



An Integrated Picture Fuzzy Decision Support Framework for Next-Generation Nuclear Reactor Technology Selection

Gülay Demir^{1,*} 

¹ Sivas Cumhuriyet University, Vocational School of Health Services, 58140, Sivas, Türkiye

ARTICLE INFO

Article history:

Received 29 June 2026

Received in revised form 12 August 2026

Accepted 23 August 2026

Available online 28 August 2026

Keywords:

Picture Fuzzy Set; nuclear reactor technologies; MCDM; SIWEC; RAWEC; Bonferroni operator; Hartigan–Wong algorithm.

ABSTRACT

The topic of selecting next generation nuclear reactors represents the multi-criteria decision-making problem which requires considering such conflicting criteria as safety, environment sustainability, economic efficiency and technological maturity. This paper proposes a multi-stage decision support process that combines expert-panel optimization, Picture Fuzzy Sets (PiFS) methodology and advanced techniques of MCDM. It includes five consecutive stages: (i) expert-panel optimization with the use of Hartigan–Wong algorithm for objective selection of 11 experts from 45 candidate-experts; (ii) aggregation of experts' opinions with the use of Picture Fuzzy Bonferroni Mean (PiFBM) operator to consider interaction effects between experts' assessments; (iii) criteria weights calculation with the use of Picture Fuzzy Simple Weight Calculation (PiF-SIWEC) technique; (iv) alternatives' ranking with the use of Picture Fuzzy Ranking of Alternatives with Weights of Criterion (PiF-RAWEC); (v) sensitivity and comparative analyses. The validity of the proposed decision-making framework is illustrated on the example of ranking five candidate reactor technologies small modular reactor, high temperature gas-cooled reactor, sodium-cooled fast reactor, molten salt reactor, advanced PWR based on eight criteria that include technical, economic, safety, environment and strategic aspects. The results were also compared to using six different Picture Fuzzy MCDM methods. The average value of Spearman rank correlation coefficient equals to 0.94, what indicates the stability of the results. According to PiF-SIWEC analysis, the most influential criterion is the Technical (38.70%), followed by Strategic (29.59%), Safety (17.60%), Environment (8.24%) and Economic (5.85%) aspects. The most important criterion is passive safety (C4) with the importance of 17.60%. The results of sensitivity analysis prove that the rankings are not sensitive to variation of criteria weight values up to 20%. Comparative analysis confirms the consistency of PiF-RAWEC with other methods of Picture Fuzzy sets. Three main contributions of the research are (i) introducing the systematic and data-driven approach for expert-panel selection with the help of clustering algorithms; (ii) presenting the novel application of PiF-SIWEC and PiF-RAWEC methods; (iii) providing the recommendations for nuclear technology planning in terms of the increasing role of long-term strategic advantages in the selection of nuclear reactors. The research offers the tool for decision-makers to make justified decisions in the difficult nuclear technology landscape during energy transition.

* Corresponding author.

E-mail address: gulaydemir@cumhuriyet.edu.tr

1. Introduction

Energy sector is experiencing an epochal shift which is based on achieving the goal of zero emissions by 2050. Climate pledges made as part of the Paris agreement and decisions of the COP thereafter have pushed the search for energy sources which would be low carbon, reliable and scalable further. Nuclear power finds its significance in such a context. Following the stagnation period after the Fukushima accident, a "nuclear renaissance" is being observed, particularly with the development of new generation nuclear technologies [1], [2].

Generation IV reactor concepts and SMRs are at the heart of this renewed interest. These systems promise improved safety features, higher thermal efficiency, reduced radioactive waste production, greater fuel flexibility, and improved economic competitiveness compared to conventional light water reactors. The United States, China, Russia, France, the United Kingdom, and various emerging economies have launched ambitious programs to commercialize molten salt reactors, high-temperature gas-cooled reactors, sodium-cooled fast reactors, and different SMR configurations [1], [3].

However, choosing the most suitable next-generation nuclear reactor technology is not simple at all. Decision makers need to simultaneously evaluate a wide range of technical, economic, environmental, safety and sustainability criteria under conditions of significant uncertainty and incomplete information.

1.1 Research Problem

Evaluating next-generation nuclear reactor technologies presents a complex MCDM problem. The key dimensions to consider are:

- ✓ Technical performance (thermal efficiency, fuel combustion rate, power density, load tracking capability),
- ✓ Economic feasibility (cost of capital, levelized value of electricity generation cost, construction time, modularity),
- ✓ Safety and risk (inherent safety characteristics, core failure frequency, passive safety systems),
- ✓ Environmental impact (waste generation, resource use, life cycle carbon footprint),
- ✓ Sustainability and acceptability (in terms of diffusion resistance, public perception, regulatory readiness, and fuel cycle implications) are among those criteria that are often contradictory, are considered on different scales, and are assessed under the conditions of epistemic uncertainty.

The conventional techniques of crisp MCDM do not sufficiently account for hesitation, objectivity, and rejection often demonstrated by experts when appraising the emerging nuclear technologies [4], [5]. In addition, the problem of proper expert selection is not adequately addressed leading to serious concerns about subjectivity and replicability of the study results [6]-[8].

The fuzzy sets and their extensions have been widely used for dealing with uncertainties in energy technology selection. PiFSs introduced by Cuong [9] are superior to traditional fuzzy and intuitionistic fuzzy sets in terms of accounting for membership, neutrality, non-membership, and rejection degrees. The application of this approach is especially relevant in the case of group decision-making where the experts can express their support, rejection, neutrality, or reluctance to give an opinion [9]-[11].

1.2 Research Gaps

Even though the field of picture fuzzy MCDM is growing in literature, there are still some shortcomings that have not been addressed yet.

- ✓ The lack of research related to the application of the Hartigan-Wong k-means method for selecting an expert group is an example of such a shortcoming [6]-[8], [12].
- ✓ A combination of the Picture Fuzzy SIWEC (PiF-SIWEC) weighting method and the Picture Fuzzy RAWEC (PiF-RAWEC) ranking method, restructured with the PiFBM summation operator, has not yet been proposed.
- ✓ An integrated decision support framework that addresses expert selection, preference summation, criterion weighting, and alternative ranking together under picture fuzzy information is still lacking.

The application of this comprehensive framework to the selection of next-generation nuclear reactor technologies has not been reported in the literature. These gaps reduce the transparency, repeatability, and robustness of existing decision support systems used in nuclear energy technology assessment.

1.3 Contributions of Research

This study addresses the identified gaps with the following contributions:

- ✓ It offers an objective expert selection procedure based on the Hartigan–Wong algorithm to reduce subjectivity in the creation of the expert panel.
- ✓ Picture Fuzzy develops an integrated picture fuzzy decision support framework that combines PiFBM, reconstructed PiF-SIWEC weighting and PiF-RAWEC ranking methods.
- ✓ Apply sensitivity and comparison analyses to test the robustness of the results.

This integrated framework provides practical insights into energy policymakers and nuclear technology investors by offering the first application of this framework to the selection of next-generation nuclear reactor technologies.

The rest of the article is organized as follows: Section 2 presents a detailed literature review. Section 3 recalls the necessary background information regarding picture fuzzy sets. Section 4 describes the proposed five-phase methodology. Section 5 applies the framework to the next-generation nuclear reactor technology selection case study. Section 6 discusses the managerial implications. Section 7 concludes the study.

2. Literature Review

The literature review is structured under two main headings. In the first part, MCDM-based studies on the selection problem of new generation nuclear reactor technologies; The criteria used are examined in terms of methodological approaches and decision support systems [13]. In the second part, the theoretical development of the PiFS approach and MCDM applications for modeling the uncertainty in problem evaluations are discussed. This structure aims to determine the position of the current study in literature by revealing the relationship between the selection literature of new generation nuclear reactor technologies and the PiFS-based MCDM literature.

2.1. Selection Studies of Next-Generation Nuclear Reactor Technologies Using MCDM

The selection of next-generation nuclear reactor technologies is a critical decision-making process requiring the balancing of numerous and often conflicting criteria such as safety, environmental sustainability, socio-economic impacts, and technical feasibility [14]. The literature shows that MCDM methods and GIS are widely used in this complex process. In this review, the main criteria and sub-criteria used in the selection of next-generation nuclear reactor technologies are given in Table 1.

Table 1

Criteria used in selecting next-generation nuclear reactor technologies

Criteria Category	Criteria / Sub-Criteria	Related Sources
Geological & Seismic	Active fault lines / Capacitive fault	[15], [16], [17], [18], [19]
	Seismicity / Seismic hazard	[15], [16], [17], [20], [21], [22]
	Tsunami risk	[21]
	Soil / Topography / Geotechnical	[15], [17], [22], [23]
	Rock structure	[22]
Environmental	Proximity to cooling water sources	[15], [17], [22]
	Flood level / Flood risk	[21]
	Hazardous areas / Proximity to hazardous facilities	[15], [17], [22]
	Protected areas / Forests / Natural parks	[16], [21]
	Biodiversity / Environmental impact	[21], [22]
	Proximity to wetlands	[22], [24]
	Land use / Land cover	[17], [22]
Meteorological & Hydrological	Meteorological conditions	[22], [25]
	Hydrology / Groundwater	[17], [22]
Population & Social	Population density	[15], [16], [17], [21], [22], [25]
	Public acceptance / Social acceptance	[22], [26]
	Tourism impact	[22]
	Historical sites / Cultural heritage	[21], [22]
	Security / Safety	[22], [26]
	Land ownership	[22]
	Legal issues / Legislation	[22], [26]
	Evacuation routes	[22]
Infrastructure & Economic	Proximity to the electricity grid / transmission line	[15], [16], [17], [22], [26], [27]
	Access to road / transportation network	[15], [16], [17], [22], [26]
	Operating costs / Economic impact	[22], [26], [28]
	Hazard-rated areas	[15], [17], [22]
	Waste management / Waste storage	[29], [30], [31]
Other	Technological readiness / Maturity	[28], [29]
	Political factors	[28]

Table 1 categorically summarizes the criteria commonly used in the literature for selecting next-generation nuclear reactor technologies. These criteria, encompassing a wide range of factors from geological and seismic influences on environmental, meteorological, social, infrastructural, and economic factors, highlight the multidimensional and interdisciplinary nature of the decision-making process.

2.2. Picture Fuzzy Sets and Extensions

PiFS was proposed by Cuong [9] as an extension of fuzzy set and heuristic fuzzy set theories. While traditional fuzzy sets only consider the degree of membership (μ), PiFS presents three independent components: positive degree of membership (μ), neutral degree of membership (η), and negative degree of membership (ν), the sum of which must be less than or equal to 1 ($\mu + \eta + \nu \leq 1$). This structure allows decision-makers to simultaneously express "for," "abstain," and "against" opinions, while also measuring the degree of rejection ($\pi = 1 - \mu - \eta - \nu$) and the extent of uncertainty [9].

Various extensions of PiFS have been developed in literature. q-rung picture fuzzy sets (q-RPiFS) have been proposed as a parametric generalization of PiFS and offer a wider decision space with the condition $\mu_q + \eta_q + \nu_q \leq 1$ [10]. Interval-valued picture fuzzy sets (IVPiFS) allow membership degrees to

be expressed with interval values, enabling more flexible modeling of uncertainty [11]. Complex picture fuzzy sets (CoPiFS) offer the capacity to model periodic and cyclical behaviors by defining membership degrees in the complex plane [32], [33]. Cubic picture fuzzy sets (CuPiFS) have been used to represent multilayer uncertainty by combining interval-valued PiFS and PiFS [34], [35]. Global picture fuzzy sets (GPiFS) have modeled positive, negative, and neutral membership functions within a global framework [36], [37].

2.2.1. PiFS-Based Measure and Information Theories

Information measures in the PiFSs given in Table 2 are critical for managing uncertainty in decision-making processes.

Table 2
PiFS-based measurement and
information theories

Measures of information	Main objectives	Function in the context of PiFS	Related studies
Measures of entropy	To measure the level of uncertainty	It enables the quantitative determination of uncertainty and information content in PiFS information	[38], [39]
Measures of distance	To measure the difference between PiFSs	It enables the identification of differences between alternatives, criteria, or decision-makers' evaluations	[40], [41], [42]
Measures of similarity	To determine the degree of similarity between PiFSs	It is used in pattern recognition, classification, and comparison of alternatives	[43], [44]
Measures of new information	To more precisely evaluate the information content of PiFS information	It aims to increase the discriminability and sensitivity of decision-making models	[4], [5], [45]
Measures of divergence	To measure the information difference/divergence between PiFSs	It enables more precise revelation of differences between decision alternatives	[4], [46]

Table 2 summarizes the information measures developed within the scope of PiFS theory and their functions in MCDM processes. Various summation operators proposed for combining PiFS information are given in Table 3.

Table 3
PiFS-based aggregation operators

Collection operators	Main objective	Function in the context of PiFS	Related studies
Bonferroni Average	Modeling the interactions between criteria	Includes interactions in the decision model when criteria are not independent of each other.	[47], [48], [49]
Hamy Average	Considering the relationships between criteria	Integrates the combined effect of multiple criteria and inter-criteria relationships in the PiFS environment.	[50]
Muirhead Average	Modeling multi-criteria interactions	Enables the aggregation of complex interactions between multiple criteria under PiFS information.	[51]
Aczél–Alsina operators	Performing flexible and parametric data aggregation	Enables flexible aggregation of PiFS information in different decision environments thanks to its parameter-controlled structure.	[52], [53]
Frank operators	Aggregating complex PFS information	Especially enables the integration of high-dimensional and complex decision information.	[54], [55]
Schweizer–Sklar operators	Parametric data aggregation	Enables flexible aggregation of criterion information in PiFS and hypersoft cluster environments.	[56], [57]

Interactive collection operators	Considering the interactions between membership levels	Aims to produce more realistic, aggregated decision results by considering the interdependence between criteria.	[10], [48], [58]
---	--	--	------------------

Table 3 summarizes the aggregation operators developed within the PiFS theory and their functions in MCDM processes. In this study, Bonferroni summation operator was preferred to integrate expert opinions in the selection of new generation nuclear reactor technologies. Three main advantages were effective in choosing the Bonferroni operator: (i) its ability to take into account binary interactions between criteria or expert evaluations, (ii) its ability to be adapted to different degrees of interaction thanks to the p and q parameters, and (iii) its ability to prevent information loss by preserving the Picture Fuzzy information structure (μ, η, ν) . These features increase the operator's effectiveness, especially in strategic decision problems such as nuclear reactor selection, where technological uncertainty is high and there may be significant differences between expert opinions.

2.2.2. PiFS-Based MCDM Methods

PiFSs have been used in various application areas by integrating them with MCDM methods.

2.2.2.1. Criterion Weighting Methods

The SWARA method was used to determine the importance levels of criteria by integrating it with PiFS [2], [59], [60], [61], [62]. The CRITIC method was adapted to calculate objective weights based on inter-criterion correlation and standard deviation in the PiFS environment [63], [64], [65]. The entropy method was widely used to determine objective criterion weights in PiFS [4], [5], [66], [67]. The IDOCRIW method was combined with PiFS for objective weighting [33]. The MEREC method was used for weighting based on the effects of criterion removal [2]. The LOPCOW method was adapted for objective weighting in PiFS [68], [69].

