Ensuring Consistency in Group Decision Making: A Systematic Review of the FWZIC Method

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***Abstract*—Subjective opinions in decision-making processes are often vague, ambiguous, and imprecise due to the inherent subjectivity and variability in individual perspectives. This systematic study examines the Fuzzy Weighted Zero Inconsistency (FWZIC) method, which addresses these challenges by achieving consistency in group consensus and effectively managing uncertainties associated with subjective human opinions. The FWZIC method is increasingly popular in the Multi-Criteria Decision Making (MCDM) field for determining criteria weights. This study comprehensively analyzes 71 empirical studies published from 2021 to March 2025, employing the FWZIC method across diverse domains such as healthcare, engineering, and supply chain. By categorizing FWZIC literature based on themes and domains, this study reveals a taxonomy of the latest techniques and methods integrated with FWZIC. It also explores fuzzy extensions and integrated MCDM methods, providing researchers with a summary of suitable techniques for various contexts. By systematically synthesizing findings, this study provides a comprehensive overview of the current state of FWZIC applications in the literature, identifies gaps and suggests potential avenues for future research in the MCDM domain.**

Keywords*—*FWZIC; MCDM; fuzzy sets; subjective judgment; group decision making

I. Introduction

Decision-making plays a crucial role in shaping the dynamics of society, influencing various aspects of human life, governance, and development. It is a cornerstone of societal progress, influencing economic development, social welfare, environmental sustainability and technological advancement [1]. In today's dynamic and complex world, decision-makers are confronted with numerous challenges, often involving multiple conflicting criteria for choosing an optimal alternative. Often, these criteria are not of equal importance, and moreover, the performance of the alternatives also varies, thereby complicating the decision-making process. Multi-Criteria Decision-Making (MCDM) methods offer a structured way to navigate these challenges by considering multiple objectives, diverse criteria, and varying preferences of everyone involved [2]. This systematic approach helps to ensure that decisions are made with a comprehensive understanding of all factors at play.

MCDM techniques enable decision-makers to systematically evaluate alternatives based on various criteria, facilitating informed decision-making across diverse domains. From business and engineering [3] to healthcare [4] and aviation [5], MCDM finds applications in a wide range of fields, helping organizations and decision-makers navigate through intricate decision landscapes. Numerous MCDM methods provide decision-makers with quantitative tools to prioritize objectives, assess trade-offs, and identify optimal solutions in real-life scenarios [6]. The decision-making process typically involves identification of the problem, criteria and alternatives, development of a decision matrix and application of an analytical model to rank the alternatives [6].

Criteria weighting is crucial in decision-making, ensuring the accurate representation of the relative importance of evaluation criteria, which significantly impacts ranking outcomes. Weighting methods can be objective, subjective, or a combination of both. Objective methods are based on mathematical models that rely solely on data, thereby excluding human expertise. These methods are ideal when abundant, precise data is available [7]. Conversely, subjective methods rely on human judgment to assign criteria weights and are often employed when expert evaluation is essential for assessing the criteria's significance in the decision-making process [8]. Subjective weighting proves more impactful as it compels decision makers to carefully assess every aspect of the decision problem, rather than relying on the availability of data. [9]. To reduce bias in subjective decisions, a structured approach involving multiple experts is required [10], [11].

Methods such as the Analytic Hierarchy Process (AHP) [12], Analytic Network Process (ANP) [13], Best Worst Method (BWM) [14] and Fuzzy Weighted Zero Inconsistency (FWZIC) [15] are popular subjective criteria weighting methods. Among these, FWZIC is the latest advanced method that overcomes the limitations of other well-known methods. AHP, BWM and ANP methods are time-consuming as they require pairwise comparisons between criteria, which can lead to inconsistencies [16]. As the number of criteria increases, it becomes increasingly difficult for experts to accurately understand how these weights relate to one another. Moreover, these methods are often extended to fuzzy environments [17] to handle uncertainty and imprecision that arises in subjective decisions, making the criteria weighting process even more complex [18]. FWZIC has been applied in multiple domains to assess criteria weights, including healthcare, supply chain, transportation and more [19]. Thus, the FWZIC method demonstrates its versatility and ability to handle various attributes while preserving the consistency of the decision-makers' judgements.

The FWZIC method utilizes a fuzzy environment to compute criteria weights and can easily achieve consensus among multiple experts and a large number of criteria without any inconsistencies in the criteria weighting process [19]. Each expert's opinion is captured with ease and integrated into the decision-making process to determine the final criteria weights.

This enables decision makers to leverage the diverse perspectives, knowledge, and skills of experts, aiming to achieve a more balanced and well-informed outcome. The goal is to enhance decision quality, gain consensus, and ensure that the criteria's weights are representative of multiple stakeholders' opinions.

Despite its advantages over other subjective criteria weighting approaches, the original FWZIC method falls short in addressing uncertainty and vagueness [20]. This limitation arises from the use of Triangular Fuzzy Numbers (TFN) to represent expert opinions. TFNs have been criticized in the literature for inadequately handling uncertainties due to constraints in dealing with membership values [21]. To overcome this limitation, recent studies have extended the FWZIC method using various fuzzy environments. Advanced fuzzy sets such as the Intuitionistic Fuzzy Sets, Pythagorean Fuzzy Sets, and Fermatean Fuzzy Sets have been utilized to broaden the uncertainty space captured by the fuzzy environment.

The decision problems involving FWZIC all deal with the evaluation and benchmarking of the alternatives in various domains ranging from physical entities to algorithms, processes and strategies. The results are used to select an optimal solution by integrating FWZIC with MCDM ranking methods. The FWZIC models built for the assessment problem in one field are applicable to other fields. Therefore, a systematic review is necessary to offer researchers and decision-makers comprehensive guidance on advancements, applications, and future directions in the utilization of the enhanced FWZIC method, which has gained tremendous popularity in the literature. By synthesizing current knowledge and identifying gaps, this study aims to enrich the ongoing discourse in MCDM research, providing decision-makers with valuable insights and directing future inquiries in this evolving field.

To date, only one systematic review on the FWZIC method exists [19]. However, this systematic review diverges from the previous study in several key aspects. The previous review focuses solely on studies that have integrated the FWZIC method with the FDOSM ranking method, limiting the scope to just twenty-three studies. In contrast, this review encompasses fifty-two studies that have utilized the FWZIC method regardless of the ranking method or MCDM approach used, thus offering a broader perspective. Additionally, unlike the previous study, this systematic review analyzes and presents a more comprehensive review of the FWZIC method, detailing the different ranking methods, fuzzy environments, aggregation methods, defuzzifying techniques used, and the criteria and expert characteristics involved, thereby providing an in-depth analysis of the FWZIC method. The novelty of this research lies in its comprehensive approach, which covers the breadth and depth of the empirical studies utilizing the FWZIC method with recommendations for advancements in the field. This study aims to offer a holistic understanding of the progress in the application and utilization of the FWZIC method.

Considering the aforementioned factors, this study seeks to fill the research gap by employing a systematic approach to review and synthesize an analysis based on empirical case studies that have utilized the FWZIC method. The study aims to categorize FWZIC literature based on themes and domains to reveal a taxonomy of the latest techniques and methods utilized with FWZIC. Additionally, it aims to outline future directions and research opportunities in the MCDM field, focusing on subjective criteria weighing with FWZIC. By examining the limitations and challenges identified in the literature, this review highlights areas requiring further research and innovation. To that effect, this study aims to answer the following research questions:

RQ1: What are the general characteristics of empirical studies that have utilized FWZIC?

RQ2: What domains and themes are the studies based on?

RQ3: Which ranking methods has FWZIC been integrated with?

RQ4: Which fuzzy environments are utilized to enhance FWZIC?

RQ5: What techniques are used for aggregation and defuzzification in the FWZIC algorithm?

RQ6: What are the characteristics of the experts involved in the studies?

RQ7: What are the characteristics of the criteria utilized in the studies?

The rest of the study is organized as follows. Section II provides a background of the FWZIC technique and an overview of MCDM and fuzzy sets pertinent to this study. Section III presents the methodology of the systematic review, while Section IV presents the results of the review, linking them to research questions. Finally, Section V delves into the research implications while Section VI concludes the study, presenting the research limitations and future work.

II. Background Information

A. FWZIC Method

The FWZIC method, proposed by [15], is a subjective criteria weighting method used for evaluating criteria weights in the MCDM process. It effectively assigns criteria weights based on multiple human expert judgments, ensuring consistency and minimizing ambiguity. By leveraging a fuzzy environment, FWZIC handles uncertainty and vagueness, making it ideal for complex scenarios with imprecise information or numerous criteria. Often combined with ranking methods like Technique for Order of Preference by Similarity (TOPSIS), Fuzzy Decision by Opinion Score Method (FDOSM), FWZIC enhances decision accuracy and robustness across various fields, including tourism, healthcare, and education [19].

The FWZIC method relies on five essential phases to achieve zero inconsistency in criteria weighting by involving multiple experts in assessing criteria significance. The FWZIC method is applied using the phases below [15]:

1) Design the evaluation form. An appraisal form is designed to assess the significance of the evaluation criteria of the MCDM case study. The appraisal form is based on a Likert scale, usually a 5-point or 10-point scale. The Likert scale is ideal for this purpose as it allows the experts to assess the criteria based on linguistic values (such as "Highly Important", "Important", "Moderately Important") and converts the expert assessment to its corresponding numerical values (5, 4, 3) which can be evaluated further using the FWZIC technique.

2) Collect expert judgement. In this step, experts in the field of study are identified. A minimum of three experts is often recommended to ensure diverse perspectives of experts are captured adequately. Section IV presents the experts' characteristics involved in extant FWZIC studies. The appraisal form is administered to the relevant experts to collect their judgment in a structured approach.

3) Develop Expert Decision Matrix (EDM): In this step, an expert decision matrix is constructed based on the data collected via the appraisal form. An EDM is constructed by intersecting each criterion with the expert importance (numerical score) assigned to that criterion, as shown in the equation below:

$$EDM = \left[e_{ij}\right]_{m\times n} = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ e_{m1} & e_{m2} & \dots & e_{mn} \end{bmatrix} \quad (1)$$

where, m represents the number of experts, and n represents the number of criteria. Moreover, $e_{ij} = Imp(e_i/c_j)$, which represents the importance of criterion *j* assigned by expert *i*. Thus, e_{13} is the significance level of criterion 3 assigned by expert 1.

4) Develop fuzzy EDM by applying fuzzy membership functions. In this step, the EDM performance values, representing the criteria significance by the expert, are fuzzified, using the integrated fuzzy membership functions, to develop a fuzzy EDM. The original FWZIC method is based on the Triangular Fuzzy Number (TFN). However, recent studies have extended FWZIC with various fuzzy environments.

$$\widetilde{EDM} = \left[\widetilde{e_{ij}}\right]_{m\times n} = \begin{bmatrix} \widetilde{e_{11}} & \widetilde{e_{12}} & \cdots & \widetilde{e_{1n}} \\ \widetilde{e_{21}} & \widetilde{e_{22}} & \cdots & \widetilde{e_{2n}} \\ \cdots & \cdots & \ddots & \cdots \\ \widetilde{e_{m1}} & \widetilde{e_{m2}} & \dots & \widetilde{e_{mn}} \end{bmatrix}, \quad (2)$$

where, $\widetilde{e_{ij}}$ represents the corresponding fuzzy membership value for e_{ij}.

5) Compute final criteria weights. Finally, the criteria weights are computed based on the respective operators of the fuzzy environment integrated with FWZIC. The computation involves five main steps:

a) Aggregation of the criteria weights using an aggregation operator, b) Determining the ratio for each criterion for each expert by dividing the fuzzy criterion value by the aggregated value, c) The fuzzy value is defuzzified using the respective fuzzy environment defuzzification techniques, and d) The criteria weight coefficients are computed by converting the defuzzified values to their corresponding weight coefficients to ensure that the sum of the weights is equal to 1. Section IV discusses prevalent aggregation and defuzzifying techniques utilized in extant literature for computing the criteria weights.

Fig. 1 illustrates the five phases of the FWZIC method.

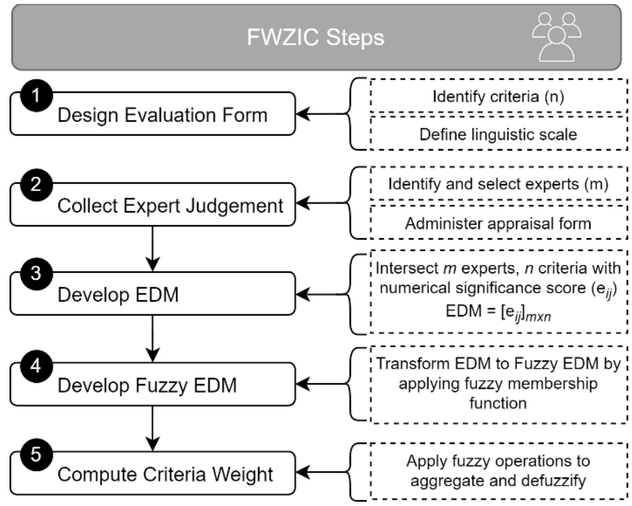

Fig. 1. FWZIC phases.

