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Evaluation and Selection of Startup Ideas Using MCDM: A Comparative Study of TOPSIS, AHP, VIKOR, PROMETHEE II and ELECTRE II

Sara Rekkal [1], **Kahina Rekkal** [2], **Mohamed Amine Yakoubi** [3]

[1] Department of Mathematics and Computer Science, Faulty of Exact Sciences, Tahri Mohammed University of Bechar, Bechar, Algeria
[2] Department of Electrical Engineering, University of Naama, Naama, Algeria
[3] Computer Science Research Laboratory, Computer Science Department, Faculty of Technology, Badji Mokhtar Annaba University, Annaba, Algeria

Corresponding author: Sara Rekkal (rekkal.sara@univ-bechar.dz)

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Abstract

Background: The selection of startup ideas to fund and develop is a complex decision-making problem regarding a multitude of conflicting criteria such as profitability, growth potential, risk, initial costs and social impact. Traditional single-criteria approaches are therefore insufficient to grasp this multidimensional complexity. This is the reason why multi-criteria decision-making (MCDM) methods are well adapted to this context.

Objective: The aim of this study is to compare several widely recognized MCDM methods to find the most promising startup ideas. Besides, we compare the consistency, robustness and convergence of the rankings obtained under controlled weighting scenarios. These scenarios are intended to simulate possible decision priorities and to test the robustness of the methods.

Methods: Five MCDM methods (AHP, TOPSIS, VIKOR, PROMETHEE II and ELECTRE II) are applied to the same dataset of startup ideas evaluated according to their profitability, growth potential, risk, initial costs and social impact. Different criterion weighting scenarios are considered to analyse the influence of decision-makers' preferences and to test the robustness of the resulting rankings.

Results: The results show strong convergence between the applied MCDM methods, despite their different underlying principles. The variations in the weighting of criteria affect intermediate rankings, but the top-ranked startup ideas remain stable across methods, demonstrating the robustness of the evaluation process.

Conclusion: The proposed multi-criteria evaluation framework is characterized by its reliability, transparency and robustness. By combining and comparing the different MCDM methods, it provides decision-makers with a valuable, evidence-based tool for selecting startup ideas and making investment decisions.

Index Terms

Startup idea selection; Multi-criteria decision-making; Analytic hierarchy process; Technique for Order of Preference by Similarity to Ideal Solution; ELimination Et Choix Traduisant la REalité; VIšeKriterijumska Optimizacija I Kompromisno Rešenje.

1 INTRODUCTION

Choosing the right startup idea is an important decision for investors and entrepreneurs. It influences the project's sustainability, growth potential and long-term success. Startup evaluation is a complex process that considers several criteria, such as profitability, growth potential, risk, initial investment and social impact.

Traditional approaches focused on a single criterion often oversimplify the problem and can introduce personal bias. In contrast, multi-criteria decision-making (MCDM) methods offer clear frameworks. These methods assist the decision-makers in comparing and ranking the different ideas systematically.

TOPSIS is one of these methods which we successfully applied in our previous study presented at the ICRAMI conference (Rekkal et al., 2025) to evaluate the startup ideas by measuring their relative proximity to an ideal solution, according to several criteria. While this approach provides clear and objective classification, relying on a single method can limit the scope of the analysis.

This article is an extended version of our conference paper presented at the ICRAMI conference (Rekkal et al., 2025). The presentation at the conference was based on the TOPSIS method, but in the present work the analysis has been extended to compare several well-known MCDM methods (AHP, VIKOR, PROMETHEE II, ELECTRE II). We introduce different weighting scenarios to simulate the preferences of potential decision-makers and to evaluate the reliability, the consistency and the effectiveness of the rankings. Such comparative analysis reveals the relevance of these methods for the assessment of startup ideas and their ability in identifying and selecting the most promising ones.

Different MCDM methods rely on diverse principles such as pairwise comparisons, distance-based evaluations, compromise solutions and outranking relationships. Various rankings can be obtained depending on the weighting of criteria and underlying methodological assumptions. To enhance the analysis, this study applies and compares these five MCDM methods using same dataset of startup ideas. The objective is to identify the most promising alternatives, thus extending and reinforcing previous evaluations based solely on the TOPSIS method.

The remainder of this paper is organized as follows: Section 2 reviews the related work; Section 3 presents the multi-criteria decision analysis (MCDA) framework; Section 4 introduces the MCDM methods used in this study; Section 5 discusses the experimental results, including the comparative analysis and sensitivity analysis; and Section 6 concludes the paper with the main findings.

2 RELATED WORKS

Several studies have applied MCDM approaches to help solve selection, ranking and evaluation problems in various fields. In the area of public health, Akhrouf and Derghoum (2022) proposed a model based on the AHP method for prioritizing projects in Algeria. Their model considers seven main criteria and eighteen sub-criteria, both qualitative and quantitative and allows sensitivity analysis to assess the robustness of the decisions.

In the field of industrial and commercial applications, Bensmaine and Benazza (2025) used the PROMETHEE method to select the optimal location for retail outlets, identifying climate as the most influential criterion. Wahiba (2019) applied the ELECTRE III method, a non-compensatory outranking approach, to the evaluation of nineteen investment projects within the ANSEJ (National Agency for Youth Employment Support). This method allows their ranking according to the risk of loan default and demonstrates its reliability in complex decision-making contexts. Benamer (2023) classified Condor products using a hybrid VIKOR-AHP approach, considering eight quality criteria inspired by Garvin's dimensions. Djaalali and Adlani (2023) applied the MCDA/TOPSIS method to select suppliers for a major maintenance programme balancing technical and financial factors. The risk assessment related to new product development was addressed by Sharifi et al. (2022) using the TOPSIS method combined with FMEA. Their approach identifies key risks, such as competitive pressure and mismatches with customer needs, and proposes mitigation strategies validated by experts. The systematic review by Mathebula & Mbuli (2025) examined 78 publications on TOPSIS applications to electrical systems highlighting research trends, key themes, gaps and future prospects.

