical data	Direct Rating, SMART, BWM	Do not require an empirical data matrix
High repeatability and objectivity	Entropy, CRITIC, PCA	Lack of subjectivity, stability, and compliance with information theory
Decision-making under uncertainty	Fuzzy AHP + Entropy	Integration of fuzzy and objective data
Need for interpretability and communication	SMART/SWING, AHP	Well-understood logic and transparent results
Rapid operational decisions	Direct Rating, SMART	Minimal time and cognitive cost of application

Source: Based on the author's own analysis.

6.3. Limitations of the approach and uncertainty of the evaluations

Despite efforts to ensure objectivity, it is important to emphasize that:

- The evaluations are expert-based and rely on literature reviews and methodological analyses (Belton, Stewart, 2002; Cinelli et al., 2021).
- The numerical values in the comparison matrix (0-5) are not absolute measures—they should be regarded as an analytical tool to support decision-making.
- The degree of uncertainty in the evaluations could be formally estimated in future research, for example, using fuzzy or probabilistic approaches.

Despite efforts to ensure methodological rigor, the presented evaluations remain inherently judgment-based and should be interpreted as a structured support tool rather than definitive measurements. Future research may enhance robustness by incorporating uncertainty modeling techniques such as fuzzy logic or probabilistic analysis.

6.4. Implications for practice and future research

For practitioners:

- It is recommended to begin by defining decision-making requirements, including data availability, number of stakeholders, and model acceptability.
- The selection of a weighting method should be treated with equal importance as the choice of an aggregation method, as both stages influence the final outcome of MCDA.

For researchers:

- Further comparative studies are encouraged, particularly those involving empirical decision cases where different weighting methods are applied to the same dataset.
- Hybrid methods show promising potential by combining the strengths of various approaches, including automated weighting systems designed for complex environments.

The results of the multi-criteria analysis demonstrate that weighting methods differ significantly in terms of usefulness, theoretical soundness, robustness to errors, and result stability. The highest-rated methods—such as BWM and hybrid approaches—offer a balanced compromise between simplicity, flexibility, and methodological rigor.

A conscious selection of the weighting method—tailored to the specifics of the decision problem—is a critical element of effective MCDA.