2.2.2.2. Ranking and Evaluation Methods

The MARCOS method was used in combination with PiFS to perform ranking based on ideal and anti-ideal solutions [33], [66], [70]-[73]. The TOPSIS method is one of the most widely used ranking methods in the PiFS environment [11], [61], [64], [74]-[78]. The VIKOR method has been integrated with PiFS to find a compromise solution [4], [5], [41], [79]-[82]. The WASPAS method has been combined with PiFS to integrate weighted sum and product models [83]-[87]. The CODAS method has been adapted to perform ranking based on Euclidean and Taxicab distances in the PiFS environment [88]-[92]. The COPRAS method has been used to perform ratio evaluation by integrating it with PiFS [93], [94]. The MULTIMOORA method combines the ratio system, reference point, and full multiplicative form in PiFS [3], [10], [51], [56]. The CoCoSo method was integrated with PiFS to evaluate linear and nonlinear criterion relationships [95]-[98].

2.2.3. Hybrid and Advanced Methods Based on PiFS

Hybrid approaches combining PiFS with other theories have also been developed in literature. The processing of uncertain information has been improved with the integration of PiFS and Dempster-Shafer theory [50], [99]. The integration of PiFS and machine learning has been applied in areas such as credit risk assessment [100] and blockchain platform selection [94]. Criterion reduction and classification have been performed with PiFS and clustering algorithms [94]. Three-way classification has been performed in decision-making processes by developing PiFS and three-way

decision-making models [101], [102]. Strategic decision-making processes have been modeled with the integration of PiFS and game theory [2].

2.2.4. Application Areas

Table 4 reveals the diversity of applications of PiFS-based MCDM approaches in different disciplines.

Table 4
Distribution of PiFS-based MCDM
applications in different research areas

Application area	Study	Problem / Application	PiFS-based method/approach
Business Management and Performance Appraisal	[33]	Business performance optimization	PIFS-IDOCRIW-RANCOM-MARCOS
	[70]	Evaluation of the financial and accounting performance of manufacturing firms	PiFS-MARCOS
	[103]	Evaluation of firm performance with a sustainability-balanced scorecard	PiFS-AHP
	[69]	Evaluation of the digital transformation capabilities of businesses	PiFS-OCRA
	[104]	Evaluation of advanced financial management policies	PiFS-Heronian Mean
Supply Chain and Logistics	[94]	Selection of blockchain platform for healthcare systems	PIFS-WENSLO-COPRAS
	[95]	Applicability of blockchain in sustainable supply chains	PiFS-CoCoSo
	[105]	Post-consumer textile waste management	PiFS-ORESTE
	[106]	Supplier selection	PiFS-Entropy-VIKOR
	[107]	Selection of third-party logistics providers	PiFS summation operators
Energy and Environmental Management	[49]	Selection of energy storage systems	q-RPiFS-Bonferroni Mean
	[3]	Ranking of wastewater treatment technologies	PiFS-MULTIMOORA
	[108]	Evaluation of greenhouse gas emission reduction strategies	Cq-RPiFS-Sugeno-Weber
	[109]	Selection of renewable energy integrated data center location	PiFS-SWARA-VIKOR
	[1]	Selection of location for small modular reactors	PiFS-SWARA-WASPAS
	[2]	Evaluation of hydro-wind-photovoltaic-hydrogen hybrid energy systems	PiFS-SWARA-MEREC-Regret-PROMETHEE
	[110]	Sustainable energy optimization	NPiFSS-Einstein summation operators

Transportation and Infrastructure	[74]	Road accident risk assessment in India	Type-2 PiFS–Distance Measures
	[79]	Evaluation of last-mile delivery in metropolitan areas	Type-2 PiFS–TODIM–VIKOR
	[86]	Selection of last-mile delivery mode in Belgrade	PiFS–WASPAS
	[111]	Evaluation of sustainable transportation strategies for campuses	PiFS–SWARA–EDAS
	[64]	Digital technologies in intermodal freight transportation Prioritization	PiFS–CRITIC–TOPSIS
Production and Industry	[66]	Selection of accounting and auditing firms for SMEs in the textile sector	PiFS–Entropy–MARCOS
	[83]	Evaluation of hybrid non-traditional processing processes	PiFS–WASPAS–CODAS–ARAS
	[75]	Selection of autonomous mobile robots	Triangular Fuzzy TOPSIS–PiFS–CoCoSo
	[60]	Selection of COBOTs in digital supply chains	PiFS–SWARA–CODAS
	[61]	Construction and demolition waste management	PiFS–FMEA–Fine–Kinney–SWARA–TOPSIS
Health and Medicine	[112]	Emotion-aware emergency triage in smart healthcare systems	q-RPiFDHG
	[96]	Selection of IoT-based healthcare systems	PiFS–Modified CoCoSo
	[113]	Evaluation of healthcare waste disposal techniques	PiFS–Gained and Lost Dominance Score
	[81]	Drug selection in medical diagnosis	PiFS–VIKOR
Public Policy and Urban Planning	[67]	Evaluation of urban planning proposals	PiFS–Entropy–ERUNS
	[59]	Evaluation of urban zero-emission vehicle technologies	PiFS–SWARA–WISP
	[101]	Development of a three-way decision-making model	PiFS–REMOV–ER
	[114]	Selection of fog management plans	Proportional Gray PiFS
Education and Technology Choices	[115]	Digital music integration in education reform	PiFS–FUCA
	[116]	Evaluation of teaching quality in higher education	PiFS–MACONT
	[51]	Evaluation of physical education quality in higher education	PiFS–Muirhead–MULTIMOORA
	[117]	ERP system selection	q-RPiFS–VIKOR–TOPSIS
Finance and Risk Management	[100]	Credit risk assessment	q-RPiFS–Ensemble Learning
	[118]	Financial outcome forecasting and strategic choices	CPiFS–MACONT
	[119]	Evaluation of consumer confidence projects	PiFS–CRITIC–ARAS

Table 4 shows that the PiFS methodology is adapted to various problem types across a wide range of fields, from business management to energy and environmental management, supply chain to health and public policy.

2.2.5 Comparison of Fuzzy Set Extensions

The advantages of PiFS over other fuzzy set extensions have been examined in the literature. While intuition fuzzy sets (IFS) only include membership and non-membership degrees, PiFS also includes neutral membership and offers richer information [9]. Pythagorean fuzzy sets (PyFS) offer a wider space than IFS with the condition $\mu^2 + \nu^2 \leq 1$ [95]. q-rung orthopair fuzzy sets (q-ROFS) provide an even wider space with $\mu^q + \nu^q \leq 1$ [51]. Global fuzzy sets (GFS) present a different constraint than PFS with the condition $\mu^2 + \eta^2 + \nu^2 \leq 1$ [36]. Comparative studies Onar et al. [120] have shown that PFSs are superior to other extensions, especially in problems where abstention and rejection degrees are important.

3. Preliminaries

This section presents the fundamental concepts, definitions, and mathematical operations upon which the proposed methodology is based.

Definition 1. Let X be a non-empty universe. A fuzzy picture set (PiFS) on X is defined by Equation (1) [9].

$$A = \{ \langle x, \mu_A(x), \eta_A(x), \nu_A(x) \rangle \mid x \in X \} \quad (1)$$

where,

$\mu_A(x) \in [0, 1]$: positive membership degree, $\eta_A(x) \in [0, 1]$: neutral membership degree, $\nu_A(x) \in [0, 1]$: negative membership degree. For every $x \in X$, the condition in Equation (2) is satisfied.

$$\mu_A(x) + \eta_A(x) + \nu_A(x) \leq 1 \quad (2)$$

The degree of refusal is calculated using Equation (3).

$$\pi_A(x) = 1 - \mu_A(x) - \eta_A(x) - \nu_A(x) \quad (3)$$

Definition 2. Basic operations for two picture fuzzy numbers $A = (\mu_A, \eta_A, \nu_A)$ and $B = (\mu_B, \eta_B, \nu_B)$ are as Equations (4)-(7) [9], [10]:

$$A^c = (\nu_A, \eta_A, \mu_A) \quad (4)$$

$$\lambda A = (1 - (1 - \mu_A)^\lambda, \eta_A^\lambda, \nu_A^\lambda), \lambda > 0 \quad (5)$$

$$A \oplus B = (\mu_A + \mu_B - \mu_A \mu_B, \eta_A \eta_B, \nu_A \nu_B) \quad (6)$$

$$A \otimes B = (\mu_A \mu_B, \eta_A + \eta_B - \eta_A \eta_B, \nu_A + \nu_B - \nu_A \nu_B) \quad (7)$$

Definition 3. For a picture fuzzy number $A = (\mu_A, \eta_A, \nu_A)$, the score function is defined by Equation (8) [121].

$$S(A) = \mu_A - \eta_A - \nu_A \text{ and } S(A) \in [-1, 1] \quad (8)$$

The higher the score value, the larger the picture fuzzy number.

Decision-makers were presented with a linguistic scale to evaluate the performance of alternatives based on criteria. This scale allows both the criterion weights and the alternative performances to be expressed using Picture Fuzzy numbers. The linguistic scale used and its Picture Fuzzy equivalents are given in Table 5 [92].

Table 5

Linguistic scale for picture fuzzy numbers

Linguistic Expression for Criteria	Linguistic Expression for Alternatives	Picture Fuzzy Number (μ, η, ν)
Very Very Unimportant (VVUn)	Very Very Low (VVLo)	(0, 0, 1)

Very Unimportant (VUn)	Very Low (VLo)	(0, 0.05, 0.9)
Unimportant (Un)	Low (Lo)	(0.2, 0.45, 0.25)
Medium (Me)	Medium (Me)	(0.45, 0.4, 0.1)
Important (Im)	High (Hi)	(0.8, 0.1, 0.05)
Very Important (VIm)	Very High (VHi)	(0.9, 0.05, 0)
Very Very Important (VVIm)	Very Very High (VVHi)	(1, 0, 0)

The scale in Table 5 allows decision-makers to express their evaluations systematically.

4. Proposed Methodology

In this study, a five-stage integrated PiFS decision support framework is proposed for the selection of next-generation nuclear reactor technology. The framework consists of: (i) objective expert selection with the Hartigan–Wong algorithm, (ii) creation of the group decision matrix with PiFBM, (iii) determination of criterion weights with PiF-SIWEAC, (iv) ranking of alternatives with PiF-RAWEC, and (v) sensitivity and comparison analysis. An illustration of the above-stated stages is given in Figure 1.

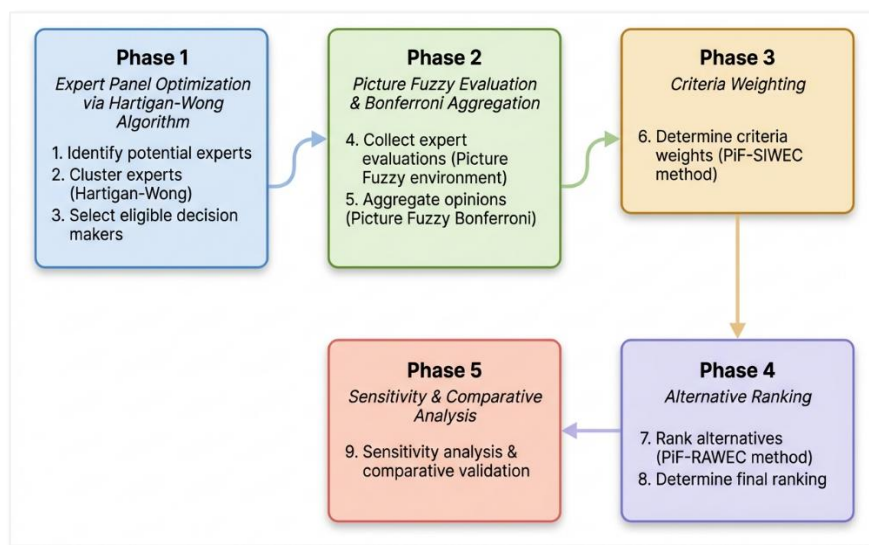


Fig. 1. Flow chart of the proposed decision support framework integration process

The research carried out in Figure 1 aims not only at determining the best-suited technology, but also at providing a sound methodological framework for the structuring of the decision support process under uncertainty.

4.1. Phase 1: Expert Panel Optimization with Hartigan–Wong Algorithm

The Hartigan-Wong algorithm Hartigan and Wong [12] is a widely used derivative of the k-means clustering method. This algorithm is based on the principle of iteratively reassigning observations based on their Euclidean distances to cluster centers and aims to minimize the sum of squares within clusters [6]–[8]. Nigro and Cicirelli [6] examined the adaptation of the algorithm to cluster clusters; Manthey and van Rhijn [8] discussed the theoretical performance guarantees of the algorithm in worst-case and smoothed analysis frameworks. Furthermore, Nigro and Cicirelli [7] proposed a combinator Hartigan-Wong variant that improves clustering performance through systematic reboot strategies. In this study, the algorithm is used to divide an expert pool into homogeneous clusters and then determine the most qualified expert team based on their total feature profiles. The implementation steps of the algorithm in the expert team selection process are presented below by Nigro and Cicirelli [7].

Step 1. Creating and Standardizing the Dataset

The initial dataset containing the features of all experts to be evaluated is defined as Equation (9).

$$X = [x_{ij}]_{e \times n} \quad (9)$$

where, e represents the total number of experts evaluated; n represents the number of attributes considered (e.g., age, years of experience, number of publications); and x_{ij} represents the value of the j attribute of the i th expert. Since the measurement units of the attributes are different, the raw data are standardized with Equation (10) using the z-score transformation.

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (10)$$

In Equation (10), $\bar{x}_j$ represents the arithmetic meaning of the j -th feature column; s_j represents the standard deviation of the same column. This transformation makes each feature dimensionless, providing comparable scale for distance-based clustering algorithms [6].

Step 2. Determining the Optimum Number of Clusters

The number of clusters is determined by Equation (11).

$$k \approx \sqrt{\frac{e}{2}} \quad (11)$$

Next, k experts are randomly selected from the standardized dataset, and their feature vectors are assigned as initial cluster centers c_t ($t = 1, 2, \dots, k$). While this initialization strategy is computationally efficient, it can affect the final convergence point, as discussed in Manthey and van Rhijn's [8] smoothed analysis.

Step 3. Iterative Assignment and Updating Cluster Centers

For each standardized expert vector z_i , the Euclidean distance to each cluster centre c_t is calculated using Equation (12).

$$d(z_i, c_t) = \sqrt{\sum_{j=1}^n (z_{ij} - c_{tj})^2} \text{ for } i = 1, 2, \dots, e; t = 1, 2, \dots, k \quad (12)$$

Based on the proximity criterion, each expert is assigned to the cluster that minimizes the distance $d(z_i, c_t)$. According to the Hartigan-Wong repositioning strategy, each reassignment is only performed if it reduces the total sum of squares within the cluster, thus ensuring monotonic convergence [7]. After all assignments are complete, the cluster centers are recalculated as the average vectors of the respective clusters. This process is repeated iteratively, recalculating the distances to the updated cluster centers and reviewing the memberships. The algorithm terminates when (i) the predefined maximum number of iterations is reached or (ii) no changes occur in the cluster assignments (i.e., when they converge to a local optimum solution) [8].

After convergence, the average feature vector is calculated for each of the k clusters. In other words, the average values of all features of the experts within each cluster are obtained. Then, the clusters are ranked comparatively according to these average values. The cluster with the highest average scores across all the considered characteristics is identified as the most successful expert team and constitutes the outcome of the team selection process [7].