The application of MCDM methods to the selection of technologies and processes was illustrated in more detail by Gülmez (2025), using a hybrid TOPSIS-VIKOR-PROMETHEE II framework to evaluate eight drying technologies for peach processing, highlighting vacuum drying as optimal and identifying energy consumption, investment costs and preservation of nutritional qualities as critical factors. Project selection under uncertainty was addressed by Salehi (2015) using a hybrid fuzzy AHP-VIKOR model, which allows decision-makers to express linguistic evaluations and demonstrates a practical application through a numerical example. Finally, Nguyen & Chu (2023) applied a PROMETHEE II fuzzy hybrid approach based on DEMATEL-ANP to classify young technology companies in acceleration programmes, analysing the interrelationships between criteria and demonstrating the effectiveness of the model for managing qualitative and quantitative data.

Overall, these studies, among others, demonstrate the versatility, robustness and broad applicability of MCDM methods, including AHP, TOPSIS, VIKOR, PROMETHEE II, ELECTRE I/III and hybrid fuzzy approaches, for solving complex MCDM problems. They offer structured frameworks for informed, evidence-based decision-making in diverse fields, such as public health, project management, industrial procurement, product development, technology selection and startup evaluation. However, few studies offer a systematic comparison of several recognized MCDM methods within the same evaluation context, particularly for the evaluation and selection of startup projects. This gap justifies the controlled multi-criteria method analysis that is carried out in this study, where different weighting scenarios are used to simulate potential decision priorities and to assess the robustness, consistency and convergence of the methods, while identifying stable and dominant alternatives.

3 MULTI-CRITERIA DECISION ANALYSIS

MCDA offers a set of tools and methodologies designed to help decision-makers solve complex problems with multiple, often conflicting, criteria (Vincke, 1992). Fundamentally, MCDA is designed as a decision-aid tool.

According to Roy's definition (Roy, 1996), it is a methodology that supports decision-makers through structured models, without replacing their judgment. In this approach, the decision-maker retains full responsibility for their final choice, while the analyst provides clear information, recommendations and rationales to inform the decision-making process.

3.1 Main concepts

MCDA is based on several key concepts, such as:

- **Action:** An alternative or candidate option evaluated within the decision-making process.
- **Criterion:** A factor or measure used to evaluate and compare options.
- **Performance:** The score or value of an option against a specific criterion.
- **Weighting:** The degree of importance assigned to each criterion in the evaluation process.
- **Preference:** A relationship indicating that one option is preferred over another, based on sufficient evidence or justification.
- **Indifference:** A situation in which two options are considered equally preferable.
- **Incompatibility:** A situation in which neither preference nor indifference can be established between two options.
- **Outranking:** A relationship in which option A is considered at least as good as option B.
- **Performance matrix:** A decision matrix in which the rows represent options, the columns represent criteria and each cell contains the corresponding performance value.

3.2 Different multi-criteria problems

MCDA problems are generally classified into three main categories:

- **Selection problem:** Identify the most suitable alternative or the smallest subset of preferred alternatives.
- **Sorting problem:** Assign alternatives to predefined classes or categories based on their characteristics.
- **Ranking problem:** Order all alternatives from most to least preferred.

4 BRIEF PRESENTATION OF MULTI-CRITERIA DECISION-MAKING METHODS

4.1 Analytic hierarchy process

The Analytic Hierarchy Process (AHP), developed by Saaty (1980), is a MCDM method that allows the consideration of both quantitative and qualitative criteria by structuring the problem in a hierarchical form (goal, criteria, alternatives). It uses pairwise comparisons to evaluate the relative importance of criteria and facilitate decision-makers' judgments (Saaty, 1980). AHP also enables the consistency of judgments to be checked and sensitivity analyses to be performed, making it a widely recognized approach for complex decision-making problems (Lee et al., 2007; Taherdoost, 2017). Detailed calculations are provided in Appendix A.

4.2 TOPSIS method

The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is a widely used MCDM approach. It is based on the principle that the best alternative is the one closest to the positive ideal solution, representing optimal performance for all criteria, and furthest from the negative ideal solution, reflecting the lowest performance (Hwang & Yoon, 1981). This principle allows a rational and intuitive ranking of alternatives, facilitating decision-making in complex situations involving conflicting criteria (Rekkal & Rekkal, 2023). Detailed calculations are available in Appendix B.

4.3 PROMETHEE II method

PROMETHEE, introduced by Jean-Pierre Brans in 1982 and further extended by Brans & Vincke (1985), is a MCDM method for ranking alternatives. It is based on pairwise comparisons of actions. In PROMETHEE II, the preference for one alternative over another is measured using the preference function $P(d)$, where d represents the difference between their performance for a given criterion. The preference value ranges from 0 (no preference) to 1 (strong preference), with intermediate values representing increasing degrees of preference. Detailed calculation steps and formulas are provided in Appendix C.

4.4 ELECTRE II method

ELECTRE (ELimination Et Choix Traduisant la REalité) is a MCDM method based on the outranking relationship, initially introduced by Roy (1968) as ELECTRE I. This method was later extended with the development of ELECTRE II, which compares alternatives pairwise to determine whether one alternative can be considered at least as good as another, taking into account both concordance indices (favourable criteria) and discordance indices (unfavourable criteria). Unlike ELECTRE I, which aims to identify the best alternative(s), ELECTRE II introduces strong and weak outranking relationships to establish a complete or partial ranking of the alternatives. The full computational procedure is included in Appendix D.

4.5 VIKOR method

VIKOR (VIšeKriterijumska Optimizacija I Kompromisno Rešenje) is a MCDM method designed to identify a compromise solution between conflicting criteria (Opricovic & Tzeng, 2004). This method ranks alternatives according to their proximity to the ideal solution, taking into account both collective utility and individual regret, making it suitable for complex decision problems. Detailed calculations are presented in Appendix E.

4.6 Classification of methods according to problem types

MCDM methods described above can be classified according to the type of problem that they aim to solve: selection, sorting or ranking. Table 1 summarizes the presented methods.

Table 1. *Classification of MCDM methods.*

Method	Selection	Sorting	Ranking
ELECTRE II	X	X	✓
PROMETHEE II	X	X	✓
VIKOR	✓	X	✓
TOPSIS	✓	X	✓
AHP	✓	X	✓

The ELECTRE II, PROMETHEE II, VIKOR, TOPSIS and AHP methods were selected because they all generate a ranking of alternatives, a crucial element for structured evaluation and selection of startup ideas. The adoption of the different MCDM ranking-based methods allows comparing the results, revealing commonalities and differences and assuring a robust, transparent and reliable decision-making process. Furthermore, these methods, as mentioned previously, are based on different theoretical principles of alternative ranking, which enhances the comparison of results.