The original FWZIC method relied on TFN to handle ambiguity and imprecision in human judgment. However, since then, several researchers have extended FWZIC using advanced fuzzy environments that capture a wider spectrum of ambiguities. The following section explores the fuzzy set theory and the various fuzzy environments with their generalizations and extensions.

B. *Comparison of FWZIC with other Criteria Weighting Methods*

The FWZIC method offers a structured and robust approach to subjective criteria weighting by combining expert judgment with fuzzy logic while eliminating inconsistency in pairwise comparisons [22]. Unlike traditional methods such as AHP, ANP, and BWM, FWZIC does not rely on complex pairwise comparison matrices that can become cumbersome and inconsistent when the number of criteria or experts increases. This is particularly advantageous in large-scale evaluations, where managing comparison consistency is a challenge. FWZIC instead allows experts to assess criteria using a linguistic scale mapped to fuzzy numbers, which are then aggregated using fuzzy mathematical operations to derive weights without introducing inconsistency errors. Table I provides a comparison of FWZIC with other subjective criteria weighting methods.

AHP and ANP, while well-established and widely used, often suffer from issues related to consistency and scalability [23]. In AHP, experts are required to perform numerous pairwise comparisons, and inconsistency indices are used to evaluate the reliability of these judgments. However, achieving acceptable consistency becomes increasingly difficult as the number of criteria grows. ANP attempts to address interdependencies among criteria, but this added complexity also makes the process more time-consuming and prone to subjective bias. Moreover, both AHP and ANP require re-adjustments when new criteria are introduced, reducing their flexibility in dynamic decision environments.

BWM simplifies the pairwise comparison process by requiring experts to identify the best and worst criteria and rate all others relative to these two [24]. While this reduces the number of required comparisons and improves consistency compared to AHP and ANP, it still assumes a linear and rigid judgment structure that might not capture the uncertainty inherent in human evaluations. FWZIC, by contrast, accommodates uncertainty more naturally through fuzzy logic and avoids the need for direct comparisons altogether. It also provides flexibility in handling a varying number of experts and criteria without increasing the computational burden or introducing inconsistency.

In summary, FWZIC stands out for its ability to integrate expert judgment in a fuzzy environment while maintaining zero inconsistency. It is computationally less intensive than ANP and more scalable than AHP. Unlike BWM, it does not constrain expert input to a fixed comparison format, making it more adaptable in diverse decision-making scenarios. These characteristics make FWZIC particularly suitable for applications involving multiple experts, complex criteria structures, and a need for robust, bias-reduced aggregation.

C. Fuzzy Sets

Human judgment is riddled with uncertainties and ambiguities. Ambiguity in decision-making refers to situations where information is unclear, incomplete, or open to multiple interpretations. Fuzzy set theory, proposed by Zadeh [17], aims at handling ambiguity by representing crisp values using membership grades ranging from [0,1]. Fuzzy sets provide a mathematical framework for modeling and reasoning with vague concepts, making them valuable in various fields such as artificial intelligence, engineering, supply chain, and healthcare, where imprecise information is common.

Since its inception, fuzzy set theory has advanced significantly, leading to new fuzzy sets that incorporate membership as well as non-membership, and hesitancy degrees [25]. The concept of Type-2 fuzzy sets further expands the traditional fuzzy set concept with a three-dimensional membership function [26]. It uses a fuzzy membership function, where the membership degree is also a fuzzy set, allowing for a more detailed representation of uncertainty. However, it is more complex due to the fuzzy nature of the membership function, requiring more computational resources and sophisticated algorithms for processing. The different types of fuzzy sets and their variations and generalizations are explained next.

1) Triangular Fuzzy Numbers (TFN). TFNs are a specific type of fuzzy number that is represented by a triangular membership function. This function is defined by three parameters (a, b, c), where a represents the lower limit, b represents the peak or mode, and c represents the upper limit. The membership function $\mu_{\tilde{a}}(x)$ of a TFN $\tilde{a} = (a, b, c)$ is defined as follows [27]:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a}{b-a}, & if\ a \leq x \leq b \\ \frac{c-x}{c-b}, & if\ b < x \leq c \\ 0, & if\ x > c\ or\ x < a \end{cases}, \quad (3)$$

where, $\leq b \leq c$. Moreover, if $a \geq 0$, then the TFN is called a positive triangular fuzzy number. If $c \leq 0$, then the TFN is called a negative triangular fuzzy number.

TABLE I. FWZIC COMPARISON WITH OTHER CRITERIA WEIGHTING METHODS

	ANP	AHP	BWM	FWZIC method
Computational Complexity (Number of comparisons, where n is the number of criteria)	$n(n-1)$	$n(n-1)/2$	$2n-3$	Zero pairwise comparisons
Nature of comparison	Comparisons are made between criteria that differ in nature and in quantity.	Comparisons are made between criteria that differ in nature and quantity.	Comparisons are made between criteria that differ in nature and quantity.	Relies on direct linguistic assessments of criteria mapped to fuzzy numbers, thus avoiding pairwise comparisons.
Expert feedback	The process of explaining and comparing in this method is time-consuming.	The process of explaining and comparing in this method is time-consuming.	The process of explaining takes time, and the comparison process is difficult.	Expert feedback is collected through online surveys, thereby reducing the explanation and collection time.
Uncertainty	Fuzzy logic is commonly employed to manage ambiguity and uncertainty in expert judgments; however, it increases computational complexity.	Fuzzy logic is commonly employed to manage ambiguity and uncertainty in expert judgments; however, it increases computational complexity.	Fuzzy logic is commonly employed to manage ambiguity and uncertainty in expert judgments; however, it increases computational complexity.	FWZIC is grounded in fuzzy logic but is specifically designed to maintain computational simplicity.
Inconsistencies	Susceptible to inconsistency due to complex interdependencies and numerous pairwise comparisons, even when fuzzy logic is applied.	Inconsistency arises from the subjective nature of pairwise comparisons, with reliability decreasing as the number of criteria increases.	While more consistent than AHP/ANP, inconsistencies may still occur when judgments about best and worst criteria lack coherence.	Designed to eliminate inconsistency by avoiding pairwise comparisons entirely and using direct fuzzy linguistic ratings.

2) Trapezoidal Fuzzy Numbers (TraFN). A TraFN is characterized by a membership function that forms a trapezoid shape. It is defined by four parameters: a, b, c, d . The membership function $\mu_{\tilde{a}}(x)$ of a TraFN $\tilde{a} = (a, b, c, d)$ is defined as follows [28]:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-a}{b-a}, & if\ a \le x \le b \\ 1, & if\ b \le x \le c \\ \frac{d-x}{d-c}, & if\ c \le x \le d \\ 0,\ if\ x > d\ or\ x < a \end{cases} \quad (4)$$

where, $a \le b \le c \le d$. Notably, when $b = c$, TraFN reduces to a TFN.

3) Hexagonal Fuzzy Numbers (HFN). An HFN $\tilde{a}$ is characterized by a membership function that is based on six parameters and forms a hexagonal shape. The membership function $\mu_{\tilde{a}}(x)$ of an HFN $\tilde{a} = (a, b, c, d, e, f)$ is defined as follows [29]:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{1}{2}\left(\frac{x-a}{b-a}\right), & if\ a \le x \le b \\ \frac{1}{2} + \frac{1}{2}\left(\frac{x-b}{c-b}\right), & if\ b \le x \le c \\ 1, & f\ c \le x \le d \\ 1 - \frac{1}{2}\left(\frac{x-d}{e-d}\right), & if\ d \le x \le e \\ \frac{1}{2}\left(\frac{f-x}{f-e}\right), & if\ e \le x \le f \\ 0, & if\ x > f\ or\ x < a \end{cases} \quad (5)$$

where, $a \le b \le c \le d \le e \le f$.

4) Intuitionistic Fuzzy sets (IFS). The IFS proposed by [30] represents an extension of classical fuzzy sets. Unlike the classical TFN, TraFN and HFN that rely solely on a membership grade (μ) to indicate the degree of satisfaction of an element, IFS introduces a non-membership grade (υ) to signify the degree of dissatisfaction. Both μ and υ values range between 0 and 1, with the constraint that their sum remains within this range: $0 \le \mu + \upsilon \le 1$. Therefore, an IFS S over a universe of discourse X is represented as:

$$S(x) = \{x, \langle \mu\ (x), \upsilon(x) \rangle\}, x \in X, \quad (6)$$

By incorporating both membership and non-membership grades, the IFS framework provides a more flexible depiction of solutions, allowing for greater flexibility in representing uncertainty or imprecision inherent in the given problem. However, in several cases, the sum of the degrees often exceeds 1. Therefore, the generalizations of the IFS were proposed.

5) Pythagorean Fuzzy Sets (PyFS): The PyFS, proposed by [31], is a generalization of the IFS, which extends the range of membership (μ) and non-membership grades (υ) with the condition that the sum of the squares of both degrees falls within the range of [0,1], $0 \le \mu^2 + \upsilon^2 \le 1$. The PyFS offers a more comprehensive and precise characterization of uncertain information compared to the IFS [32].

6) Fermatean Fuzzy Sets (FFS). The FFS [33] further expands the uncertainty space that cannot be adequately captured by the IFS and PyFS in cases, where the sum of the squares of the grades is above 1. Therefore, in FFS, the sum of the cubes of the membership and non-membership grades falls within the range of [0,1], $0 \le \mu^3 + \upsilon^3 \le 1$. FFS offers a better way of handling vagueness than its counterparts, IFS and PyFS.

7) q-rung orthopair (q-ROFS). The q-ROFS [34] emerged as a generalization of both IFS and PyFS with a membership constraint that the sum of the qth power of the membership and non-membership grades is within the range [0,1], $0 \le \mu^q + \upsilon^q \le 1$, where $q > 1$. The increasing value of q offers decision-makers a broader spectrum to express their perspectives on the membership and non-membership degrees. Thus, the q-ROFS demonstrates a greater capability in handling uncertainty more effectively than IFS and PyFS [35]. Fig. 2 illustrates the comparison between IFS, PyFS and q-ROFS.

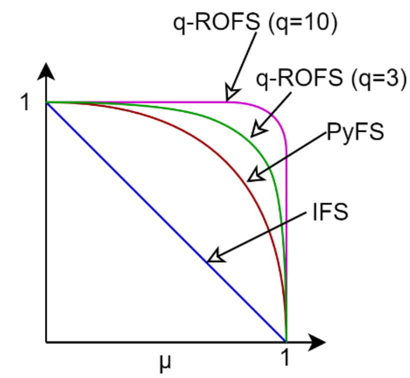

Fig. 2. IFS, PyFS and q-ROFS.

8) Picture Fuzzy Sets (PFS). The PFS, proposed by [36], is an extension of the IFS, which introduces the degree of neutrality(η), also referred to as abstinence, along with the membership (μ) and non-membership (υ) degrees, with the condition that $0 \le \mu + \eta + \upsilon \le 1$. The refusal degree is represented as $1 - (\mu + \eta + \upsilon)$. The PFS effectively mirrors human behavior and addresses decision-making challenges in a similar way by capturing the complexities of real-life information [37].

$$S(x) = \{x, \langle \mu\ (x), \eta(x), \upsilon(x) \rangle\}, x \in X \quad (7)$$

9) Spherical Fuzzy Sets (SFS). The SFS [38] emerged as a generalization of the PFS, which extends the uncertainty space of the membership (μ), non-membership (υ) and neutral grade (η), offering a wider decision space under the restriction that $0 \le \mu^2 + \eta^2 + \upsilon^2 \le 1$.

10) T-Spherical Fuzzy Sets (T-SFS). The T-SFS proposed by [39], further widens the uncertainty space covered by the SFS with a membership constraint that the sum of the t power of the membership (μ), non-membership (υ) and neutral (η) grades are within the range [0,1], $0 \le \mu^t + \eta^t + \upsilon^t \le 1$, where $t > 1$. The increasing value of t offers decision-makers a broader spectrum to express their perspectives on the membership and non-membership degrees and abstinence degrees. Notably, when t = 2 the T-SFS reduces to SFS.

11) Linear Diophantine Fuzzy Sets (LDFS). Despite the broader space covered by these FS, the grade dependency still exists as a limitation of the IFS and PFS and all their generalizations. Hence, [40] proposed a new fuzzy environment, the Linear Diophantine Fuzzy set (LDFS), which extends IFS and PyFS by introducing two reference parameters (a,b), each within the range of [0,1] corresponding with the membership (μ), non-membership (υ) grade, respectively. The LDFS essentially allows decision makers to choose membership degrees without restrictions, but with a constraint that the sum of the reference parameters lies between 0 and 1, $0 \leq a + b \leq 1$ and $0 \leq a\mu + b\upsilon \leq 1$.

$$S(x) = \{x, \langle \mu(x), \upsilon(x) \rangle, \langle a, b \rangle\}, x \in X \quad (8)$$

12) Interval Valued Fuzzy Set (IVFS). Grattan-Guinness (1976) [41] developed the concept of IVFS based on type 2 fuzzy set theory [42], further extending the fuzzy research space. A type 2 fuzzy set is characterized by fuzzy membership grades. In an IVFS, the membership degree is given as a closed subinterval $[\mu^L, \mu^U]$ with $0 \leq \mu^L \leq \mu^U \leq 1$, where:

- μ^L is the lower bound of the membership interval.
- μ^U is the upper bound of the membership interval.