4.2. Phase 2: Picture Fuzzy Bonferroni Aggregation

The Picture Fuzzy evaluations of the selected experts $\tilde{a}_{ij}^{(e)} = (\mu_{ij}^{(e)}, \eta_{ij}^{(e)}, \nu_{ij}^{(e)})$ ($e = 1, \dots, E$) PiFBM operator is combined with Equation (13) [47], [48]:

$$PFBM^{p,q}(\tilde{a}_1, \dots, \tilde{a}_E) = \left(\left(\frac{1}{E(E-1)} \sum_{i \neq j}^E \mu_i^p \mu_j^p \right)^{\frac{1}{p+q}}, \left(\frac{1}{E(E-1)} \sum_{i \neq j}^E \eta_i^p \eta_j^p \right)^{\frac{1}{p+q}}, \left(\frac{1}{E(E-1)} \sum_{i \neq j}^E \nu_i^p \nu_j^p \right)^{\frac{1}{p+q}} \right) \quad (13)$$

where, p and $q > 0$ are the interaction parameters. The result is the group decision matrix $\tilde{R} = [\tilde{r}_{ij}]$.

4.3. Phase 3: Picture Fuzzy SIWEC (PiF-SIWEC) Method

The SIWEC method is a current weighting approach based on the direct evaluation of criterion weights by decision makers [122]. Integrating the method with fuzzy sets enabled the transfer of vague and linguistic expert evaluations to decision models. When current studies in the literature are examined, it is seen that Fuzzy SIWEC and different fuzzy SIWEC extensions are used in various decision problems. Yalcin et al. [123] evaluated central bank communication strategies by integrating Koch Snowflake fuzzy sets, SIWEC and RATGOS methods with a machine learning-based expert weighting approach. Ecer et al. [124] used the Pythagorean fuzzy SIWEC-COPRAS model to prioritize performance improvement strategies of metal-organic cages in liquid hydrogen energy systems. Bosna et al. [125] evaluated the management strategies of overtourism in Zadar County, Croatia, with the Intuitionistic fuzzy SIWEC-TOPSIS approach. Katranci and Kundakci [126] applied the FSIWEC-FRADAR model in the evaluation of cryptocurrency exchanges and determined Binance as the most successful alternative. Boz [127] used the p, q -quasirung orthopair fuzzy SIWEC-AROMAN approach in the selection of agricultural spraying drones; has determined load capacity, ease of use and flight duration as the most important criteria. Çizmecioğlu et al. [128] applied the p, q -quasirung orthopair fuzzy SIWEC-MABAC model in the selection of competitive intelligence platforms and showed that data security and reliability are the most important criteria. Zhao [129] used the SIWEC-MOOSRA approach under Fermatean neutrosophic fuzzy sets to evaluate ideological and political education in the new media era in higher education. Gao and Qian [130] applied the SIWEC-MACONT model to the evaluation of cost risks of municipal water supply and drainage projects under trapezoidal fuzzy neutrosophic sets.

However, the Picture Fuzzy SIWEC (PiF-SIWEC) approach, which takes advantage of PiFS's capacity to simultaneously express positive, neutral, negative and rejection degrees, has not yet been discussed in literature. In this regard, the current study aims to address this methodological gap in the literature by adapting the SIWEC method to the Picture Fuzzy Set environment.

The steps of the PiF-SIWEC method are given below:

The picture fuzzy decision matrix ($\tilde{X} = [\tilde{x}_{ej}]_{e \times j}$) from Phase 2 is used as input, where e represents the experts ($e = 1, \dots, k$), and j ($j = 1, \dots, m$) represents the criteria.

Step 1. Experts (or group matrix) evaluate each criterion with a PiF number: $\tilde{x}_{ej} = (\mu_{ej}, \eta_{ej}, \nu_{ej})$.

Step 2. The initial PiF decision matrix is created (from Phase 2).

Step 3. Using the score function, the score matrix is obtained with Equation (14).

$$S(\tilde{x}_{ej}) = \mu_{ej} - \eta_{ej} - \nu_{ej} \quad (14)$$

Step 4. The normalized score matrix is obtained with Equation (15).

The minimum ($S_{\min}$) and maximum ($S_{\max}$) values in the entire score matrix is found. Each score is normalized to the range $[0, 1]$ using these values:

$$n_{ej} = \frac{S(\tilde{x}_{ej}) - S_{\min}}{S_{\max} - S_{\min}} \quad (15)$$

Step 5. The standard deviation $st. dev_e$ is calculated for each expert (or row).

Step 6. Weighted values are calculated using Equation (16).

$$v_{ej} = n_{ej} \times st. dev_e \quad (16)$$

Step 7. The total based on the criterion is obtained using Equation (17).

$$s_j = \sum_e v_{ej} \quad (17)$$

Step 8. Final weights are calculated using Equation (18).

$$w_j = \frac{s_j}{\sum_j s_j}, \sum_j w_j = 1 \quad (18)$$

4.4. Phase 4: Picture Fuzzy RAWEC (PiF-RAWEC) Method

The RAWEC method is an MCDM approach that allows the ranking of alternatives by considering their criterion weights [131]. Integrating the method with fuzzy sets has enabled the transfer of uncertain and linguistic expert evaluations to the alternative ranking process. Nedeljković et al. [132] applied the Fuzzy MEREC-Fuzzy RAWEC model in the selection of agricultural product sales channels and determined the online sales channel as the most suitable alternative. Zhang et al. [133] used the Interval Type-2 Fuzzy PIPRECIA-RAWEC approach in the evaluation of renewable energy systems and determined wind farms as the most suitable alternative. Tešić et al. [134] extended the RAWEC method with Fermatean fuzzy numbers to develop the FF-RAWEC method and showed that the method yielded stable results under different types of criteria. Katrancı et al. [135] used the Fuzzy SIWEC-Fuzzy RAWEC integrated model in the selection of sustainable waste disposal technologies and determined composting as the most suitable technology. Shamsi et al. [136] weighed the criteria with Fuzzy SIWEC in the selection of green concrete mixes containing recycled materials and ranked the alternatives with a multiple MCDM approach that also included RAWEC. Albahri et al. [137] combined Orthopair Z-Numbers, FWZIC, and modified RAWEC methods to evaluate vegetables in terms of dental health. These studies show that RAWEC is a flexible alternative ranking approach that can be integrated with different fuzzy sets and weighting methods.

However, no study addressing the RAWEC method in a Picture Fuzzy Set environment has been found. Therefore, the development of the PiF-RAWEC approach aims to provide a unique methodological contribution that will expand the fuzzy decision-making capacity of RAWEC literature.

The steps of the PiF-RAWEC method are given below:

Step 1. The Group Picture Fuzzy decision matrix $\tilde{R} = [\tilde{r}_{ij}]$ is created (from Phase 2).

Step 2. Double normalization (via the score function) is obtained with Equation (19).

For benefit criteria:

$$n_{ij} = \frac{S(\tilde{r}_{ij})}{\max_i S(\tilde{r}_{ij})}, n'_{ij} = \frac{\min_i S(\tilde{r}_{ij})}{S(\tilde{r}_{ij})} \quad (19)$$

The inverse is applied for cost criteria.

Step 3. Weighted deviations are calculated with Equation (20).

$$v_{ij} = \sum_j w_j (1 - n_{ij}), v'_{ij} = \sum_j w_j (1 - n'_{ij}) \quad (20)$$

Step 4. The RAWEC score is calculated using Equation (21).

$$Q_i = \frac{v'_i - v_i}{v'_i + v_i} \quad (21)$$

The alternative with the highest Q_i value is the best solution. $Q_i \in [-1,1]$ is in the interval.

5. Case Study

The case study applies the five main stages of the proposed methodology (expert panel optimization, PiFBM, criterion weighting with PiF-SIWECC, alternative ranking with PiF-RAWEC, and sensitivity/comparative analysis) step by step.

5.1. Identification of Alternatives and Evaluation Criteria

This case study considers five alternative next-generation nuclear reactor technologies with different design features, safety approaches, fuel cycle characteristics, and technological maturity levels. Eight main criteria were defined for evaluating these alternatives. These criteria encompass technical, economic, safety, environmental, and strategic dimensions. The definition, measurement direction (benefit/cost), and literature equivalent of each criterion are presented in Table 6.

Table 6
Definition and characteristics of
evaluation criteria

Criteria/Code	Size	Measurement Direction	Definition	Reference
Technological Maturity (C1)	Technical	Benefit	The commercially proven level of reactor technology, the degree of maturity from the prototype/test phase to full commercial operation	[28]
Thermal Efficiency (C2)	Technical	Benefit	The reactor's efficiency in converting thermal energy into electrical energy (%). High efficiency means reduced fuel consumption	[22], [23]
Investment Cost (C3)	Economic	Cost	The capital cost required for the construction and commissioning of the reactor (USD/kW). High cost may limit the feasibility of the technology	[29]
Passive Safety Level (C4)	Security	Benefit	The reactor's ability to ensure its safety through natural physical principles without operator intervention. Passive safety significantly reduces the risk of accidents	[138]
Fuel Sustainability (C5)	Strategic	Benefit	The reactor's capacity to efficiently utilize existing uranium resources and contribute to long-term fuel supply security	[14]
Radioactive Waste Management (C6)	Environmental	Benefit	The volume, activity level, and management difficulty of the radioactive waste produced by the reactor. Low waste production and effective waste management are preferred	[22], [31]
Operational Flexibility (C7)	Strategic	Benefit	The reactor's load monitoring, partial power operation, and integration capabilities with renewable energy sources	[23]; [29]
Construction Complexity / Duration (C8)	Technical	Cost	The estimated duration of reactor construction and the degree of technical challenges that may be encountered during construction.	[138]

Table 6 presents the eight criteria used in evaluating next-generation nuclear reactor technologies and their descriptive characteristics. The five alternative reactor technologies evaluated in this study are defined in Table 7.

Table 7
Nuclear reactor technology alternatives

Alternative/Code	Power Range	Coolant	Fuel Type	Reference
Small Modular Reactor (A1)	≤ 300 MWe	Light Water	Low Enriched Uranium	[29]
High Temperature Gas Cooled Reactor (A2)	100–300 MWe	Helium	TRISO (Uranium/Carbide)	[22]
Sodium Cooled Fast Reactor (A3)	300–1500 MWe	Liquid Sodium	MOX, Metal	[138]
Molten Salt Reactor (A4)	100–1000 MWe	Molten Salt (Fluoride/Chloride)	Liquid Salt (Uranium/Thorium)	[23]
Advanced Pressurized Water Reactor (A5)	1000–1200 MWe	Light Water	Low Enriched Uranium	[28]

These alternatives in Table 7 will be evaluated by experts in the Picture Fuzzy environment.

5.2. Application of the Proposed Framework

5.2.1. Phase 1: Expert Panel Optimization via the Hartigan–Wong Algorithm

Step 1. Data set creation and standardization (z-score transformation)

45 potential experts (E1 to E45) with at least 10 years of experience in nuclear engineering, reactor safety, energy economics, and environmental sciences were evaluated. Each expert was represented by the following three qualitative characteristics:

Professional experience years (in years)

Number of publications on nuclear energy in international peer-reviewed journals (pieces)

Number of national/international nuclear projects participated in (pieces)

The created raw data matrix is defined as $DS = [x_{ij}]_{45 \times 3}$. Since the measurement units of the features are different, the z-score transformation in Equation (10) was applied to the raw data. As a result of this transformation, each feature is normalized to have a mean of 0 and a standard deviation of 1. Table 8 presents the global mean and standard deviation values for three characteristics of 45 experts.

Table 8
Descriptive statistics of the expert pool
(n=45)

Attribute	Average ($\bar{x}$)	Standard Deviation (s)
Years of Experience	23,56	5,12
Number of Publications	18,11	5,46
Number of Projects	11,07	3,91

Step 2. Determining the optimum number of clusters

The optimum number of clusters (k) was initially estimated using Equation (11).

$$k \approx \sqrt{\frac{e}{2}} = \sqrt{\frac{45}{2}} \approx 4,74$$

This value was rounded to the nearest integer and determined as k=4. To test the validity of this determined value, the sum of squares within the cluster was calculated using Equation (22) for different k values.

$$\text{Total sum of squares within the set} = \sum_{t=1}^k \sum_{z_i \in C_t} \|z_i - \mu_t\|^2 \quad (22)$$

It was visually verified using the elbow method given in Figure 2.

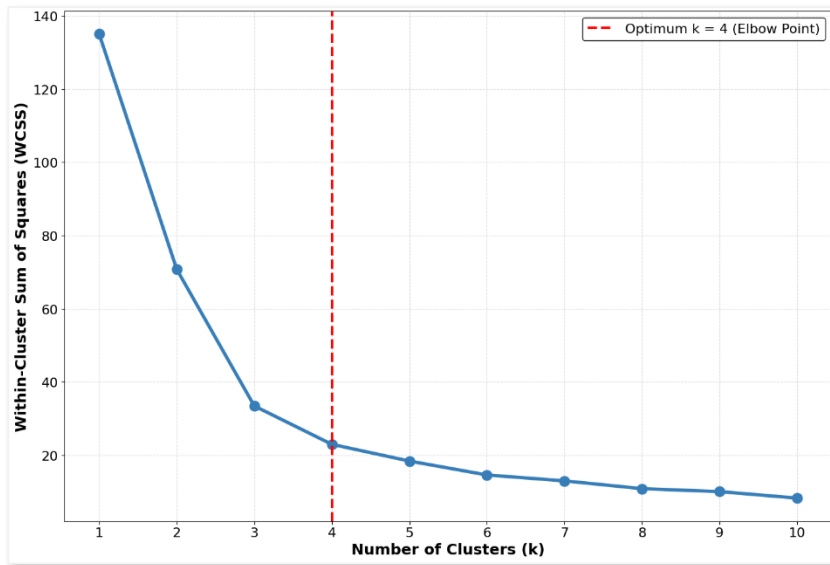


Fig. 2. Elbow method for determining optimal number of clusters

Examining the elbow method graph presented in Figure 2, the total sum of squares within the set values show a significant decrease from $k=1$ to $k=4$, and after $k=4$, this decrease slows down and follows an asymptotic course. The point $k=4$, indicated by the red dashed line, has been determined as the elbow point, and this value is both consistent with the rule in the literature and empirically verified. Accordingly, the optimum number of clusters in this study was fixed at $k=4$.

Step 3. Determination of initial cluster centers and iterative assignment

$k = 4$ experts were randomly selected from the standardized dataset and assigned as initial cluster centers ($\text{center}_t, t = 1, 2, 3, 4$). Then, the Euclidean distance between each standardized expert vector z_i and each cluster center was calculated using Equation (12).

Each expert was assigned to the closest cluster. Following the basic principle of the Hartigan-Wong method, the assignment was done only if the sum of squared deviations from the cluster center decreased in the process. Such an approach guarantees the monotonous convergence of the algorithm [7]. After 14 iterations, the algorithm converged, and the local minimum solution was obtained. Cardinality and mean feature vectors of the four clusters at the end of the convergence are provided in Table 9.

Table 9
Average raw data and cardinalities of clusters

Cluster No	Number of Members	Average Experience (years)	Average Number of Publications	Average Number of Projects
Cluster 1	9	30,2	41,5	10,3
Cluster 2	14	24,8	5,2	15,1
Cluster 3	11	30,1	30,5	14,9
Cluster 4	11	9,9	5,1	3,2

Table 9 contains the unstandardized means, which have been standardized according to Equation 10. The resulting standardized cluster centers and the total competency scores calculated for each

cluster ($S_t = \sum_{j=1}^3 \bar{z}_{tj}$) are given in Table 10.

