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Review

Failure Mode and Effects Analysis Integrated with Multi-Attribute Decision-Making Methods Under Uncertainty: A Systematic Literature Review

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Abstract

Failure Mode and Effects Analysis (FMEA) is a proactive management technique widely used to improve the reliability of products and processes across various business sectors. Due to rapid changes stemming from uncertain environments, numerous studies have proposed different approaches to enhance the effectiveness of the FMEA method. However, there is a lack of systematic literature reviews and classification of research on this topic. The purpose of this paper is to systematically review the literature on the integration of FMEA with Multi-Attribute Decision-Making (MADM) theories and various mathematical models. This study analyses a total of 68 papers published between 2015 and 2024, selected from 51 peer-reviewed journals indexed in Scopus and/or Web of Science. Furthermore, a bibliometric analysis was conducted based on the frequency of different mathematical theories used to model existing uncertainties, methods for determining the weighting vectors of risk factors (RFs), the use of MADM theories extended with uncertain numbers for weighting RFs and prioritizing identified failure modes, publication years, journals, and application domains. This research aims to support both researchers and practitioners in effectively adopting uncertain MADM methods to address the limitations of traditional FMEA and provide insight into the current state of the art in this field.

Keywords: Failure Mode and Effect Analysis; uncertain environments; Multi-Attribute Decision-Making; literature review

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1. Introduction

As customer requirements evolve rapidly and continuously, maintaining competitiveness has become a crucial management objective for industrial companies. Based on on-site data from industry practitioners, it can be inferred that failures occurring during production constitute the primary causes leading to either non-fulfilment or partial fulfilment of this business objective. Numerous well-established methods can be found in the literature to measure and analyse failures within manufacturing processes, aiming to eliminate or reduce their likelihood and associated safety risks. Examples include Fault Tree Analysis (FTA), Failure Mode and Effects Analysis (FMEA), Root Cause Analysis (RCA), and Event Tree Analysis (ETA) [1,2].

In practice, the most commonly used method for identifying and prioritizing known or potential failures before they occur is FMEA. This method was initially introduced in the aerospace industry during the 1960s and was applied to the naval aircraft flight control system at Grumman Aircraft Corporation [3]. FMEA is particularly prevalent in the automotive industry, as it is mandated by the IATF 16949 standard [4]. In companies within the automotive industry, the FMEA analysis is carried out by the FMEA team [5]. Also, FMEA has been widely adopted as a powerful tool for risk assessment and reliability analysis across various industries [6].

In conventional FMEA, it is assumed that identified failures can be evaluated based on three risk factors (RFs), severity, occurrence of failure realization, and difficulty of failure detection, using a standardized measurement scale defined within the interval [1–10]. The risk priority number (RPN) is calculated as the product of these three RFs—occurrence (O), severity (S), and detection (D)—where O and S represent the likelihood and severity of a failure, respectively, and D denotes the probability that the failure will not be detected before reaching the customer [7]. Failures are then ranked according to their RPN values. Numerous researchers have described the application of the FMEA method across various industrial enterprises [8].

Numerous studies highlight the existing limitations of conventional FMEA. Several significant shortcomings of the FMEA approach should be emphasized.

Many papers can be found advocating that there are existing disadvantages of conventional FMEA. Some of the important shortcomings of FMEA should be pointed out [9,10].

- The relative importance of the considered RFs, as well as their specific aspects, is not equal.
- Natural language is often employed to assess the relative importance and values of the RFs in order to express the subjective perceptions of decision makers (DMs). It is well known that natural language expressions may lack clear and well-defined meanings. Therefore, using precise numerical values for quantification is not always appropriate. The development of mathematical theories has allowed predefined linguistic expressions to be represented in a fairly quantitative manner. In the analyzed literature, linguistic terms are modeled by (1) fuzzy set theory [11–18], (2) rough set theory [19], (3) cloud theory [20], and (4) Fuzzy Belief Structure (FBS) [21,22], among others.
- Many authors express doubts regarding the reliability of the mathematical formula used for calculating the RPN. Numerous studies emphasize different approaches proposed to address the shortcomings of FMEA, including methods that integrate (1) Multi-Attribute Decision-Making (MADM) techniques combined with fuzzy set theory [23,24] and rough set theory [25,26], as well as (2) methodological modifications defined in the latest FMEA manual for the automotive industry, published in 2019, titled the *FEMA Handbook* [27]. Consequently, improving the efficiency and effectiveness of FMEA has attracted increasing attention from both academic and practical domains. Many authors emphasize that the shortcomings of FMEA may negatively impact its reliability and consistency.

A substantial number of studies can be found in the literature where various MADM methods have been applied for the evaluation and ranking of different items under uncertainty [28] across diverse domains such as engineering, technology, and management science. In recent decades, MADM approaches extended with mathematical theories for modeling uncertainty have received considerable attention from both practitioners and researchers. This paper aims to document the growing interest in the application of MADM under uncertainty and to provide a state-of-the-art review of the literature regarding their applications and methodologies. In [29], a classification of MADM methods is proposed, and the analysis in this paper is based on this classification.

The reviewed papers are classified based on the year of publication, application domains, and the MADM approaches integrated with mathematical theories for modeling uncertainty. In this study, the literature published between 2015 and 2024, related to the descriptors of FMEA, MADM, and mathematical theories, has been comprehensively reviewed using academic databases of Scopus and Web of Science. A total of 68 papers published across 51 journals were analyzed in the scope of this research.

Nowadays, the FMEA framework for identifying and analyzing failure modes, combined with MADM methods extended by the use of uncertain numbers, is applied to problems existing in various economic sectors. It should be noted that this combination of methods is mostly used in different types of industries, such as manufacturing, energy and chemical, automotive, etc. Researchers and practitioners consider the application of this approach to be suitable for improving the reliability of products and processes in other economic sectors as well, such as project management, waste management, transport, and others.

The research gap addressed by this study is that there is no existing review in the literature covering papers where FMEA analysis is combined with MADM methods extended by various theories for modeling uncertainty, specifically within the last 10 years.

The present paper aims to address the following research questions. (1) Which types of uncertain numbers have been frequently used for modeling the relative importance and values of RFs? (2) Which MADM methods have been combined with FMEA, and in which research domains have they been applied? (3) What is the publication trend of papers integrating FMEA and MADM under uncertainty?

The rest of the paper is organized as follows. Section 2 introduces the research methodology and the review process employed in this study. Section 3 analyzes the selected papers focusing on the modeling of uncertainty in the relative importance and values of RFs. Section 4 presents MADM methods extended with uncertain data in combination with FMEA, which have been applied for determining the weights of RFs and prioritizing failures. Section 5 discusses the key findings based on the reviewed literature. Finally, Section 6 provides conclusions and directions for future research.

2. Research Methodology

A systematic review of the MADM methods under uncertain environments was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (see Figure 1), as was performed in the study by [30,31]. This procedure includes a literature search, selection, and analysis of the papers.

In the present research, a total of 68 papers were considered reliable, as they were indexed in the Scopus and Web of Science electronic databases. These databases were selected due to their relevance and wide acceptance within the scientific community. They index peer-reviewed journals that have undergone rigorous scientific evaluation prior to being included. Therefore, such journals can be considered reliable sources. Another criterion for selecting papers was that they be written in English.

The reasons why the Scopus and Web of Science databases were used in this research can be justified by the following facts:

- These databases include journals and publications from various fields such as engineering, medicine, natural sciences, and others. In other words, they are not limited to a single scientific discipline, unlike some other databases.
- They represent the most prominent databases of scientific journals and publications. All journals indexed in these databases must be peer-reviewed and undergo a rigorous quality control process.

