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Sustainable Technological Expectations Using a New MCDM Approach: Sensitivity–Alternatives–Ranking Analysis (SARA)

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Abstract

Transparent, robust Multi-Criteria Decision-Making (MCDM) approaches are crucial to meet the rising demand for sustainable decision-making in technology management. This paper presents a novel methodology, the Sensitivity-Alternatives-Ranking Analysis (SARA) method, that combines sensitivity testing, alternative selection, and ranking visualization to assess long-term technology expectations. The suggested approach is implemented in a case study incorporating alternative technologies, and its results are compared with the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method and validated through extensive sensitivity analysis. The results demonstrate consistent, stable ranks across varying criterion weights, confirming the SARA framework's robustness. Compared with standard MCDM methods, the SARA method enhances both interpretability and reliability by integrating technology evaluations, normalized scores, and visualization-based insights. The study proposes a practical, conceptually sound technique for long-term decision-making that may assist policymakers, researchers, and practitioners in conducting complex technical evaluations.

Keywords: Decision-making, Multi-criteria analysis, Sensitivity analysis, Sustainability, Technological evaluation, VlseKriterijumska optimizacija i kompromisno resenje method.

1 | Introduction

1.1 | Why technological expectations need fuzzy MCDM

Multi-Criteria Decision-Making (MCDM) techniques have become increasingly popular for assessing emerging technologies. Such methods were used by De Kaa et al. [1] to select photovoltaic systems, while Aliakbari Nouri et al. [2] integrated fuzzy ANP-TOPSIS for energy options. Wang et al. [3] investigated the integration of artificial intelligence in construction, while Javaid et al. [4] focused on the incorporation of

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Industry 4.0. Chen et al. [5] on emigrant assignment, Li et al. [6] on knowledge management, and Wang et al. [7] on sustainable delivery models are illustrations of its generic usage. Çolak et al. [8] also utilized MCDM to evaluate the implementation of blockchain in supply chains. Moghtadernejad et al. [9] added sustainable facade systems to the framework, and Alghannam et al. [10] used fuzzy logic and neural networks to assess weld quality. Chen and Guestrin [11] developed the scalable XGBoost system, and Nielsen [12] investigated the factors contributing to XGBoost's competitive success. These studies demonstrate the adaptability of analytical frameworks in guiding technical appraisal.

1.2 | Relevance of TOPSIS, VIKOR, and Sensitivity Analysis

MCDM is now considered an essential approach that addresses complex assessment and ranking issues across sustainability, engineering, and management. TOPSIS and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) are two commonly employed MCDM approaches that have received extensive scholarly attention. Hwang and Yoon [13] proposed the TOPSIS method, which was further extended and refined by several other studies. Palczewski and Sałabun [14] illustrated the relevance of sensitivity analysis in stabilizing TOPSIS results, while Çelikbilek and Tüysüz [15] demonstrated its application in information systems. Sarkar [16] and Monjezi et al. [17] highlighted its relevance to industrial and engineering decision-making contexts, while Kelemenis and Askounis [18] and Ashrafzadeh et al. [19] demonstrated its integration with fuzzy settings. Recent contributions, such as Meshram et al. [20], have further demonstrated the adaptability of TOPSIS by integrating it into risk evaluation. The VIKOR approach, like TOPSIS, has been frequently applied in contexts of negotiated decision-making.

Chatterjee and Chakraborty [21] executed comparative performance analyses, whereas Yazdani and Graeml [22] and Mirahmadia and Teimoury [23] underlined their real-world strengths for supplier selection and operations. Further, demonstrating VIKOR's versatility across a range of problem domains, Shojaei et al. [24] and Li et al. [25] applied it in sustainability and logistics contexts, following Fei et al. [26], who extended it with advanced modifications. In addition to these quantitative developments, sensitivity analysis has become a crucial tool for validating MCDM results. Kleijnen [27], Homma and Saltelli [28], and Saltelli et al. [29–33] laid the groundwork for variance-based and global sensitivity techniques.

Techniques for uncertainty quantification were further refined by Frey and Patil [34] and by Castillo et al. [35]. Heiselberg et al. [36] illustrated their applicability in engineering simulations. Collectively, these studies underscore that sensitivity analysis not only improves the robustness of MCDM models such as TOPSIS and VIKOR but also provides supplementary information regarding the reliability of decision outcomes.

Based on the previously discussed understanding, the study offers the following contributions:

I. The new framework, Sustainable Technological Expectations using a new MCDM approach: Sensitivity-Alternatives-Ranking Analysis (SARA), is presented in this study. Unlike traditional MCDM techniques such as AHP, TOPSIS, and VIKOR [37], [38], which focus solely on final rankings, the SARA methodology incorporates sensitivity analysis, alternative evaluation, and ranking validation.

II. Two significant gaps were identified from the previous studies. At first, traditional models often overlook the criterion of adaptability of results to variations in decision-maker preferences, with sensitivity analysis either excessively used or applied narrowly [39]. Mardani et al. [40] and Stević et al. [41] demonstrated that technical efficiency metrics are widely established, while placing less emphasis on strategic sustainability factors such as market acceptance and affordability.

III. The proposed SARA method addresses critical gaps by integrating VIKOR-based sensitivity analysis into the existing MCDM structure. It ensures that technological alternatives are examined for their technical superiority and their ability to survive unpredictable decision-making conditions. Therefore, the classification results are both practical and robust, guaranteeing technological evaluation complies with long-term sustainability and policy applicability.