5 EXPERIMENTAL STUDY

5.1 Experimentation objectives

The primary objective of this experiment is to identify the best overall compromise by selecting the option that balances all criteria. Furthermore, the study assesses the sensitivity of the rankings to changes in criterion weights, using multiple weighting scenarios designed to simulate the different priorities of decision-makers and to test the robustness, consistency and convergence of the outcomes of the different MCDM methods. This approach ensures a robust and transparent evaluation even when criterion weights change.

5.2 Proposed test set

To our knowledge, there is currently no widely adopted public dataset or standardized framework specifically designed for accurate comparison of MCDM methods in the context of evaluating and selecting startup ideas. This deficiency stems primarily from the sensitivity and confidentiality of data used by business incubators, investment funds and public institutions. Furthermore, actual selection processes typically involve a limited number of projects, ranging from a few to a few dozen. In this context, the proposed test set consists of six startup ideas (identified by the letters A to F) evaluated according to the criteria defined below. Data anonymization ensures transparency and neutrality, while providing a realistic and reproducible basis for analysing the method performance under different weighting scenarios and assessing the consistency, sensitivity and robustness of the MCDM approaches. This evaluation framework can also be applied to other sets of startup ideas, using the same criteria or alternative criteria defined according to the requirements of future studies.

5.3 Evaluation criteria selection

Numerous criteria can be used to evaluate startup ideas, including profitability, growth potential, risk level, initial costs, social impact, team and skills and innovation, in addition to technical, environmental and institutional aspects such as technical feasibility, market competitiveness, environmental sustainability and compliance with public policies.

It is worth noting that the adopted multi-criteria framework is flexible. It allows adding or removing both criteria and alternatives based on the research objectives, the decision context or the decision-maker's preferences. This flexibility is one of the most significant advantages of MCDM methods.

Within the scope of this study, six alternatives (startup ideas) and five criteria were selected, as they provide a balanced coverage of the most relevant economic, strategic and social dimensions for evaluating the startup ideas. The selected criteria are defined below:

- **Profitability (P) –** Economic: the ability of the alternative to generate sustainable long-term profits.
- **Growth potential (G) –** Strategic: the capacity of the idea to develop and expand on the market.
- **Risk (R) –** Technical/Financial: the degree of uncertainty, complexity or difficulty associated with project implementation.
- **Initial COSTS (IC) –** Financial: the level of financial resources required to launch the alternative.
- **Social impact (SI) –** Social: the influence of the alternative on society and the community.

This selection aims to ensure a comprehensive, realistic and coherent evaluation, while remaining adaptable to other study contexts in which the number of criteria or alternatives may differ.

5.4 Decision matrix construction

To operationalize the multi-criteria assessment, the data were organized into a 6 × 5 decision matrix, in which:

- the rows represent the six startup ideas,

- the columns correspond to the five selected evaluation criteria.

The performance of the alternative solutions was evaluated using a standardized five-level rating scale, ranging from 1 (very poor performance) to 5 (excellent performance). This scale allows qualitative judgments to be translated into comparable numerical values, which can be used by multi-criteria analysis methods. Transforming qualitative assessments into numerical data facilitates:

- the application of mathematical procedures required by methods such as TOPSIS, AHP, PROMETHEE II, VIKOR and ELECTRE II;
- future adaptation of the model, particularly in the event of adding or removing criteria or alternatives.

The resulting decision matrix is presented in Table 2, which summarizes the performance scores of the six startup ideas on the five selected evaluation criteria.

Table 2. *Performance matrix.*

Idea	Profitability	Growth potential	Risk	Initial costs	Social impact
A	3	4	3	3	4
B	4	3	2	2	3
C	5	5	4	5	5
D	3	4	3	3	4
E	4	5	3	4	5
F	5	4	2	4	5

5.5 Criteria nature and preference direction

The criteria were classified according to their preference orientation to reflect the decision-maker's objectives:

- Benefit-type criteria (to be maximized): profitability (P), growth potential (G), social impact (SI).
- Cost-type criteria (to be minimized): risk (R), initial costs (IC).

5.6 Experimental results and discussion

5.6.1 Comparison result

This study begins by comparing the results obtained in Rekkal et al. (2025), where the TOPSIS method was applied to the decision matrix (Table 2), with those obtained in this work using additional MCDM methods, namely AHP, PROMETHEE II, VIKOR and ELECTRE II. The comparative results are presented in Table 4. To ensure consistency and comparability between the methods and scenarios, the criterion weights are normalized as follows:

$$\sum_{j=1}^{5} w_j = 1 \tag{1}$$

This normalization guarantees the consistency of the overall weight distribution, even when individual criterion weights vary across scenarios. It provides a unified and comparable evaluation framework and serves as the basis for subsequent sensitivity analysis.

The criterion weighting is not universal and may vary depending on the application context, the nature of the alternatives and the preferences of the decision-makers. Its determination is generally based on participatory approaches involving experts in the field and/or decision-makers or on MCDM techniques.

The weights (Table 3) in this paper represent the relative importance of the criteria within the proposed framework for evaluating the startup ideas. The authors chose the following prioritization order to represent one possible decision-making scenario: profitability as the most important criterion, followed by risk, social impact, growth potential and initial costs. The assigned weights reflect this prioritization order. In this weighted structure, higher weights reflect greater importance and guide the evaluation of potentially conflicting criteria.

***Table 3.** Preference-based criteria weights.*

	Profitability	Growth potential	Risk	Initial costs	Social impact
Weights	0.35	0.1	0.3	0.05	0.2

It is important to note that the model handles normalization differently depending on the MCDM method. PROMETHEE II uses min–max normalization (although not theoretically required, it is used in some implementations). TOPSIS applies vector normalization. VIKOR incorporates scaling within its best–worst formulation. ELECTRE II typically relies on normalized data. AHP does not require explicit normalization of the decision matrix.

In this implementation, ELECTRE II uses predefined concordance thresholds (c1 = 0.75 and c2 = 0.60) to define strong and weak outranking conditions. To reduce computational complexity, a simplified concordance-based implementation was adopted. Although some values and ranking positions differed from the complete ELECTRE II procedure, the overall conclusions and the dominant alternatives remained unchanged.