- All journals indexed in these databases have a review process, which serves as a guarantee that the paper has undergone an initial check and that the research is validated.
- They contain adequate and accurate data about authors, affiliations, publications, and journals.

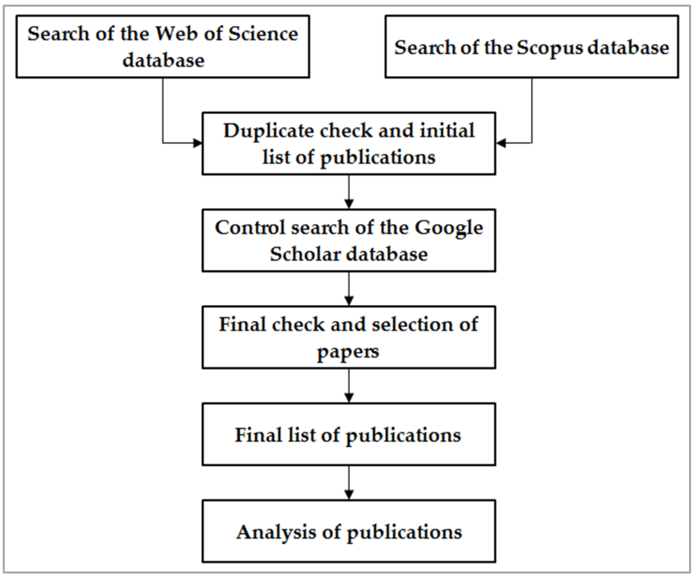

Figure 1. Search and sorting methodology of the publications.

As can be seen in Figure 1, the process of selecting and analyzing publications was carried out through six main steps. In the first step, the search was conducted in the two mentioned databases, Scopus and Web of Science. The search was filtered for the period from 2015 to 2024. The following keywords were used during the search:

- Fuzzy FMEA;
- Fuzzy FMEA MADM;
- FMEA + name of each individual MADM method;
- FMEA + name of each individual approach for describing uncertainty.

The search was conducted each time up to a maximum of the twentieth page of results, although often no (relevant) papers were found even after the fifth page. After completing the search, in the second step, the identified papers were compared. Through all the presented search methods, a total of 125 papers were found in Scopus and 116 papers in the Web of Science database, including duplicates. After duplicates were eliminated, a total of 80 papers were retrieved from the Scopus database and 74 from Web of Science. Among these, 71 papers overlapped. In the Scopus database, there were 9 papers not found in Web of Science, while 3 papers appeared only in Web of Science but not in Scopus.

To verify the search in these two databases, a search was also conducted in Google Scholar in the third step. A total of 96 papers were found, including those published in non-indexed journals and conferences. All papers found in the Scopus and Web of Science databases were also found in Google Scholar. This served as an additional verification of the initial search.

In the fourth step, a final check and selection of the papers to be included in the analysis was carried out. All papers that did not meet any of the following criteria were excluded from further analysis.

- The FMEA framework was not applied;
- No approach for modeling uncertainty was used;
- No MADM method was applied, nor the RPN parameter.

In the fifth step, a final list of 68 publications was compiled. All these papers were considered in the conducted analysis. The applied MADM approaches, approaches for modeling uncertainty, and the research application domain, as well as the publications and authors themselves, were analyzed in the sixth step.

The review included papers published from 2015 up to those published in 2024, including articles that were available online in the selected databases and had been assigned a DOI number by December 2024.

3. Modeling of Risk Factors

In this section, the improvement of the analyzed research papers is conducted through a systematic review. A set of 68 articles published in prestigious journals between 2015 and 2024 was identified. The analysis of RFs, as well as the modeling of their relative importance and values, is carried out.

3.1. Analysis of Risk Factors and Their Aspects

In 51 (75%) of the analyzed papers, the authors consider that the identified failures can be adequately evaluated using the RFs defined in conventional FMEA. In [32], the authors argue that these RFs should be decomposed into sub-risk factors. In [33], the authors also suggest that RFs should be decomposed, where severity is broken down into safety, environment, production losses, performance losses, labor cost, and spare cost; detection is divided into visibility and inspection; and occurrence does not have a hierarchical structure.

Some authors evaluate the alternatives using four RFs (11.76%). The majority of them introduce Cost as the fourth RF [34–36]. In [37], the authors expand the set of RFs from the conventional method by including maintenance costs. In [36], the authors introduce the assumption that all considered RFs are hierarchically structured.

In five articles (7.35%), five RFs are considered. In addition to the RFs defined in the conventional FMEA method, the following RFs are introduced: range and cost [38]; internal severity of failure to the internal customer and external severity of the failure to the external customer [39]; and severity with quality, cost, and time [40–42]. In [43], the authors considered the following RFs: severity time, severity cost, severity quality, occurrence, and detection.

In one study, the assumption was introduced that alternatives are evaluated based on six RFs. The first three factors were taken from the FMEA model. The additional RFs are time, cost, and quality [44], as well as complexity of failure resolution and impact on business [45].

It should be noted that in conventional FMEA, severity is considered primarily from the quality perspective and only partially from the safety perspective. For example, in a large number of the analyzed papers, severity is examined from multiple aspects. In [46], the authors divided severity into social, economic, and environmental aspects. In [47], the authors considered severity through the following aspects: product importance, cost, and quality. In [33], severity is decomposed into the following components: safety, environment, production losses, performance losses, labor cost, and spare cost. The same authors argued that the RF referred to as detection has a hierarchical structure, including visible and inspection. Occurrence is analyzed in the same way as in the conventional FMEA method.

3.2. Modeling of Uncertainties

Due to rapid and continuous changes occurring in the environment, various uncertainties exist in almost all management problems. It can be stated that uncertainty is a key characteristic of decision-making models. Reasoning without appropriate modeling tools may lead to inaccurate conclusions [48].

The development of many mathematical theories, such as the fuzzy set theory, rough set theory, probability theory, uncertainty theory [49], etc., has enabled verbal phrases to be quantitatively described in an adequate manner.

In this section, special attention is given to the fuzzy set theory, as it is widely applied in modeling and handling uncertainties in the relevant literature. In addition, the application of some other mathematical theories is considered in modeling and processing uncertain data in problems aimed at improving the reliability and effectiveness of decision-making processes.

3.2.1. Fuzzy Set Theory

The fuzzy set theory was introduced by Zadeh [50]. This theory is designed to model the vagueness or imprecision of the human cognitive process. The basic characteristics of fuzzy sets are the membership function, granularity, and domain. The degree of membership typically takes values between 0 and 1. If the membership degree of an element in a set is zero, that element is completely excluded from the set, whereas if it is equal to one, the element is fully included.

A fuzzy number is a specific type of fuzzy set in which at least one value in the domain has a membership degree of 1. Granularity refers to the number of fuzzy numbers assigned to represent relative importance parameters, their values, and their level of effectiveness. Lootsma [51] suggested that no more than seven categories should be used. The domain of fuzzy sets can be defined on different measurement scales.

In real-world problems, uncertainties are often modeled using fuzzy numbers, as they require significantly less computational effort and complexity compared to fuzzy sets.

Different types of fuzzy membership functions, such as triangular, trapezoidal, and Gaussian fuzzy numbers, have been employed in modeling the relative importance and values of RFs. Higher-type fuzzy sets and higher-level fuzzy sets have not yet played a significant role in practical applications of fuzzy set theory [52].