The interval $[\mu^L, \mu^U]$ represents the range within which the membership degree of x is expected to lie. The length of this interval $(\mu^L - \mu^U)$ is interpreted as a measure of the uncertainty associated with the membership degree of the element.

13) Neutrosophic Sets (NS). The Single-Valued NS, proposed by [43], is a generalization of the classical fuzzy set in which there is no restriction on the sum of the membership degrees. Hence, the membership degree, abstinence degree, and non-membership degree lie within the range [0,3], $0 \leq \mu + \eta + \upsilon \leq 3$. The NS has a significant capacity to effectively manage imprecise and unclear data in a comprehensive manner.

14) Hesitant Fuzzy Sets (HFS). HFS, also known as multisets, was proposed by [44], extending the traditional fuzzy set theory to better handle situations where there is hesitation or multiple degrees of membership for an element. This concept is useful in capturing uncertainty and ambiguity when a single membership value is insufficient to represent an element's degree of belonging to a set. Fuzzy multisets allows for capturing hesitation in the membership degrees, providing a richer and more flexible representation of uncertainty. A generalization of the HFS, known as the dual HFS, allows for the representation of dual hesitancy, meaning elements can be partially or fully hesitant towards multiple membership degrees [45].

Other generalizations and extensions of the classical fuzzy sets include the probabilistic fuzzy sets, which assign a probability to each element's membership degree [46]. The Complex Fuzzy Sets (CFS), on the other hand, extend the concept of fuzzy sets to complex-valued membership degrees by representation of membership degrees as a complex number [47]. CFS has been applied in signal processing and control systems applications.

Despite the notable efforts of the researchers, the lack of precision, uncertainty, and vagueness in information still remains an unresolved issue [48]. To encompass a broad spectrum of uncertainty in experts' opinions for determining criteria weight, researchers have extended the FWZIC method under various fuzzy environments ranging from simple classical sets to advanced type 2 fuzzy sets. The results section of the review presents the various fuzzy environments integrated with FWZIC.

D. Overview of MCDM Ranking Methods

MCDM ranking techniques enable decision-makers to systematically assess alternatives using various criteria, facilitating informed decision-making across different sectors. Several benchmarking techniques are used in MCDM to perform ranking in various decision-making case study problems, such as FDOSM, VIKOR, SAW, MULTIMOORA, TOPSIS, MAIRCA, MABAC, and DEMATEL. Below are brief introductions to some of the popular ranking methods integrated with FWZIC:

1) Fuzzy Decision by Opinion Score Method (FDOSM). The Fuzzy Decision by Opinion Score Method (FDOSM) is an innovative MCDM technique designed for use in a fuzzy environment, utilizing the concepts of ideal solutions and opinion matrices. This method addresses and largely overcomes the inconsistencies often found in human judgment, reducing the time required for comparisons [49]. Additionally, FDOSM minimizes the number of mathematical equations needed, preserving data integrity and facilitating logical decision-making based on expert opinions represented in the Decision Matrix. It eliminates issues related to normalization and weighting in mathematical approaches and resolves data vagueness using fuzzy numbers. FDOSM employs positive and negative ideal solutions, comparing each alternative's criteria with the ideal solution. Furthermore, FDOSM uses different aggregation operators with an Opinion Matrix adopted from various MCDM techniques [50].

2) VlseKriterijumska optimizacija I kompromisno resenje (VIKOR). VIKOR, a Serbian term for "multi-criteria optimization and compromise solution" [51] is a method based on the concepts of positive and negative ideal points, and on the compromise programming of MCDM [52]. VIKOR focuses on ranking and selecting from a broad range of alternatives that are evaluated based on criteria. VIKOR determines compromise solutions for problems with conflicting and non-comparable criteria and provides a feasible solution that is the closest to the positive ideal solution. A key feature of VIKOR is that, the final decision relies on rules regarding an acceptable advantage of the optimal solution over the second-best solution and the stability of the optimal solution to changes in the decision-maker's risk choice. It reflects any hesitation the decision-maker has in selecting the final option, allowing for a nuanced comparison of alternatives [53].

3) Simple Additive Weighting (SAW). The SAW method is well-known for its simplicity, user-friendly, and effective approach of MCDM. Also referred to as a weighted linear combination or scoring method. SAW determines the overall score of a candidate solution based on the weighted sum of all of the attribute values [54]. The SAW method involves three major steps: normalizing the decision matrix X, assigning the weight vector W, and calculating the overall score. One major advantage of the SAW method is its ability to maintain the relative magnitude order of the original data, and no data is lost during evaluation [54].

4) Multi-Objective Optimization by Ratio Analysis (MULTIMOORA). The MULTIMOORA method is the extension version of the MOORA method, incorporating multiplicative elements. MOORA, a multi-objective optimization technique, is based on ratio analysis. In this approach, the score of an alternative is calculated by subtracting the sum of performance scores for the benefit criteria and adding the sum of performance scores for the cost criteria [4].

5) Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS is a renowned classical MCDM method that introduces two reference points: a positive ideal solution and a negative ideal solution. TOPSIS was originally developed by Hwang and Yoon in 1981, and was further developed by Chen and Hwang in 1992 [54]. The positive ideal solution maximizes benefit criteria and minimizes cost criteria, while the negative ideal solution does the opposite, maximizing cost criteria and minimizing benefit criteria. TOPSIS identifies the best alternative by minimizing its distance to the positive ideal solution and maximizing its distance to the negative ideal solution. It employs Euclidean distances to measure how close each alternative is to these ideal solutions, and the preference order of alternatives is determined by comparing these distances [53].

6) Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA). MAIRCA is recognized for its stability compared to other popular MCDM ranking methods. It employs a straightforward mathematical approach that maintains stability despite changes in the nature and characteristics of the criteria. One key advantage of MAIRCA is its ability to objectively compute the probability of each alternative, providing both quantitative and qualitative assessments. This method measures the difference (gap) between ideal and empirical evaluations, providing an objective assessment of each alternative [55].

7) Multi-Attributive Border approximation Area Comparison (MABAC). MABAC method ranks the alternatives using their distance to the border approximation, while partitioning them into upper approximation area (best performing) and lower approximation area (worst performing) [4].

8) The decision-making trial and evaluation laboratory (DEMATEL). DEMATEL methodology is a robust tool for analyzing complex interrelationships between various factors. Pairwise comparisons are used to determine the significance and influence of different elements. By constructing cause-effect diagrams, DEMATEL assesses the interdependencies among factors, proving effective in diverse domains such as site selection, criteria identification, and effects evaluation. However, due to the inherent uncertainty and subjectivity of experts' judgments, an important challenge remains in effectively representing uncertain and linguistic judgments [56].

Numerous other ranking methods are also used in MCDM problems, such as the Additive Ratio Assessment (ARAS), Conditional Probabilities by Opinion Scores (CPOS), Combinative Distance-Based Assessment (CODAS), Complex Proportional Assessment (COPRAS), Evaluation Based on Distance from Average Solution (EDAS), and Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS), Technique for Reorganizing Opinion Order to Interval Levels (TROOIL). FWZIC has been combined with these ranking methods to benchmark various alternatives in different case studies, employing various approaches to achieve a robust framework. A review of these FWZIC studies will provide us with a clear understanding and knowledge of their various characteristics and their combined ranking methods. The next section describes the methodology used to achieve this systematic review.

III. Methodology

This study examines the existing literature on the applications of the FWZIC method using the systematic review framework established by [57]. This framework was selected over other frameworks because it provides guidelines specifically for conducting reviews in the technical field. Employing a rigorous theoretical framework is crucial for guiding the comprehensive data collection and analysis methods required to ensure the reliability of the results. The systematic literature review guidelined by [57] offers a thorough approach for collecting, analyzing, and documenting findings from secondary data sources and from various systematic reviews [58], [59], [60]. By following this methodology, we aim to answer the research questions and uncover the latest application techniques and extensions of the FWZIC method, guiding practitioners and researchers to further study in this field.

The review process is divided into three phases: planning the review, conducting the review, and reporting the results. Each phase is further subdivided into several steps, each of which is described in the following subsections.

A. Planning the Review

In the last three years, the studies applying the FWZIC method to compute criteria weights have accelerated due to its superiority over other subjective criteria weighting methods. Therefore, it is crucial to provide researchers with the current state-of-the-art regarding the applications of the FWZIC method, including the fuzzy environments used, the number of experts involved, the number of criteria and the MCDM ranking methods it has been integrated with.

To initiate the systematic review, the planning phase defines the inclusion and exclusion criteria, and identifies the data sources for selecting the study articles. The quality assessment checklist is then described to evaluate the quality of the articles, establishing a threshold for their inclusion. The study encompasses all articles published since the FWZIC method was proposed, ensuring a comprehensive scope.

1) Inclusion and exclusion criteria. To select the articles for this review, it is essential to define the criteria that characterize the included studies. Table II summarizes the inclusion and exclusion criteria used in the selection process.

TABLE II. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Exclusion Criteria
Empirical studies that have employed the FWZIC method for determining criteria weights	Studies that do not utilize the FWZIC method
Article is published in a peer-reviewed journal, conference papers or book chapters	Reviews, errata, PhD studies
Written in English	Non-English articles
Published in 2021 – March 2025	Published after March 2025

First, only empirical studies employing the FWZIC method for determining criteria weights were considered. Second, the review focused exclusively on peer-reviewed journals, conference papers and book chapters to ensure inclusion of all studies that have utilized the FWZIC method, thereby excluding reviews, errata, and PhD dissertations. Third, only articles published in English were included to avoid biases from poor translations. Finally, the study period was set from 2021 to 2025 to encompass all relevant studies using the FWZIC method to date.

2) Data sources. Since MCDM methods are utilized in diverse domains, a wide range of data sources was considered to ensure the inclusion of relevant publications from various fields. Accordingly, the search was conducted using three digital databases: Scopus, Web of Science (WoS), and ScienceDirect. Both Scopus and Web of Science are multidisciplinary databases of peer-reviewed literature on science, technology, medicine, social science, arts and humanities, making them valuable for retrieving a broad spectrum of research. ScienceDirect is a comprehensive resource for articles in the scientific, technical and medical fields.

3) Quality assessment checklist. Quality assessment is essential in systematic reviews to ensure the validity of the results and minimize bias from including less robust studies [61]. It also refines the inclusion and exclusion criteria [57].

To ensure a rigorous assessment of the articles included in the systematic review, a quality assessment checklist is adapted from [62]. The checklist consists of ten questions, as shown in Table III. This checklist focuses on the essential elements for data extraction and coding phases, such as the relevance of the study, clear identification of the problem statement, experts and the expert selection process. Additionally, the credibility of the sources were evaluated by considering the ranking of the journal or conference and the number of citations of each study received. A point scale from 0 to 1 will be used to rate each assessment criterion, where 1 represents that the requirement is wholly met, 0.5 represents it is partially met, and 0 indicates that it is not met. Moreover, Q09 will be evaluated by the source ranking of the published study, whereby Q01 or Q02 ranked journal is assigned 1 point, while Q03 is assigned 0.5 and 0 point is assigned to a journal ranked below or not ranked. Finally, 1 point will be assigned to the article having at least two citations per year for Q10. Thus, each article scored out of 10 points in total. The cut-off criteria for including an article after the quality assessment are set at 75%.

TABLE III. QUALITY ASSESSMENT CHECKLIST

Q01	Is the study relevant to our research?
Q02	Are the research aims and contributions clearly identified?
Q03	Is the problem statement clear?
Q04	Does the study define the number of experts used?
Q05	Is the selection process of the experts clearly explained?
Q06	Are the techniques/methods employed in the study clearly documented?
Q07	Is the proposed technique evaluated using established metrics?
Q08	Is the conclusion explained clearly and linked to the purpose of the study?
Q09	Is the source of the article credible (published in a ranked venue)?
Q10	Has the study been cited in other publications?

B. *Conducting the Review*

The implementation phase of the review involves searching for and retrieving the articles. The articles for this review were collected in March 2025. The articles were screened using the previously defined inclusion and exclusion criteria, as well as the quality assessment checklist.

1) Search process. The systematic review focuses on a specific MCDM criteria weighting method. Hence, only two main keywords were deemed necessary to retrieve the articles for this study, combined with the logical operator OR ("FWZIC" OR "Fuzzy Weighted Zero Inconsistency"). Additionally, the search was conducted on titles, abstracts, and keywords to ensure comprehensive coverage and to increase the likelihood of finding highly relevant studies.

The search results, presented in Table IV, yielded a total of 192 studies, with the highest number retrieved from the Scopus database, due to its broad coverage across multiple domains and the lowest from ScienceDirect, due to its specific coverage.