The AHP implementation is inspired by Zarour et al. (2019) for alternatives and Rodrigues de Oliveira and Duarte (2024) for criteria. The remaining steps follow the standard AHP methodology proposed by Saaty.

***Table 4.** Comparative evaluation of six startup ideas across AHP, TOPSIS, PROMETHEE II, ELECTRE II and VIKOR methods.*

Alternatives / methods	**A**	**B**	**C**	**D**	**E**	**F**
AHP_SCORE	0.126287	0.164996	0.169680	0.142879	0.174984	0.221174
AHP_RANK	6	4	3	5	2	1
TOPSIS_SCORE	0.363631	0.629111	0.487659	0.363631	0.553129	0.886648
TOPSIS_RANK	5	2	4	5	3	1
PROMETHEEII_SCORE	-0.42	-0.01	0.13	-0.42	0.12	0.60
PROMETHEE II_RANK	5	4	2	5	3	1
ELECTRE II_SCORE	1.0	1.5	2.5	1.0	3.0	5.0
ELECTRE II_RANK	5	4	3	5	2	1
VIKOR_SCORE	1.000000	0.585714	0.645238	1.000000	0.444048	0.000000
VIKOR_RANK	5	3	4	5	2	1

To synthesize the evaluation results and to obtain an overall ranking of the alternatives, a ranking aggregation method, the Borda method, was applied. This approach combines the different scores or ranks obtained through the various MCDM methods considered, providing a coherent overall ranking of the alternatives.

The Borda method is a multi-criteria voting and aggregation technique, where each alternative receives points based on its rank under each criterion. The higher an alternative is ranked, the more points it receives. The total score of each alternative is calculated by summing the points across all the criteria, and the alternatives are then ranked in descending order of their total scores (Borda, 1781).

Depending on the implementation adopted, the highest or the lowest Borda score may represent the best overall alternative. Mathematically, the Borda score of the alternative A_i is given by:

$$B(A_i) = \sum_{k=1}^{m} (n - r_{ik}) \tag{2}$$

Where:

- n is the total number of alternatives,
- m is the number of rankings (or methods/scenarios) considered,
- r_{ik} is the rank of the alternative A_i in ranking k.

The alternative with the highest Borda score is considered the best overall alternative in the classical Borda formulation. In other implementations based on the direct summation of the ranks, the alternative with the lowest cumulative score is considered the best. The results of the Borda ranking are shown in Figure 1 below. It illustrates the final order of the alternatives, obtained by aggregating the different scores.

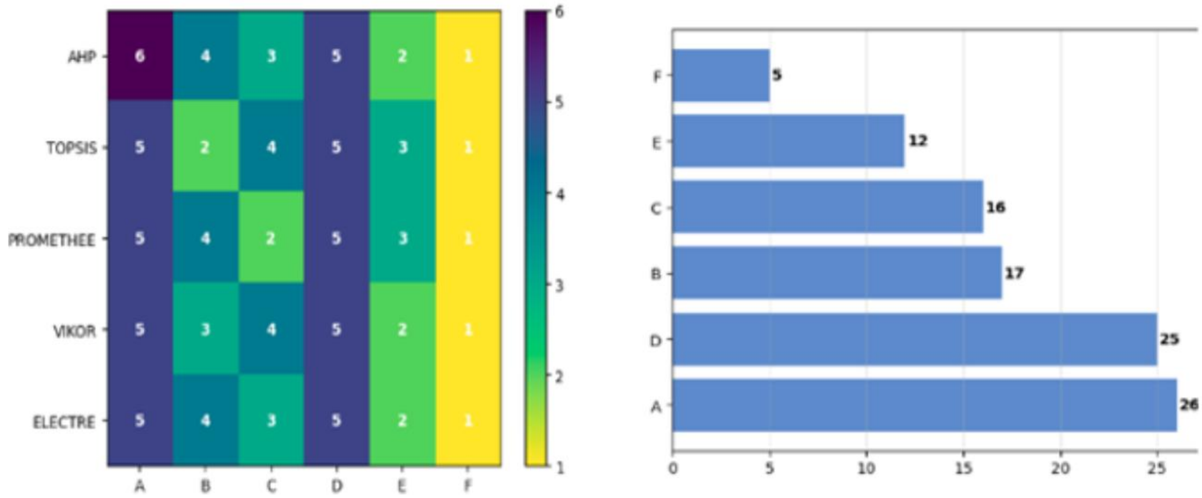

Figure 1. *Borda rankings and heatmap visualization of ranks.*

Despite the variety of the multi-criteria decision methods, the alternative F stands out, achieving the highest scores across all the assessments. The alternatives A and D appear the least effective, with average results, and are therefore generally not recommended. The alternatives E, B, and C occupy intermediate positions. Alternative E is a good choice, ranking close to alternative F, while alternatives B and C demonstrate inconsistent performance and may be appropriate in specific situations, but are less stable than the other alternatives F and E. The strong convergence of the results underscores the robustness and the reliability of this multi-criteria approach to informed decision-making.

The results show a consistent ranking among the different methods, with all ranking the option F as the best alternative, indicating strong ranking rather than absolute superiority. The divergence typically emerges when the alternatives perform both strongly and weakly across the criteria or when their overall scores are very close.

Finally, this first part of the experiment concluded with a concordance study across the methods to assess the degree of the agreement between the different classification techniques. Concordance measures allow us to evaluate the consistency of the results obtained by several methods applied to the same set of alternatives.