7. Conclusion and final remarks

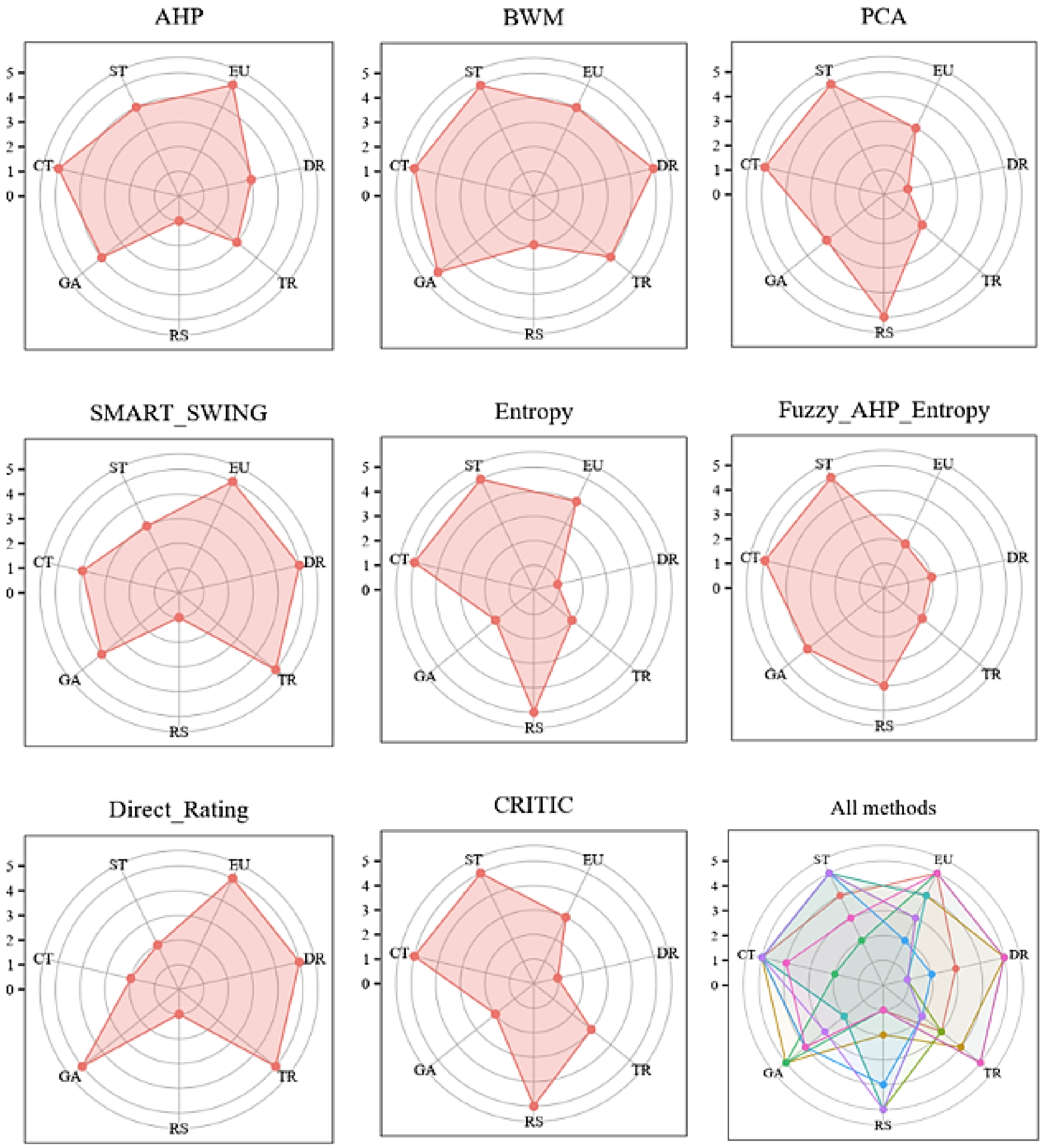
This paper presented a multi-criteria comparison of selected weighting methods used in Multi-Criteria Decision Analysis (MCDA). Eight representative techniques were examined and classified as subjective, objective, or hybrid. The evaluation was based on seven qualitative criteria related to ease of use, transparency, resistance to subjectivity, stability, and compliance with decision theory.

The results indicated that:

- Subjective methods, such as AHP and SMART/SWING, offer high intuitiveness but lower repeatability.
- Objective methods (CRITIC, PCA, Entropy) provide strong stability and theoretical consistency but require more demanding data inputs.
- Hybrid methods, such as Fuzzy AHP combined with Entropy, offer flexibility at the cost of greater complexity.

It was also emphasized that the choice of a weighting method should be adapted to the specific decision-making context, rather than relying solely on formal efficiency or methodological rigor.

The visualization shown in Figure 2, presented as a radar chart, provides an intuitive qualitative comparison of the methods, supporting the identification of their functional differences.



EU – ease of use, DR – data requirements, TR – transparency, RS – resistance to subjectivity, GA – group applicability, CT – compliance with decision theory, ST – stability of results.

Figure 2. Comparison of criteria weighting methods.

Source: Own study.

Figure 2 presents a series of radar charts visualizing the performance profiles of individual weighting methods across the seven evaluation criteria. Each plot highlights the specific strengths and weaknesses of a given method, forming a distinct polygonal area that reflects its evaluative footprint. The composite chart ("All methods") provides a consolidated view, illustrating the diversity of profiles and trade-offs among the methods. As a final summary visualization, Figure 2 reinforces the conclusion that no single method consistently outperforms others across all dimensions. Instead, each technique offers context-specific advantages and limitations, indicating that method selection should be guided by the priorities and constraints of the particular decision-making scenario.

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