TABLE IV. SEARCH RESULTS

Database	Search Results
Scopus	81
Web of Science (WoS)	62
ScienceDirect	49
Total	**192**

Following the retrieval of search results, a bibliometric analysis was conducted to examine the research areas. Fig. 3

illustrates the visualization of terms within the results, generated using VOS Viewer [63]. This diagram highlights the significance and interconnections among frequently occurring terms extracted from the abstracts, titles, and keywords of the search results. The size and label of each term indicate its importance, while the color represents clusters in the visualization. Each cluster comprises terms related to one another within the group, and the distance between clusters signifies their relatedness.

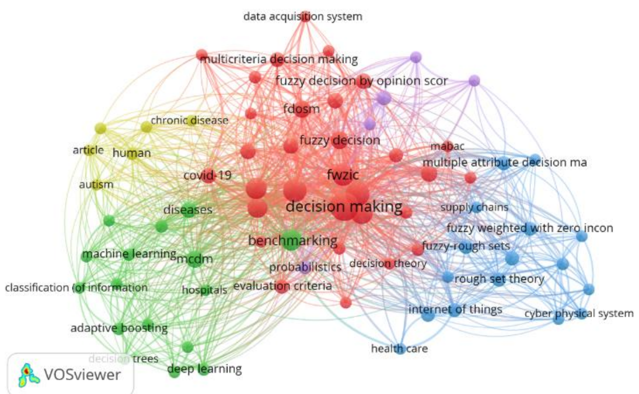

Fig. 3. Visualization of search results.

The visualization of terms within the extracted studies uncovers several distinct clusters, indicating multiple dimensions in the application of FWZIC in MCDM studies. These clusters are closely intertwined, suggesting interconnected aspects within the studies. The term "decision making" is prominently linked to all clusters, indicating that the retrieved results are applied studies in the decision-making field.

Focusing on clusters with highly weighted terms, four main clusters emerge in the visualization. The first and central red cluster encompasses keywords such as FWZIC, FDOSM, fuzzy decision, and linguistics, revealing the technical aspects of research utilizing FWZIC, including its integration with ranking algorithms, application of linguistic scales, and use of fuzzy decision sets. The second, green cluster features keywords like adaptive boosting, decision trees, deep learning, and machine learning, indicating the application of FWZIC in the domain of Artificial Intelligence. In the third, blue cluster, the significant keywords include cyber-physical systems, healthcare, internet of things, and supply chain, highlighting various areas of study in which the FWZIC method is utilized. Lastly, the light green cluster includes terms such as human, autism, and chronic diseases, indicating the predominant utilization of FWZIC for solutions in the healthcare industry.

Examining these clusters provides insight into the distribution of research findings, facilitating a more informed analysis and discussion of the studies.

2) Article selection. In this phase, the inclusion and exclusion criteria were applied to screen the retrieved articles for eligibility following the PRISMA framework [64]. This framework offers a comprehensive guideline and structured approach for document screening. The steps of the screening process are illustrated in Fig. 4.

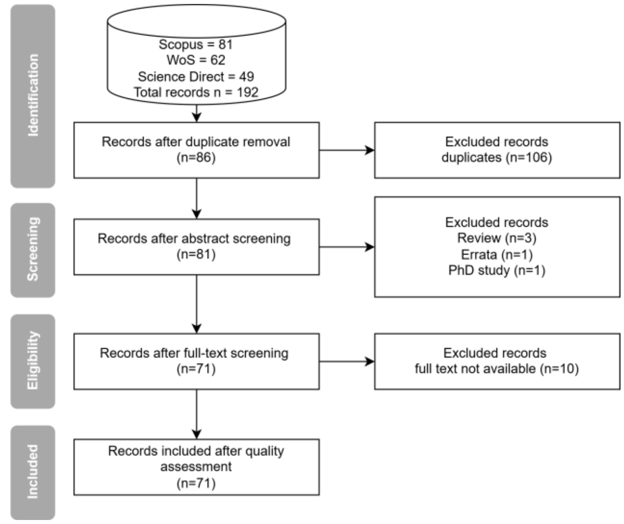

Fig. 4. Prisma flowchart.

The PRISMA framework consists of four phases. In the identification phase, 192 articles were retrieved from the three data sources using the identified search term. Following this, the duplicate records were removed, resulting in 86 articles. During the screening phase, the inclusion and exclusion criteria were applied through abstract screening to ensure that only relevant articles were included. Each author independently performed a title and abstract screening of the studies to remove irrelevant articles, resulting in the exclusion of four articles, two of which were reviews, one erratum, and one PhD dissertation, resulting in 81 studies. In the eligibility phase, a full-text screening of the articles was performed. Each author performed this step independently by equally dividing the studies to be reviewed. In cases where eligibility was unclear, the authors discussed resolving the discrepancy. This phase resulted in 10 studies being excluded due to the unavailability of the full text, resulting in a total of 71 eligible articles. The excluded studies were within the context of the systematic review; however, unavailability would prevent the coding and analysis required for the comprehensive review.

In the final phase, a quality assessment was performed on the remaining articles (n = 71). In this step, the authors rescreened the articles initially screened by the other to reduce bias and ensure that each article is screened twice. Each author independently conducted a quality assessment using the assessment checklist outlined in Fig. 4. Remarkably, all included articles met the required threshold of 75% and demonstrated sound quality. It is important to emphasize that the quality assessment aims to ascertain the relevance of selected articles to the contribution of this study, without any intention to criticize the studies or their findings.

3) Data analysis and coding. The objective of this phase is to comprehensively document the systematic review findings by gathering meta-data from the primary studies included in the review, with a focus on the research questions. A thorough data analysis of the relevant features identified during the planning phase is conducted to achieve this objective. The meta-data analysis encompasses various characteristics crucial for addressing the research questions, including publication type and year, and the classification of studies based on themes and application areas to gain a deeper insight into the domains of application. Additionally, technical aspects of subjective decision making, such as the number of experts, the criteria weighted, the fuzzy environment, the aggregation operators, and defuzzifying methods employed in the studies, are also examined.

C. *Reporting the Review*

In the concluding phase of the systematic review, the study results are unveiled. Section IV presents a comprehensive analysis of the meta-data extracted from the full-text review, with the aim of addressing each research question. This analysis presents and discusses the insights from the collected data, providing a thorough understanding of the findings and their implications within the context of the study's objectives.

IV. Results

This section reveals the outcomes from the meta-analysis and comprehensive review of the selected articles, guided by our research questions. This study examines seventy-one papers (listed in the Appendix) published over a span of five years to explore the applications of the FWZIC method. The following subsections detail the findings for each of the research questions.

A. *Study Characteristics*

RQ1: What are the general characteristics of empirical studies that have utilized FWZIC?

This subsection provides an overview of general characteristics found in the reviewed studies. It includes details on the distribution of studies by year of publication, author, journals and publishers. These attributes offer a summary of the significance of the FWZIC method within the MCDM research field.

Fig. 5 presents the distribution of the seventy-one studies reviewed by year of publication. It is evident from the graph that there is significant interest in the FWZIC method since its proposal in 2021. Notably, the graph reveals a sharp rise in the utilization of the FWZIC method since 2022. FWZIC has been extended to many fuzzy environments to improve consistency and decrease the hesitancy of human judgment. In addition, this method has been integrated with numerous MCDM ranking methods to evaluate and select alternatives used in these studies.

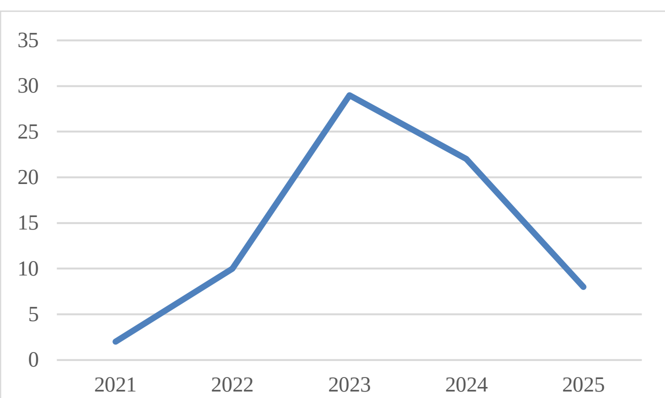

Fig. 5. Distribution of studies by publication year.

Fig. 6 displays the distribution of the seventy-one reviewed studies across forty-two different sources, including journals, conferences, and book chapters, underscoring the extensive influence and significance of the FWZIC method within the MCDM research field. Notably, most of the studies are published in ranked journals, while only one study is published in a conference and one in a book chapter. The included studies span over a diverse range of journals, including those focused on technology, decision science, healthcare, innovation, knowledge, and engineering. The journal "Expert Systems with Applications" features the highest number of studies (n = 10), followed by "Applied Soft Computing" (n = 6) and "Neural Computing and Applications" (n = 5). Most of these journals are ranked in the Q1 category, reflecting the high quality of the published research.

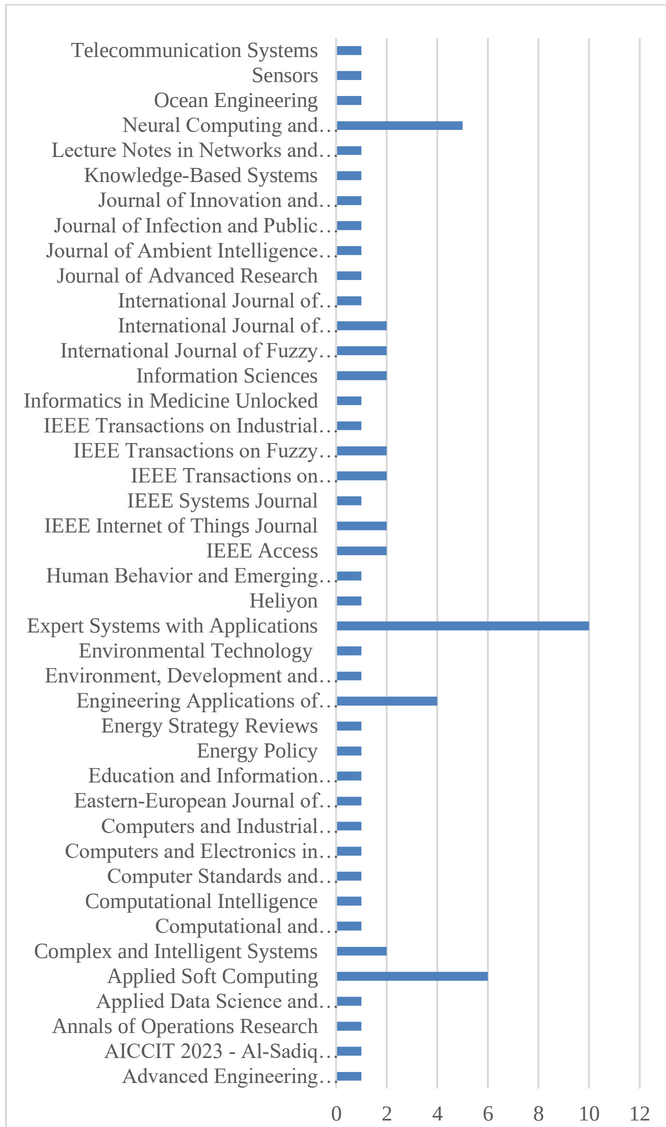

Fig. 6. Distribution of studies by source.

Fig. 7 shows the distribution of seventy-one reviewed studies among nine major publishers, indicating that Elsevier is the leading publisher with 48% of these studies (n = 34), followed by Springer (n = 15) with 21%, and IEEE (n = 11) with

16%, all of which are significant contributors to the research field. John Wiley and Sons Ltd. published 6% of studies (n = 4), while World Scientific published 3% of studies (n = 2) and only 2% in MDPI, and all other studies were 1% in Technology Center, Taylor and Francis, ScienceDirect, and Mesopotamian Press.

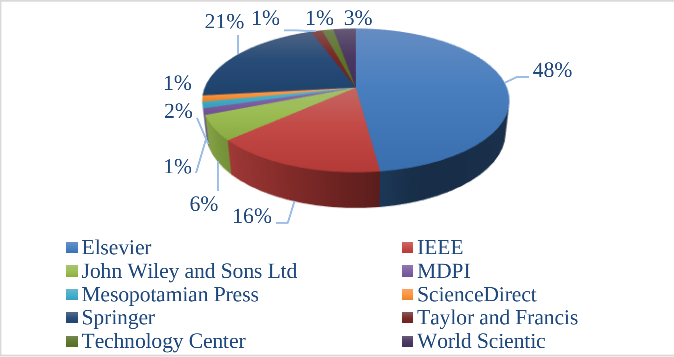

Fig. 7. Distribution of studies by publisher.

According to Fig. 8, the distribution of these studies by the first author's country spans over seven countries: Australia, China, Iraq, Malaysia, Tunisia, and the United Arab Emirates (UAE). Notably, the highest number of studies originates from Iraq (n = 31), followed by Malaysia (n = 21), highlighting the particularly active research communities in these countries.