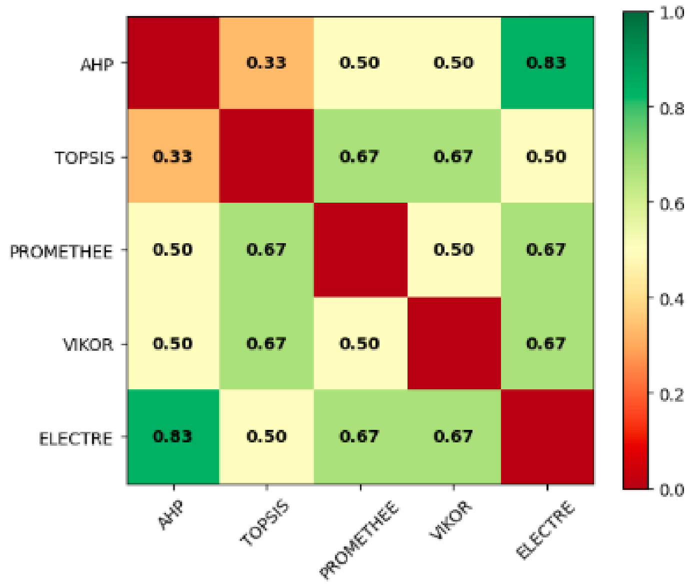

Figure 2. *Concordance results across methods.*

Mathematically, the concordance index C between two methods M_1 and M_2 can be expressed as:

$$C(M_1, M_2) = \frac{Number\ of\ concordant\ pairs}{Total\ number\ of\ pairs} \tag{3}$$

Where the pair of the alternatives is considered concordant if both methods rank them in the same order. The index ranges from 0 (no agreement) to 1 (perfect agreement). The obtained results are summarized in Figure 2. This concordance analysis illustrates the level of agreement between the different classification methods.

A concordance study conducted across all the MCDM methods showed an overall agreement of at least 50% indicating a moderate consistency in the ranking. This means that the methods agree on the relative ranking of more than half of the alternative pairs. Despite some differences in intermediate alternatives, the dominant alternative (F) and the least dominant alternatives (A and D) were consistently identified, confirming the robustness and reliability of the multi-criteria evaluation framework for informed decision-making.

5.6.2 Sensitivity to criteria weights

The second study conducted in this work focuses on analysing the sensitivity of the results to the criterion weighting. This analysis relies on several weighting scenarios, each of them adhering to the normalization constraint. Two types of scenarios were considered:

- global scenarios, which depend on the decision-maker and/or experts and represent different decision-making profiles, in which several criteria are weighted according to their relative priorities; and
- unidimensional sensitivity scenarios, in which only one criterion is prioritized while the others are assigned lower but equal weightings, thus allowing us to examine the isolated impact of this criterion on the overall ranking of alternatives.

Accordingly, eight scenarios were identified, each reflecting a specific weighting system that focuses on profitability, growth, risk, initial costs or social impact, summarized in Table 5. This approach allows a clear understanding of how changes in decision priorities affect the ranking of the alternatives and underscores the robustness and reliability of the multi-criteria evaluation framework.

Table 5. *Different sensitivity scenarios.*

Scenario	Weights	Principle and justification	Strategic focus
S1	[0.20, 0.20, 0.20, 0.20, 0.20]	Equal weighting: all criteria treated equally	Balanced strategy considering all dimensions equally
S2	[0.30, 0.25, 0.15, 0.15, 0.15]	Economic focus: emphasizes profitability and growth	Offensive growth strategy aiming to maximize financial returns
S3	[0.15, 0.15, 0.30, 0.25, 0.15]	Risk/cost focus: prioritizes minimizing risks and initial costs	Defensive, cautious approach for risk-averse or budget-constrained organizations
S4	[0.15, 0.15, 0.15, 0.15, 0.40]	Social impact focus: emphasizes social value	Socially responsible organizations or NGOs with strong social objectives
S5	[0.40, 0.15, 0.15, 0.15, 0.15]	Profitability focus: maximizes immediate returns	Short-term profit-oriented organizations under financial pressure
S6	[0.15, 0.40, 0.15, 0.15, 0.15]	Growth focus: prioritizes long-term growth	Startups or expanding businesses aiming for market penetration
S7	[0.15, 0.15, 0.40, 0.15, 0.15]	Risk focus: minimizes risks above all	Highly regulated sectors or organizations with low risk tolerance
S8	[0.15, 0.15, 0.15, 0.40, 0.15]	Initial cost focus: minimizes upfront investment	Resource-limited organizations or lean startups

The results obtained after applying the different methods to the eight proposed scenarios are summarized in Tables 6 and 7.

Table 6. *Best alternative by method across scenarios.*

Scenario	AHP	TOPSIS	PROMETHEE II	VIKOR	ELECTRE II
S1	F (0.2036)	F (0.6307)	F (0.3200)	F (0.0000)	F (5.00)
S2	F (0.2049)	F (0.6685)	F (0.3400)	F (0.0000)	F (5.00)
S3	F (0.2039)	B (0.7366)	F (0.3200)	F (0.0556)	F (5.00)
S4	F (0.2046)	F (0.7172)	F (0.3900)	F (0.0000)	F (5.00)
S5	F (0.2083)	F (0.7256)	F (0.4400)	F (0.0000)	F (5.00)
S6	F (0.1977)	E (0.6739)	E (0.3200)	E (0.0000)	E (4.00)
S7	F (0.2143)	F (0.7676)	F (0.4400)	F (0.0000)	F (5.00)
S8	B (0.1989)	B (0.7681)	B (0.2200)	B (0.0800)	F (3.50)

Table 7. *Borda ranking by scenario.*

Scenario	A	B	C	D	E	F
S1	6	3	4	5	2	1
S2	6	4	3	5	2	1
S3	5	2	6	4	3	1
S4	5	6	3	4	2	1
S5	6	4	2	5	3	1
S6	5	6	3	4	1	2
S7	5	2	6	4	3	1
S8	5	1	6	3	4	2

Option F stands out clearly in all scenarios, consistently ranking first in most methods and achieving lowest Borda scores. Options B and E perform well in some scenarios while options A and C are generally the least common. Overall, option F demonstrates high stability and is widely preferred across all the methods and scenarios.

Afterwards, a statistical preference is calculated. This method allows evaluating and comparing alternatives in a MCDM context, based on quantitative measures of their performance. It is not limited to identifying the "best" alternative in a given scenario; it also takes into account:

- The average rank of an alternative across all scenarios and methods:

$$Average\ Rank = \frac{\sum_{i=1}^{N} Rank_i}{N} \tag{4}$$

  Where N is the total number of rankings (methods × scenarios) and $Rank_i$ is the rank of the alternative in the i-th method/scenario.

- Stability of performance, indicating whether the preference remains consistent or fluctuates depending on the methods and scenarios:

$$Std = \sqrt{\left[\frac{(\sum_{i=1}^{N} Rank_i - Average\ Rank)^2}{N}\right]} \tag{5}$$

A lower value indicates higher stability, meaning that the ranking of the alternative is consistent across different scenarios and methods.