Type-1 fuzzy numbers (FNs) and the associated fuzzy algebra rules [11,12] are well suited for representing the linguistic assessments of experts and are widely used in MADM studies. However, with increasing vagueness and uncertainty in the evaluation information provided by DMs, type-1 fuzzy sets often become inadequate for handling subjective assessments of high complexity.

To address this, interval type-2 fuzzy sets (IT2FSs) were introduced by Zadeh [50] as an extension of the classical fuzzy set concept. IT2FSs provide more accurate and robust results and offer greater design flexibility than type-1 fuzzy sets [53]. To overcome this, interval type-2 fuzzy numbers (IT2FNs) have been proposed as a simplified alternative. IT2FNs reduce computational burden while retaining key advantages. Therefore, introducing IT2FNs into FMEA and MADM frameworks can significantly enhance the applicability of these methods in dealing with highly uncertain problems.

An intuitionistic fuzzy theory was proposed by Atanassov and Gargov [54] to describe cognitive uncertainty and human hesitancy in decision-making. The advantages of using intuitionistic fuzzy sets (IFSs) include (1) the ability to represent interim stages during the decision-making process through intuitionistic indices and (2) the possibility of forecasting both best and worst-case outcomes.

An IFS is defined by three parameters, a membership function, a non-membership function, and an intuitionistic fuzzy index (or degree of uncertainty), which are all defined on a finite set. Intuitionistic fuzzy numbers (IFNs) represent special cases of IFSs [55], and they are defined over the real number line within the range (0,1). In the literature, two basic forms of IFNs are most commonly used: those with triangular and trapezoidal membership and non-membership functions. In [56], the authors introduced fuzzy soft numbers for representing uncertainty, and this approach has been increasingly applied in decision-making problems in recent years.

It should be emphasized that based on IFNs, several extensions have been developed: Pythagorean fuzzy numbers (PFNs), second-order intuitionistic fuzzy numbers [15]; Fermatean fuzzy sets (FFNs), third-order intuitionistic fuzzy numbers [17]; q-rung orthopair fuzzy sets (q-ROFSs), where q > 0; and p,q-rung orthopair fuzzy sets (p,q-ROFSs), where $p > 0$ and q > 0.

Many authors consider PFNs to be a novel tool for handling uncertainty and vague information. Compared with intuitionistic fuzzy sets, certain similarities as well as differences can be observed. A characteristic of both IFNs and PFNs is that they consider the membership degree and non-membership degree to describe the fuzzy characteristics of DMs. In PFNs, the assumption is introduced that the sum of the squares of the membership degree and non-membership degree is less than or equal to 1. On the other hand, IFSs only consider the sum of the membership degree and non-membership degree to be less than or equal to 1. This represents the fundamental difference between PFNs and IFSs. Therefore, PFNs fully consider the "true psychological" behavior of decision experts, and PFNs can adapt to more situations and have more practical applications [57]. These sets are generalized IFSs and are used in some cases where IFSs cannot address uncertainty [38]. PFNs present a more powerful method to resolve the uncertainty of real-world projects [58].

The concept of q-ROFSs was proposed by [59]. These fuzzy sets emerged from IFSs and PFNs but provide a more extensive range for decision makers to express imprecise and uncertain data compared to IFSs and PFNs. The interval-valued q-rung orthopair fuzzy sets (IVq-ROFSs) adopted for modeling uncertainties were introduced by [60] and have been applied in the relevant literature [36].

The Fermatean fuzzy sets (FFSs) were defined by Senapati and Yager [17]. One of the most significant elements of FFSs is the introduction of a new independent component: the degree of non-membership in IFSs. The novel q-ROFS concept, denoted as FFSs, is established with q = 3. The term "q" is used interchangeably with "level," referring to the rung of the complement. FFSs grant decision makers greater autonomy in expressing their assessments through the articulation of agreement (membership) or disagreement (non-membership) with viewpoints regarding the current state of a particular subject [61].

The Z-number theory was proposed by Zadeh [18] as a generalized version of uncertainty theory to handle unreliable numbers. This theory takes the concept of reliability into consideration. A Z-number can be defined as an ordered pair of two fuzzy sets $Z = (\widetilde{A}, \widetilde{B})$. The first fuzzy number, $\widetilde{A}$, is a fuzzy subset of the domain X, and it is considered the "value" or "assessment." The second component, $\widetilde{B}$, is a fuzzy subset of the unit interval representing the reliability of component $\widetilde{A}$, and it is considered the "certainty" or "confidence." The ordered triple $(X, \widetilde{A}, \widetilde{B})$ is referred to as a Z-valuation, which corresponds to an assignment statement and is defined as a general constraint on X [62]. This constraint is known as a probabilistic constraint, representing a random variable X that has a certain possibility distribution.

The spherical fuzzy sets (SFSs) and neutrosophic sets (NFSs) were introduced in [16]. A fundamental characteristic of NFSs is their membership functions, which are defined based on three components called truth-membership, falsity-membership, and indeterminacy-membership. The sum of the values of these three components lies within the interval from 0 to 3. The membership functions of neutrosophic sets are defined so that the squared degrees of each component, separately, can vary between 0 and 1, allowing independent definition of each parameter within this range [63]. The degrees of membership functions in spherical fuzzy sets effectively express decision makers' awareness and accurately represent the extent of decision-making information [24].

The concept of picture fuzzy sets presents direct extensions of fuzzy set theory IFSs developed in [64]. Picture fuzzy sets can be represented by four membership functions: positive membership degree, neutral membership degree, negative membership degree, and refusal membership degree. These fuzzy sets may be suitable in situations where human opinions involve multiple possible responses, such as yes, abstain, no, refusal.

The concept of soft sets was defined as a new mathematical theory for handling uncertainty by [65]. A soft set is defined as a set characterized by an approximate function representing a mapping of elements of the universe. This function can be arbitrary, empty, or non-empty. It should be noted that the parameters and approximate functions are described by precise numbers. In fuzzy soft sets, parameters are crisp, and approximate functions are fuzzy subsets of the universe.

Fuzzy Belief Structure (FBS) presents an extension of the Belief Structure (BS) introduced by [21,22]. It can be said that FBS is defined as an extension of ordinal fuzzy sets. In BS, the linguistic variables of evaluation grades are considered as crisp values. In order to increase the accuracy of the assessment of ambiguity and vagueness that exist in real-world problems, [66] introduces FBS. In FBS, evaluation grades deal with fuzziness or vagueness, while the belief degrees handle incompleteness or ignorance. In fact, an FBS is a combination of fuzzy set theory and the evidence combination rule of Dempster–Shafer theory and, therefore, it is a powerful method for dealing with uncertainty [67].

Probabilistic interval-valued hesitant fuzzy sets (PIV-HFSs) were developed from probabilistic hesitant fuzzy sets (P-HFSs) in [68]. When probability information is provided by decision makers, interval values are widely used to express evaluation information. Utilizing PIV-HFSs to express information requires less skill and experience. The main characteristics of PIV-HFSs are the membership function and hesitant fuzzy element. In the relevant literature, PIV-HFSs have been applied in [32,69].

3.2.2. Rough Set Theory

Rough set theory was introduced by Pawlak [19]. It can be defined as an effective and efficient tool to handle imprecision, vagueness, and ambiguous information from DMs. According to rough set theory, it enables DMs to express true and objective evaluations without any prior information. Objects are classified into similarity clusters (elementary sets) by rough set theory. The objects in a cluster may have relationships with the corresponding attributes. These similarity clusters are then employed to determine hidden patterns, as in data mining [70].