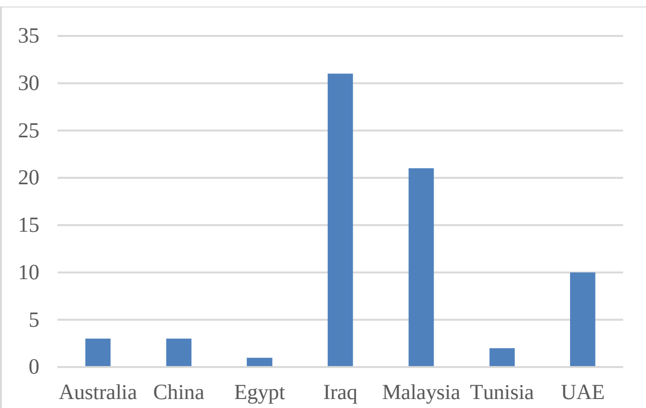

Fig. 8. Distribution of studies by country.

B. *FWZIC Application*

1) This subsection addresses RQ2 through five themes. A comprehensive meta-analysis of the reviewed studies revealed distinct thematic and domain-based applications of the FWZIC method. In addition, it identified the ranking methods commonly integrated with FWZIC and highlighted the various fuzzy extensions employed. The analysis also examined the most frequently used aggregation and defuzzification techniques. The following subsections present and discuss these findings. Details of the reviewed studies are provided in the Appendix.

2) Themes and domains of application

RQ2: What domains and themes are the studies based on?

A taxonomy of the reviewed studies, illustrated in Fig. 9, categorizes the articles into six main themes: Artificial Intelligence, COVID-19, Services, Sustainability, Technology, and Metaverse. These themes are further distributed across ten domains, including healthcare, agriculture, tourism, education, engineering, business, supply chain, manufacturing, and transport. A separate category is included for studies that do not align with any of the identified domains. Fig. 9 also highlights the popular MCDM methods that have been integrated with FWZIC in multiple studies, while a broader set of less frequently used methods is categorized under "Other". The following subsections provide a detailed review of the studies within each theme.

a) Artificial intelligence: Artificial intelligence (AI) is the ability of a computer system to carry out tasks that are usually performed by humans [65], [66]. It is one of the main themes adopted in these studies, with a total of ten studies distributed across two domains: nine in healthcare and one in engineering. Many healthcare studies focus on detecting and prioritizing autism spectrum disorder (ASD) patients based on sociodemographic and medical features. One study integrated machine learning (ML) and MCDM to classify ASD patients [67]. The study utilized an enhanced FWZIC method to determine the importance of the ASD features used in the training dataset [68]. In the same vein, another study used a hybrid approach to develop fifteen machine learning models for diagnosing patients with ASD and then benchmarked the models using FDOSM and FWZIC, based on seven performance metrics as evaluation criteria [67]. Similarly, another study developed a multimodal autism triage levels system using the Delphi method with FWZIC to determine the significance of ASD features and ML models for predicting severity levels [69]. The study further develops an explainable AI model to facilitate comprehension of the AI model's results.

Two studies in the healthcare domain utilise AI and VIKOR as a benchmarking method for respiratory diagnosis. While one study evaluates lung cancer diagnosis using class balancing approaches [70]. The other develops a framework to rank hybrid deep learning models based on chest X-ray analysis for computer-aided diagnosis (CAD) systems [71]. The remaining two healthcare studies focus on different objectives. One utilized a hybrid approach to first develop a labelled dataset of indoor air quality pollutants using the Unified Process for Labelling Pollutants Dataset (UPLPD), extended with the IT2TR-FWZIC weighting method [72]. The study further applied machine learning models to the developed dataset. Another study evaluates AI healthcare applications based on trustworthiness attributes using the CODAS method integrated with q-ROF2TL-FWZIC [73].

The final study in the AI theme belongs to the engineering domain and aims to benchmark optimization techniques for semi-polar III-V semiconductor materials using the FDOSM benchmarking method, integrated with the classical FWZIC method [74].

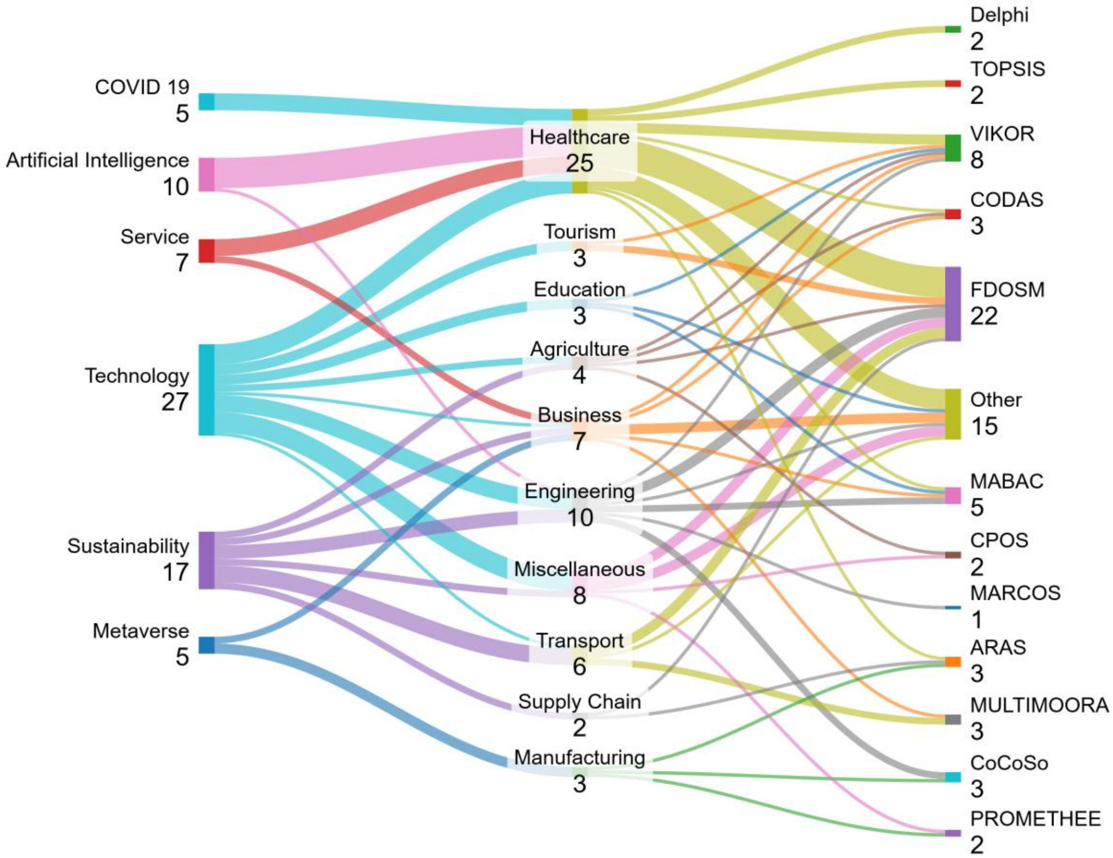

Fig. 9. Taxonomy of FWZIC application themes and domains.

b) COVID-19: Research continues to emphasize the significance of COVID-19, with five of the review studies belonging to this theme. Notably, all the studies in this theme are focused on the healthcare domain. Three studies aim to prioritize COVID-19 vaccine dose recipients using the FDOSM benchmarking method, but with different extensions of FWZIC methods using T-SF, q-ROF and PF as fuzzy sets [75], [76], [77]. Another study aims to develop a framework that benchmarks deep transfer and machine learning models based on chest X-rays to diagnose COVID-19 cases [78]. The study employs the dynamic localization-based decision (DLBD) method for benchmarking with PSVNHFS to extend FWZIC. The final study aims to develop a benchmark for the distribution of Anti-SARS-CoV-2 monoclonal antibody to eligible high-risk patients using the TOPSIS ranking method and using IVSH2 to extend FWZIC [79].

c) Services: Service is highlighted as one of the primary themes in these review studies, with five of them exploring this theme in connection with the healthcare domain. Two studies aim to prioritize autism patients with moderate emergency levels: one develops a framework using the VIKOR method for benchmarking using the classical FWZIC weighting method [80], and the other creates an intelligent triage method for classifying ASD patients into three severity levels using the Delphi method integrated with FWZIC [81]. Two additional studies focus on prioritizing remote patients with high-risk multiple chronic diseases: one uses emotion and sensory criteria with the TROOIL method for benchmarking and extends FWZIC with FOFS [82], and the other employs the FDOSM method for prioritizing hospital selection and uses QROF fuzzy sets for benchmarking and weighting method [83]. The final study aims to weight and prioritize the criteria for managing patients with cardiac problems using the classical FWZIC method [84].

d) Metaverse: Metaverse is an emerging area of research interest [60], with a focus evident in five of the review studies within the business domain (n = 2) and manufacturing domain (n = 3). Among these studies, one study developed a model concerning anonymity and privacy within the Bitcoin network-based metaverse in Industry 5.0, utilizing the MULTIMOORA benchmarking method with the extended LDFS-FWZIC weighting technique [85]. Another study [86] evaluated virtual commerce solutions for the metaverse utilizing the RATMI ranking method integrated with SLDFS-FWZIC.

Additionally, two studies concentrate on developing models to enhance control engineering tools, employing the same extended IVSFRS-FWZIC weighting method, which aims to support the Industrial Cyber-Physical Metaverse using the PROMETHEE II benchmarking method [87], while the others evaluate digital twin technology in manufacturing with the CoCoSo benchmarking method [88]. Lastly, the study aims to develop a model for evaluating Metaverse Tools based on a privacy model, integrated with the ARAS benchmarking method and the HF-FWZIC extended method [89].

e) Sustainability: Sustainability plays a vital role in many of these research studies, largely because of its importance in environmental research. There are thirteen studies focusing on sustainability across various fields like Agriculture, Transport, Engineering, Business, Supply Chain and more. For instance, one study in the agriculture domain evaluated water quality monitoring systems based on remote sensing techniques using VIKOR with FWZIC [90].

Within sustainable transportation, one study applies the MULTIMOORA method to model electronic passenger vehicles and utilizes the P-H-FWZIC weighting method [48]. Another study in this area developed a fuel supply system modelling approach for electric vehicles based on MARCOS and used the PPH-FWZIC weighted method [91]. A third study evaluated and ranked international oil companies for sustainable oil transportation based on MULTIMOORA and the extended LDFRS-FWZIC weighting method [92]. A fourth study has established a performance assessment of ship energy systems for transportation in the shipping industry based on FDOSIM and extended the q-ROFRS-FWZIC weighting method [93]. The last study in this domain built a pavement strategy selection based on FDOSIM, and using the DH-FWZIC extended weighting method [94].

Two of these review studies are associated with the engineering domain. One study developed a model to benchmark an energy systems integration framework for efficient resource utilization based on the MABAC ranking method integrated with TFN-FWZIC [95]. And another study evaluated management strategies in construction and demolition wastes based on FDOSIM-MULTIMOORA and based on the extended q-ROPHFAM FWZIC method [96].

On the other hand, two studies are connected to the business sector: one study evaluated sustainable circular business model innovation tools using the CODAS benchmarking method and the NBFS-FWZIC extended method [97]. Another study in this sector developed a model to assess palm oil industry 4.0 technologies for circular economy applications based on EDAS and using IVPFRS fuzzy sets with FWZIC [98]. Only one study in the sustainability theme is related to the smart living domain. The study developed a model to benchmark smart living frameworks using conditional probabilities by opinion scores and extended FWZIC under Bayesian rules in circular-Pythagorean fuzzy sets [99].

Finally, two studies in this theme are related to the supply chain domain: one study evaluated real-time IoT devices for monitoring food wastage in a supply chain system. The study used ARAS as a benchmarking method and extended the FWZIC using circular intuitionistic fuzzy set [100]. And a second study in this domain built a model for evaluating agriculture-food 4.0 supply chain using FDOSM as a benchmarking method and extended FWZIC under Fermatean probabilistic hesitant-fuzzy sets [50].

f) Technology: Most reviewed studies are primarily focused on the Technology theme, with studies from these reviews falling within this category across various domains. Three studies in the tourism sector are focused on evaluating e-tourism applications using various benchmarking methods. One study integrated Interval type 2 trapezoidal-FWZIC with VIKOR [101], while another study developed a framework based on FDOSM and FWZIC utilizing Neutrosophic fuzzy sets [102]. A third study focused on developing a decision modelling approach for smart e-tourism data management applications utilizing a spherical fuzzy rough environment and FDOSM as the benchmarking method [103].

Six studies focused their research on the healthcare domain. One study involves a benchmarking model for Sign Language Recognition Systems, utilising FDOSM and the extended CP-FWZIC method [104]. Another study utilized another benchmarking model using FDOSM with the original FWZIC, but this time used to evaluate smartphone applications for obesity management [105]. Two studies are centered on security and privacy in Blockchain-Based IoT Healthcare Industry 4.0 Systems. Both studies employed the extended S-FWZIC weighting method, with one using the TOPSIS-GRA [96] benchmarking method and the other using COPRAS [97]. The next study in this domain evaluated intrusion detection classifiers for Internet of Medical Things (IoMT) devices based on security and performance attributes. The study utilized the FDOSM method for benchmarking and extended FWZIC using the Rough Fermatean Fuzzy Sets [108]. Finally, the last study in the healthcare domain utilized the FWZIC method to assess the criteria for digital genetic tools [109].