A higher value indicates less stability and more sensitivity to scenario/method changes.

- Frequency of first place, i.e., how many times an alternative has been ranked first:

$$First\ Place\ Frequency\ (\%) = (Number\ of\ times\ ranked\ 1st\ \div N) \times 100 \quad (6)$$

This shows how often the alternative is ranked best across all methods and scenarios.

Table 8 and Figure 3 summarize the obtained results.

Table 8. *Statistical preference summary of alternatives.*

Alternative	Average rank	Standard deviation	Min rank	Max rank	First places / total (%)	Stability comment
A	5.38	0.52	5	6	0/40 (0.0%)	Stable
B	3.50	1.85	1	6	5/40 (12.5%)	Less stable
C	4.12	1.64	2	6	0/40 (0.0%)	Less stable
D	4.25	0.71	3	5	0/40 (0.0%)	Stable
E	2.50	0.93	1	4	4/40 (10.0%)	Stable
F	1.25	0.46	1	2	31/40 (77.5%)	Very stable

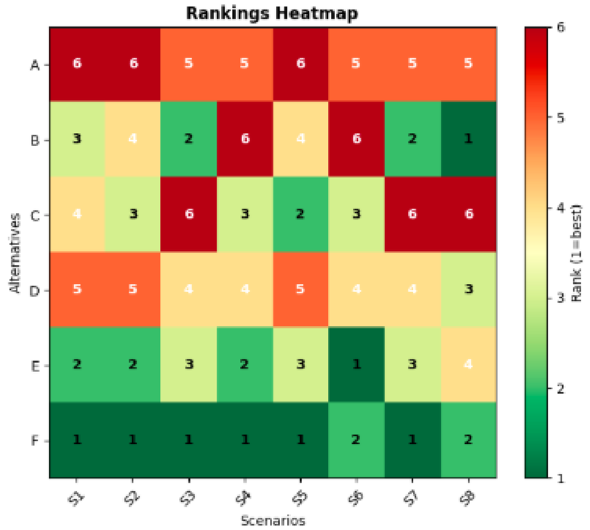

Figure 3. *Ranking heatmap.*

Finally, the average pairwise and overall agreement between methods was calculated as the percentage of identical rankings in all the alternatives and scenarios, reflecting the degree of agreement between each pair of methods as well as across all the methods, as shown in Table 9 and Figure 4.

Table 9. *Pairwise and global average concordance between methods.*

Method	AHP	TOPSIS	PROMETHEE II	VIKOR	ELECTRE II
AHP	100	35.4	52.1	41.7	41.7
TOPSIS	35.4	100	50.0	60.4	56.3
PROMETHEE	52.1	50.0	100	85.4	64.6
VIKOR	41.7	60.4	85.4	100	68.8
ELECTRE	41.7	56.3	64.6	68.8	100
Global average concordance	57.8%				

Finally, the concordance analysis shows that some methods produce very similar rankings, while others differ noticeably. PROMETHEE II and VIKOR are the most aligned pair reflecting strong agreement. In contrast, AHP differs the most from the other methods, especially from TOPSIS, VIKOR and ELECTRE II, indicating that it often ranks alternatives differently. Overall, the global average concordance is less than 60%, meaning that while many alternatives are ranked similarly by most methods, the choice of method can still influence the final ranking of some alternatives.

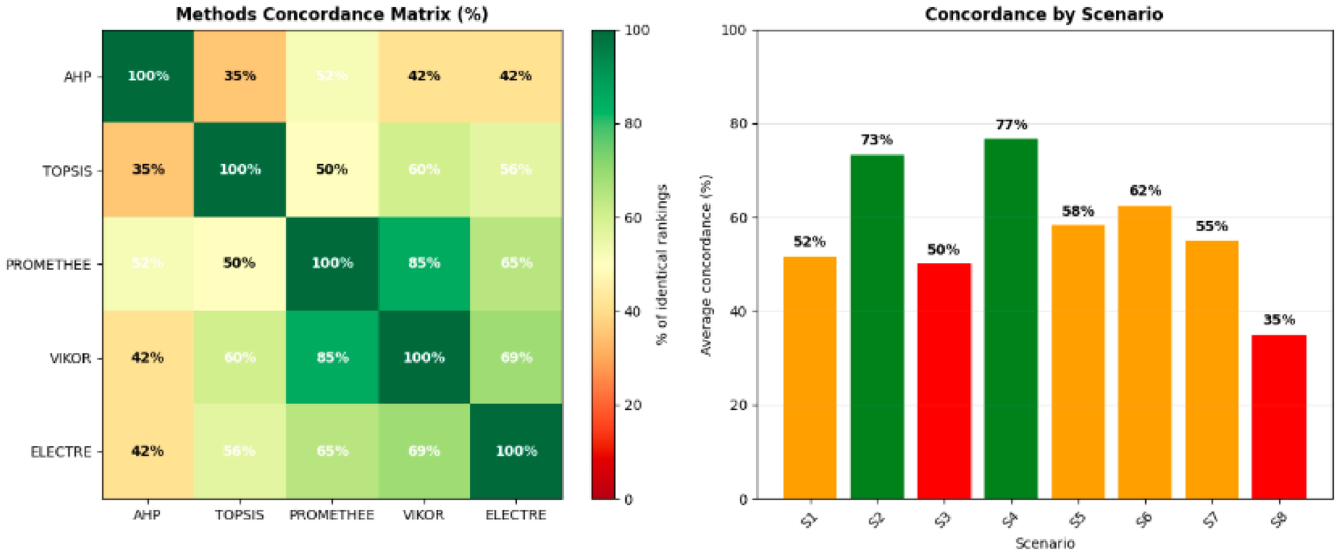

Figure 4. *Concordance by scenarios and methods.*

In this study, the alternative F consistently emerged as the best option among all the MCDM methods. The human evaluation of the alternatives confirms that the alternative F outperforms (is preferred) all the others according to the defined criteria, demonstrating the effectiveness and robustness of these methods in identifying the optimal compromise. While the weighting of criteria plays a significant role in ranking, the results underscore the high efficiency of these methods and their importance in identifying promising startups. Despite differing underlying principles, all the methods consistently highlighted the same leading alternative, providing decision-makers with a reliable and informed choice.