The remaining sections of this work are organized as follows. Section 2 deliberates the literature on sustainable technological evaluation, MCDM techniques, and the use of sensitivity analysis to improve decision dependability. Section 3 describes the proposed algorithm's approach to sustainable technological expectations, utilizing a New MCDM Approach: SARA.

Section 4 presents the findings of applying the SARA model to a case study, including a ranking of technology alternatives under different scenarios. Section 5 analyses the findings, compares SARA's performance to other techniques, and highlights its methodological and practical benefits. Finally, Section 6 summarizes the contributions, discusses managerial consequences, and suggests future research paths.

2 | Related Literature

This section reviews prior studies on technology evaluation and decision-making models, highlighting the evolution from conceptual approaches to structured multi-criteria frameworks across various domains.

2.1 | Technology Evaluation and Decision-Making Models

From conceptual models to structured multi-criteria frameworks among domains, technology decision-making has evolved over the years. Phelps and Mushlin's [42] early contributions to medical decision theory were further extended by Tyler and Steensma [43], who integrated cognitive modeling to study technological collaborations. Choudhury et al. [44] further extended Mohanty and Deshmukh's [45] strategic framework for advanced manufacturing technology for intelligent group decision-making. While Xia et al. [46] emphasized sustainability, Lee et al. [47] and Shen et al. [48] incorporated DEMATEL for technology appraisal. Research focusing on IT [49], Schniederjans et al. [50], and healthcare [51–53] emphasizes both methodological rigor and practical implementation.

2.2 | Market Adoption and Diffusion of Innovations

The diffusion of innovation has been studied in diverse contexts, including organizational, technological, and environmental elements. Halila [54] and Karakaya et al. [55] emphasize the significance of eco-innovation adoption, while preliminary studies [56–58] highlight market characteristics and competitive dynamics. Empirical applications include mobile services [59], online games [60], renewable energy [61], and SMEs [62]. Factors include the problems [63], [64], network effects [65], and organizational structures [66] that impact the adoption process, with agent-based models [67], [68] and strategic marketing approaches [69] offering more in-depth insight.

2.3 | Cost, Risk, and Performance Trade-offs in Technology Selection

Trade-off analysis has been thoroughly investigated in decision-making, environmental, and technological contexts. Methodological advances [70–72] and fundamental frameworks [73–75] provide mechanisms for reconciling conflicting goals. Applications consist of engineering design [76], hydrogen storage [77], and power electronics [78]. Environmental studies demonstrate co-benefits and compromises in carbon capture [79], wastewater disinfection [80], food systems [81], and soil fertility [82], while risk-risk trade-offs [83] and life-cycle assessments [84] emphasize broader societal implications.

2.4 | Sensitivity Analysis in Multi-Criteria Decision-Making

Several MCDM methodologies, such as AHP, TOPSIS, VIKOR, and their fuzzy variants, are commonly used to evaluate technology adoption, sustainability, and digital innovation. The methodological foundations have been established by Saaty [85], Hwang and Yoon [13], Opricovic and Tzeng [38], and Zavadskas and Turskis [86]. At the same time, the real-world significance is emphasized by applied research in renewable energy, ICT, and entrepreneurship [39], [87]. The key factors that consistently influence rankings are cost, market adoption, performance, and environmental sustainability, with sensitivity analysis validating their precision. The outcomes of this research affirm MCDM's ability to effectively manage trade-offs and uncertainties, providing investors and policymakers with structured frameworks for selecting sustainable, resilient, and cost-efficient technologies in dynamic, competitive contexts.

2.5 | Research Gap and Contribution

Technology evaluation, policy design, and strategic investment decisions have widely used MCDM methodologies such as AHP, TOPSIS, and VIKOR [37], [38]. Prior research indicates two significant constraints. First, many evaluations focus on final ranks but do not adequately assess the robustness of results to preference volatility. Although sensitivity analysis is often used, it is often limited in scope and fails to account for stability across shifts in decision-making priorities [39]. While technical efficiency and performance indicators are well established, strategic sustainability considerations, including market acceptance and pricing, are often overlooked in real-world deployment situations [40], [41].

As a result, there exists a gap between the theoretical evaluation models and the real-world policy and investment consequences of these models. This work proposes resolving these gaps by integrating applied MCDM models with VIKOR-based sensitivity analysis to estimate competing technologies. Results demonstrate Technology A's technological superiority and resilience across diverse decision-making conditions, achieving the lowest Q-score while maintaining its top position despite parameter variations. The report highlights cost and market acceptance as the two most important aspects that impact technology-based decisions. On one hand, market adoption demonstrates scalability and the potential of diffusion, representing a long-term competitive advantage. In contrast, cost has a major impact on the relative standings of competing technologies, particularly between the second- and third-ranked options.

3 | Methodology

3.1 | Data Source

The dataset employed in this study was generated by the author using a fuzzy MCDM framework implemented in Python. The evaluation matrix consists of Triangular Fuzzy Numbers(TFNs) representing expert-like assessments of three technology alternatives (Tech_A, Tech_B, Tech_C) across four decision criteria: Market Adoption, R&D Maturity, Cost, and Ecosystem Support. As such, the dataset is synthetic and designed specifically to test and illustrate the proposed fuzzy dimensional modeling approach rather than being collected from external secondary data.