Table 10

Standardized (z-score) center values
and total scores of the clusters

Cluster No	$Z_{Experience}$	$Z_{Publication}$	$Z_{Project}$	Total Proficiency Score (S_t)	Z-Score Variance
Cluster 1	1,26	4,01	-0,27	5,00	3,14
Cluster 2	0,28	-2,40	1,00	-1,12	2,37
Cluster 3	1,26	2,18	1,00	4,44	0,26
Cluster 4	-2,66	-2,40	-1,89	-6,95	0,10

The expert panel was chosen from Cluster 3, which is the only cluster that simultaneously satisfies all three criteria of objectivity: having a positive z-score ($z_j > 0$), a high overall competency score (S_t), and low z-score variance. For visual representation of clustering, PCA was conducted on the standardized dataset, and the output is shown in Figure 3.

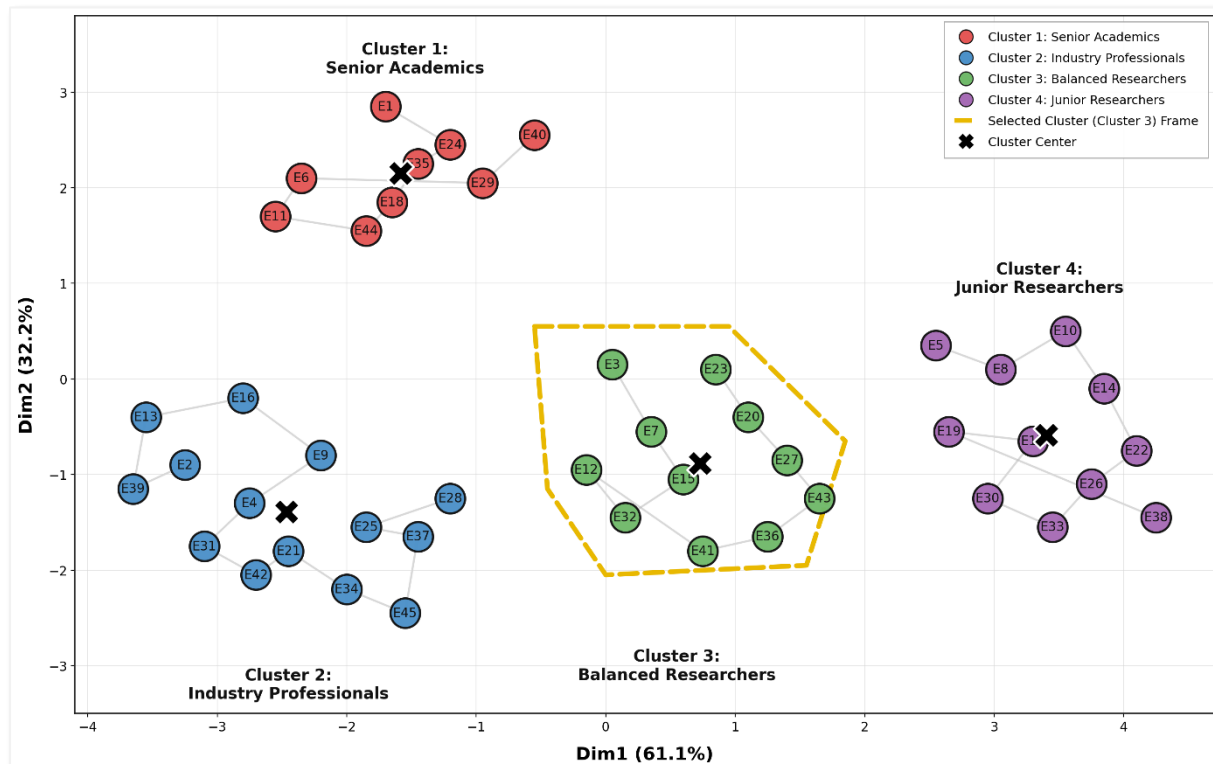


Fig. 3. PCA projection of expert clusters obtained via the Hartigan–Wong algorithm

Figure 3 presents the two-dimensional PCA projection obtained by decomposing 45 potential experts into 4 clusters using the Hartigan–Wong algorithm. Each expert (E1 to E45) is indicated by the color of the cluster to which it belongs. The selected Cluster 3 (Balanced Researchers) is separated from the other clusters by a thick, dashed golden convex hull frame. The geometric center of each cluster is indicated by the "x" symbol. The first two principal components (Dim1 and Dim2) explain 61.1% and 32.2% of the total variance, respectively. The PCA projection confirms that the separation between the clusters is clear and that Cluster 3 is distinctly separated from the other clusters.

5.2.2. Phase 3: Picture Fuzzy SIWEC Method

After the expert panel was optimized in Phase 1, the 11 selected experts (E3, E7, E12, E15, E20, E23, E27, E32, E36, E41, E43) provided their evaluations for both criteria weights and alternative performances using the linguistic scale defined in Table 5. The assessments of all 11 experts are given in Table 11.

Table 11

Linguistic evaluations of criteria
importance by the 11 experts

Expert	C1	C2	C3	C4	C5	C6	C7	C8
E3	VVIm	Im	Me	VVIm	Im	Me	VIm	Un
E7	VIm	VIm	Un	VVIm	VIm	Im	Me	VUn
E12	Im	VVIm	Me	VIm	Me	Un	Im	VUn
E15	VVIm	Im	VUn	VVIm	VIm	Me	Im	Un
E20	Im	VIm	Me	VIm	Im	Un	VIm	VUn
E23	VIm	VVIm	VUn	VVIm	VIm	Me	Me	Un
E27	VVIm	Im	Un	VVIm	Me	VUn	VIm	VUn
E32	Im	VIm	Me	VIm	VIm	Me	Im	Un
E36	VIm	VVIm	VUn	VVIm	Im	VUn	VIm	Me
E41	VVIm	Im	Un	VVIm	VIm	Me	Im	VUn
E43	Im	VIm	Me	VIm	Me	Un	VIm	VUn

Table 11 presents the linguistic evaluations of 11 experts selected using the Hartigan–Wong algorithm regarding the importance levels of eight evaluation criteria (C1–C8). A score matrix was first obtained from the data in this table. Then, the standard deviation was calculated from the normalized scores of each expert (row). For each cell, the weighted value was obtained by multiplying the normalized score by the standard deviation of the corresponding expert. For each criterion, the weighted values of all experts were summed. The sum of each criterion was normalized by dividing it by the sum of all criteria. At this stage, the condition $\sum_{j=1}^8 w_j = 1$ was satisfied. The resulting criterion weights are given in Figure 4.

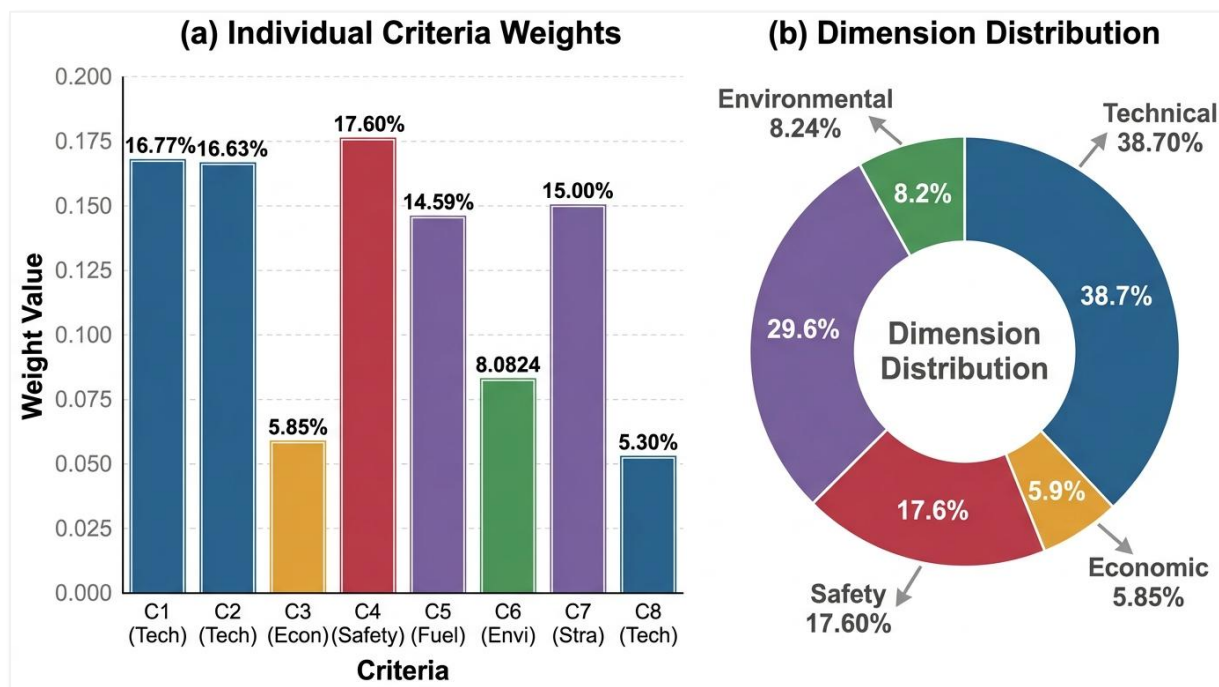


Fig. 4. Criteria weights from PiF-SIWE method

In Figure 4(b), the technical dimension is by far the most important (38.70%). Experts prioritize proven technology, high efficiency, and low construction complexity. The strategic dimension is second (29.59%). Fuel sustainability and operational flexibility (renewable integration) are becoming increasingly important. In Figure 4(a), passive safety alone has the highest individual weight at 17.60%. This quantitatively confirms the nuclear sector's C4 principle. The economic dimension has

the lowest weight (5.85%). In other words, investment cost is the least decisive dimension in early-stage technology selection.

5.2.3. Phase 2: Picture Fuzzy Bonferroni Agregasyonu

At this stage, the individual assessments of the 11 experts identified in Phase 1 using the Hartigan–Wong algorithm regarding five alternative reactor technologies were compiled based on eight criteria and are presented in Table 12.

Table 12
Evaluation of Alternatives

	C1	C2	C3	C4
A1	Hi, VHi, Hi, VHi, Hi, VHi, Hi, VHi, Hi, Hi, VVHi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi	Hi, VHi, Hi, Hi, VHi, Hi, VHi, Hi, Hi, VVHi, VHi	VHi, VVHi, VHi, VVHi, VHi, VVHi, VHi VVHi, VHi, Hi, VVHi
A2	Me, Me, Me, Me, Me, Me, Me, Me, Me, Lo, Lo	VHi, VHi, VHi, VHi, VVHi, VHi, VVHi, VHi, VHi, VHi, Hi	Me, Me, Me, Me, Me, Me, Me, Me, Me, Lo, Lo	VHi, VHi, Hi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi
A3	Me, Me, Me, Me, Me, Me, Me, Me, Me, Lo, Lo	VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi	Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Me, Me	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VHi
A4	Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Me, Me	VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, Hi, VVHi	Me, Me, Me, Me, Me, Me, Me, Me, Me, Lo, Lo	VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi
A5	VVHi, VVHi, Hi, VVHi, VVHi, VHi, VVHi, VVHi, VVHi, VHi, VVHi	Hi, Hi, Hi, Hi, Hi, Hi, VHi, Hi, VHi, VVHi, VHi	Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Me, Me, Me	Hi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, VVHi, Hi, VHi
	C5	C6	C7	C8
A1	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi	Hi, Hi, Hi, VHi, VHi, Hi, Hi, Hi, VHi, Hi, VVHi, Hi	VHi, VHi, VHi, VHi, VHi, Hi, VHi, VHi, VHi, Hi, VHi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi
A2	VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi, VHi, Hi, Hi	VHi, Hi, VHi, Hi, Hi, VHi, Hi, VHi, Hi, VHi, Hi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, Hi	Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Me, Me
A3	VVHi, VVHi, Hi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VHi	Hi, Hi, VHi, Hi, Hi, VHi, Hi, VHi, Hi, VVHi, Hi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, Hi	Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Lo, Me, Me
A4	VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, VVHi, Hi, VVHi	VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi	VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, VHi	VLo, VLo, VLo, VLo, VLo, VLo, VLo, VLo, Lo, Lo, Lo
A5	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi, Hi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi, Hi	Hi, Hi, Hi, Hi, Hi, Hi, Hi, Hi, VHi, VVHi, Hi	VHi, VHi, VHi, VHi, VHi, VHi, VHi, VHi, Hi, Hi, VVHi

The combined decision matrix obtained using Equation (13) is given in Table 13. This matrix served as input for the PiF-RAWEC ranking.

Table 13
Combined Decision Matrix

	C1	C2	C3	C4
A1	(0.8453, 0.0769, 0.0261)	(0.8000, 0.1000, 0.0500)	(0.8362, 0.0815, 0.0309)	(0.9544, 0.0213, 0.0000)
A2	(0.4500, 0.4000, 0.1000)	(0.9271, 0.0357, 0.0000)	(0.4500, 0.4000, 0.1000)	(0.8909, 0.0544, 0.0000)
A3	(0.4500, 0.4000, 0.1000)	(0.9000, 0.0500, 0.0000)	(0.2000, 0.4500, 0.2500)	(0.8000, 0.1000, 0.0500)
A4	(0.2000, 0.4500, 0.2500)	(1.0000, 0.0000, 0.0000)	(0.4500, 0.4000, 0.1000)	(0.9000, 0.0500, 0.0000)
A5	(1.0000, 0.0000, 0.0000)	(0.8000, 0.1000, 0.0500)	(0.2000, 0.4500, 0.2500)	(0.8909, 0.0544, 0.0000)
	C5	C6	C7	C8
A1	(0.8000, 0.1000, 0.0500)	(0.8271, 0.0861, 0.0357)	(0.9000, 0.0500, 0.0000)	(0.8000, 0.1000, 0.0500)
A2	(0.9000, 0.0500, 0.0000)	(0.8635, 0.0678, 0.0165)	(0.8000, 0.1000, 0.0500)	(0.2000, 0.4500, 0.2500)
A3	(1.0000, 0.0000, 0.0000)	(0.8362, 0.0815, 0.0309)	(0.8000, 0.1000, 0.0500)	(0.2000, 0.4500, 0.2500)
A4	(1.0000, 0.0000, 0.0000)	(0.9000, 0.0500, 0.0000)	(0.9000, 0.0500, 0.0000)	(0.0000, 0.0500, 0.9000)
A5	(0.8000, 0.1000, 0.0500)	(0.8000, 0.1000, 0.0500)	(0.8000, 0.1000, 0.0500)	(0.9000, 0.0500, 0.0000)

The matrix in Table 13 contains performance values in terms of triplets (μ, η, ν) in each cell for 5 alternatives (A1–A5) and 8 criteria (C1–C8).

5.2.4. Phase 4: Picture Fuzzy RAWEC Method

Using the integrated Picture Fuzzy decision matrix in Table 13 and the criterion weights in Figure 4, the alternatives were ranked using the PiF-RAWEC method (Equations 19–21). The obtained PiF-RAWEC scores and the final ranking are presented in Table 14.