The rough number was first proposed in [71], inspired by rough set theory, with the purpose of handling subjective judgments of customers and determining boundary intervals. A rough number usually contains a lower limit, an upper limit, and the rough boundary interval, which depends solely on the original data. Thus, it does not require any auxiliary information and can better capture experts' real perceptions and improve the objectivity of decision-making [26].

Certain researchers advocate combining two or more mathematical areas to determine quantitative values of treated uncertainties more precisely [25]; for instance, fuzzy set theory and rough set theory. In [72], the authors considered the problem of the evaluation and ranking of failures for the oblique multi-petal envelope check valve. According to the authors, during normal operation, the disc of the check valve remains open to allow forward flow. When the fluid changes direction, the disc closes under hydraulic pressure to prevent reverse flow and protect critical equipment from damage. The relative importance of RFs, as well as their values at the level of identified failures, are described by fuzzy rough numbers. The weight vector is determined by applying the proposed Analytic Hierarchy Process (AHP) with fuzzy rough numbers. The priority of critical equipment protection from damage is determined using the multi-criteria optimization and compromise solution (the acronym in Serbian is VIKOR) method with fuzzy rough numbers.

3.2.3. Cloud Theory

The cloud model theory is based on probability theory and fuzzy set theory, which considers randomness by randomizing the fuzzy membership. This theory was proposed in [20]. It represents a new approach for reciprocal conversion between qualitative concepts and quantitative representation based on the interaction between probability theory and fuzzy mathematics [73]. Uniquely considering randomness and uncertainty, the cloud model is able to represent qualitative concepts with uncertainty. In this way, distortion and loss of information in linguistic information processing can be significantly reduced. According to many authors, the cloud theory has exceptional capability in handling uncertainty.

3.2.4. Other Approaches

The concept of Probabilistic Linguistic Term Set (PLTS) was proposed in [74] by combining linguistic terms and their respective probabilities. PLTS can be defined as a useful extension of fuzzy sets, which fully expresses the hesitation of DMs as well as the probability that the hesitation of DMs occurs. The linguistic terms should be converted into certain semantic values during the evaluation, and different values should be assigned according to different usage situations [75]. A new linguistic function was defined in [76], through which linguistic terms are converted into numerical scales. It should be emphasized that the fact that the same linguistic terms can express different semantics in different situations is ignored, which leads to problems of information loss and distortion [77].

Evaluations of different uncertain data using different linguistic term sets bring difficulties in calculating evaluations by fuzzy logic. Linguistic variables obtained by applying any algebraic rule are converted into elements that are difficult to compare with predefined linguistic expressions. Furthermore, this approximation will lead to information loss and a lack of precision in the final results [78]. In order to overcome these deficiencies, based on symbolic transformation, in [79] an interval 2-tuple linguistic variable (ITLV) composed of two linguistic terms and two crisp numbers is proposed. The advantages of ITLV are as follows: decision makers use different linguistic term sets to express their evaluations, and its computations can be compared without an approximation process [80].

4. Failure Mode and Effect Analysis Integrated with Multi-Attribute Decision-Making Under Uncertainty

In this section, all analyzed papers are classified according to two criteria: (1) methods for determining the weights of RFs and (2) methods for prioritizing failure modes. In Section 4.1, MADM methods, as well as some subjective methods, extended with uncertain numbers and used for determining the weights of RFs, are analyzed. In Section 4.2, MADM methods extended with uncertain numbers, which have been used in combination with the FMEA framework for prioritizing failure modes, are analyzed. The order of these MADM methods is based on the classification provided in studies [29,81].

It makes sense to apply conventional FMEA if it is assumed that RFs have equal weights and if it is possible to assess the RFs using the standard evaluation prescribed in the conventional FMEA method. However, best practice experience shows that in companies operating across different economic sectors, it is more realistic to assume that RFs do not have equal weights. Due to rapid and continuous changes occurring in an uncertain business environment, the values of RFs cannot be described using precise numerical values. Based on these facts, it follows that the assessment and ranking of failure modes should be based on the application of FMEA combined with MADM methods extended by uncertain numbers, especially in companies that operate under uncertainty and belong to various economic sectors.

4.1. Determination of Weight Vectors

Generally, the weights of RFs can be determined using subjective and objective methods. In this research, special attention is focused on MADM methods with uncertain data that have been used in the analyzed papers.

All methods for determining weight vectors can generally be divided into two groups: subjective and objective methods. It should be emphasized that the accuracy of the solutions obtained using subjective methods depends entirely on the knowledge and experience of the decision makers. These methods are easy to understand and apply for practitioners, which is why they are frequently used in solving real-life problems. On the other hand, obtaining weight vectors in an exact manner, i.e., using objective methods, requires more complex calculations and greater expertise from decision makers, but at the same time, the accuracy of the resulting weights is higher. The following section presents some basic characteristics of the objective methods analyzed in this paper.

The AHP method is based on the assumption that DMs can more easily assess the relative importance of attributes when comparing each pair of attributes individually. In the Best Worst Method (BWM), two matrices are constructed: one for the Best-to-Others and one for the Worst-to-Others comparisons. The main characteristic of these two MADM methods is that the input data depend on the knowledge and experience of the DMs. Both methods include procedures for consistency checking, which makes it possible to assess whether the errors made by DMs affect the accuracy of the solution. By applying the Decision-Making and Trial Evaluation Laboratory (DEMATEL) method, in addition to determining the weight vectors, it is also possible to assess the strength of the interrelationships among RFs. The weight values of RFs obtained using the Entropy and Criteria Importance Through Inter-criteria Correlation (CRITIC) methods are not influenced by the subjective opinions of DMs. However, this statement does not hold in cases where the values in the decision matrix are described using linguistic terms. It can be said that the main drawback of the Entropy and CRITIC methods is the absence of a procedure for evaluating how decision makers' estimation errors affect the accuracy of the solution.

4.1.1. Analytic Hierarchy Process

AHP was introduced by Saaty in the 1970s. This method is one of the most widely used MADM techniques for solving various managerial problems, primarily for determining the weights of attributes. The consistency of the DMs' assessments is verified by applying the eigenvalue method [82].

Today, various extensions of the AHP method based on the fuzzy set theory exist. The extent analysis method [83] is widely used in the literature to address uncertainty and has been applied in [43,84]. In this method, a fuzzy pairwise comparison matrix is constructed to evaluate the relative importance of attributes based on the consensus of DMs [43,84,85]. The authors examined the consistency of the constructed fuzzy pairwise comparison matrices.

In [85], the authors obtained representative scalars of FNs describing the weights of RFs by applying a defuzzification procedure. In a large number of studies found in the literature, this method is used to determine the weights of attributes regardless of the type of fuzzy numbers used to handle the uncertainty of attribute importance. The weights vector is provided through the application of this method in [39,86–88].

The weights vector is determined by the proposed AHP method extended with Pythagorean Fuzzy Sets (PFSs) in [89]. The aggregation of evaluations of failure modes is performed using the Fermatean fuzzy weighted average operator by [61], and the weights are determined by AHP with FFSs.

4.1.2. Ranking-Based Procedure Using Fuzzy Numbers

In some of the analyzed studies [90,91], the relative importance of RFs is expressed using a fuzzy pairwise comparison matrix, following the FAHP approach. These authors argue that the determination of the weights vector should be based on a procedure for comparing fuzzy numbers.

In the analyzed studies, it was assumed that multiple DMs evaluate the relative importance of each pair of RFs using predefined linguistic variables, which are modeled by interval type-2 trapezoidal fuzzy numbers (IT2TrFNs). The aggregated value is obtained by applying the fuzzy arithmetic mean. By applying the proposed procedure, the RF weights are determined and expressed as crisp values.