Four studies in the engineering sector are highlighted. One study focuses on evaluating the risk analysis of offshore wind turbines, utilizing the DEMATEL method along with the extended LP-FWZIC weighting method for determining the relationships between the factors [110]. Another study is centered on evaluating active cooling systems, based on performance and technical attributes, employing the MABAC benchmarking system and the 2 TLP-FWZIC weighting method [111]. The other two studies applied the CoCoSo method, one focused on optimizing Control Engineering tools using digital twin Capabilities and a Cyber-Physical Metaverse manufacturing system using the IVFRS extensions[112], and the other study involved a design concept evaluation method using q-ROFS extensions [113].

Three studies in the technological realm are focused on education. Both studies involve developing frameworks for benchmarking brain–computer interface applications. One study utilized VIKOR as the Benchmarking method alongside the TFN extended weighted method [114], the second focus on evaluating speech-recognition chatbots for language learning using MCRAT methods and implementing the (T-SFS) [23]. The other study applied MABAC as the benchmarking method and extended FWZIC using the Neutrosophic Cubic Fuzzy Set [115].

Moreover, five studies are centered on network analysis. One study developed a model for evaluating routing algorithms in a multiprocessor system by utilizing Z-Cloud Rough Numbers (ZCRNs) environment to extend the weighting method and FDOSM for benchmarking [112]. The second study focused on selecting an optimal architecture for 5G-radio access network employing the type-2 N-FWZIC extended method for weighting and FDOSM for benchmarking [116]. The third study develops a modelling framework for 6G based blockchain technology using RAFSI method and extends FWZIC with Normal Wiggly Hesitant Fuzzy sets [117]. The fourth study involved in evaluating a Dynamic locally based-utility approach for developing an internet self-reconfiguration robot extending FWZIC with type 2 Pythagorean [118]. And the fifth focuses more on the superiority of a robust cloud network using PROMETHEE and the spherical cubic fuzzy environment [119].

The last five studies on this theme cover various sectors, including marine robotics, transport, business, and agriculture. One of these studies aims to optimize the motion trajectory of an autonomous underwater vehicle by evaluating the optimization algorithms [120]. The study utilized FDOSM for benchmarking and FWZIC for criteria weighting. Another study focused on evaluating driver assistance systems for vehicles utilizing FDOSM for benchmarking and FWZIC for criteria weighting within Intuitionistic fuzzy sets [121]. Additionally, a separate study delved into organizational culture within companies to promote digital innovation, employing the q-rung picture FWZIC method for criteria weighting and simple additive weighting SAW for benchmarking [122]. The last two studies in this theme, related to Agriculture, one study developed of a modelling approach for drones for Precision Agriculture, utilizing FDOSM for benchmarking and FWZIC criteria weighting [123]; the other one involved in evaluating and swarm robots effectiveness in mechanized agricultural operations using CPOS methods and Circular Quintic Fuzzy Sets extensions [105].

These findings reveal the versatility of the FWZIC method and its use in several fields spanning across various domains such as healthcare, supply chain, manufacturing, engineering, business and more. Thus, the FWZIC method can be an ideal choice for practitioners and researchers in various fields when weighing a large number of criteria based on subjective human opinions.

3) MCDM methods and Fuzzy extensions

RQ3: Which ranking methods has FWZIC been integrated with?

RQ4: Which fuzzy environments are utilized to enhance FWZIC?

The seventy-one reviewed studies show that FWZIC has been extended with numerous fuzzy sets and integrated with several ranking methods. FWZIC was most frequently combined with the FDOSM ranking method (n = 22). While fifteen studies utilized the original TFNs with FWZIC [67], [69], [70], [71], [74], [80], [81], [84], [90], [95], [114], [120], [123], [124], [125], [126] all other studies enhanced the FWZIC method under various fuzzy environments such as the Spherical FS (T-SFS), Neutrosophic Sets (NS) [102], Q-Rung Orthopair (q-ROF) [76], [83], Pythagorean Fuzzy (PF) [77], Cubic Pythagorean FS (CPFS) [104], Spherical Fuzzy Rough Sets (SFR) [103], Z-Cloud Rough Numbers (Z-CRN) [112], -rung Orthopair Fuzzy Rough Sets (Q-ROFRS) [93], Rough Fermatean FS (RFFS) [108], Dual-Hesitant Fuzzy (DH), Type-2 Neutrosophic Numbers (T2NN) [116], and Intuitionistic FS (IFS) [121]. Two studies integrated FWZIC with FDOSM and another ranking method, MAIRCA and MULTIMOORA, using Fermatean Probabilistic Hesitant (FPH) [50] and q-rung Orthopair probabilistic hesitant fuzzy set (Q-ROPHFS) [96], respectively.

The second most common ranking method, which utilizes FWZIC for criteria weighting, is VIKOR (n = 9). Out of the eight studies, five did not enhance the original FWZIC method and utilized it with TFNs [70], [71], [80], [90], [114], while one study enhanced the fuzzy environment and applied the Interval Type 2 Trapezoidal Fuzzy sets (IT2TR) [101]. The other study used the single value Neutrosophic to enhance the fuzzy sets [116].

Eleven studies combined FWZIC with the MABAC, MULTIMOORA and ARAS ranking methods, respectively. Taha Aljburi et.al [95] integrated the MABAC method with FWZIC in its original form using TFN; while the four other studies used MABAC, enhancing FWZIC under Neutrosophic Cubic Sets (NCS) [115] and 2-Tuple Linguistic Pythagorean (2TLP) [111], q-runq Orthopair (q-ROF) [127], and Single-Valued Neutrosophic 2-tuple Linguistic (SVN2TL) [128]. The MULTIMOORA method was utilized with enhanced FWZIC under Probabilistic Hesitant (P-H) [48], Linear Diophantine FS (LDFS) [85], and Linear Diophantine Fuzzy RS (LDFRS) [92]. On the other hand, the ARAS ranking method was combined with an enhanced FWZIC method under the Circular Intuitionistic Fuzzy Set (C-IFS-FWZIC) [100]. Additionally, two other studies integrated the ARAS method with an enhanced FWZIC method, one study under Hexagonal FN (HF-FWZIC) [89], and the other study under Pythagorean Fuzzy sets (PF-FWZIC)[109].

FWZIC was paired with TOPSIS (n = 2) in two studies, one under Interval-Valued Spherical Fuzzy Hesitant 2-tuple (IVSH2) FS [79]. The other study enhanced FWZIC under the Spherical (S) FS [106]. Two studies combined FWZIC with SAW (n = 2) for criteria weighting by extending FWZIC under the q-Rung Picture FS (Q-RP) [122] and Spherical Fuzzy Rough Sets (SFR) [103], while another two studies paired FWZIC with ARAS (n=2), extending it using Circular Intuitionistic FS (C-IFS) [100] and Hexagonal FN (HF) [89]. FWZIC was also combined with the CODAS (n=2) ranking method in two studies, which extended the criteria weighting method using Q-Rung Orthopair Fuzzy 2-Tuple Linguistic (q-ROF2TL) [73] and Neutrosophic Bipolar FS (NBFS) [97]. FWZIC was also utilized with the Delphi (n=2) method in two studies under the original TFN fuzzy environment [69], [81].

CoCoSo and CODAS were integrated with FWZIC in three studies (n =3). The CoCoSo method was implemented with the Interval-Valued Spherical Fuzzy Rough Sets extension in two studies (IVSFRS), [88], [129]. The other study applied CoCoSo with Q-rung Orthopair Fuzzy rough sets (Q-rungOFRS) FWZIC extensions, [113]. On the other hand, one study integrated CODAS with the q-rung Orthopair Fuzzy type 2 linguistic FWZIC extensions on intelligent healthcare applications. [73], while the other study used CODAS with Neutrosophic bipolar (NBFS) FWZIC enhancements on circular sustainable business tools. [97], and the last study used hyperbolic fuzzy sets extensions (Hy) for sustainability. [130].

CPOS was integrated twice with FWZIC. Alsattar, Qahtan, et al. [99] utilized the CPOS method with FWZIC in Circular-Pythagorean Fuzzy environment (C-PFS). The other study used

CPOS and implemented Circular-Quintic Fuzzy Sets extensions (cQuFS) on FWZIC[105] for sustainability. MARCOS was integrated with FWZIC in two studies for sustainability, one extended FWZIC with Pythagorean Probabilistic Hesitant (PPF) [91]. The other study used the Interval value, Fermatean Fuzzy sets (IVFFH) [131]. Similarly, PROMETHEE II was integrated twice with FWZIC. One study used an Interval-valued spherical fuzzy rough environment (IVSFRS) [87]. The other study used Spherical Cubic Fuzzy (SCFS) [124].

All other MCDM methods (n=14) utilized in the literature were only integrated with FWZIC in one study. Zaidan, Alsattar, et al. (2023) extended the COPRAS method using FWZIC, extending it using the Interval-Valued Spherical Fuzzy sets (IVSFS) [107]. Bilquise et al. [86] integrated the RATMI method with the FWZIC method and extended it under the spherical linear Diophantine FSs (SLDFSs). The EDAS method was integrated with FWZIC using a type 2 fuzzy environment, Interval-valued Pythagorean Fuzzy Rough set (IVPFRS) [132]. The remaining studies extended FWZIC under various fuzzy sets such as Fractional Orthotriple Fuzzy sets (FOFS) [82], Interval Type 2 Trapezoidal-Fuzzy sets (IT2TR) [72], Linguistic Pythagorean Fuzzy sets (LPFS) [110], Probabilistic Single-Valued Neutrosophic Hesitant Fuzzy set (PSVNHFS) [78] with MCDM methods MARCOS, TROOIL, UPLPD, DEMATEL, and DLBD, respectively. Finally, one study extended FWZIC using Complex T-spherical FWZIC (CT) fuzzy sets and employed a machine learning model for benchmarking the alternatives [68], and another study utilized FWZIC for prioritizing criteria weights under the original TFNs without ranking any alternatives [84].

The findings reveal the ability of FWZIC to be seamlessly integrated with multiple MCDM methods. Overall, it is observed that the most popular ranking method integrated with FWZIC is FDOSM (n = 22), followed by VIKOR (n = 8). Moreover, FWZIC was utilized in its original form, using TFN, in n=20 studies only. All other studies (n =51) have enhanced FWZIC in various fuzzy environments, ranging from classical FS to type-2 fuzzy sets, to capture a broader uncertainty space. Notably, ambiguity and imprecision in human judgement remain open issues, due to which FWZIC extensions are being extensively researched.

4) Aggregation and Defuzzyfying techniques

RQ5: What techniques are used for aggregation and defuzzification in the FWZIC algorithm?

a) Aggregation techniques: This section explores the common aggregation methods utilized by the reviewed studies for aggregating the fuzzy EDM values. Aggregation of the fuzzy numbers is one of the most crucial steps in FWZIC method. The fuzzy expert judgement for each criterion is aggregated with the aim of merging all the experts' opinions for that criterion so that the resulting aggregated output fully considers each individual criterion. This ensures that the final criterion weight is based on the overall evaluation. Aggregation is critical for producing appropriate results from EDM. In literature, several aggregation methods exist for various fuzzy environments [19].

All studies that employed the classical FWZIC using TFN utilized a pseudo-arithmetic operator $\oplus$ to aggregate the fuzzy values of each criteria expert opinion in the EDM. Similarly, the pseudo-arithmetic operator was utilized for HFNs [89]. For instance, two TFN $\bar{x} = (a_1, b_1, c_1), \bar{y} = (a_2, b_2, c_2)$, the TFN pseudo-arithmetic operation between $\bar{x}\ and\ \bar{y}$ is defined as follows: $\bar{x} \oplus \bar{y} = (a1 + a2, b1 + b2, c1 + c2)$.

Although advanced aggregation operators, like geometric aggregation, weighted aggregation and quasi-fuzzy weighted aggregation have been proposed in literature for these classical fuzzy numbers [133], none of the studies employed the aggregation operators.

Similarly, the other studies that enhanced FWZIC with various advanced fuzzy environments, such as IFS, PyFS, SFS, IVFS, and more, employed the arithmetic weighted aggregation operator of the respective fuzzy environment. For instance, [115] utilized the NCN weighted arithmetic averaging (NCNWAA) operator for the NCS-FWZIC technique, while [96] utilized the q-ROPHF arithmetic mean (q-ROPHFAM) operator, and [106] employed the spherical weighted arithmetic mean (SWAM) operator. Ref [102], on the other hand, employed a geometric aggregation operator for NS-FWZIC. Other aggregation operators, like Bonferroni [134] and Einstein [135] aggregation operators were not considered in any of the studies. Notably, different aggregation operators may impact the criteria weighing results, which may be explored for further research.

b) Defuzzification techniques: Defuzzification is a process that converts a fuzzy set or fuzzy number into a crisp value or number. Defuzzification is used in fuzzy modeling to convert the fuzzy output values to their corresponding crisp weight values. This process is necessary because all fuzzy sets inferred by fuzzy inference in the fuzzy rules must be aggregated to produce one single number as the output of the fuzzy model. There are numerous techniques for defuzzifying a fuzzy set.