Table 14
Ranking of alternatives according to PiF-RAWEC score

Alternative	PiF-RAWEC Score (Q_i)
A4	0.2262
A5	-0.1218
A1	-0.4197
A2	-1.5982
A3	-1.6234

According to Table 14, the Molten Salt Reactor (A4) exhibited by far the highest performance and was the only alternative to achieve a positive Q_i value. This superiority stems particularly from its excellent values in the investment cost (C3) and construction complexity/time (C8) cost criteria. Since MSRs operate at atmospheric pressure, they do not require thick pressure vessels; this reduces capital costs and shortens construction time. Furthermore, thanks to the liquid fuel cycle, it received the highest scores in fuel sustainability (C5) and radioactive waste management (C6) criteria. Despite being relatively immature (C1), the advantages of this technology both economically and environmentally substantially outweigh this disadvantage. The Advanced PWR (A5) occupies second place because of its mature technology (C1) and good technical performance; nevertheless, its high-pressure circuit design prolongs the period of construction and increases its cost. The example shows that proven technology is not the most important parameter; capital intensity and time consumption matter equally. The Small Modular Reactor (A1) stands out with its ability to produce modules and inherent safety characteristics, but it suffers from the lack of power output (≤ 300 MWe) and thus cannot benefit from economies of scale, which results in third place. The High Temperature Gas Reactor (A2) has some unique strengths, including high efficiency and the ability to produce hydrogen, but loses competitiveness because of the excessive cost of TRISO fuel and helium cooling system. Despite having the highest rating of fuel sustainability, the Sodium-Cooled Fast Reactor (A3) takes the last place overall. The main reason is that the highly reactive nature of the sodium metal in

case of contact with air and water reduces the value of the passive safety (C4) of this reactor, while the extra engineering measures needed to cope with it increase the construction cost (C3) and complexity (C8). The fact shows that theoretically superior fuel efficiency is not enough to compensate for the drawbacks of the technology. Overall, the ranking proves that the maturity of the technology itself, as well as long-term strategic and environmental perspectives of it, matter when choosing the right nuclear technology. As follows from the ranking, technologies such as molten salt reactors (MSR), which have not yet achieved maturity but demonstrate excellent technical and environmental properties, should be seriously considered by the decision makers.

5.2.5. Phase 5: Sensitivity and Comparison Analysis

The current phase involved carrying out two different types of analyses to check the reliability and consistency of the rankings obtained using the PiF-RAWEC approach.

5.2.5.1. Weight Sensitivity Analysis

In the weight sensitivity analysis, the criterion with the highest weight, C4 (Passive Safety), and the criterion with the lowest weight, C8 (Construction Complexity), were selected. The weights of these two criteria were changed by $\pm 10\%$ and $\pm 20\%$, respectively, and the weights of the other criteria were proportionally renormalized to keep the total at 1. PiF-RAWEC scores were recalculated for each scenario, and alternative rankings were obtained and given in Table 15.

Table 15
Weight sensitivity analysis scenarios

Scenarios	Variable Criteria	Rate of Change	C4 Weight	C8 Weight	Rank
S0 (Basic)	-	-	0.1760	0.0530	A4> A5> A1> A2> A3
S1	C4 (Passive Security)	+20%	0.2112	0.0530	A4> A5> A1> A2> A3
S2	C4	-20%	0.1408	0.0530	A4> A5> A1> A2> A3
S3	C8 (Construction Complexity)	+20%	0.1760	0.0636	A4> A5> A1> A2> A3
S4	C8	-20%	0.1760	0.0424	A4> A5> A1> A2> A3
S5	C4 +20%, C8 -20%	Together	0.2112	0.0424	A4> A5> A1> A2> A3
S6	C4 -20%, C8 +20%	Together	0.1408	0.0636	A4> A5> A1> A2> A3

As shown in Table 15, the ranking remained unchanged in all scenarios (A4> A5> A1> A2> A3). This demonstrates that the ranking obtained using the proposed PiF-RAWEC method is highly resistant to weighting changes. Even a 20% change in the highest and lowest weighted criteria did not affect the final decision. This finding quantitatively confirms the robust superiority of the A4 (MSR) alternative and its significant difference from other alternatives.

5.2.5.2. Comparative Method Analysis

To test the validity of the results obtained with the PiF-RAWEC method, five different PiF-MCDM methods, namely PiF-MARCOS, PiF-CoCoSo, PiF-WASPAS, PiF-CODAS, and PiF-TOPSIS, were applied using the same Picture Fuzzy decision matrix (Table 13) and the same criterion weights. The rankings obtained were compared with Figure 5.

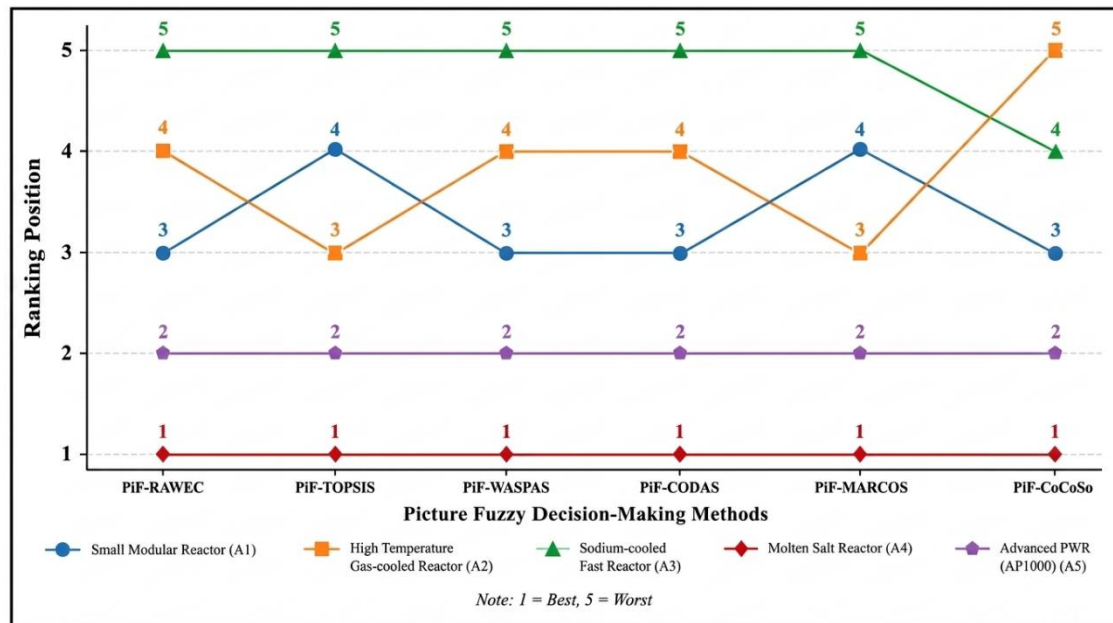


Fig. 5. Alternative rankings according to different picture fuzzy methods

Figure 5 shows the comparative ranking of five next-generation nuclear reactor technologies using six different PiF-MCDM methods (PiF RAWEC, PiF TOPSIS, PiF WASPAS, PiF CODAS, PiF MARCOS, and PiF CoCoSo). The ranking scale ranges from 1 (best) to 5 (worst). The results show that the Molten Salt Reactor (A4) consistently ranks highest (1st) across all methods, while the Sodium Cooled Fast Reactor (A3) consistently ranks last (5th). The ranking process shows consistency and is independent of the technique used. The average Spearman rank correlation coefficient calculated among all possible combinations of methods is 0.94, which indicates high agreement between the six different decision techniques. This finding provides quantitative evidence that the integrated Picture Fuzzy decision support system is indeed sound and appropriate for decision-makers.

6. Discussion, Practical and Managerial Implications

First, the case study provides substantial information regarding both the proposed decision-making methodology and the ranking of the next generation nuclear reactors.

Contributions to Methodology: The proposed decision support framework proves itself quite an effective integration of such components as optimization based on expert panel (Hartigan-Wong algorithm), PiFBM, PiF-SIWEK and PiF-RAWEC. Robustness of the proposed methodology is testified by the consistency of the results received using six Picture Fuzzy MCDM techniques: PiF-RAWEC, PiF-TOPSIS, PiF-WASPAS, PiF-CODAS, PiF-MARCOS, PiF-CoCoSo. The obtained average Spearman rank correlation coefficient of 0.94 for all pair-wise method comparisons shows high stability and independence of rankings. It is worth noting that the problem under consideration is rather complicated because of the uncertain nature of next-generation nuclear technologies, in which expert opinions might differ substantially from one another and traditional approach cannot consider all criteria of the problem.

Ranking of Alternatives: Uniform order $A4 > A5 > A1 > A2 > A3$ provided by all six methods of the problem solution clearly presents the preference hierarchy. As can be seen, the Molten Salt Reactor (A4) ranks first and is considered to be the most appropriate technology mainly due to its outstanding parameters concerning such criteria as thermal efficiency ($C2: \mu = 1,000$), fuel sustainability ($C5: \mu = 1,000$) and radioactive waste management ($C6: \mu = 0,900$). Despite the low performance of A4 in

terms of technological maturity (C1: $\mu = 0,200$), it wins because of advantages in strategic and environmental aspects.

The second-best alternative was the Advanced Pressurized Water Reactor (A5). The good performance of this technology can be explained by its high level of technological maturity (C1: $\mu = 1.000$) and passive safety (C4: $\mu = 0.8909$). The proven record of operation, reliable supply chain and regulatory recognition of this Generation III+ technology make it a valid choice, especially for those countries seeking low risk and proven solution to nuclear power.

The Small Modular Reactor (A1) took third place, being a balanced technology with respect to all criteria but two. The advantages of the small-scale technology with reduced risk, increased modularity, and high level of operational flexibility (C7: $\mu = 0.900$) make it a valid choice for those countries with small-sized electricity grids and limited infrastructures. Nevertheless, the moderate level of performance of this reactor in terms of fuel sustainability (C5: $\mu = 0.800$) and waste management (C6: $\mu = 0.8271$) can explain why it could not beat the first two technologies. The High Temperature Gas-Cooled Reactor (A2) and the Sodium-Cooled Fast Reactor (A3) ranked fourth and fifth places correspondingly. Both technologies face problems hindering their applicability at the moment: A2 has lower level of technological maturity (C1: $\mu = 0.450$) and higher degree of complexity in construction (C8: $\mu = 0.200$, $v = 0.250$); whereas A3 demonstrates only moderately passive safety performance (C4: $\mu = 0.800$, $\eta = 0.100$, $v = 0.050$) because of the risks related to chemical reactivity of sodium coolant.

Findings Concerning Criterion Weights: The PiF-SIWEC revealed that the technical dimension (38.70%) was the most important one among the other five criteria (Strategic – 29.59%, Safety – 17.60%, Environmental – 8.24%, Economic – 5.85%). The clear predominance of technical factors in this evaluation stems from the fact that nuclear technology and industry in general have a conservative and risk-averse nature in which proven technology is a key factor. The relatively low importance of economic factors (5.85%) indicates that costs of investment are not the main barriers to the selection of technology at an early stage.

Practical Implications: The findings of this study suggest some useful implications for the stakeholders involved in nuclear technology planning and selection.

For Policymakers and Energy Planners: Support advanced generation technologies: Despite their low technological maturity level, MSRs show a high potential in terms of sustainability and efficiency. It is necessary for the policymakers to consider the support of research, demonstration programs and regulatory compliance to commercialize such technologies. Focus on safety and technological maturity: Passive safety (C4) and technological maturity (C1) are the most significant criteria among all. The investments should be focused on conducting safety research, developing regulatory framework and capacity building. Rethink cost-oriented decision-making: Due to the low importance of economic aspects, cost should not be the key criterion. It is needed to choose a balanced portfolio strategy which will include safety, sustainability and energy security.

For Nuclear Industry Operators and Technology Developers: MSR developers: Technological maturity needs to be emphasized through pilot projects and regulatory compliance. High efficiency and waste management performance give an opportunity for competitive advantages. AP1000 developers: Technological maturity and safety must be emphasized. There is a need to explore ways to increase efficiency to compete with emerging technologies. SMR developers: Benefits of modularity, flexibility and lower construction risk should be emphasized. Fuel cycle and waste management issues must be solved to create competitive advantages. HTGR and SFR developers: HTGR must focus on simplicity of construction and technological maturity. It is important to improve passive safety characteristics in the case of SFR due to the sodium problems.

Regulatory Agencies & Standards Organizations: Design flexible, risk-based licensing schemes which can embrace new technologies (molten salt reactor – MSR) while keeping high safety standards. Set up clear performance requirements for emerging technologies with special regard to fuel sustainability, passive safety and waste management.

Investors & Financial Institutions: Remember about potential long-term strategic advantages like energy security, carbon footprint reduction, and technological superiority that can outweigh increased costs of innovation. Think about developing green financing or government-sponsored investment opportunities for next generation nuclear technologies.

Managerial Implications: In terms of managerial practice, the offered decision support model provides a structured, justified approach to technology choice in conditions of uncertainty:

Strategic Decision Support: An integrated approach gives managers a systematic, evidence-based approach to decision making which can be easily explained to diverse groups of people: board members, regulators, the public etc. Ability to involve experts' opinions and account for uncertainty using Picture Fuzzy Clusters provides for sound and reliable decision making that is unlikely to be arbitrary and/or biased. The sequential process (experts' selection → aggregation → weighting → ranking → sensitivity analysis) allows justifying each step of decision-making process.

Risk Management: A clear account of uncertainty provided by Picture Fuzzy approach allows managers to consider not only performance (μ) but also neutrality (η), opposition (ν), and abstention (ρ). This comprehensive view helps to manage risks proactively. Application of several MCDM approaches and sensitivity analyses provides an additional risk-management tool since the final decision will not be biased by methods or expert opinion.

Resource Allocation: Criteria weights clearly indicate priorities in resource allocation: focus on improving safety and technical characteristics before considering costs. In case of emerging technologies, the model can help in identifying the most promising areas for research and development which will improve overall ranking.

Stakeholder Engagement: A transparent, systematic approach to decision making increases trust in managerial decisions. Graphical representation of results (ranking charts, sensitivity analyses) provides managers with effective tools for communicating their decisions to non-technical stakeholders including policy makers and the public.

7. Conclusion, Limitations, and Future Work

This paper offers an integrated decision support system for choosing next-generation nuclear reactor types, which includes using the Hartigan-Wong algorithm for expert panel selection, as the tool for aggregating opinions of experts, PiF-SIWEC for criteria weights and PiF-RAWEC for alternative ranks. Validity of the offered framework is proved through case study of selecting 5 reactor types based on 8 criteria by the panel of 11 experts chosen out of 45 possible evaluators. Main results of the research are summarized below.

Methodological validity: The framework proves to be efficient in addressing the complexity and uncertainty of nuclear technologies choice. High consistency of six methods based on Picture Fuzzy MCDM (with an average Spearman correlation of 0.94) testifies the reliability of the framework. Hartigan-Wong algorithm helps to make an objective selection of experts, while PiFBM reflects important interactions between judgments of experts.

Results: The Molten Salt Reactor (A4) was chosen as the best option, then goes Advanced Pressurized Water Reactor (A5), Small Modular Reactor (A1), High Temperature Gas-Cooled Reactor (A2) and Sodium-Cooled Fast Reactor (A3). This rank does not change for any of the six methods or for sensitivity scenarios considered.

Priorities of criteria: Technical (38.70%) was the most important criterion, then came Strategic (29.59%), Safety (17.60%), Environmental (8.24%) and Economic (5.85%) criteria. Among criteria, the most important one was the passive safety (C4, 17.60%), while the least ones were the investment cost (C3, 5.85%) and construction complexity (C8, 5.30%).