6 CONCLUSION

A comparison of the various multi-criteria evaluation methods used in this study highlights the diversity of decision-making approaches and their impact on the results obtained. Each method relies on a specific computational principle, which explains the observed differences in some rankings. Methods based on trade-offs and preference logic, such as PROMETHEE II and VIKOR, tend to produce relatively consistent and similar results, reflecting a comprehensive comparative evaluation of the performance of alternatives.

In contrast, methods based on hierarchy or distance to the ideal solution, such as AHP and TOPSIS, may lead to different rankings, particularly when the weights of the criteria vary. These differences demonstrate the sensitivity of these methods to assumptions regarding normalization, weighting and clustering. However, these differences remain limited and do not call into question the overall validity of the results.

It is important to emphasize that despite the methodological differences, all the methods share common orientations, especially in identifying the most effective alternatives. This convergence strengthens the credibility of the evaluation process and confirms that the results are not entirely dependent on a single method. Therefore, the observed differences should be interpreted as an analytical advantage, not a contradiction.

Ultimately, this comparison demonstrates the value of a multi-criteria approach in addressing MCDM problems. Combining multiple methods allows integration of diverse perspectives, reduces individual methodological biases and improves the reliability of the final ranking. Thus, this methodological combination provides a robust and relevant analytical framework for making informed and justified decisions.

This proposed model can help decision-makers, such as business incubators and startup evaluators, systematically compare startup ideas against multiple and conflicting criteria. It provides a structured decision support tool that facilitates transparent and consistent prioritization, reducing subjectivity in the evaluation process and supporting more informed investment and selection decisions.

ADDITIONAL INFORMATION AND DECLARATIONS

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: S.R.: Conceptualization, Methodology, Software, Investigation, Writing – Original Draft. K.R.: Data Curation, Writing – Original Draft. M.A.Y.: Writing – Review & Editing.

Statement on the Use of Artificial Intelligence Tools: The authors used ChatGPT for language improvement and error checking. All AI-assisted content was reviewed and edited by the authors, who take full responsibility for the integrity and accuracy of this work.

Data Availability: Additional data that support the findings of this study are available from the corresponding author.

APPENDIX A: AHP STEPS

Step 1: Problem Definition and Hierarchical Structure

The decision problem is structured into a hierarchy with three main levels:

- **Goal:** the overall objective of the decision.
- **Criteria** (and sub-criteria, if any)**:** factors influencing the decision.
- **Alternatives:** possible options to be evaluated.

This hierarchical decomposition helps decision-makers clearly understand the relationships between the elements.

Step 2: Construction of the Pairwise Comparison Matrix

For each level of the hierarchy, elements are compared pairwise with respect to their importance relative to an element at the higher level.

The pairwise comparison matrix $C=[c_{ij}]$ is defined as:

$$C = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ c_{21} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & 1 \end{bmatrix}, \boldsymbol{C_{ji}} = \frac{\mathbf{1}}{\boldsymbol{C_{ij}}}, \qquad \boldsymbol{C_{ii}} = \mathbf{1} \tag{7}$$

where:

- c_{ij} represents the relative importance of element i over element j.
- Saaty's Fundamental Scale, Table 10:

Table 10. *Saaty's Fundamental Scale for Pairwise Comparisons (AHP).*

Numerical value	Interpretation
1	Equal importance
3	Moderate importance
5	Strong or essential importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

Step 3: Normalization of the Pairwise Comparison Matrix

Each element of the matrix is normalized by dividing it by the sum of its column:

$$\tilde{c}_{ij} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}} \tag{8}$$

This produces the normalized matrix $\tilde{C}$

Step 4: Computation of the Priority Vector (Weights)

The weight of each criterion is obtained by averaging the normalized values of each row:

$$w_i = \left(\frac{1}{n}\right) \sum_{j=1}^{n} \tilde{c}_{ij} \tag{9}$$

This vector represents the relative weights of criteria (or alternatives).

Alternatively, weights can be obtained using the principal eigenvector method:

$$Cw = \lambda_{max} w \tag{10}$$

Step 5: Consistency Check of Judgments

AHP evaluates the consistency of the decision-maker's judgments.

- Maximum Eigenvalue

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{(Cw)_i}{w_i}\right) \tag{11}$$

- Consistency Index (CI)

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{12}$$

- Consistency Ratio (CR)

$$CR = \frac{CI}{RI} \tag{13}$$

Interpretation:

- If CR<0.10, the judgments are acceptable.
- If CR≥0.10, the comparisons should be revised.

Step 6: Evaluation of Alternatives

For each criterion, a pairwise comparison matrix of alternatives is constructed and normalized in the same manner. Each alternative receives a local priority weight with respect to each criterion.

Step 7: Aggregation of Weights and Final Ranking

The global priority score of each alternative is calculated as:

$$S_k = \sum_{i=1}^{m} w_i \cdot v_{ik} \tag{14}$$

where:

- w_i is the weight of criterion i,

- v_{ik} is the local priority of alternative k under criterion i,
- m is the number of criteria.

The alternative with the highest score is considered the best option.

APPENDIX B: TOPSIS STEPS

Step 1: Construct the Decision Matrix

- Identify alternatives A = {a_1, a_2, ..., a_n} and criteria C = {c_1, c_2, ..., c_m}
- Build the decision matrix X = [x_{ij}], where x_{ij} is the performance of alternative a_i on criterion c_j.

$$X = [x_{ij}], \qquad i = 1, \dots, n; \quad j = 1, \dots, m \tag{15}$$

Step 2: Normalize the Matrix

Use the normalization vector

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{16}$$

Step 3: Compute Weighted Normalized Matrix

$$v_{ij} = w_j * r_{ij} \tag{17}$$

Step 4: Determine Ideal Solutions

- Positive ideal:

$$v_j^+ = \max_i v_{ij}\,(benefit), \qquad \min_i v_{ij}(cost) \tag{18}$$

- Negative ideal:

$$v_j^- = \min_i v_{ij}\,(benefit), \qquad \max_i v_{ij}(cost) \tag{19}$$

Step 5: Compute Distances to Ideals

- Distance to positive ideal:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2} \tag{20}$$

- Distance to negative ideal:

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2} \tag{21}$$

Step 6: Compute Relative Closeness to Ideal

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{22}$$

Step 7: Rank Alternatives

Rank alternatives in descending order of C_i^* (higher is better).

$$a_p \succ a_q \Leftrightarrow C_p^* > C_q^* \tag{23}$$

APPENDIX C: PROMETHEE II STEPS

Step 1: Problem Definition

- Identify the decision objective.
- Define the set of alternatives A= {a_1, a_2, …, a_n}.
- Define the criteria G= {g_1, g_2, …, g_m}

Step 2: Evaluate Alternatives

Construct the decision matrix containing the performances $g_j(a_i)$ of each alternative for each criterion.