The centroid method mathematically derives the Center of Gravity (COG) to convert a fuzzy number to its corresponding crisp value. However, this method is computationally complex for complex membership functions. For instance, for a TFN $\bar{x} = (a, b, c)$, the defuzzified crisp value is computed as $\bar{x} = (a + b + c)/3$, while for HFNs $\bar{x} = (a, b, c, d, e, f)$, the crisp value is derived using the equation $\bar{x} = (3a + 3b + 10c + 10d + 5e + 3f)/34$.

All studies that utilized TFNs and HFN applied the centroid method for defuzzifying the fuzzy weight values. Other methods proposed in literature, such as max-membership, weighted-average and mean-max methods [18] were not employed by any of the studies. All other reviewed studies that employed advanced fuzzy sets consistently utilized a single score function of the respective fuzzy environment to compute the defuzzified crisp value. Notably there exists multiple score functions in fuzzy sets, each of which may yield different results [136]. None of the studies evaluated the criteria weights based on multiple score functions.

Overall, the findings in this section reveal a gap in literature, showing that there are multiple avenues of further research to evaluate the impact of the use of different aggregation and defuzzification techniques with the various fuzzy environments to further enhance the FWZIC method.

C. Expert and Criteria Characteristics

This section explores the characteristics of the experts and evaluation criteria employed in studies utilizing the FWZIC method. In addressing the first part, we examine the background, qualifications, and experience of the experts involved, along with how their input was used in the decision-making process. We also highlight patterns in expert selection, including the number of experts typically engaged and how their opinions were considered. In the second part, we analyze the nature, structure, and sources of the criteria used across the reviewed studies. This includes how the criteria were evaluated, the scales and linguistic terms applied, and the integration of fuzzy sets to ensure consistency. Together, these insights provide a comprehensive understanding of how FWZIC accommodates expert-driven input and diverse criteria sets in multi-criteria decision-making contexts.

1) Expert characteristics

RQ6: What are the characteristics of the experts involved in the studies?

All experts employed in the studies possess expertise within the field of study, including cardiologists, academicians, tourism experts, data scientists, and others. In [112], the authors identified members of the technical community as experts. Two studies [109], [86] explicitly list the qualifications and details of the experts. Some studies stipulated the minimum experience requirements to be considered as experts in that field. For instance, [67] and [104] require experts with over 5 years of experience, while others, such as those by [71], [95] and [110] selected experts with more than 10 years of experience. In numerous case studies, the evaluation forms and criteria adopted are also assessed by experts chosen for their knowledge and expertise in relevant fields [81]. Notably, only one study [110] differentiated the experts' opinions based on seniority and years of experience, assigning each expert an objective score to determine the overall criteria weight. All studies considered the opinion of the expert at an equal level, without differentiating them based on their expertise.

Most case studies (n = 46) involve three experts to assess and weigh the evaluation criteria and consider this a minimum requirement. Few studies (n = 7) employed four experts, while three studies opted for five experts. Some studies involved a large number of experts. For instance, [106] used 17 experts to evaluate security and privacy in Blockchain-Based IoT Healthcare Industry 4.0 Systems, while [101], [102] both employed 11 experts to determine the criteria's significance for evaluating smart e-tourism applications. In [95], the study utilized 12 experts to assess various energy sources for sustainability and efficient resource usage. Three studies employed 6 experts for assessing criteria weights for lung cancer diagnosis techniques [70] [123], for evaluating indoor air quality pollutants [72] and for evaluating the significance of hybrid deep learning models based on chest X-ray analysis in CAD systems [71]. Three studies, which involved five experts [85] evaluated the privacy model of the Bitcoin network for the Metaverse, while [89] assessed the significance of privacy features for metaverse tools and [86] evaluated virtual commerce applications for the Metaverse. Several studies selected four experts, primarily in the medical field [67], [84], [137], [138].

It is observed that the minimum number of experts employed for weighing criteria using FWZIC ranges from a minimum of 3 to a maximum of 43 experts, with a large percentage utilizing three experts. This finding reveals the ease of use of the FWZIC method regardless of the number of experts involved. FWZIC proves to be reliable and robust in consolidating opinions from multiple experts, each with diverse expertise, to reduce bias in the criteria weighting process while maintaining consistency. In other subjective criteria weighting methods, such as AHP, the process of consolidating criteria weightings using multiple experts would be a time-consuming process and prone to inconsistencies as well. Notably, only one study differentiated the experts' opinions based on their seniority and experience level.

2) Criteria characteristics

RQ7: What are the characteristics of the criteria utilized in the studies?

The number of criteria across the 71 reviewed studies varies significantly, ranging from a minimum of 3 to a maximum of 75 criteria. Most of these criteria are structured at a single level, while some studies have utilized multi-level criteria ranging from two-levels, three-levels and four levels.

The criteria utilized in the studies originate from various sources. Several studies (n = 43) source their evaluation criteria from root articles. A root article may be defined as an existing systematic review, survey, or case study which has extracted the criteria from literature [139]. Others use only a portion of these criteria (n = 7). Additionally, some studies derive their criteria from existing datasets when integrating FWZIC with machine learning techniques. Other studies source their criteria from literature (n=12), while a few studies (n = 4) identify their criteria as performance metrics or specific methods for selecting optimal machine learning algorithms.

The criteria are assessed by experts using an online evaluation form. All studies have consistently utilized a 5-point Likert scale to assess the criteria's significance using linguistic values such as "Very High Importance", "High Importance", "Moderate Importance", "Low Importance", "Very Low Importance". Only one study employed a 10-point Likert scale [104]. All studies mapped the linguistic values to a numerical scale and converted them to the corresponding fuzzy number to generate a fuzzy Expert Decision Matrix.

Overall, the FWZIC method has been utilized with as few as three criteria and as many as seventy-five. These findings demonstrate the robustness of the FWZIC method in weighting a large number of criteria without any inconsistencies, thereby demonstrating its superiority over other subjective methods, such as AHP, ANP, and BWM, which would not only be computationally intensive but also prone to inconsistencies.

V. Research Implications

By analyzing seventy-one studies across diverse domains such as healthcare, engineering, supply chain, agriculture, and technology, this review confirms the FWZIC method's versatility, robustness, and growing popularity since its inception.

The findings highlight that FWZIC effectively addresses the limitations of traditional subjective weighting methods by ensuring consistency, accommodating a wide range of fuzzy environments, and facilitating decision-making even with large numbers of criteria and experts. Moreover, the increasing integration of FWZIC with various MCDM ranking techniques, particularly FDOSM and VIKOR, underlines its adaptability and relevance across multidisciplinary fields.

This review establishes that FWZIC offers a transformative approach to subjective criteria weighting by minimizing inconsistency and bias, which are persistent challenges in MCDM. It encourages a shift from conventional time-consuming methods like AHP and BWM towards more streamlined, reliable techniques, particularly in environments characterized by ambiguity.

The systematic integration of FWZIC with advanced fuzzy environments (e.g., q-ROFS, T-SFS, IVFS) has expanded the spectrum of uncertainty that can be modeled. This evolution enhances the realism and flexibility of decision models, paving the way for more human-centric decision support systems.

Despite extensive applications, the study uncovers that most researchers have relied on standard aggregation (e.g., pseudo-arithmetic operators) and centroid-based defuzzification methods. This opens an important avenue for future exploration: investigating alternative aggregation and defuzzification strategies could yield even more robust, interpretable, and precise decision-making frameworks.

The breadth of FWZIC's application, from medical diagnosis prioritization to supply chain resilience, demonstrates its critical role as an enabler of informed decision-making in complex, multidisciplinary problems. Organizations can leverage FWZIC-based models to improve strategic planning, risk assessment, resource allocation, and sustainability efforts.

The study confirms FWZIC's practical utility in real-world contexts by facilitating expert opinion consolidation without overburdening decision-makers. Its ability to integrate three to forty-three expert opinions efficiently, without inconsistency, empowers organizations to make collective, evidence-based decisions more effectively.

Unlike traditional subjective methods that are unstable with increasing numbers of criteria or experts, FWZIC demonstrates strong scalability. This robustness supports its deployment in emerging fields such as AI-driven healthcare, Industry 5.0, digital twin technologies, and the Metaverse, where complex, multi-criteria evaluations are the norm.

Although FWZIC's flexibility is a strength, the diversity of its applications also signals a need for establishing best practices or standardized frameworks for its use across different fuzzy environments and MCDM settings. Future work should aim to benchmark FWZIC applications across domains to strengthen comparability and reliability.

A. Future Directions

This section presents some additional research areas that emerge from the review, thereby offering practitioners and researchers a means to further enhance research in this field.

1) Fuzzy scale. Most of the reviewed studies have utilized a 5-point Likert scale for assessing criteria importance, with only one study utilizing a 10-point Likert scale. A scale is essential for a comparison reference when assessing the criteria’s significance. It may be reasonable to assume that a higher-level scale would cover a wider spectrum of uncertainty in expert opinion. Therefore, a future area of research could be to explore the impact of various scales (5-point, 7-point, 10-point) on the criteria weighting results.

2) Experts. Most reviewed studies employed at least 3 experts to assess the criteria's weighting significance. While some studies designated minimum requirements for expert selection, only one study employed an objective approach in the criteria weighting process to differentiate experts based on their seniority and experience level. This opens an avenue for further research in this area to study the difference in the criteria weights with or without an objective approach. Furthermore, researchers could also employ objective criteria other than seniority in job title and experience years, such as preferred area of practice (industry experts, academicians, researchers), expert qualification and more.

3) Aggregation and Defuzzification. Most of the reviewed studies employed the arithmetic weighted aggregation operator of the respective fuzzy environment, while only a few studies have employed the geometric aggregation operator, which signifies that more research is encouraged to investigate the use of these aggregators. Moreover, none of the studies employed aggregation operators like Bonferroni [134] and Einstein [135] aggregation operators, allowing future research possibilities to employ these and other new aggregation operators that were not considered in the review studies.

From the defuzzification techniques point of view, most of the studies utilized the centroid method for defuzzifying the fuzzy weight values or used a single score function for defuzzifying; none of the reviewed studies used other proposed methods in literature, such as max-membership, weighted-average and mean-max methods. Additionally, no studies used multiple score functions to calculate the final weight methods that would impact the ranking results. This gap in the literature presents an opportunity for further research to explore the application of these alternative defuzzifying methods or to use multiple scores to evaluate and finalize the criteria weights.

4) Fuzzy extensions. Although several studies have enhanced the FWZIC method under various fuzzy environments, the issue of inconsistency and ambiguity in human judgment remains unresolved when calculating criteria weights. The FWZIC method can be further extended with different fuzzy environments that encompass a broader uncertainty range, such as interval-valued Neutrosophic sets. Moreover, future research could also analyze the soft versus rough characteristics in fuzzy sets and their effect on criteria weighting using FWZIC.

5) MCDM integration. FWZIC has been integrated with several MCDM methods for the purpose of ranking and studying the causal effects on the attributes. Notably, several MCDM ranking methods have not yet been integrated with FWZIC, such as MACBETH, MCRAT, RAMS, and others. Integrating FWZIC with these methods presents a potential research opportunity to analyze and test the results and effectiveness of these integrations.

6) Domain. The FWZIC method has been utilized in numerous sectors to determine criteria weights such as healthcare, tourism, agriculture, transport and more. However, there are still many unexplored domains that present an opportunity for future research, such as real estate, aviation, media and telecommunication.

7) Other criteria weighting methods. FWZIC is a comparatively superior criteria weighting method when compared to other traditional weighting methods, such as AHP. Not only is FWZIC computationally simple, but it also eliminates the need for criteria comparison and leads to zero inconsistencies in subjective evaluation. A possible future area of research is a comparative study of FWZIC and other methods, such as the Full Consistency Method (FUCOM) [140] and Opinion Weight Criteria Method (OWCM) [141]. FUCOM provides a strategy with fewer pairwise comparisons to reduce inconsistency, while OWCM combines both subjective and objective criteria weighting methods to eliminate inconsistency. This comparison could highlight the strengths and weaknesses of each method, potentially leading to further advancements in criteria weighting techniques.

VI. Conclusion

This systematic review presents a comprehensive synthesis of the FWZIC method's applications in MCDM. By examining seventy-one empirical studies across a range of domains, including healthcare, engineering, supply chain, and sustainability, the review highlights FWZIC's versatility in addressing the challenges of subjective decision-making, particularly in managing expert opinions with consistency and minimal bias.

The findings demonstrate that FWZIC has been widely adapted through the integration of various fuzzy environments and has been successfully combined with multiple MCDM ranking techniques, reflecting its flexibility and growing acceptance. Despite its advantages, gaps remain regarding the exploration of alternative aggregation and defuzzification methods, offering valuable opportunities for future research to further enhance decision-making accuracy and robustness.