Strategic insight: The analysis of results shows that the strategic benefit of technologies becomes more important than their economic aspect in choosing the reactors. Technologies like the MSR show good results despite their low maturity.

Practical contribution: The framework provides a systematic, transparent, and justifiable decision-support tool for assisting policymakers, energy planners, industry operators, and regulators in dealing with the complicated domain of nuclear technology.

Limitations considering the methodological rigor and validation: Expert Panel Composition: The panel consisted of 11 experts from the fields of nuclear engineering, safety, energy economics, and environmental sciences. While the use of the Hartigan-Wong algorithm made the composition objective, the number and diversity of experts in the panel may limit the generalization of the findings. A larger panel could lead to different weightings or rankings. Geographic Specificity: The case study has been conducted in the framework of Türkiye's energy planning, where the experts have been selected from Turkish institutions. National energy policies, regulatory frameworks, and infrastructures may be hard to transfer to any other national or regional context. Future research could apply the framework to different national contexts to check its generalizability. Scope of Technologies Under Assessment: The technologies analyzed in the study include five typical next generation reactor technologies. Since the nuclear technology field changes rapidly and there appears a variety of new technologies and hybrids, the analysis included only certain configurations (for example, other SMR designs or other fast reactors). Technical depth: The study targets the high-level strategic and performance criteria while omitting the engineering parameters such as neutronics or thermal hydraulics. It is justified by the multi-criteria approach, but a more technical approach could make it possible to refine the ranking. Time dependency: The analysis has been carried out under the assumption of the static criterion importance and technology performance. However, technology maturity, regulatory conditions, and the market situation may change over time. This framework does not include any time dependency that may become very important for long-term energy planning. Data collection: Despite the rigorous methodological approach, the analysis relies on the expert judgement. Although the Picture Fuzzy Clusters have been used to address the mentioned issue, additional validation by using the empirical data (operational performance, costs, etc.) would increase the reliability of the findings.

Future Research Directions: Further research can build upon the results and limitations presented:

Technological Scope Expansion: The scope of additional technologies can be expanded to include such technologies as SCWR (supercritical water-cooled reactors), LFR (lead-cooled fast reactors), and GFR (gas-cooled fast reactors). It can also include nuclear-renewable hybrids and cogeneration systems (hydrogen production, district heating, seawater desalination).

Generalization in Geographic and Contextual Settings: By applying the developed framework in different national settings (for instance, for countries with nuclear experience, for nations with high share of renewable energy in the grid, for emerging markets, etc.) it is possible to enhance the structure of criteria and their weightings. Additional geopolitical and regional criteria may include regional stability, nuclear proliferation risks, dependence on the international supply chain, etc.

Dynamic Model Development: Dynamic versions of the framework may be developed, which will account for time-based factors (learning curves for technologies, development of regulation, carbon

pricing, etc.). Scenario-planning and Monte-Carlo simulations may be used to model uncertainties in criteria weightings and performance evaluations. Possible influence of shifts in public acceptance and energy policy on choice of reactors can be accounted for.

Incorporation with Economic and Financial Models: To increase the validity of the economic criterion, detailed economic modeling (levelized electricity cost, variation of capital costs, uncertainties in construction time and costs, etc.) should be added. Sensitivity analysis of fundamental economic parameters (discount rates, inflation, growth factors, etc.) may be incorporated in the process.

Interaction with Advanced Models: Integration of the decision framework with artificial intelligence (neural networks, natural language processing) may be done to automatically extract the knowledge of experts from textual sources.

Stakeholder and Public Involvement: The proposed decision framework may be extended to include stakeholder perspectives and considerations of public acceptance. Interactive decision-support tools may be developed to let stakeholders test various criterion weightings and see the effect on ranking of candidate technologies.

Life Cycle Analysis of Technology: Whole life cycle of nuclear technology may be taken into consideration. Evaluation of impact of technology modularization, advances in manufacturing and construction methods on construction time and cost may be done

Sustainability and Carbon Footprint Evaluation: A complete life cycle assessment (LCA) can be performed for each candidate's technology to evaluate its carbon footprint, resource consumption, and environmental impact. Sustainability indicators (resource depletion, land use, water consumption, etc.) may be incorporated in decision criteria.

Regulation and Policy Effects: The influence of technological approval process and licensing timelines as well as nuclear safety requirements may be modeled. The alignment of technologies with national and international decarbonization commitments (such as Paris Agreement, net-zero commitments, etc.) may be evaluated.

Empirical Validation: The framework may be validated by using historical examples of nuclear technology choices, performance of existing reactors and cost of completed projects. Longitudinal analysis of changes in rankings due to the availability of new information can be done.

This paper shows that proposed Picture Fuzzy decision-support framework provides efficient, flexible and transparent method for selection of next generation nuclear reactor technologies. The integration of objective expert selection, advanced uncertainty management and sensitivity analysis ensures support for well-informed and defensible decisions in an area of significant strategic and societal importance. As global energy transition continues, such frameworks will play increasing role in balancing safety, sustainability, economic viability and energy security in nuclear energy sector.

Author Contributions

Conceptualization, GD.; methodology, GD.; software, GD.; validation, GD.; formal analysis, GD.; investigation, GD.; resources, GD.; data curation, GD.; writing—original draft preparation, GD.; writing—review and editing, GD.; visualization, GD.; supervision, GD.

Funding

This research received no external funding.

Data Availability Statement

The data supporting the reported results are presented in the study.

Conflicts of Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was not funded by any grant.

References

- [1] Ayyildiz, E., Yildirim, B., Erdogan, M., & Aydin, N. (2025). Strategic site selection methodology for small modular reactors: A case study in Türkiye. *Renewable and Sustainable Energy Reviews*, 215, 115545. <https://doi.org/10.1016/j.rser.2025.115545>
- [2] Mao, Q., Fan, J., & Gao, Y. (2025). An investment framework for hydro-wind-photovoltaic-hydrogen hybrid power system based on the improved picture fuzzy regret-PROMETHEE model. *International Journal of Hydrogen Energy*, 106. <https://doi.org/10.1016/j.ijhydene.2025.01.505>
- [3] Priyanka, Kumar, S., & Kalia, S. (2026). MULTIMOORA-based MCDM model for sustainable ranking of wastewater treatment technologies under picture fuzzy environment. *Expert Systems*, 43(6), e13286. <https://doi.org/10.1111/exsy.13286>
- [4] Arya, V., & Kumar, S. (2020). A new picture fuzzy information measure based on shannon entropy with applications in opinion polls using extended VIKOR–TODIM approach. *Computational and Applied Mathematics*, 39(3), 197. <https://doi.org/10.1007/s40314-020-01228-1>
- [5] Arya, V., & Kumar, S. (2021). A Picture Fuzzy Multiple Criteria Decision-Making Approach Based on the Combined TODIM-VIKOR and Entropy Weighted Method. *Cognitive Computation*, 13(5), 1172- 1184. <https://doi.org/10.1007/s12559-021-09892-z>
- [6] Nigro, L., & Cicirelli, F. (2023). Adapting Hartigan & Wong K-means for the efficient clustering of sets. *Open Access Biostatistics & Bioinformatics*, 3(3), 1-8.
- [7] Nigro, L., & Cicirelli, F. (2026). Clustering performance of a recombinator Hartigan–Wong algorithm. *Computers*, 15(6), 394. <https://doi.org/10.3390/computers15060394>
- [8] Manthey, B., & van Rhijn, J. (2023). Worst-case and smoothed analysis of the Hartigan–Wong method for k-means clustering. *arXiv preprint arXiv:2309.10368*. <https://doi.org/10.48550/arXiv.2309.10368>
- [9] Cuong, B.C. (2014). Picture fuzzy sets. *Journal of Computer Science and Cybernetics*, 30(4), 409-420. <https://doi.org/10.15625/1813-9663/30/4/5032>
- [10] Lin, M., Li, X., Chen, R., Fujita, H., & Lin, J. (2022). Picture fuzzy interactional partitioned Heronian means aggregation operators: an application to MADM process. *Artificial Intelligence Review*, 55(2), 1171-1208. <https://doi.org/10.1007/s10462-021-09953-7>
- [11] Ma, Q., Sun, H., Chen, Z., & Tan, Y. (2023). A novel MCDM approach for design concept evaluation based on interval-valued picture fuzzy sets. *Plos One*, 18(11), e0294596. <https://doi.org/10.1371/journal.pone.0294596>
- [12] Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 28(1), 100–108. <https://doi.org/10.2307/2346830>
- [13] Haseli, G. (2026). BCM: Base-criterion method for multi-attribute decision-making. In *Encyclopedia of Multi-Attribute Decision Making (MADM)* (pp. 391-402). Morgan Kaufmann. <https://doi.org/10.1016/B978-0-443-33275-3.00098-1>
- [14] Adiutomo A.B., Novendah I., Prasetyo Y.T. (2026). Determinants of public acceptance of nuclear power plant reactivation in Taiwan's energy transition: A hybrid DEMATEL–ANP Analysis. *Nuclear Engineering and Technology*, 58(7), 104288. <https://doi.org/10.1016/j.net.2026.104288>
- [15] Abdullah A.G., Nugraha R., Shafii M.A., ... Nandi N., Setiadiptura T. (2026). Hybrid Approaches in Decision- Making in GIS Environment for Nuclear Power Plant Site Selection: Evidence from Indonesia. *International Journal of Energy Research*, 2026(1), 5524118. <https://doi.org/10.1155/er/5524118>
- [16] Basegmez M. (2025). Strategic multi-criteria framework for nuclear plant siting: Integrating AHP, EWM, and Game Theory with GIS. *Progress in Nuclear Energy*, 188, 105897. <https://doi.org/10.1016/j.pnucene.2025.105897>

- [17] Shafii M.A., Fitriyani D., Muldarisnur M., ... Abdullah A.G., Nur'aini Mahmudah R.S. (2025). Integration of multiple decision-making methods with GIS for nuclear power plants siting in Bangka Belitung, Indonesia. *Ain Shams Engineering Journal*, 16(8), 103487. <https://doi.org/10.1016/j.asej.2025.103487>
- [18] Das A., Kumar V., Dutta S. (2024). A fuzzy-based AHP-VIKOR framework for risk analysis of safety-critical systems: A case study of nuclear power plants. *Annals of Nuclear Energy*, 209, 110841. <https://doi.org/10.1016/j.anucene.2024.110841>
- [19] Ovalle Flores D.L., Pena Gallardo R., Palacios Hernandez E.R., Soubervielle Montalvo C., Ospino Castro A. (2024). Holistic Analysis of the Impact of Power Generation Plants in Mexico during Their Life Cycle. *Sustainability Switzerland*, 16(16), 7041. <https://doi.org/10.3390/su16167041>
- [20] Elsohty A.M., Ali M.H., Adail A.S., Eisa A.A., Othman E.-S.A. (2025). Developing a dynamic combined powerquality index for assessing the performance of a nuclear facility. *Scientific Reports*, 15(1), 6792. <https://doi.org/10.1038/s41598-025-89383-5>
- [21] Tuncer B., Akkaya A.D., Yucemen M.S. (2024). Multicriteria Decision Making in Site Selection for Nuclear Power Plants. *Nuclear Technology*, 210(8). <https://doi.org/10.1080/00295450.2023.2299078>
- [22] Abdullah A.G., Shafii M.A., Pramuditya S., Setiadipura T., Anzhar K. (2023). Multi-criteria decision making for nuclear power plant selection using fuzzy AHP: Evidence from Indonesia. *Energy and AI*, 14, 100263. <https://doi.org/10.1016/j.egyai.2023.100263>
- [23] Rivero-Iglesias J.M., Puente J., Fernandez I., Leon O. (2025). A Novel Combined Hybrid Group Multi-Criteria Decision-Making Model for the Selection of Power Generation Technologies. *Systems*, 13(9), 742. <https://doi.org/10.3390/systems13090742>
- [24] Bogнар F., Benedek P. (2022). A Novel AHP-PRISM Risk Assessment Method—An Empirical Case Study in a Nuclear Power Plant. *Sustainability Switzerland*, 14(17), 11023. <https://doi.org/10.3390/su141711023>
- [25] Di Maio F., Matteo Coscia T., Zio E. (2024). Data Adequacy by an Extended Analytic Hierarchy Process for Inverse Uncertainty Quantification in Nuclear Safety Analysis. *Nuclear Engineering and Design*, 419, 112971. <https://doi.org/10.1016/j.nucengdes.2024.112971>
- [26] Abdullah A.G., Khairunnisa N.S., Shafii M.A., ... Hakim D.L., Setiadipura T. (2025). The social factors considered in site selection for nuclear power plants: A case study of Borneo Island, Indonesia. *Progress in Nuclear Energy*, 180, 105626. <https://doi.org/10.1016/j.pnucene.2025.105626>
- [27] Lo H.-W., Liou J.J.H., Yang J.-J., Huang C.-N., Lu Y.-H. (2021). An Extended FMEA Model for Exploring the Potential Failure Modes: A Case Study of a Steam Turbine for a Nuclear Power Plant. *Complexity*, 5766855. <https://doi.org/10.1155/2021/5766855>
- [28] Almonte G.J.C., Promentilla M.A.B. (2024). Evaluation of Nuclear Power and Other Low-Carbon Energy System Alternatives in the Philippines by AHP-TOPSIS. *Chemical Engineering Transactions*, 113. <https://doi.org/10.3303/CET24113073>
- [29] Erol I., Oztel A., Medeni I.T., Ar I.M. (2026). Enhancing small modular reactor adoption for sustainable energy transition: a Fermatean fuzzy ISM-MICMAC framework for analyzing challenges. *Nuclear Engineering and Design*, 450, 114805. <https://doi.org/10.1016/j.nucengdes.2026.114805>
- [30] Leite Maia Y., Ferreira Frutuoso E., Melo P.F., Quintela De Linhares T., Estanqueira Pinho B. (2022). Decommissioning of Nuclear Submarines and the Interim Storage of Their Reactor Compartments. *ASCE ASME Journal of Risk and Uncertainty in Engineering Systems Part B Mechanical Engineering*, 8(4), 041103. <https://doi.org/10.1115/1.4054385>
- [31] Bilgilioglu S.S. (2022). Site selection for radioactive waste disposal facility by GIS based multi criteria decision making. *Annals of Nuclear Energy*, 165, 108795. <https://doi.org/10.1016/j.anucene.2021.108795>
- [32] Akram, M., Bashir, A., & Garg, H. (2020). Decision-making model under complex picture fuzzy Hamacher aggregation operators. *Computational and Applied Mathematics*, 39(3), 226. <https://doi.org/10.1007/s40314-020-01251-2>
- [33] Huang, Y., & Wu, Q. (2026). Smart decision engine for performance optimization in enterprise management. *Scientific Reports*, 16(1), 3034. <https://doi.org/10.1038/s41598-025-32966-z>
- [34] Riaz, M., Kausar, R., Jameel, T., & Pamucar, D. (2024). Cubic picture fuzzy topological data analysis with integrating blockchain and the metaverse for uncertain supply chain management. *Engineering Applications of Artificial Intelligence*, 131, 107827. <https://doi.org/10.1016/j.engappai.2023.107827>