4.1.3. Best Worst Method

The BWM was introduced by Rezaei [92]. Many authors suggest that it is much easier for DMs to assess the relative importance of attributes using the logic behind the BWM than when using pairwise comparison matrices as in AHP. In [34], the authors determined the weights vector by applying the conventional BWM.

In the analyzed studies, many authors extended the BWM with FNs and determined the weights vector using the developed procedure [93] (e.g., [41,94]). It should be noted that the authors in [94] considered the assessment of the relative importance of RFs as a fuzzy group decision-making problem. Using a fuzzy weighted averaging operator, the assessments of the DMs were aggregated into a single evaluation.

Several authors of the analyzed papers extended the BWM with IT2FNs [47,95,96]. In [47,95], it is assumed that multiple DMs evaluate the relative importance of the RFs. The aggregation of the DMs' assessments was performed by the fuzzy geometric mean in [95] and by the fuzzy arithmetic mean in [47]. By applying the proposed procedure [97], a fuzzy weights vector was determined in both [95,98].

In [47], the authors determined the weight of an RF component denoted as severity. These authors first transformed the two BWM matrices with IT2FNs into conventional BWM matrices using a defuzzification procedure [99] and then determined the weights of the components using the conventional BWM.

Some authors used the BWM for determining the RF weights by extending it with different fuzzy sets: (i) the BWM with SFSs in [100], (ii) the BWM with Z-numbers in [42], and (iii) the BWM with PLTS in [101]. These authors used the multiple semantics probabilistic linguistic averaging operator to aggregate the evaluations of the DMs.

4.1.4. Decision-Making and Trial Evaluation Laboratory

The DEMATEL [102] method is one of the widely used methods for determining attribute weights. The elements of the influence matrices are modeled by IT2TrFNs in [46]. The aggregated values of this matrix are obtained using weighted averaging methods. The normalized direct-relation matrix is derived by applying a linear normalization procedure. The total relation matrix with IT2FNs, structural correlation analysis, and weights vector is provided by following the procedure of conventional DEMATEL combined with type-2 fuzzy algebra rules [13].

4.1.5. Step-Wise Weight Assessment Ratio Analysis

The Step-Wise Weight Assessment Ratio Analysis (SWARA) approach for assigning appropriate weights to the attributes was introduced in [103]. Mavi [104] suggests that various factors, such as incomplete information, qualitative judgments of DMs, inaccessible data, and uncertainty, make decision-making challenging in a fuzzy environment. Therefore, the determination of the weights vector significantly depends on the knowledge and experience of the DMs. The coefficient of an RF for each DM is determined by (i) applying the weighted averaging operator with PFSs [105] in [38], (ii) following the conventional SWARA procedure combined with Z algebra rules in [40], and (iii) using the spherical weighted geometric mean [106] in [41]. The initial and relative weights are calculated according to the proposed procedure of the conventional SWARA approach, the (i) Pythagorean fuzzy algebra rules [105] in [38], and (ii) the spherical fuzzy algebra rules [16] in [41]. In this way, the weights of the RFs are described by precise (crisp) values. In [40], SWARA with Z-numbers is proposed, and by applying it, a fuzzy weights vector is obtained.

4.1.6. Entropy Method

Shannon's entropy (see [107,108]) is a measure of information uncertainty defined within probability theory. In this way, the uncertainties of DMs evaluating the relative importance of RFs in the analyzed papers can be adequately expressed. Many authors argue that this method can be successfully applied to determine the objective weights of RFs [37,109–111]. The entropy method with triangular fuzzy numbers (TFNs) is applied in [110]. The authors converted the fuzzy decision matrix into crisp values using the simple gravity method. Then, the weights vector was determined using the conventional entropy method.

In [112], the authors introduced the assumption that the relative importance of RFs was formulated as a fuzzy group decision-making problem. The aggregated values were obtained using the fuzzy geometric mean and the proposed procedure, respectively. In the remaining four analyzed papers, the weights vector was determined according to the procedure proposed in the conventional entropy method. In [109], the evaluations of DMs were aggregated using the fuzzy number intuitionistic fuzzy geometric operator. The weights were then derived using the procedure proposed in the conventional entropy method combined with a distance-based approach. Similarly, in [113], the authors determined the RF weights using the fuzzy entropy method combined with the interval intuitionistic fuzzy distance [114]. By applying the similarity degree based on cross-entropy with interval-valued neutrosophic sets (IVNSs) [115], the weights of RFs were determined in [111]. The cloud entropy method was proposed and applied in [37].

4.1.7. Subjective Methods

In some papers, the authors determined the RF weights by applying subjective methods. Many authors [33,73,116–118] assumed that the weights are described by precise numbers and are mutually equal. Several authors [119–121] defined the RFs by consensus using predefined linguistic expressions, which were modeled by type-1 fuzzy numbers. Many authors formulated the evaluation of the relative importance of RFs as a fuzzy group decision-making problem. The weights of RFs were determined by applying (i) the fuzzy averaging method [122], (ii) the power average operator method in [90], (iii) a fuzzy geometric mean with IFNs in [123], a fuzzy geometric mean with type-1 fuzzy numbers [45], (iv) the spherical weighted arithmetic mean operator [16] in [124], (v) the interval-valued q-rung orthopair fuzzy weighted Maclaurin symmetric mean operator [125] in [36], and (vi) the Delphi technique with TFNs in [44].

4.1.8. Other Methods

In many of the analyzed papers, the authors used various proposed methods to determine the weights vector, which are briefly presented below. Many authors assessed the relative importance of RFs by consensus [56,67,72,113,126–130]. The assessment of the relative importance of RFs is stated as a fuzzy group decision-making problem in many papers [75,131–134]. Aggregation was carried out using different operators; for instance, the intuitionistic fuzzy weighted averaging operator [131,132], the interval-valued Pythagorean fuzzy priority power weight average operator [133], the 2-tuple weighted average in [75], and the interval-valued intuitionistic fuzzy weighted averaging [134]. The weights vector was determined by applying different methods as follows: (i) the normal distribution technique is adopted to derive these weights [56,132], (ii) the maximization deviation model [129,130,133,134], (iii) the proposed procedure [75,131], (iv) combining Fuzzy Analytic Hierarchy Process (FAHP) and Shannon entropy [72,126], (v) combining the maximum deviation method and AHP [113], (vi) logarithmic fuzzy preference programming [127], (vii) the combination weighting model of game theory, and (viii) a non-linear programming model [135]. In [69], the authors proposed a new FMEA framework in combination with hesitant fuzzy aggregation tools and the CRITIC method.

4.2. Determination of Priorities

The MADM methods extended with uncertain numbers represent a branch of operations research that has been extensively used by researchers to overcome one of the shortcomings defined by [9,10]. As is well known, the implementation of any MADM method—whether conventional or extended with uncertain data—is carried out through several steps: (1) construction of the decision matrix, (2) construction of the aggregated decision matrix, (3) construction of the normalized decision matrix, and (4) application of the proposed algorithms.

In this section, each of the above-mentioned steps is analyzed separately. The applied algorithms of MADM methods are analyzed according to the categories given in the classification of MADM [29,81]. The main characteristics of MADM methods belonging to the following classes are as follows. (1) Outranking methods are characterized by comparing the values of each pair of alternatives at the level of each criterion. (2) Distance-based methods are defined by calculating the distance of each alternative's value for each attribute from the maximum and minimum values of the considered attribute. (3) Utility-based methods are characterized by ranking alternatives based on a utility function, which is defined differently for each method. (4) For MADM methods classified under the fourth category (other methods), no general characteristic can be defined.