Overall, this review not only consolidates the existing knowledge on FWZIC but also identifies emerging trends, methodological gaps, and potential directions for advancing subjective criteria weighting techniques. It serves as a vital resource for researchers and practitioners seeking to implement or extend the FWZIC method in increasingly complex and uncertain decision-making contexts. This study not only underscores the value of FWZIC as a cornerstone method in subjective decision-making but also charts a pathway for future research directions. By systematically identifying gaps and proposing avenues for further methodological refinements, this review serves as a critical reference for researchers, practitioners, and policymakers aiming to enhance decision quality in increasingly complex, uncertain, and multi-stakeholder environments.

This study may have been subject to certain limitations attributable to various factors. Primarily, the research employed three bibliographic databases, encompassing multiple disciplines, to retrieve pertinent studies. This approach may have led to the inadvertent exclusion of relevant empirical studies that utilized the FWZIC method. Additionally, ten studies were excluded from the meta-analysis of the present study due to the unavailability of full-text access. Despite these constraints, the examination of the seventy-one reviewed articles has yielded a comprehensive and detailed review of the FWZIC method, which is expected to provide valuable guidance for both practitioners and researchers in this domain.

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APPENDIX

Themes	Domain	Study	Objective	MCDM Method	FWZIC Extension	#Experts	#Criteria	Criteria Source
Artificial Intelligence	Engineering	[74]	To develop optimization techniques for semiconductor materials.	FDOSM	Triangular Fuzzy Numbers	3	8	Root article
	Healthcare	[142]	To evaluate hybrid diagnosis models for autism spectrum disorder patients	FDOSM	2-Tuple Linguistic Neutrosophic Fuzzy Set	4	9	Root article
		[128]	To prioritize autism spectrum disorder cases based on behavioral and medical characteristics.	MABAC	Single-Valued Neutrosophic 2-Tuple Linguistic Fuzzy Set	3	19	Literature
		[67]	To evaluate machine learning models for diagnosing autism spectrum disorder patients.	FDOSM	Triangular Fuzzy Numbers	4 3	48 7	Performance metric of ML
		[70]	To evaluate machine learning approaches for lung cancer diagnosis.	VIKOR	Triangular Fuzzy numbers	6	5	Performance metric of ML
		[72]	To develop a labelled dataset of indoor hospital air quality pollutants.	UPLDP	Interval Type 2 Trapezoidal-Fuzzy Sets	6	9	Root article
		[68]	To integrate MCDM with Machine learning for classifying patients with autism spectrum disorder.	ML	Complex T-Spherical Fuzzy Set	3	7	Performance metric of ML
		[73]	To evaluate AI healthcare applications based on trustworthiness attributes.	CODAS	q-Rung Orthopair Fuzzy 2-Tuple Linguistic	3	7	Root article
		[71]	To benchmark deep learning models for chest X-ray analysis and computer-aided diagnosis.	VIKOR	Triangular Fuzzy Numbers	6	7	Performance metric of ML

		[69]	To combine MCDM and ML to predict ASD patients and build an explainable AI for model comprehension.	Delphi	Triangular Fuzzy numbers	4	19	Existing dataset
COVID 19	Healthcare	[78]	To benchmark AI models for diagnosing COVID-19 patients using chest x-rays.	DLBD	Probabilistic Single-Valued Neutrosophic Hesitant Fuzzy Set	3	7	Literature
		[75]	To prioritize COVID-19 vaccine dose recipients.	FDOSM	T-Spherical Fuzzy Sets	3	5	Root article
		[76]	To prioritize COVID-19 vaccine dose recipients.	FDOSM	Q-Rung Orthopair Fuzzy Sets	3	5	Root article
		[77]	To prioritize COVID-19 vaccine dose recipients.	FDOSM	Pythagorean Fuzzy Sets	3	5	Root article - case study
		[79]	the prioritize the distribution of COVID-19 monoclonal antibody to eligible high-risk patients.	TOPSIS	Interval-Valued Spherical Fuzzy and Hesitant 2-Tuple	3	15	Literature
Metaverse	Business	[85]	To evaluate bitcoin network platforms for the Metaverse.	MULTIMOORA	Linear Diophantine Fuzzy Sets	5	24	Root article (partial)
		[86]	To evaluate virtual commerce solutions for the Metaverse	RATMI	Spherical Linear Diophantine Sets	5	13	Root article
	Manufacturing	[89]	To assess cyber-physical manufacturing systems based on privacy features.	ARAS	Hexagonal Fuzzy Numbers	5	21	Unspecified
		[87]	To assess cyber-physical manufacturing systems based on privacy features.	PROMETHEE II	Interval-Valued Spherical Fuzzy Rough Sets	3	26	Root article
		[88]	To assess cyber-physical manufacturing systems based on privacy features.	CoCoSo	Interval-Valued Spherical Fuzzy Rough Sets	3	16	Root article
Service	Business	[127]	To rank power transformer suppliers based on quality standards to maintain safe and stable grid operations.	MABAC	Q-Rung Orthopair Fuzzy Sets	4	10	Literature
		[143]	to assess blood supply chain management alternatives against sustainability-focused criteria	VIKOR	Single-Valued Neutrosophic Fuzzy Set	3	7	Root article
	Healthcare	[80]	To prioritize the treatment of autism spectrum disorder patients.	VIKOR	Triangular Fuzzy Numbers	4	19	Root article
		[83]	To prioritize hospital selection for patients with multi-chronic diseases.	FDOSM	Q-Rung Orthopair Fuzzy Sets	3	7	Root article
		[82]	To prioritize patients with multiple chronic illnesses based on sensor and emotion data.	TROOIL	Fractional Orthotriple Fuzzy Sets	3	12	Root article
		[81]	To classify autism spectrum disorder patients based on severity level for early diagnosis.	Delphi	Triangular Fuzzy Numbers	13	19	Existing dataset
		[84]	To prioritize the criteria for managing patients with cardiac related issues.	N/A	Triangular Fuzzy Numbers	4	11	Root article
Sustainability	Agriculture	[130]	To critically assess decision support systems for enabling the choice of systems that can effectively drive sustainable smart agriculture.	CODAS	Hyperbolic Fuzzy Sets	3	8	Root article
		[90]	To evaluate water quality monitoring systems based on remote sensing techniques.	VIKOR	Triangular Fuzzy Numbers	3	15	Root article
	Business	[98]	To evaluate circular economy and sustainability practices in the palm oil industry.	EDAS	Interval-valued Pythagorean Fuzzy Rough Set	3	14	Root article

		[97]	To evaluate sustainable circular business model innovation tools.	CODAS	Neutrosophic Bipolar Fuzzy Sets	3	10	Root article
	Engineering	[96]	To evaluate sustainable strategies for construction waste management.	FDOSM-MULTIMOORA	Q-Rung Orthopair Probabilistic Hesitant Fuzzy Set	3	26	Root article
		[131]	To develop a comprehensive investment decision-making framework for offshore Carbon Capture, Utilization, and Storage (CCUS) projects to promote sustainable development	MARCOS	Interval value, Fermatean Fuzzy Sets	3	18	Literature
		[124]	To assess and rank research based micro-grid to ensure sustainable energy resources.	VIKOR	Triangular Fuzzy Numbers	3	9	Root article
		[95]	To benchmark energy systems integration frameworks for efficient resource utilization.	MABAC	Triangular Fuzzy Numbers	12	6	Root article
	Miscellaneous-Energy Optimization	[125]	To evaluate energy economy optimization models for efficient energy systems.	FDOSM	Triangular Fuzzy Numbers	3	5	Root article
	Miscellaneous-Smart living	[99]	To evaluate sustainable smart living frameworks based on multi-layer assessment factors.	CPOS	Circular-Pythagorean Fuzzy Sets	3	19	Root article
	Supply Chain	[100]	To rank real-time IoT devices for food waste monitoring in a supply chain system.	ARAS	Circular Intuitionistic Fuzzy Set	3	10	Root article
		[50]	To benchmark sustainable agriculture food supply chain strategies.	FDOSM-MAIRCA	Fermatean Probabilistic Hesitant Fuzzy	3	27	Root article (partial)
	Transport	[48]	To evaluate sustainable electronic passenger modelling strategies.	MULTIMOORA	Probabilistic Hesitant Fuzzy Sets	3	49	Root article
		[91]	To assess fuel supply modelling approaches for electric vehicles.	MARCOS	Pythagorean Probabilistic Hesitant	3	28	Root article (partial)
		[93]	To evaluate energy systems for sustainable transportation in the shipping industry.	FDOSM	q-rung orthopair fuzzy Rough Sets	3	10	Root article
		[92]	To evaluate and rank international oil companies for sustainable oil transportation.	MULTIMOORA	Linear Diophantine Fuzzy Rough Sets	3	11	Root article
		[94]	To assess pavement selection approaches for sustainable transportation.	FDOSM	Dual-Hesitant Fuzzy	4	30	Literature
Technology	Agriculture	[123]	to evaluate drones based on performance attributes for precision farming.	FDOSM	Triangular Fuzzy Numbers	3	3	Literature
		[105]	To evaluate and measure the effectiveness of swarm robots in mechanized agricultural operations	CPOS	Circular Quintic Fuzzy Sets	3	7	Literature
	Business	[122]	To evaluate organizational culture based on features that promote digital innovation.	SAW	Q-Rung Picture Fuzzy	3	9	Root article
	Education	[115]	To evaluate smart training environments based on brain computer interface attributes.	MABAC	Neutrosophic Cubic Sets	3	10	Root article
		[23]	To evaluate speech-recognition chatbots for language learning	MCRAT	T-Spherical Fuzzy Sets	5	9	Root article
		[114]	To evaluate smart training environments based on brain computer interface attributes.	VIKOR	Triangular Fuzzy Numbers	3	10	Root article
	Engineering	[112]	To evaluate routing algorithms in a multiprocessor network system.	FDOSM	Z-Cloud Rough Numbers	3	9	Literature

		[129]	To Optimize Control Engineering Tools Using Digital Twin Capabilities and Other Cyber-Physical Metaverse Manufacturing System attributes	CoCoSo	Interval Value Spherical Fuzzy Rough Sets	3	26	Root Article
		[113]	To develop a design concept evaluation method to compromise solutions of uncertainties	CoCoSo	Q Rung Orthopair Fuzzy Rough Sets	5	12	Root Article
		[111]	To evaluate cooling systems based on performance and technical perspective.	MABAC	2-Tuple Linguistic Pythagorean	3	11	Literature
		[110]	To assess the risk factors associated with offshore wind turbines.	DEMATEL	Linguistic Pythagorean Fuzzy	4	75	Literature
	Healthcare	[104]	To evaluate sign language recognition systems.	FDOSM	Cubic Pythagorean Fuzzy Sets	3	11	Root article - case study
		[126]	To develop a framework of smartphone-based mobile applications for obesity management	FDOSM	Triangular Fuzzy sets	3	5	Root Article
		[106]	To benchmark blockchain based healthcare systems using security and privacy features.	TOPSIS	Spherical Fuzzy Sets	17	6	Root Article
		[108]	To evaluate intrusion detection classifiers for Internet of Medical Things (IoMT) devices based on security and performance attributes.	FDOSM	Rough Fermatean Fuzzy Sets	3	17	Root Article
		[109]	To benchmark digital tools for genetic counselling	ARAS	Pythagorean Fuzzy Set	3	9	Root Article
		[107]	To benchmark blockchain based healthcare systems using security and privacy features.	COPRAS	Interval-Valued Spherical Fuzzy Sets	3	6 and 7	Root Article
	Misc-Marine Robotics	[120]	To evaluate optimization algorithms for motion of autonomous underwater vehicles.	FDOSM	Triangular Fuzzy Numbers	3	9	Literature
	Network	[117]	To develop a modelling framework for 6G based blockchain technology	RAFSI	Normal Wiggly Hesitant Fuzzy Set	3	7	Literature
	Network	[118]	To evaluate a Dynamic locally based-utility approach for developing internet of Modular self-reconfiguration robot things	Dynamic Localization-Based Utility	Type 2 Pythagorean	3	6	Root Article
	Network(Cloud computing)	[119]	To determine the superiority of a robust cloud fault tolerance of a solution mechanism	PROMETHEE	Spherical Cubic Fuzzy Sets	3	9	Root Article
	Network (not sure why??)	[144]	To evaluate of industry 4.0 adoption strategies in small and medium enterprises	TOE	Circular-Fermatean Fuzzy sets	3	30	Root Artricle
	Network	[116]	To select an optimal architecture for 5G Radio Access Networks.	FDOSM	Type-2 Neutrosophic Numbers	3	25	Root Article
	Tourism	[101]	To evaluate smart e-tourism applications.	VIKOR	Interval Type 2 Trapezoidal-Fuzzy Sets	11	12	Root Article
		[102]	To evaluate smart e-tourism applications.	FDOSM	Neutrosophic Fuzzy Sets	11	12	Root Article - case study
		[103]	To evaluate smart e-tourism applications.	FDOSM	Spherical Fuzzy Rough Sets	3	12	Root Article - case study
	Transport	[121]	To evaluate data acquisition systems for the vehicle development and analysis.	FDOSM	Intuitionistic Fuzzy Set	3	15	Root Article