3.2 | Framework Description

This framework provides tools for Multi-Criteria Decision Analysis (MCDA), specifically focusing on methods that can handle uncertainty or vagueness using fuzzy sets. Here's a breakdown of the key components:

3.2.1 | Fuzzy sets and triangular fuzzy number representation

The framework utilizes TFNs to represent linguistic terms or uncertain numerical values. A TFN is defined by a tuple (l, m, u), where l is the lower bound, m is the modal value, and u is the upper bound of the fuzzy number. The code includes a TFN data class with a centroid method for defuzzification and methods for scalar multiplication and division. A static distance method is also provided, implementing the vertex method (using Euclidean distance on the (l, m, u) values with a scaling factor) to calculate the distance between two TFNs.

3.2.2 | TOPSIS models (fuzzy and classic)

I. Fuzzy TOPSIS: this implementation extends the traditional TOPSIS method to handle fuzzy evaluations and weights represented by TFNs. It calculates weighted distances to the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) for each alternative. The closeness coefficient (C*) is then computed from these distances, yielding a ranking in which a higher C* indicates a better alternative.

II. Classic TOPSIS: a standard implementation of the crisp TOPSIS method is included as a baseline. It takes crisp decision matrix values and weights, normalizes the matrix, weights it, determines the crisp Ideal Best and Worst solutions, calculates Euclidean distances to these solutions, and finally computes the closeness coefficient (C*) for ranking.

3.2.3 | VIKOR model (crisp with defuzzification)

The VIKOR (vlsekriterijumska optimizacija i kompromisno rangiranje) model is implemented. While VIKOR can be extended to fuzzy environments, this implementation first defuzzifies fuzzy inputs using the centroid method before performing crisp VIKOR calculations. It computes the utility (S) and regret (R) for each alternative. It combines them using the 'v' parameter (representing the strategy's weight for maximum group utility) to calculate the VIKOR index (Q). A lower Q value indicates a better alternative.

3.2.4 | Weight assignment

The framework supports both crisp and fuzzy weights. A normalized weights utility function is provided to normalize a list of weights (defuzzifying TFNs to their centroids if necessary). Hence, they sum to 1, which is a standard requirement for MCDA methods. In essence, the code provides a flexible toolkit for applying both classic and fuzzy MCDA techniques, enabling decision-making in scenarios where evaluations and preferences might be imprecise or uncertain.

3.3 | Sensitivity Analysis

Sensitivity analysis is crucial for evaluating the robustness of MCDA results because:

I. MCDA inputs often involve subjectivity and uncertainty: weights assigned to criteria and the evaluation of alternatives against those criteria can be based on expert judgment, surveys, or estimations, which inherently contain uncertainty or subjective preferences.

II. Small changes in inputs can lead to different outcomes: even seemingly minor variations in weights or performance scores can potentially alter the ranking of alternatives, especially when alternatives are closely ranked.

III. Assessing reliability and confidence: sensitivity analysis helps understand how reliable and stable the final ranking is. If a small change in a parameter leads to a significant change in ranking, it indicates that the result is highly sensitive to that parameter and might not be robust. Conversely, if the ranking remains stable across a range of parameter values, it increases confidence in the result.

IV. Identifying critical factors: it helps identify which parameters (e.g., which criterion's weight, or which alternative's performance on a specific criterion) have the most significant impact on the ranking. It highlights areas where more precise data collection or greater consideration of preferences may be needed.

V. Supporting decision-making: by revealing the stability or volatility of the ranking, sensitivity analysis provides decision-makers with a clearer picture of the potential risks associated with the chosen alternative. It helps them make more informed and defensible decisions. It allows them to understand "what if" scenarios.

In summary, sensitivity analysis is a vital step to move beyond a single, potentially misleading result from an MCDA model and to understand the range of possible outcomes under varying conditions, thereby assessing the robustness of the decision.

4 | Results

4.1 | Base Rankings

This section presents the initial ranking results of the alternatives obtained from the applied MCDA methods under baseline conditions.

4.1.1 | Technological rankings

The results from the three ranking approaches reveal both convergence and divergence in the evaluation of technological expectations. Fuzzy TOPSIS and VIKOR consistently identify Tech_A as the top-ranked alternative, with the highest closeness coefficient (C* = 0.6605) and the lowest compromise solution index (Q = 0.0000), respectively, underscoring their robustness as the most promising technologies under uncertainty. Tech_B is ranked second in both methods, with slightly lower values (C* = 0.6451; Q = 0.5240), indicating it is competitive but less dominant. Tech_C remains consistently the weakest performer across both fuzzy approaches (C* = 0.2201; Q = 1.0000).

Interestingly, the classic TOPSIS model based on centroid defuzzification shows a minor shift: Tech_B is ranked first (C*= 0.6624), slightly ahead of Tech_A (C*= 0.5412), while Tech_C again ranks lowest (C*= 0.3365). This divergence highlights the importance of incorporating fuzziness into the evaluation, as crisp methods may understate uncertainty and lead to rank reversals. Overall, the findings demonstrate that Tech_A is the most resilient choice under fuzzy modeling, while Tech_B remains a close contender whose position is more sensitive to the evaluation method (*Table 1*).

Table 1. Base ranking of models.