- [35] Qawaqneh, H., Shihadeh, A., Salameh, W.M.M., Zeeshan, M., & Fujita, T. (2026). A novel cubic circular picture fuzzy set framework with Bonferroni means operators and an illustrative application to quantum computing technology selection. *Aims Mathematics*, 11(5), 14412-14456. <https://doi.org/10.3934/math.2026591>
- [36] Ahmad, S., Rome, B.-E., Begum, A., & Ahmad, N. (2025). Spherical Picture Fuzzy Sets with Application to Multicriteria Decision-Making. *European Journal of Pure and Applied Mathematics*, 18(3), 6354. <https://doi.org/10.29020/nybg.ejpam.v18i3.6354>
- [37] Ramesh, R., Krishnaprakash, S., Ivkovic, N., Konecki, M., & Jana, C. (2025). Spherical Picture Fuzzy Sets: Enhancing Decision-Making with Geometric Bonferroni Methods. *International Journal of Analysis and Applications*, 23, 135. <https://doi.org/10.28924/2291-8639-23-2025-135>
- [38] Kumar, R., & Bisht, D.C.S. (2023). Picture Fuzzy Entropy: A novel measure for managing uncertainty in multi-criteria decision-making. *Decision Analytics Journal*, 9, 100351. <https://doi.org/10.1016/j.dajour.2023.100351>
- [39] Van Pham, H., Thai, K.P., Nguyen, Q.H., Phan, T.T.K., & Thao, N.X. (2023). Proposed distance and entropy measures of picture fuzzy sets in decision support systems. *Journal of Intelligent and Fuzzy Systems*, 44(4). <https://doi.org/10.3233/JIFS-221556>
- [40] Duong, T.T.T., & Thao, N.X. (2021). A novel dissimilarity measures on picture fuzzy sets and its application in multi-criteria decision making. *Soft Computing*, 25(1), 15-25. <https://doi.org/10.1007/s00500-020-05405-6>
- [41] Zhao, R., Luo, M., & Li, S. (2021). A dynamic distance measure of picture fuzzy sets and its application. *Symmetry*, 13(3), 436. <https://doi.org/10.3390/sym13030436>
- [42] Adak, A.K., Gunjan, M.K., & Haghighi, A.M. (2024). Distance Measure of Picture Fuzzy Sets and Its Application in Multi-Criteria Decision-Making Problem. *Journal of Fuzzy Extension and Applications*, 5(4). <https://doi.org/10.22105/jfea.2024.449236.1420>
- [43] Thao, N.X. (2020). Similarity measures of picture fuzzy sets based on entropy and their application in MCDM. *Pattern Analysis and Applications*, 23(3), 1203–1213. <https://doi.org/10.1007/s10044-019-00861-9>
- [44] Ahmed, D., & Dai, B. (2021). Novel similarity measures and multi-expert TOPSIS method using picture m-polar fuzzy sets. *Journal of Intelligent and Fuzzy Systems*, 40(5). <https://doi.org/10.3233/JIFS-202309>
- [45] Joshi, R., & Kumar, S. (2022). A novel VIKOR approach based on weighted correlation coefficients and picture fuzzy information for multicriteria decision making. *Granular Computing*, 7(2), 323–336. <https://doi.org/10.1007/s41066-021-00267-1>
- [46] Kadian, R., & Kumar, S. (2022). A new picture fuzzy divergence measure based on Jensen–Tsallis information measure and its application to multicriteria decision making. *Granular Computing*, 7(1), 113–126. <https://doi.org/10.1007/s41066-021-00254-6>
- [47] Ates, F., & Akay, D. (2020). Some picture fuzzy Bonferroni mean operators with their application to multicriteria decision making. *International Journal of Intelligent Systems*, 35(4). <https://doi.org/10.1002/int.22220>
- [48] Liu, L., Wu, X., & Chen, G. (2023). Picture Fuzzy Interactional Bonferroni Mean Operators via Strict Triangular Norms and Applications to Multicriteria Decision Making. *IEEE Transactions on Fuzzy Systems*, 31(8). <https://doi.org/10.1109/TFUZZ.2023.3234589>
- [49] Sarucan, A., Ozcan, E., & Guler, B. (2026). Bonferroni Mean-Based Aggregation Operators on q-Rung Picture Fuzzy Sets for Multi-Criteria Decision Making in Energy Storage Systems. *Symmetry*, 18(6), 966. <https://doi.org/10.3390/sym18060966>
- [50] Punetha, T., Komal, & Pamucar, D. (2024). Novel picture fuzzy power partitioned Hamy mean operators with Dempster-Shafer theory and their applications in MCDM. *Artificial Intelligence Review*, 57(6), 145. <https://doi.org/10.1007/s10462-024-10757-8>
- [51] Xue, R. (2025). Evaluating Physical Education Quality in Higher Education Using a Picture Fuzzy Decision Framework with Muirhead Mean Operator and MULTIMOORA Method. *IEEE Access*, 13, 18277 – 18293. <https://doi.org/10.1109/ACCESS.2025.3532949>
- [52] Wang, H., Xu, T., Feng, L., Mahmood, T., & Ullah, K. (2023). Aczel–Alsina Hamy Mean Aggregation Operators in T-Spherical Fuzzy Multi-Criteria Decision-Making. *Axioms*, 12(2), 224. <https://doi.org/10.3390/axioms12020224>
- [53] Deva, K., Marimuthu, K., Ali, N., Tolasa, F.T., & Karabiyik, U. (2025). Picture fuzzy Aczel–Alsina power geometric aggregation operators with confidence level and their application to multi-criteria decision-making. *Discover Applied Sciences*, 7(9), 953. <https://doi.org/10.1007/s42452-025-07605-x>
- [54] Jin, J., Pamucar, D., Shi, S., Zhang, H., & Teng, W. (2024). Generalized picture fuzzy Frank aggregation operators and their applications. *Alexandria Engineering Journal*, 109. <https://doi.org/10.1016/j.aej.2024.09.081>

- [55] Fathima Banu, M., Petchimuthu, S., Kamaci, H., & Senapati, T. (2024). Evaluation of Artificial Intelligence-Based Solid Waste Segregation Technologies through Multi-Criteria Decision-Making and complex q-rung picture fuzzy Frank aggregation operators. *Engineering Applications of Artificial Intelligence*, 133, 108154. <https://doi.org/10.1016/j.engappai.2024.108154>
- [56] Tian, C., Peng, J.J., Zhang, Z.Q., Wang, J.Q., & Goh, M. (2022). An extended picture fuzzy MULTIMOORA method based on Schweizer–Sklar aggregation operators. *Soft Computing*, 26(7), 3435–3454. <https://doi.org/10.1007/s00500-021-06690-5>
- [57] Xue, X., Dhumras, H., Thakur, G., Bajaj, R.K., & Shukla, V. (2025). Schweizer-Sklar T-Norm Operators for Picture Fuzzy Hypersoft Sets: Advancing Sustainable Technology in Social Healthy Environments. *Computers Materials and Continua*, 84(1). <https://doi.org/10.32604/cmc.2025.066310>
- [58] Wu, X.X., Zhu, Z., Wang, T., & Zhang, X. (2025). Picture Fuzzy Interactional Aggregation Operators Via Strict Triangular Norms and Applications to Multi-Criteria Decision Making. *Applied and Computational Mathematics*, 24(1). <https://doi.org/10.48550/arXiv.2204.03878>
- [59] Yildirim, B., Kara, B., Ayyildiz, E., & Aydin, N. (2026). A systematic decision model for selecting urban zero-emission vehicle technologies. *Sustainable Cities and Society*, 139, 107225. <https://doi.org/10.1016/j.scs.2026.107225>
- [60] Kesici, B. (2025). A Fuzzy Picture Decision-Making Framework for COBOT Selection in Digital Supply Chains. *Revista Internacional De Metodos Numericos Para Calculo Y Diseno En Ingenieria*, 41(4), 85. <https://doi.org/10.23967/j.rimni.2025.10.72342>
- [61] Ayyildiz, E., Karaca, T.K., Kara, B., Kavus, B.Y., & Aydin, N. (2025). Picture-Fuzzy Decision-Making Tool for Enhanced Risk Prioritization in Construction and Demolition Waste Management: A Hybrid FMEA–Fine–Kinney–SWARA–TOPSIS Approach. *Buildings*, 15(22), 4143. <https://doi.org/10.3390/buildings15224143>
- [62] Seker, S. (2025). Evaluation of agile attributes for low-cost carriers to achieve sustainable development using an integrated MCDM approach. *Management Decision*, 63(4). <https://doi.org/10.1108/MD-10-2023-1896>
- [63] Haktanir, E., & Kahraman, C. (2022). A novel picture fuzzy CRITIC & REGIME methodology: Wearable health technology application. *Engineering Applications of Artificial Intelligence*, 113, 104942. <https://doi.org/10.1016/j.engappai.2022.104942>
- [64] Bakioglu, G. (2025). Prioritization of Digital Technology Applications in Intermodal Freight Transport using CRITIC-based Picture Fuzzy TOPSIS Method. *International Journal of Automotive Science and Technology*, 9(2). <https://doi.org/10.30939/ijastech..1639635>
- [65] Razzaq, A., Khan, Z.A., Naeem, K., & Riaz, M. (2025). Picture fuzzy complex proportional assessment approach with stepwise weight assessment ratio analysis and criteria importance through intercriteria correlation. *Engineering Applications of Artificial Intelligence*, 139, 109554. <https://doi.org/10.1016/j.engappai.2024.109554>
- [66] Durmus, C.N., & Gorgun, O.F. (2026). Evaluation of Suitable Accounting and Auditing Firms for SMEs in the Textile Industry with Picture Fuzzy Set-based Entropy & MARCOS Approach. *Journal of Operations Intelligence*, 4(1). <https://doi.org/10.31181/jopi41202658>
- [67] Govindarajan, V., Shahab, S., Yousef, A., Dutta, A.K., & Anjum, M. (2026). A picture fuzzy multi-criteria decision-making framework for evaluating urban planning proposals under uncertainty. *Ain Shams Engineering Journal*, 17(5), 104098. <https://doi.org/10.1016/j.asej.2026.104098>
- [68] Zhang, D. (2025). Applying multi-criteria decision-making to text analysis for optimizing engineering knowledge management. *Alexandria Engineering Journal*, 117. <https://doi.org/10.1016/j.aej.2025.01.028>
- [69] Liu, T., Gao, K., & Rong, Y. (2024). An integrated picture fuzzy operational competitiveness ratings group decision approach for evaluating the enterprise digital transformation capability. *Granular Computing*, 9(2), 32. <https://doi.org/10.1007/s41066-024-00451-z>
- [70] Alkahtani, B.S.T., Simic, V., Anjum, M., Algahtani, O., & Alzaid, S.S. (2025). Decision Support System for Financial and Accounting Performance Assessment in Manufacturing Industries. *International Journal of Computational Intelligence Systems*, 18(1), 314. <https://doi.org/10.1007/s44196-025-01066-1>
- [71] Simic, V., Sousek, R., & Jovcic, S. (2020). Picture fuzzy MCDM approach for risk assessment of railway infrastructure. *Mathematics*, 8(12), 2259. <https://doi.org/10.3390/math8122259>
- [72] Gorgun, O.F., & Iyigun, I. (2025). Evaluation of the Selection of Low-Bed Trailers in the Transportation of Oversized and Overweight Cargo: A Hybrid Picture Fuzzy CRITIC-MARCOS Model. *Journal of Soft Computing and Decision Analytics*, 3(1). <https://doi.org/10.31181/jscda31202556>

- [73] Peng, J.J., Chen, X.G., Tan, H., Long, Q.Q., & Jiang, L.L. (2024). A heterogeneous picture fuzzy SWARA-MARCOS evaluation framework based on a novel cross-entropy measure. *International Journal of Systems Science*, 55(8). <https://doi.org/10.1080/00207721.2024.2312881>
- [74] Prabakaran, R., Suvitha, K., Kalaiselvan, S., Yuksel, S., & Narayanamoorthy, S. (2026). Assessment of road accident risk in India under a type-2 picture fuzzy framework with novel distance measures. *Scientific Reports*, 16(1), 21535. <https://doi.org/10.1038/s41598-026-52037-1>
- [75] Tarafdar, A., Shaikh, A., Ali, M.N., & Haldar, A. (2026). An integrated fuzzy decision-making framework for autonomous mobile robot selection: balancing subjective and objective measures with fuzzy TOPSIS and picture fuzzy CoCoSo approach. *Journal of the Operational Research Society*, 77(2). <https://doi.org/10.1080/01605682.2025.2486705>
- [76] Kahraman, C., Oztaysi, B., & Onar, S.C. (2022). A Novel Interval Valued Picture Fuzzy TOPSIS Method: Application on Supplier Selection. *Journal of Multiple Valued Logic and Soft Computing*, 39(5-6), 615-635.
- [77] Salsabeela, V., & John, S.J. (2024). TOPSIS Techniques on Picture Fuzzy Soft Sets. *Engineering Letters*, 32(3).
- [78] Emam, W., Amin, M., Imran, R., Ullah, K., & Ali, Z. (2025). TOPSIS has driven complex picture fuzzy approach for speech matching and sports training feature recognition. *Scientific Reports*, 15(1), 34136. <https://doi.org/10.1038/s41598-025-03572-w>
- [79] Rani, V., & Kumar, S. (2025). Type-2 picture fuzzy VIKOR approach based on TODIM for evaluating last-leg delivery in metro cities in India. *Applied Soft Computing*, 183, 113640. <https://doi.org/10.1016/j.asoc.2025.113640>
- [80] Aydogan, B., Olgun, M., Smarandache, F., & Unver, M. (2024). A Decision-Making Approach Incorporating TODIM Method and Sine Entropy in q-Rung Picture Fuzzy Set Setting. *Journal of Applied Mathematics*, 3798588. <https://doi.org/10.1155/2024/3798588>
- [81] Jin, J., Garg, H., & You, T. (2023). Generalized picture fuzzy distance and similarity measures on the complete lattice and their applications. *Expert Systems with Applications*, 220, 119710. <https://doi.org/10.1016/j.eswa.2023.119710>
- [82] Dhumras, H., & Bajaj, R.K. (2023). On prioritization of hydrogen fuel cell technology utilizing bi-parametric picture fuzzy information measures in VIKOR & TOPSIS decision-making approaches. *International Journal of Hydrogen Energy*, 48(96). <https://doi.org/10.1016/j.ijhydene.2022.09.093>
- [83] Chowdhury, S.R., Chatterjee, S., & Chakraborty, S. (2025). Optimization of hybrid non-traditional machining processes using multi-criteria decision-making methods in picture fuzzy environment. *International Journal on Interactive Design and Manufacturing*, 19(11). <https://doi.org/10.1007/s12008-025-02315-5>
- [84] Xu, Y., & Zhang, D. (2025). Identifying AI-Driven Emerging Trends in Service Innovation and Digitalized Industries Using the Circular Picture Fuzzy WASPAS Approach. *Symmetry*, 17(9), 1546. <https://doi.org/10.3390/sym17091546>
- [85] Hezam, I.M., Cavallaro, F., Lakshmi, J., Rani, P., & Goyal, S. (2023). Biofuel Production Plant Location Selection Using Integrated Picture Fuzzy Weighted Aggregated Sum Product Assessment Framework. *Sustainability Switzerland*, 15(5), 4215. <https://doi.org/10.3390/su15054215>
- [86] Simic, V., Lazarevic, D., & Dobrodolac, M. (2021). Picture fuzzy WASPAS method for selecting last-mile delivery mode: a case study of Belgrade. *European Transport Research Review*, 13(1), 43. <https://doi.org/10.1186/s12544-021-00501-6>
- [87] Tengfei, L., Jing, W., Yuan, X., Meijin, Y., & Baoliang, L. (2024). Assessment of Hand Hygienic Materials for Nursing Staff at Hospitals with WASPAS Technique and Picture Fuzzy Information. *IEEE Access*, 12. <https://doi.org/10.1109/ACCESS.2024.3515096>
- [88] Aydogmus, H.Y., Kamber, E., & Kahraman, C. (2021). ERP selection using picture fuzzy CODAS method. *Journal of Intelligent and Fuzzy Systems*, 40(6). <https://doi.org/10.3233/JIFS-202564>
- [89] Simic, V., Karagoz, S., Deveci, M., & Aydin, N. (2021b). Picture fuzzy extension of the CODAS method for multi-criteria vehicle shredding facility location. *Expert Systems with Applications*, 175, 114644. <https://doi.org/10.1016/j.eswa.2021.114644>
- [90] Niu, G., Zhang, F., & Guo, M. (2025). Terminal Forensics in Mobile Botnet Command and Control Detection Using a Novel Complex Picture Fuzzy CODAS Algorithm. *Symmetry*, 17(10), 1637. <https://doi.org/10.3390/sym17101637>
- [91] Kara, B., Ayyildiz, E., Kavus, B.Y., & Karaca, T.K. (2025). Evaluating Cybersecurity Measures for Smart Grids Under Uncertainty: A Picture Fuzzy SWARA-CODAS Approach. *Applied Sciences Switzerland*, 15(19), 10704. <https://doi.org/10.3390/app151910704>