4.2.1. Decision Matrix Under Uncertainty

In the analyzed papers, the authors have used different theories for handling uncertain elements of the decision matrix: (i) FNs [43–45,84,94,110,113,118–120,122,126,127,136–142], (ii) IT2FNs [46,47,86,90,91,95,143,144], (iii) PFNs [38,89,132,133], (iv) IFNs [123,128,131,134,135,137,145–148], (v) other fuzzy numbers [24,34,36,39–41,56,61,62,100,111,116], (vi) cloud theory [33,37,73], (vii) crisp [85,87,149], and (viii) other mathematical theories [67,75,101,109,117,129,130].

4.2.2. Aggregated Decision Matrix Under Uncertainty

In the 27 analyzed papers, the authors assumed that the evaluation of RFs was obtained by consensus. In the remaining 41 papers, these values were defined as a group decision-making task. The used aggregation operators are as follows:

- Fuzzy averaging mean: (i) with FNs and IT2FNs [43,44,120,122,137], (ii) with PFSs [89,134], (iii) with the fuzzy soft number [56], and (iv) with Z-numbers [42].
- Fuzzy geometric mean: (i) with FNs [112], (ii) with intuitionistic fuzzy numbers [109], (iii) with Z-numbers [39], and (iv) the single-valued spherical geometric mean weight [100].
- The weighted operator: (i) with FNs and IT2FNs [73,120], (ii) the interval intuitionistic weighted averaging operator [113,128], (iii) with PFSs [132] and the interval-valued Pythagorean fuzzy priority power weight average operator [133], (iv) the picture fuzzy weighted arithmetic average operator [34], (v) with FFSs [61], (vi) the single-valued neutrosophic weighted averaging operator [116], the interval-valued neutrosophic weighted averaging operator [111], and the spherical weighted geometric mean [41], (vii) the interval-valued q-rung orthopair fuzzy weighted geometric operator [36], (viii) the cloud weighted averaging operator [33], (ix) the 2-tuple weighted average operator [75], and (x) the probabilistic interval-valued hesitant fuzzy weighted average operator [32].
- Others: (i) the individual belief degree [67], (ii) the single semantic probabilistic linguistic averaging operator [101], (iii) the cloud hybrid aggregation operator [37], (iv) the different proposed procedures [45,84,117], (v) the power aggregation operator [90], and (vi) IFNs [150].

4.2.3. Normalization Procedures

The RFs, as well as their components, can be of both benefit and cost types. In order for the values of the decision matrix elements to be comparable, a normalization procedure must be applied. When assessing the values of the decision matrix elements, many authors suggest that DMs should take into account the type of attribute. On the one hand, this approach requires DMs to invest greater effort during the evaluation, which increases the likelihood of errors that may be unacceptable. On the other hand, the computational complexity and workload are significantly reduced.

In many studies, the authors did not apply a normalization procedure. Also, numerous proposed normalization procedures exist. The choice of a normalization procedure represents a problem in itself. The following are the normalization procedures used in the analyzed studies:

- The linear normalization procedure [42,43,45,46,56,84,110,120,126];
- The vector normalization procedure [40,41,62,118];
- The max–min normalization procedure [110];
- The min–max normalization procedure [100];
- Weitendorf's linear normalization [110];
- Other proposed normalization procedures [34,36,38,39,41,46,61,67,95,117,128,149].

4.2.4. Outranking Methods

In this section, an analysis of the papers is presented in which failures were ranked using the proposed outranking MADM methods.

Preference Ranking Organization METHod for Enrichment of Evaluations

The Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) was proposed by [151]. This method can be efficiently applied when alternatives are compared in pairs. It adopts the concept of rank-no-lower relationship as its core idea, uses a preference function to compare alternatives, and incorporates the objective assessment of DMs. There are six commonly used criteria for determining the preference function.

In [135], the authors employed the Gaussian preference function, which exhibits a non-linear variation characteristic. In [130], the authors first converted the decision matrix with linguistically labeled numbers into a numerical decision matrix. The preference of an alternative was then described using a linear function defined over an interval.

In [73], the elements of the decision matrix using cloud theory are described. The distances between intervals were characterized by the second-type preference function [151]. The net flows were calculated following the procedure of the conventional PROMETHEE method [73,130,135]. The ranking of the considered alternatives was determined based on the global risk index, which was expressed using precise numbers.

Decision-MAking Trial and Evaluation Laboratory

The DEcision-MAking Trial and Evaluation Laboratory (DEMATEL) method with triangular fuzzy numbers (TFNs) was applied in [121], while DEMATEL with trapezoidal fuzzy numbers (TrFNs) was applied in [136]. In these studies, the fuzzy initial direct-relation matrix is constructed. Normalization is carried out using the adopted max normalization procedure. In this way, the elements of the normalized initial direct-relation matrix are described by TrFNs.

The fuzzy total relation matrix, as well as the causal diagram, are obtained following the procedure proposed in the conventional DEMATEL method and the fuzzy algebra rules [12]. The ranking of alternatives is determined based on the crisp coefficient values.

Interactive and Multi-Criteria Decision-Making Method

The Interactive and Multi-criteria Decision-Making method (the acronym in Portuguese is TODIM) [152] is based on prospect theory. The core idea of this method is to determine the dominance degree of each alternative over the others using a utility function derived from prospect theory.

The dominance of each alternative relative to the others at the level of each attribute is calculated according to the procedure proposed in the conventional TODIM method, employing different distance measures: Hamming distance with IVFs in [111], a combination of Hamming and Hausdorff distances with IVFSs [48] in [120], a novel Hausdorff distance for PLTSs [74] in [101], and distance measures between two probabilistic interval-valued hesitant fuzzy sets (PIV-HFEs) [68] in [129].

In [153], the authors applied the TODIM method in combination with IT2TFNs. In all the aforementioned papers, the dominance degree of each alternative, the overall dominance degree, and the global prospect values of the alternatives are computed following the procedure proposed in the conventional TODIM approach.

Measurement of Alternatives and Ranking According to COmpromise Solution

The Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) method was developed in [154]. The MARCOS method was extended with IT2FNs [46]. In that study, the weighted normalized fuzzy decision matrix is converted into a crisp weighted normalized decision matrix by applying a defuzzification procedure [155].

The ideal and anti-ideal solutions, as well as the utility functions with respect to the reference values, are calculated in accordance with the procedure defined in the conventional MARCOS method. The ranking of the alternatives is then determined based on the obtained utility function values.

Organization, Ranking, and Synthesis of Relational Data

The Organization, Ranking, and Synthesis of Relational Data (the acronym in French is ORESTE) method was proposed by [156]. The ORESTE method does not require the quantification of criteria weights or the exact evaluation of alternatives but rather relies solely on their ordinal assessment. In this way, a global preference structure over the alternatives is constructed. This method is particularly useful in situations where decision makers are unable to provide precise evaluation data.

The ORESTE method was extended with IT2FNs in the studies by [90,143]. In both analyzed papers, Besson's ranks and the global preference scores were calculated following the conventional ORESTE procedure. The determination of the global weak ranking was carried out according to the approach proposed in [153] and the comparison procedure for two IT2FNs developed in [157]. The preference intensities and the partial information ranking structure were established in accordance with the standard ORESTE methodology.