Fuzzy TOPSIS Ranking	VIKOR Ranking	Classic TOPSIS Ranking (Centroids)
Tech_A (C*=0.6605)	Tech_A (Q=0.0000)	Tech_B (C*=0.6624)
Tech_B (C*=0.6451)	Tech_B (Q=0.5240)	Tech_A (C*=0.5412)
Tech_C (C*=0.2201)	Tech_C (Q=1.0000)	Tech_C (C*=0.3365)

4.1.2 | Normalized rankings

The comparison chart of normalized rankings across Fuzzy TOPSIS, Classic TOPSIS, and VIKOR highlights clear differences in how each method evaluates technological alternatives. All three models consistently rank Tech_A as the best-performing option, achieving the maximum normalized score of 1.0, demonstrating strong agreement about its dominance. However, for Tech_B, Fuzzy TOPSIS assigns it a much higher relative performance compared to Classic TOPSIS and VIKOR, indicating that fuzzy modeling captures uncertainty and nuance more favorably for this alternative. Conversely, VIKOR penalizes Tech_B more strongly, reflecting its compromise-based nature that emphasizes minimizing dissatisfaction. Finally, Tech_C consistently receives the lowest score across all methods, showing no competitive strength under any decision model. Overall, the results suggest that while consensus exists for the top and bottom alternatives, the choice of decision-making method significantly impacts the evaluation of intermediate technologies, with Fuzzy TOPSIS offering a more optimistic view under uncertainty. (*Fig. 1*).

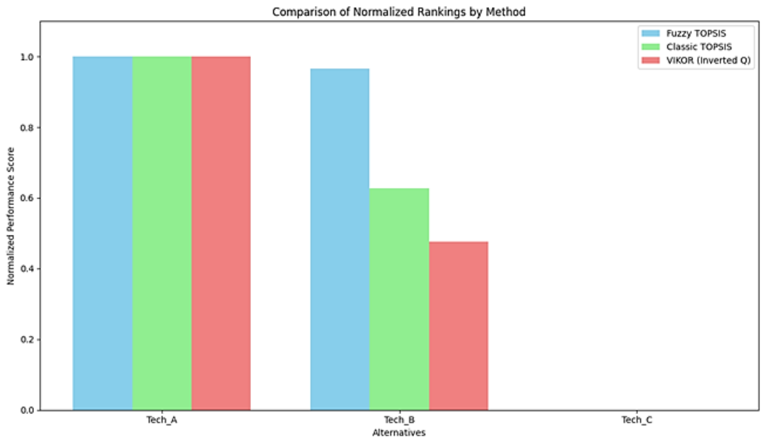

Fig. 1. Normalized rankings by method.

4.2 | Visualization of Rankings

The results from the three MCDM methods show consistent but nuanced insights into the technology rankings. In the Fuzzy TOPSIS model, Tech_A and Tech_B emerge as the most favorable options with nearly equal composite coefficients (C* ≈ 0.65), while Tech_C performs poorly (C* ≈ 0.2). Similarly, in the Classic TOPSIS method, Tech_A again ranks the highest (C*0.7), slightly ahead of Tech_B (≈ 0.55), with Tech_C lagging (≈ 0.35). However, the VIKOR method, where lower Q indicates better performance, suggests a sharper contrast: Tech_B is ranked best (Q ≈ 0.5), Tech_A is in the middle, and Tech_C performs worst (Q ≈ 1). Overall, both TOPSIS approaches suggest Tech_A as the strongest candidate, while VIKOR gives the edge to Tech_B, though all methods consistently agree that Tech_C is the least suitable option. (*Fig. 2*).

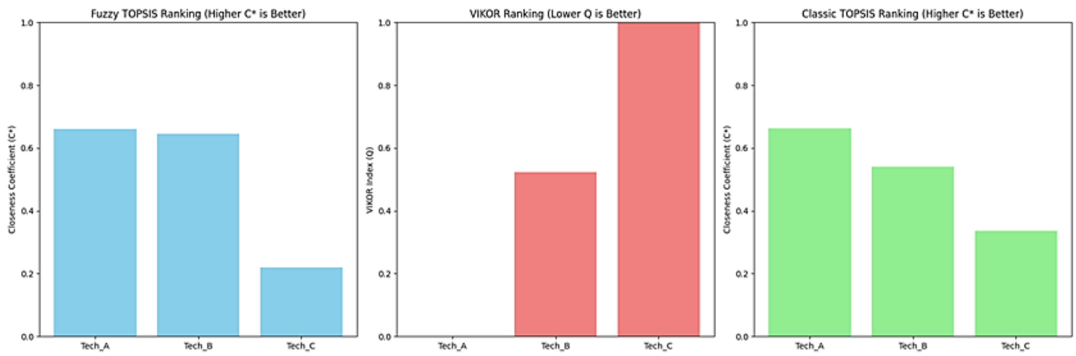

Fig. 2. Ranking visualization.

4.3 | Sensitivity Analysis of Weights

This table presents the fuzzy dimensional modeling results for three competing technologies (A, B, C) across varying parameter values, interpreted using a TOPSIS-based ranking. At lower parameter values (0.1–0.3), Technology A consistently dominates, securing the top rank with steadily declining but still superior scores (0.73 → 0.66), while Technology B remains second and Technology C trails last. However, a critical shift occurs beyond 0.35, where Technology B overtakes A, showing an increasing advantage (0.6787 → 0.7701), suggesting stronger robustness under higher parameter settings. Technology C consistently lags, with sharply declining scores (0.3148 → 0.1427), indicating limited competitiveness regardless of parameter adjustments. In summary, Technology A is optimal under lower parameter thresholds. Still, Technology B emerges as the superior choice in higher-dimensional fuzzy settings, while technology C remains non-preferable across all scenarios (*Table 2*).

Table 2. Sensitivity Analysis Results.