- [92] Kamber, E., Aydogmus, U., Yumurtaci Aydogmus, H., Gumus, M., & Kahraman, C. (2024). Prioritization of drip-irrigation pump alternatives in agricultural applications: An integrated picture fuzzy BWM&CODAS methodology. *Applied Soft Computing*, 154, 111308. <https://doi.org/10.1016/j.asoc.2024.111308>
- [93] Razzaq, A., Khan, Z.A., Riaz, M., & Pamucar, D. (2025). Sustainable decision support system in Industry 4.0 under uncertainties with m-polar picture fuzzy information aggregation. *Alexandria Engineering Journal*, 116. <https://doi.org/10.1016/j.aej.2024.11.104>
- [94] Boz, E., Calik, A., Cizmecioglu, S., & Tirkolae, E.B. (2026). A machine learning-enhanced fuzzy decision-making model for blockchain platform selection in healthcare systems. *Expert Systems with Applications*, 309, 131150. <https://doi.org/10.1016/j.eswa.2026.131150>
- [95] Li, X., & Liu, M. (2025). Scrutinizing the applicability of blockchain in the sustainability of supply chains using intelligent fuzzy multi criteria decision making. *Scientific Reports*, 15(1), 27442. <https://doi.org/10.1038/s41598-025-06776-2>
- [96] Garg, M., & Kumar, S. (2025). IoT based healthcare system selection with picture fuzzy modified combined compromise solution based on distance measure and score function. *International Journal of Machine Learning and Cybernetics*, 16(11), 8631–8660. <https://doi.org/10.1007/s13042-025-02639-4>
- [97] Korucuk, S., Aytekin, A., Ecer, F., Pamucar, D.S., & Karamasa, C. (2023). Assessment of ideal smart network strategies for logistics companies using an integrated picture fuzzy LBWA–CoCoSo framework. *Management Decision*, 61(5). <https://doi.org/10.1108/MD-12-2021-1621>
- [98] Svadlenka, L., Simic, V., Dobrodolac, M., Lazarevic, D., & Todorovic, G. (2020). Picture Fuzzy Decision-Making Approach for Sustainable Last-Mile Delivery. *IEEE Access*, 8, 9262845. <https://doi.org/10.1109/ACCESS.2020.3039010>
- [99] Bausys, R., Juodagalviene, B., Kazakeviciute-Januskeviciene, G., Cepulionis, E., & Zavadskas, E.K. (2026). Hybrid Decision-Making Method within Dempster-Shafer Framework. *International Journal of Computers Communications and Control*, 21(1), 7246. <https://doi.org/10.15837/ijccc.2026.1.7246>
- [100] Yucel Altay, S., & Turanoglu Sirin, B. (2026). Q-rung picture fuzzy sets theory-based ensemble learning method for credit risk assessment. *Knowledge Based Systems*, 341, 115581. <https://doi.org/10.1016/j.knosys.2026.115581>
- [101] Li, J., Fan, J., Chen, R., & Wu, M. (2026). Three-Way Decision Based on Removal Effects of Criteria and Evidential Reasoning Approach Under Picture Fuzzy Multi-criteria Environment. *International Journal of Fuzzy Systems*, 28(2). <https://doi.org/10.1007/s40815-024-01962-2>
- [102] Zhao, R., Ma, L., Li, S., & Luo, M. (2022). A Multi-Criteria Three-Way Decision-Making Method in a Picture Fuzzy Probabilistic Decision System. *Cognitive Computation*, 14(6). <https://doi.org/10.1007/s12559-021-09900-2>
- [103] Dagidir, B.D., & Ozkan, B. (2024). A comprehensive evaluation of company performance using sustainability balanced scorecard based on picture fuzzy AHP. *Journal of Cleaner Production*, 435, 140519. <https://doi.org/10.1016/j.jclepro.2023.140519>
- [104] Yu, Z., Kou, J., Liu, Y., & Chu, H. (2025). Decision algorithm with fuzzy framework and evaluation of advanced financial management policy. *Scientific Reports*, 15(1), 31184. <https://doi.org/10.1038/s41598-025-07662-7>
- [105] Karadayi-Usta, S. (2024). Sustainable post-consumer textile waste management: Picture fuzzy set-based ORESTE approach. *Journal of Cleaner Production*, 482, 144231. <https://doi.org/10.1016/j.jclepro.2024.144231>
- [106] Chung, H.-Y., & Chang, K.-H. (2025). Integrating Entropy and Picture Fuzzy Set Methods Supplier Selection. *International Journal of Industrial Engineering Theory Applications and Practice*, 32(3). <https://doi.org/10.23055/ijietap.2025.32.3.10533>
- [107] Riaz, M., & Farid, H.M.A. (2022). Picture fuzzy aggregation approach with application to third-party logistic provider selection process. *Reports on Mechanical Engineering*, 3(1), 227-236. <https://doi.org/10.31181/rme20023062022r>
- [108] Petchimuthu, S., Fathima Banu, M., Pillai, S.T., & Senapati, T. (2025). Advancing greenhouse gas emission reduction strategies: Integrating Multi-Criteria Decision-Making with Complex q-Rung Picture Fuzzy Sugeno–Weber Operators. *Engineering Applications of Artificial Intelligence*, 151, 110621. <https://doi.org/10.1016/j.engappai.2025.110621>
- [109] Ayyildiz, E., Yildirim, B., & Aydin, N. (2025). Location selection methodology for data center with renewable energy integration. *Renewable Energy*, 250, 123270. <https://doi.org/10.1016/j.renene.2025.123270>

- [110] Kamran, M., Zhang, Q., Pamucar, D., Tehreem, & Simic, V. (2026). Sustainable energy optimization and complex data management: Data-driven methodology based on neutrosophic picture fuzzy soft sets. *Engineering Applications of Artificial Intelligence*, 167, 113644. <https://doi.org/10.1016/j.engappai.2025.113644>
- [111] Bakioglu, G. (2024). Selection of sustainable transportation strategies for campuses using hybrid decision-making approach under picture fuzzy sets. *Technological Forecasting and Social Change*, 206, 123567. <https://doi.org/10.1016/j.techfore.2024.123567>
- [112] Khan, W.A., Junaid, M., Ghazal, T.M., Ngoc Tong, T.M., & Pham, H.V. (2026). Novel concepts of q-Rung picture fuzzy directed hypergraphs with application in intelligent and emotion-aware healthcare decision-making. *Results in Engineering*, 32, 111816. <https://doi.org/10.1016/j.rineng.2026.111816>
- [113] Mishra, A.R., Rani, P., Saeidi, P., Alrasheedi, A.F., & Alshamrani, A.M. (2024). Decision support framework for healthcare waste disposal techniques assessment using an integrated picture fuzzy gained and lost dominance score-based approach. *Engineering Applications of Artificial Intelligence*, 138, 109394. <https://doi.org/10.1016/j.engappai.2024.109394>
- [114] Zhao, J., Zhang, J., Lei, Y., & Yi, B. (2025). Proportional grey picture fuzzy sets and their application in multi-criteria decision-making with high-dimensional data. *Aims Mathematics*, 10(1), 208-233. <https://doi.org/10.3934/math.2025011>
- [115] Hu, Y., & Duan, L. (2026). Decision Support Framework for Digital Music Integration in Education Reform Using Picture Fuzzy FUCA and Industry–Academia Collaboration. *Symmetry*, 18(1), 145. <https://doi.org/10.3390/sym18010145>
- [116] Chen, Z., Liang, W., & Luo, S. (2024). A Novel Integrated Picture Fuzzy MACONT Method and Its Application in Teaching Quality Evaluation in Higher Education. *IEEE Access*, 12. <https://doi.org/10.1109/ACCESS.2024.3418035>
- [117] Akram, M., Bashir, A., & Edalatpanah, S.A. (2021). A hybrid decision-making analysis under complex q-rung picture fuzzy Einstein averaging operators. *Computational and Applied Mathematics*, 40(8), 305. <https://doi.org/10.1007/s40314-021-01651-y>
- [118] Lang, F., & Liu, Y. (2025). Smart system for forecasting financial outcomes and supporting strategic choices. *Scientific Reports*, 15(1), 44197. <https://doi.org/10.1038/s41598-025-27980-0>
- [119] Yu, L., Fang, H., Rong, Y., Min, J., & Xing, Y. (2023). A Novel Picture Fuzzy Set-Based Decision Approach for Consumer Trust Project Risk Assessment. *Systems*, 11(3), 160. <https://doi.org/10.3390/systems11030160>
- [120] Onar, S.C., Oztaysi, B., & Kahraman, C. (2022). A Comparison of Fuzzy Extensions of TOPSIS Method: Evaluating Creative Thinking Tool Alternatives. *Journal of Multiple Valued Logic and Soft Computing*, 39(5-6).
- [121] Garg, H. (2017). Some picture fuzzy aggregation operators and their applications to multicriteria decision-making. *Arabian journal for science and engineering*, 42(12), 5275-5290. <https://doi.org/10.1007/s13369-017-2625-9>
- [122] Puška, A., Nedeljković, M., Pamučar, D., Božanić, D., & Simić, V. (2024). Application of the new simple weight calculation (SIWEC) method in the case study in the sales channels of agricultural products. *MethodsX*, 13, 102930. <https://doi.org/10.1016/j.mex.2024.102930>
- [123] Yalcin, N., Eti, S., Yuksel, S., Ergun, E., & Yazici, M. (2026). Modeling trust in central bank communication under uncertainty: A machine learning-driven fractal fuzzy decision support mechanism. *Array*, 31, 101113. <http://dx.doi.org/10.2139/ssrn.6319288>
- [124] Ecer, F., Acar, M., Eti, S., Yuksel, S., & Dincer, H. (2026). A Pythagorean fuzzy decision-making framework for prioritizing performance enhancement strategies of metal–organic frameworks in liquid hydrogen energy systems. *Energy Conversion and Management: X*, 31, 101916. <https://doi.org/10.1016/j.ecmx.2026.101916>
- [125] Bosna, J., Štilić, A., & Puška, A. (2026). Selection of urban overtourism management strategies in Croatia: The case of Zadar County. *Urban Science*, 10(3), 139. <https://doi.org/10.3390/urbansci10030139>
- [126] Katranci, A., & Kundakci, N. (2026). Evaluation of cryptocurrency exchanges using the integrated FSIWEC and FRADAR methods. *Journal of Economic Studies*. <https://doi.org/10.1108/JES-09-2025-0735>
- [127] Boz, E. (2025). Evaluation for the selection of agricultural spraying drones using p,q-quasirung orthopair fuzzy logic and multi-criteria methods. *Scientific Reports*, 15, 27606. <https://doi.org/10.1038/s41598-025-11656-w>
- [128] Çizmecioğlu, S., Çalık, A., & Tirkolaee, E. B. (2025). An integrated p,q-quasirung orthopair fuzzy decision-making approach for strategic selection of competitive intelligence platforms. *Engineering Applications of Artificial Intelligence*, 158, 111498. <https://doi.org/10.1016/j.engappai.2025.111498>

- [129] Zhao, W. (2025). Analysis factors of ideological and political education in colleges and universities in the new media era under the Fermatean neutrosophic sets. *Neutrosophic Sets and Systems*, 83.
- [130] Gao, H., & Qian, K. (2025). Risk assessment of municipal water supply and drainage project costs using neutrosophic numbers. *Neutrosophic Sets and Systems*, 81.
- [131] Puška, A., Štilić, A., Pamučar, D., Božanić, D., & Nedeljković, M. (2024). Introducing a Novel multi-criteria Ranking of Alternatives with Weights of Criterion (RAWEC) model. *MethodsX*, 12, 102628. <https://doi.org/10.1016/j.mex.2024.102628>
- [132] Nedeljković, M., Puška, A., Pamučar, D., & Marinković, D. (2024). Selection of agricultural product sales channels using fuzzy double MEREC and fuzzy RAWEC method. *Agriculture and Forestry*, 70(3), 45–58. <https://doi.org/10.17707/AgricultForest.70.3.03>
- [133] Zhang, R., Puška, A., Stević, Ž., & Zavadskas, E. K. (2025). A novel interval type-2 fuzzy MCDM model for evaluation of suitable systems of renewable sources from financial and sustainable aspects. *Economic Computation and Economic Cybernetics Studies and Research*, 59(2), 329. <https://doi.org/10.24818/18423264/59.2.25.20>
- [134] Tešić, D., Božanić, D., Mondal, S. P., & Puška, A. (2025). Modification of the Ranking of Alternatives with Weights of Criterion (RAWEC) method and improvement with Fermatean fuzzy numbers. *Journal of Soft Computing and Decision Analytics*, 3(1), 146–157. <https://doi.org/10.31181/jsdda31202570>
- [135] Katrancı, A., Kundakci, N., & Arman, K. (2026). Fuzzy SIWEC and Fuzzy RAWEC methods for sustainable waste disposal technology selection. *Spectrum of Operational Research*, 3(1), 87–102. <https://doi.org/10.31181/sor31202633>
- [136] Shamsi, M., Zakerinejad, M., & Zareifard, M. R. (2025). Optimal, reliable, and sustainable technology selection for mining overburden waste utilization using green & climate-smart mining (GCSM): A hybrid fuzzy multi-criteria decision-making tool. *Journal of Environmental Chemical Engineering*, 13(3), 116118. <https://doi.org/10.1016/j.jece.2025.116118>
- [137] Albahri, O. S., Khaleel, Y. L., Habeeb, M. A., Al-Obaidi, J. R., Albahri, A. S., Alamoodi, A. H., et al. (2026). Evaluating vegetable nutrition for dental health maintenance using an orthopair fuzzy Z-number decision-making model. *Cognitive Computation*, 18(1), 13. <https://doi.org/10.1007/s12559-026-10545-2>
- [138] Mahmudah R.S., Widiatmono R., Darmawan D., ... Shafii M.A., Hanum L. (2026). Robust nuclear power plant site selection using SWARA, MABAC, and SMART: A GIS-Based study on the Muria Peninsula. *Sustainable Futures*, 11, 101689. <https://doi.org/10.1016/j.sftr.2026.101689>