4.2.5. Distance-Based Methods

Distance-based methods have a wide application in solving evaluation and failure selection problems that exist across different domains. Furthermore, an analysis is presented of the considered papers in which the proposed methods belong to this class.

Technique for Order Preference by Similarity to Ideal Solution

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the most powerful and widely used MADM methods for ranking various alternatives [28]. It was introduced by [158]. The best alternative is defined as the one with the greatest distance from the negative ideal solution and the smallest distance to the positive ideal solution.

In the analyzed papers, many authors have suggested the use of the TOPSIS method extended with FNs for the ranking of failures [43,84,119,120,126,127]. The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) can be determined in two ways: (i) the procedure proposed by [157], as applied in [84,119], and (ii) the veto concept [159], used in [43,120,126,127].

The distances between the elements of the weighted normalized fuzzy decision matrix and FPIS/FNIS are determined using the Euclidean distance [160] in all analyzed papers. In this way, the closeness coefficient values are described by precise numbers. The rank of alternatives is determined according to the procedure proposed in conventional TOPSIS.

Some authors [46,91] have proposed the use of TOPSIS with IT2FNs for ranking failures. The fuzzy positive ideal solution with IT2FNs (IT2FPIS) and the fuzzy negative ideal solution with IT2FNs (IT2FNIS) are determined according to the veto concept [46,91], which transformed the weighted normalized fuzzy decision matrix into a decision matrix with precise numbers by applying a defuzzification procedure.

The distances to IT2FPIS and IT2FNIS are calculated according to the procedure proposed in conventional TOPSIS combined with fuzzy algebra rules [13], as in [91]. In this way, the closeness coefficient values are modeled using IT2FNs. The ranking of alternatives is given using representative scalars obtained through the defuzzification procedure proposed in [155]. The distances and ranking of alternatives are determined by applying conventional TOPSIS in [46].

Some authors have proposed TOPSIS with IFNs [131]. The PIS and NIS with IVFNs can be denoted as IFPIS and IFNIS, which are determined by respecting the procedure proposed in [157] combined with intuitionistic fuzzy sets and applied in [131]. The distances from IFPIS and IFNIS are calculated using the Intuitionistic Fuzzy Hybrid Weighted Euclidean Distance [137].

In [132], TOPSIS with PFNs is proposed. The positive ideal solution (PIS) with PFNs–PFPIS—and the negative ideal solution (NIS) with PFNs–PFNIS—are determined according to the procedure proposed in [157] combined with PFSs. The distances from PFPIS and

PFNIS are determined using the procedure given in [137]. The ranking of failures is obtained by applying the procedure proposed in conventional TOPSIS.

Using single-valued neutrosophic sets (SVNSs), which are a special version of neutrosophic sets (NSs), the conventional TOPSIS method was extended in [116]. It is known that SFSs represent an integration of PFSs and NSs, as introduced by [16]. TOPSIS with SFSs was proposed by [24].

The fuzzy positive ideal solution with SFSs (IVSFPIS) and with SVNSs (RNPIS) and the fuzzy negative ideal solution with SFSs (IVSFNIS) and with SVNSs (RNNIS), as well as the distances to IVSFPIS or RNPIS and IVSFNIS or RNNIS, are defined in [16] or [161,162]. The ranking of failures is determined according to the procedure of conventional TOPSIS.

TOPSIS extended with cloud theory was proposed in [33]. The cloud positive ideal solution (CPIS) and the cloud negative ideal solution (CNIS) are defined by an analogy procedure [157]. In this paper, the distance used between arbitrary clouds is defined in [163]. The ranking of failures is given according to conventional TOPSIS.

In [75], the authors extended the TOPSIS method with 2-tuple linguistic variables (ITLVs). The positive ideal solution with ITLVs and the fuzzy negative ideal solution with ITLVs are constructed by analogy to the conventional TOPSIS procedure. The ranking of failures is based on crisp closeness coefficient values.

TOPSIS with Fermatean bipolar sets was proposed in [117]. The positive ideal solution with Fermatean bipolar sets (PIBSs) and the negative ideal solution with Fermatean bipolar sets (NIBSs) are defined by analogy to conventional TOPSIS. The values of PIBSs and NIBSs are the maximum and minimum values, respectively, with respect to each RF. Separation measures from PIBSs and NIBSs are calculated according to the procedure proposed in [164].

Multi-Criteria Optimization and Compromise Solution

VIKOR stands for multi-attribute optimization and compromise solution, which was developed in [165]. Many authors of the analyzed papers proposed VIKOR with FNs, which they used for ranking different failures. The FIS and NIS are determined according to the procedure proposed by [157], combining fuzzy set theory [44,94,113,118,122,137]. The fuzzy group utility value, the fuzzy minimum individual regret value for each failure, and the fuzzy index values are calculated using the proposed conventional VIKOR and fuzzy algebra rules [12] in [44,94,118,122]. The group utility values and minimum individual regret values are given by applying the proposed VIKOR combined with Euclidean distance [94,113,137]. The representative scalar values are obtained using graded mean integration [166] according to the performed ranking of failures [44,94,118,122]. The index values are crisp and provided according to the proposed VIKOR [94,113,137].

In [84], the authors transformed the weighted normalized fuzzy decision matrix into a decision matrix by graded mean integration [166]. After that, the conventional VIKOR method was applied to determine the ranking. The set of compromise solutions is determined by applying both condition rules in all the above analyzed papers.

The extension of VIKOR with IT2FNs is proposed in [95]. The IT2FPIS and IT2FNIS are determined according to the veto concept. The group utility values and the minimum individual regret values are calculated respecting the conventional VIKOR method combined with type-2 fuzzy algebra rules [13] so that these values are modeled by IT2FNs. Using distances between two interval type-2 triangular fuzzy numbers (IT2TFNs) [167] and the conventional VIKOR, the index values are calculated and described by precise numbers. The set of compromise solutions is determined by applying both condition rules.

VIKOR with IFNs is suggested in some analyzed papers [109,123,128], proposing VIKOR extended with Interval Type-2 Intuitionistic Fuzzy Numbers (IT2IFNs). The FPIS and FNIS are determined according to the procedure proposed in [168] in studies applying IFNs and IT2FNs. The fuzzy group utility value, fuzzy minimum individual regret value for each failure, and fuzzy index values are calculated using the proposed conventional VIKOR method combined with fuzzy algebra rules. The crisp index values are obtained by applying the graded mean integration with IFNs. The group utility values and minimum individual regret values are calculated by applying the proposed VIKOR combined with distance measures between two IFNs as follows: (i) according to [160] in [123], (ii) according to [169] in [128], and (iii) according to [170] in [109] so that the index values are crisp and given according to the proposed VIKOR method. The set of compromise solutions is determined by applying the condition rules [123,128],

In [72], the authors proposed VIKOR with fuzzy rough sets. The FPIS and FNIS are determined according to the procedure proposed in their paper. The fuzzy group utility value, the fuzzy minimum individual regret value for each failure, and the fuzzy index values are calculated using the proposed conventional VIKOR method combined with fuzzy rough algebra rules. The crisp index values are obtained by applying the procedure proposed in [25].

VIKOR extended with cloud theory is proposed in [37]. The FPIS and FNIS are determined according to the procedure in conventional VIKOR combined with cloud theory. The procedure for determining the fuzzy group utility value and the fuzzy minimum individual regret value for each failure is proposed in [171]. The index values are calculated by applying the conventional VIKOR method using the Hamming distance [170].