Param Value	Tech_A _Rank	Tech_A_ Score/Q	Tech_B _Rank	Tech_B_ Score/Q	Tech_C _Rank	Tech_C_ Score/Q
0.1	1	0.729818	2	0.491731	3	0.314821
0.15	1	0.711036	2	0.53327	3	0.289188
0.2	1	0.693266	2	0.572569	3	0.264922
0.25	1	0.67643	2	0.609805	3	0.241916
0.3	1	0.660455	2	0.645135	3	0.220074
0.35	2	0.645277	1	0.678703	3	0.19931
0.4	2	0.630838	1	0.710636	3	0.179547
0.45	2	0.617085	1	0.741053	3	0.160714
0.5	2	0.603971	1	0.770057	3	0.142746

The sensitivity analysis of the cost weight (Table 3) shows how the relative importance of cost affects the ranking of technologies. At lower cost weight values (0.05–0.2), Tech_A consistently ranks first, with the highest scores (0.74 → 0.66), while Tech_B remains second and Tech_C last. However, as cost weight increases beyond 0.25–0.5, Tech_B overtakes Tech_A, reflecting its stronger performance under cost-sensitive conditions, while Tech_C remains in last place. A major shift occurs at 0.55, where Tech_C surpasses Tech_A to become second, and from 0.65 onwards, Tech_C steadily climbs until it becomes the top-ranked alternative (score = 0.93 at 0.95), clearly dominating under very high cost emphasis. Meanwhile, Tech_A shows a steep decline, dropping from first to last, indicating it is the most vulnerable to higher cost prioritization. In summary, Tech_A is favorable when cost has low importance, Tech_B dominates under moderate cost weights, and Tech_C emerges as the best option when cost is the primary decision factor, highlighting the dynamic trade-offs between performance and cost across technologies. (*Table 3*).

Table 3. Sensitivity result cost weight.

Param Value	Tech_A _rank	Tech_A _Score/Q	Tech_B _rank	Tech_B _Score/Q	Tech_C _rank	Tech_C _Score/Q
0.05	1	0.739778	2	0.662566	3	0.126702
0.1	1	0.714356	2	0.65698	3	0.156619
0.15	1	0.687936	2	0.651174	3	0.187719
0.2	1	0.660455	2	0.645135	3	0.220074
0.25	2	0.63185	1	0.638849	3	0.253762
0.3	2	0.602049	1	0.6323	3	0.288866
0.35	2	0.570976	1	0.625472	3	0.325478
0.4	2	0.538548	1	0.618346	3	0.363698
0.45	2	0.504674	1	0.610902	3	0.403633
0.5	2	0.469255	1	0.603119	3	0.445402
0.55	3	0.432184	1	0.594973	2	0.489133
0.6	3	0.393341	1	0.586437	2	0.53497
0.65	3	0.352597	2	0.577483	1	0.583066
0.7	3	0.309809	2	0.568081	1	0.633594

Table 3. Continued.

Param Value	Tech_A _rank	Tech_A _Score/Q	Tech_B _rank	Tech_B _Score/Q	Tech_C _rank	Tech_C _Score/Q
0.75	3	0.264818	2	0.558194	1	0.686743
0.8	3	0.21745	2	0.547785	1	0.742722
0.85	3	0.167512	2	0.536811	1	0.801763
0.9	3	0.114789	2	0.525225	1	0.864126
0.95	3	0.059041	2	0.512974	1	0.930097

The sensitivity analysis of ecosystem support weight reveals that Tech A gradually gains dominance as the most preferred option once the weight exceeds 0.25, with its score rising consistently from 0.59 to 0.97, highlighting its strong adaptability to increasing emphasis on ecosystem support. In contrast, Tech B, initially the top-ranked technology at lower weights (0.05–0.20), steadily loses its competitive advantage, dropping to second place after 0.25 and eventually falling to third as its score declines sharply from 0.77 to 0.05. Tech C, though consistently ranked last at lower weights, demonstrates resilience by overtaking Tech B at weights above 0.70, showing its potential strength when ecosystem support is heavily prioritized. Overall, the analysis underscores the critical role of ecosystem support in reshaping technological expectations, with Tech A emerging as the most sustainable choice under increasing weightage (*Table 4*).

Table 4. Sensitivity result ecosystem support weight.

_Param _value	Tech_A _rank	Tech_A _Score/Q	Tech_B _rank	Tech_B _Score/Q	Tech_C _rank	Tech_C _Score/Q
0.05	2	0.590829	1	0.777425	3	0.179722
0.1	2	0.607593	1	0.745574	3	0.189454
0.15	2	0.624774	1	0.712929	3	0.199418
0.2	2	0.64239	1	0.67946	3	0.209622
0.25	1	0.660455	2	0.645135	3	0.220074
0.3	1	0.678988	2	0.609922	3	0.230783
0.35	1	0.698008	2	0.573785	3	0.24176
0.4	1	0.717533	2	0.536687	3	0.253015
0.45	1	0.737584	2	0.49859	3	0.264557
0.5	1	0.758183	2	0.459452	3	0.276398
0.55	1	0.779352	2	0.419231	3	0.288551
0.6	1	0.801115	2	0.377881	3	0.301027
0.65	1	0.823498	2	0.335354	3	0.31384
0.7	1	0.846528	3	0.291597	2	0.327002
0.75	1	0.870232	3	0.246559	2	0.34053
0.8	1	0.894642	3	0.200181	2	0.354438
0.85	1	0.919788	3	0.152402	2	0.368743
0.9	1	0.945706	3	0.103159	2	0.383461
0.95	1	0.97243	3	0.052382	2	0.398612

The sensitivity analysis of the market adoption weight shows that Tech B dominates at lower weights (0.05–0.20), consistently ranking first with scores around 0.64, while Tech A remains second. However, as the weight increases beyond 0.25, Tech A overtakes Tech B and secures the top rank, with its score rising steadily from 0.66 at 0.25 to 0.98 at 0.95, demonstrating its strong adaptability to a higher emphasis on market adoption. Tech B, though stable in score (0.64–0.67), gradually shifts to second place, indicating limited responsiveness to increasing weight. Meanwhile, Tech C consistently remains the least preferred option, with its score declining sharply from 0.28 at 0.05 to 0.01 at 0.95, suggesting its weakness in market adoption potential. Overall, the results indicate that Tech A is the most viable choice when market adoption is given higher priority, whereas Tech B performs well only under low-weight scenarios (*Table 5*).