Step 3: Select Preference Functions

Assign a preference function $P_j(d)$ to each criterion g_j

Compute the performance difference:

$$d_j(a,b) = g_j(a) - g_j(b) \tag{24}$$

Step 4: Compute Preference Indices

For each alternative pair (a, b), calculate the global preference index:

$$\pi(a,b) = \sum_{j=1}^{m} w_j\, P_j\left(d_j(a,b)\right) \tag{25}$$

Where: w_j is the weight of criterion j.

Step 5: Compute Preference Flows

- Positive flow:

$$\varphi^{+(a)} = \frac{1}{n-1} \sum_{b \in A, b \neq a} \pi(a,b) \tag{26}$$

- Negative flow:

$$\varphi^{-(a)} = \frac{1}{n-1} \sum_{b \in A, b \neq a} \pi(b,a) \tag{27}$$

Step 6: Compute Net Flow

- Net flow:

$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a) \tag{28}$$

Step 7: Rank Alternatives

Rank alternatives in descending order of net flow ϕ(a). The highest net flow corresponds to the preferred alternative.

APPENDIX D: ELECTRE II STEPS

Step 1: Construction of the Decision Matrix

Let A = {a_1, a_2, …, a_n} be the set of alternatives and C = {c_1, c_2, …, c_m} the set of criteria.

The decision matrix is defined as:

$$X = [x_{\mathrm{ij}}], \qquad i = 1, \dots, n\,;\; j = 1, \dots, m \tag{29}$$

Step 2: Normalization of the Decision Matrix

To make criteria comparable, the matrix is normalized.

For benefit criteria:

$$r_{\mathrm{ij}} = \frac{x_{\mathrm{ij}}}{\sqrt{\sum_{i=1}^{n} x_{\mathrm{ij}}^2}} \quad (30)$$

Step 3: Weighted Normalized Matrix

Each criterion is assigned a weight w_j, such that:

$$\sum_{j=1}^{m} w_{\mathrm{j}} = 1, wj \geq 0 \quad (31)$$

The weighted normalized matrix is:

$$v_{\mathrm{ij}} = w_{\mathrm{j}} \cdot r_{\mathrm{ij}} \quad (32)$$

Step 4: Concordance Set and Concordance Index

For each pair of alternatives (a, b), the concordance set is:

$$C(a,b) = \{ j \mid v_{a_j} \geq v_{b_j} \} \quad (33)$$

The concordance index is computed as:

$$c(a,b) = \sum_{\mathrm{j} \in C(a,b)} w_{\mathrm{j}} \quad (34)$$

Step 5: Discordance Index

The discordance index measures the largest disagreement:

$$d(a,b) = \frac{\max_{j \notin C(a,b)} |v_{aj} - v_{bj}|}{\max_{i,k,j} |v_{ij} - v_{kj}|} \quad (35)$$

Step 6: Establishment of Outranking Relations

Alternative a outranks b if:

$$c(a,b) \geq c^* \ \ and \ \ d(a,b) \leq d^* \quad (36)$$

where c^* and d^* are predefined concordance and discordance thresholds.

Step 7: Ascending and Descending Distillation

ELECTRE II applies:

- Descending distillation (best to worst)
- Ascending distillation (worst to best)

The final ranking is obtained by combining both procedures to produce a partial or complete ranking of alternatives.

APPENDIX E: VIKOR STEPS

Step 01: Construction of the Decision Matrix

Let A = {a1, a2, …, an} be the set of alternatives and C = {c1, c2, …, cm} the set of criteria.

The decision matrix is defined as:

$$X = [x_{\mathrm{ij}}], i = 1, \dots, n; \ \ j = 1, \dots, m \quad (37)$$

Step 2: Determination of Best and Worst Values

For each criterion j, determine:

- the best value f_j^*
- the worst value f_j^-

For benefit criteria:

$$f_j^* = \max_i x_{ij}, f_j^- = \min_i x_{ij} \tag{38}$$

For cost criteria:

$$f_j^* = \min_i x_{ij}, f_j^- = \max_i x_{ij} \tag{39}$$

Step 3: Computation of the Utility Measure (S)

The group utility measure for alternative a_i is:

$$S_i = \sum_{j=1}^{m} \frac{w_j(f_j^* - x_{ij})}{f_j^* - f_j^-} \tag{40}$$

Step 4: Computation of the Regret Measure (R)

The individual regret measure for alternative a_i is:

$$R_i = \max_j \left[\frac{w_j(f_j^* - x_{ij})}{f_j^* - f_j^-}\right] \tag{41}$$

Step 5: Computation of the VIKOR Index (Q)

The VIKOR index is calculated as:

$$Q_i = v\frac{S_i - S^*}{S^- - S^*} + \frac{(1-v)(R_i - R^*)}{R^- - R^*} \tag{42}$$

where:

$$\begin{aligned} S^* &= min_i\, S_i, \quad & S^- &= max_i\, S_i \\ R^* &= min_i\, R_i, \quad & R^- &= max_i\, R_i \end{aligned} \tag{43}$$

and v ∈ [0,1] is the weight of the strategy (usually v=0.5).

Step 6: Ranking of Alternatives

Alternatives are ranked in **ascending order** according to:

- S_i (group utility)
- R_i (individual regret)
- Q_i (compromise solution)

The alternative with the smallest Q_i is considered the best compromise solution.

$$a_p \prec a_q \Leftrightarrow Q_p < Q_q \tag{44}$$

Step 7: Compromise Solution Conditions

The best alternative $a^{(1)}$ is accepted if:

- Acceptable advantage:

$$Q(a^2) - Q(a^1) \geq \frac{1}{n-1} \tag{45}$$

Acceptable stability: $a^{(1)}$ must also be ranked first by S or R. If these conditions are not satisfied, a set of compromise solutions is proposed.

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