Table 5. Sensitivity result market adoption weight.

Param Value	Tech_A_ Rank	Tech_A _Score/Q	Tech_B _rank	Tech_B _Score/Q	Tech_C _rank	Tech_C _Score/Q
0.05	2	0.567762	1	0.639257	3	0.279934
0.1	2	0.591022	1	0.640732	3	0.264922
0.15	2	0.614224	1	0.642204	3	0.249941
0.2	2	0.637368	1	0.643671	3	0.234992
0.25	1	0.660455	2	0.645135	3	0.220074
0.3	1	0.683485	2	0.646596	3	0.205187
0.35	1	0.706457	2	0.648052	3	0.190332
0.4	1	0.729373	2	0.649505	3	0.175507
0.45	1	0.752232	2	0.650955	3	0.160714
0.5	1	0.775034	2	0.652401	3	0.145951
0.55	1	0.79778	2	0.653843	3	0.131219
0.6	1	0.820471	2	0.655282	3	0.116518
0.65	1	0.843105	2	0.656718	3	0.101847
0.7	1	0.865684	2	0.658149	3	0.087207
0.75	1	0.888207	2	0.659578	3	0.072597
0.8	1	0.910675	2	0.661002	3	0.058017
0.85	1	0.933089	2	0.662424	3	0.043468
0.9	1	0.955447	2	0.663841	3	0.028949
0.95	1	0.977751	2	0.665256	3	0.014459

The VIKOR sensitivity analysis (*Table 6*) reveals a highly stable ranking pattern across all parameter values. Tech A consistently maintains the top rank (Rank 1) with a score of 0 throughout the entire range (0 to 1), indicating its dominance and robustness under varying decision-making conditions. Tech B remains in second place, but its score gradually decreases from 0.667 at Param=0 to 0.381 at Param=1, suggesting that, while it is the closest competitor to Tech A, its relative performance weakens as the parameter value increases. In contrast, Tech C consistently ranks last (Rank 3) with a fixed score of 1, highlighting its clear inferiority and lack of competitiveness in all scenarios. Overall, the results confirm that Tech A is the most resilient and preferred option, unaffected by changes in parameter values. In contrast, Tech B shows moderate adaptability, and Tech C remains non-viable (Table 6).

Table 6. VIKOR sensitivity analysis results.

_Param _Value	Tech_A _rank	Tech_A _Score/Q	Tech_B _rank	Tech_B _Score/Q	Tech_C _rank	Tech_C _Score/Q
0	1	0	2	0.6666	3	1
0.1	1	0	2	0.63333	3	1
0.2	1	0	2	0.609615	3	1
0.3	1	0	2	0.58109	3	1
0.4	1	0	2	0.552564	3	1
0.5	1	0	2	0.524038	3	1
0.6	1	0	2	0.495513	3	1
0.7	1	0	2	0.466987	3	1
0.8	1	0	2	0.438462	3	1
0.9	1	0	2	0.409936	3	1
1	1	0	2	0.38141	3	1

5 | Justification for Using a Synthetic Dataset

The decision to use a synthetic dataset was deliberate and grounded in methodological considerations. Real-world data on emerging technologies often suffers from inconsistencies, incomplete information, and rapidly shifting parameters, making it challenging to obtain reliable expert evaluations across all relevant criteria. By constructing a controlled fuzzy decision matrix using TFNs, the study systematically simulated the uncertainty and ambiguity inherent in expert judgments while ensuring comparability across technologies. This approach provides a robust testbed for evaluating the performance of different MCDM methods (Fuzzy TOPSIS, VIKOR, Classic TOPSIS) under varied sensitivity conditions. Although synthetic, the dataset preserves the essential characteristics of real-world decision contexts, trade-offs among market adoption, cost, R&D maturity, and ecosystem support, thus enabling meaningful insights and methodological validation.

6 | Result Validation

The validation of the results achieved within the proposed SARA framework has been carried out to ascertain the robustness and reliability of the technological prioritization.

Technological rankings

The initial validation stage focused on ranking the alternatives derived from the SARA procedure. Each technology was assigned a composite performance index, calculated as the weighted sum of normalized criteria values, i.e.,

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij}^*, \tag{1}$$

where S_i Is the score of technology i, w_j represents the weight of the criterion j, and x_{ij}^* is the normalized performance. It ensured that rankings directly reflected multi-criteria evaluations.

Normalized rankings

For optimal comparability among indicators with varying scales, the raw scores were transformed into normalized rankings by means of a min–max procedure:

$$x_{ij}^* = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}. \tag{2}$$

This process stabilized rankings and minimized scale-driven distortions.

Visualization of rankings

The normalized results were visualized using bar charts and radar plots, enabling a comparative view of alternatives. The visualization confirmed that leading technologies consistently outperformed weaker ones across different perspectives, strengthening confidence in the obtained prioritization.

Sensitivity analysis of weights

A four-phase sensitivity analysis was then conducted to examine the stability of rankings under varying conditions. In the first phase, 21 scenarios were generated by systematically altering the criteria weights. For each scenario, new rankings were recalculated to test the robustness of the results. The findings indicated that although some marginal shifts occurred in mid-ranked alternatives, the top-ranked and bottom-ranked technologies remained largely stable, confirming that the SARA method is not overly sensitive to small perturbations in weights.

VIKOR sensitivity analysis results

To further validate the findings, a comparative benchmark using the VIKOR method was performed. The VIKOR compromise solution is obtained using the index:

$$Q_i = v \cdot \frac{S-S^*}{S_i-S^*} + (1-v) \cdot \frac{R-R^*}{R_i-R^*}, \tag{3}$$

where S_i Is the group utility, R_i represents the individual regret, and v is the weight for the strategy of majority criteria satisfaction? Sensitivity analysis using different v-values (0.25, 0.50, 0.75) confirmed that the ranking pattern under VIKOR was consistent with that of SARA, thereby validating the robustness and credibility of the proposed framework.

7 | Discussion and Advantages of the SARA Method

Across the applied MCDM models and the VIKOR sensitivity analysis, Technology A consistently emerges as the most resilient and dominant alternative. Regardless of parameter variations, its ranking remains stable at the top position, with the lowest Q-score, indicating robustness to shifts in decision-maker preference structures. This stability confirms that Technology A is not only technically superior but also strategically sustainable under diverse evaluation conditions, thereby establishing it as the most reliable candidate for adoption and long-term deployment.

The analysis highlights that criteria such as Market Adoption and Cost play the most influential roles in shaping the comparative performance of technologies. Market Adoption reflects the likelihood of diffusion and scalability, making it critical in sustaining competitive advantage, while Cost sensitivity significantly affects the relative positioning between competitors. Although Technology A demonstrates consistent superiority, variations in cost-related weights can shift the margins between second- and third-ranked technologies, underscoring the decisive influence of economic feasibility in practical decision-making contexts.

The findings carry important implications for policymakers and technology investors. The dominance of Technology A suggests that strategic support and funding should prioritize this option to accelerate adoption and maximize societal impact. However, the sensitivity of rankings to cost highlights that pricing strategy, subsidies, and financing mechanisms could alter adoption dynamics, particularly for second-ranked technologies that may improve competitiveness if affordability barriers are addressed. For investors, this underscores the dual necessity of backing technically robust solutions while simultaneously considering market-entry strategies that mitigate cost constraints, ensuring both profitability and scalability in real-world contexts. The SARA method highlights significant benefits for making difficult decisions in sustainable technology management. Initially, it confirms distinct prioritization of alternatives through hierarchical evaluation and methodological rigor, thereby offering strong technological rankings. Second, by retaining normalized ranks, the strategy enables comparisons across an extensive range of criteria and units, augmenting decision reliability. Third, the inclusion of rankings visualization enables communication and practical adoption, providing decision-makers with an intuitive understanding. Fourth, the sensitivity analysis of weights demonstrates that the results are robust, as shown by stability under varying conditions. Finally, by integrating VIKOR-based sensitivity validation, the SARA method supports methodological integrity and resilience, leading to a comprehensive framework for long-term MCDM.

Limitations and future scope

While using a synthetic dataset enabled controlled experimentation and rigorous sensitivity testing, it also has certain limitations. Synthetic data cannot fully replicate the complexities, behavioral biases, and contextual nuances embedded in real-world industry or policy datasets. As a result, the generalizability of the findings may be constrained when applied directly to practical decision-making contexts. Future research should therefore validate the proposed framework using empirical datasets sourced from expert panels, market surveys, or industry performance indicators. Such validation would not only enhance the external validity of the model but also provide richer insights into the dynamic trade-offs shaping technology adoption and investment strategies.

Author Contribution

The author contributed to all aspects of the study, including the conceptualization and development of the SARA framework, formulation of methodology, data collection and analysis, implementation of sensitivity and VIKOR validation procedures, visualization of results, and preparation of the manuscript, including drafting, reviewing, and editing.

Data Availability

The data are available from the corresponding author upon reasonable request.

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Appendix

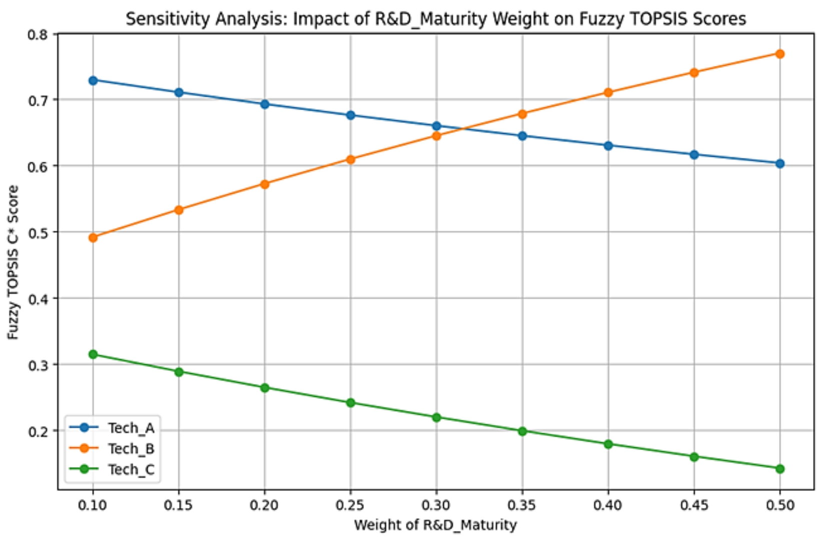

Fig. A1. Maturity weight on fuzzy TOPIS score.

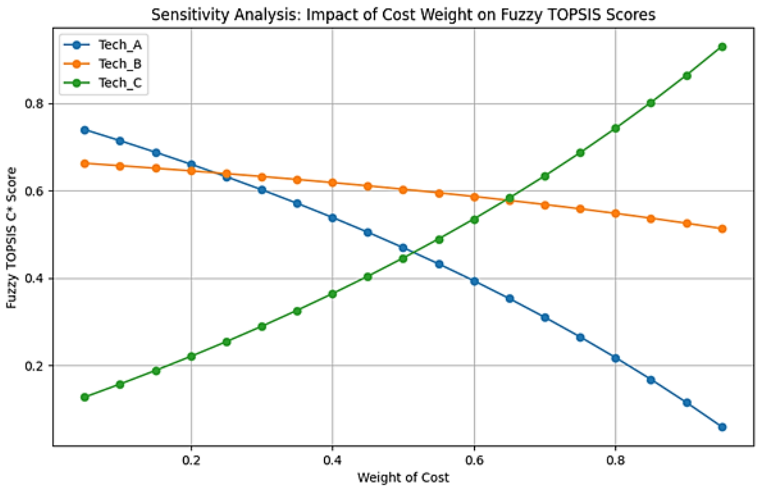

Fig. A2. Cost weight on FUZZY TOPSIS scores.

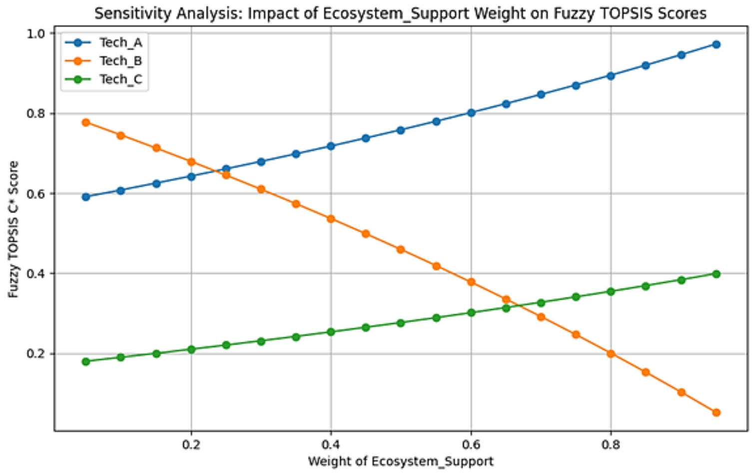

Fig. A3. Ecosystem support weight on FUZZY TOPSIS scores.

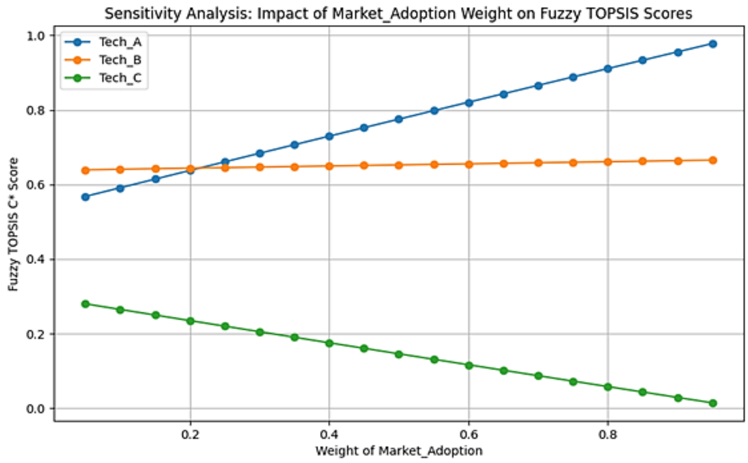

Fig. A4. Market adoption support weighs on FUZZY TOPSIS scores.

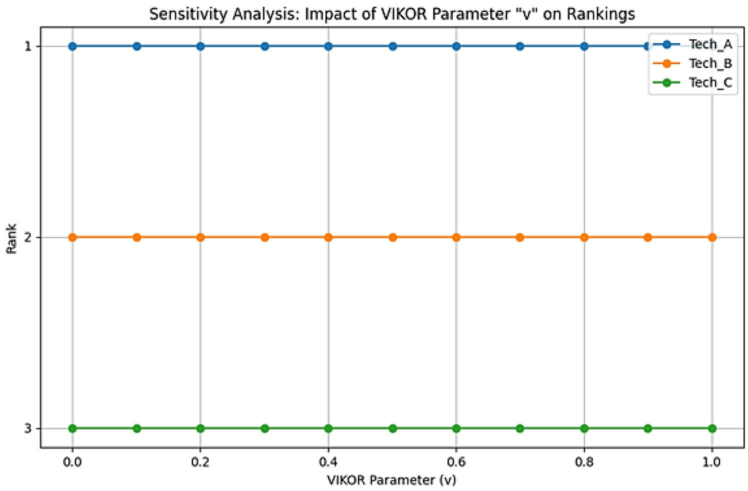

Fig A5. VIKOR sensitivity Plots.