Using FFSs, in [67], the VIKOR method is extended. The elements of the PIS and NIS with FFSs are evaluation grades consisting of crisp numbers in ordinal FFSs. The group utility value and the minimum individual regret value for each failure are calculated by applying the conventional VIKOR procedure and the distance between two FFSs [164]. The crisp index values are obtained by applying the conventional VIKOR procedure.

Multi-Attributive Border Approximation Area Comparison

The Multi-Attributive Border Approximation Area Comparison (MABAC) method was introduced in [172]. The fundamental concept of the MABAC method involves defining the distance of the criteria function for each considered alternative from the border approximation area. The weighted decision matrix and the border approximation area vector are determined by applying the proposed procedure within conventional MABAC combined with fuzzy algebra rules [13]. Based on the Euclidean distance between two PFNs [34], membership to the upper or lower approximation areas is determined. The closeness coefficient to the border approximation areas and the ranking of alternatives are provided according to the conventional MABAC method.

Multi-Attributive Ideal Real Comparative Analysis

The Multi-Attributive Ideal Real Comparative Analysis (MAIRICA) [173] was extended with IT2FNs in [46]. The preferences for alternative selection are calculated according to conventional MAIRICA. It is assumed that decision makers (DMs) are unbiased towards the selection of alternatives, and each alternative has an equal probability of being chosen as the most critical one. The fuzzy matrix of theoretical weights and the fuzzy matrix of actual weights are constructed following the proposed MAIRICA procedure and fuzzy algebra rules [13]. The total gap matrix is obtained using the defuzzification procedure developed in [155]. The criteria function values and the ranking of alternatives are determined by analogy with conventional MAIRICA.

4.2.6. Utility-Based Methods

The analyzed papers in which utility-based methods are proposed are presented in this section.

Weighted Aggregates Sum Product ASsessment

The Weighted Aggregates Sum Product ASsessment (WASPAS) method was introduced in [174]. The weighted fuzzy decision matrix is constructed using FNs in [118]. The ranking of identified failures is performed using a crisp common criterion, which is calculated by applying the graded mean integration method [166]. In [61], the authors considered the problem of risk assessment for occupational hazards in aquaculture operations with respect to RFs defined in conventional FMEA analysis. The values of the fuzzy decision matrices are modeled by FFSs. The aggregated fuzzy decision matrix is obtained by applying the Fermatean fuzzy weighted average operator [17]. The common criteria values are calculated by applying the conventional WASPAS procedure and fuzzy algebra rules [17]. The ranking of identified occupational hazards is determined according to crisp values of the common criterion, which are obtained by the score function.

COmplex PRoportional ASsessment

The preference ranking method of COmplex PRoportional ASsessment (COPRAS) was proposed in [175]. It assumes direct and proportional dependencies between the significance and utility degree of the available alternatives in the presence of mutually conflicting criteria.

COPRAS with FNs was proposed in [176]. The sums of benefit-type RF values, which are larger values, and the sums of cost-type RF values, which are smaller values, are calculated according to the procedure proposed in conventional COPRAS combined with fuzzy set theory.

Similarly, the relative weight of each alternative is calculated so that these values are described by FNs. The ranking of failures is given according to the representative scalar values of the calculated relative weights. These representative scalar values are obtained using the simple gravity method.

In [86], the authors proposed COPRAS with IT2FNs. These authors transformed the weighted fuzzy decision matrix into a decision matrix using a defuzzification procedure [155]. The sum of benefit-type values, the sum of cost-type values, the relative weight values, and the ranking of failures are calculated by applying the procedure proposed in conventional COPRAS.

The ranking of failures is performed by COPRAS with PFSs in [38]. These authors determined the sum of benefit-type and sum of cost-type values based on the weighted normalized fuzzy decision matrix, whose elements are described by PFSs. Thus, the calculated values are represented by PFNs. The determination of relative weight values is based on the basic concept of PFSs and their functions [177].

COPRAS with fuzzy soft sets was proposed in [56]. The sum of benefit-type and sum of cost-type values is determined based on the procedure proposed in conventional COPRAS and fuzzy algebra rules [65]. Using the Choquet integral and based on the normalized fuzzy soft sets [65], the relative weight values are described by fuzzy soft numbers. The ranking of failures is given according to crisp relative weight values, which are obtained by applying the graded mean integration method [166].

Combined Compromise Solution

The Combined Compromise Solution (CoCoSo) was proposed in [178]. In [110], the authors proposed the CoCoSo with FNs. The CoCoSo with spherical fuzzy numbers

(SFNs) [16,63] is proposed in [41,100]. The sum of weighted comparability sequences and the sum of powered weights of comparability sequences for each alternative, as well as relative weights, are calculated according to the conventional CoCoSo combined with fuzzy set theory [12] in [110] and with spherical fuzzy numbers [16] in [41]. In [100], the authors transformed the fuzzy decision matrix into a crisp decision matrix. The ranking of alternatives is provided using the conventional CoCoSo method in all three analyzed papers.

4.2.7. Other Methods

Many MADM methods cannot be classified into any of the previously mentioned groups. In [29], the authors introduced a fourth group, labeled "other MADM." This section presents the proposed MADM methods that belong to this group and that have been developed in the analyzed papers.

Additive Ratio ASsessment

The Additive Ratio Assessment (ARAS) method was introduced in [179]. There are numerous papers in which the ARAS is extended with FNs [45,110,118]. The utility function values are calculated according to the procedure proposed in the conventional ARAS combined with fuzzy algebra rules [12], and they are also described by FNs [45,110,118]. The fuzzy utility function values are transformed into crisp values by applying the moment method in [118] or the defuzzification procedure [180] in [45]. The ranking of failures is performed according to the defined rules in the conventional ARAS. In [110], the authors transformed the weighted normalized fuzzy decision matrix into a decision matrix using the moment method. After that, these authors calculated the utility function values and ranking of failures according to the procedure proposed in the conventional ARAS.

The weighted normalized fuzzy decision matrix is constructed respecting the assessment of DMs and fuzzy algebra rules [181]. The ranking of failures is performed according to the degree of criticality values, which are described by precise numbers. The degree of criticality values is calculated as the Minkowski distance between the fuzzy overall criticality index and the fuzzy score function of the overall criticality index of the optimal failure. The distance used is the Minkowski distance [182].

In [39,42], the authors calculated the utility function values according to the conventional ARAS method and fuzzy algebra rules. The transformation of fuzzy values into crisp values was performed using the procedure by [183] in [39] and the graded mean integration method [166] in [42]. The ranking of failures is given with respect to the conventional ARAS method.

Multi-Objective Optimization on the Basis of Ratio Analysis

Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) is the process of optimizing two or more conflicting attributes concurrently with reference to certain constraints, developed in [184]. The traditional MOORA and MULTIMOORA (Multi-Objective Optimization on the basis of Ratio Analysis and the full MULTIplicative form) method consists of three submethods: the ratio system method, the reference point method, and the full multiplicative form method. MOORA focuses on identifying one or more feasible solutions that correspond to extreme values of one or more objectives. The MULTIMOORA method is characterized by simple calculations and strong robustness [184].

Some authors determined the rank of failures by applying the MOORA method extended with various types of fuzzy numbers. In [89], the authors proposed MOORA with PFSs. The ranking of failures is given according to crisp values.

In [40,62], three submodels of MOORA with Z-numbers were proposed. The difference between the sum of weighted benefit attribute values and the sum of weighted cost attribute values is calculated according to fuzzy algebra rules. The representative scalar values are obtained using the simple gravity method. The ranking of failures is determined according to the conventional MOORA.

In the second submodel, the authors defined a reference point whose elements are Z-numbers, following the procedure proposed in [157]. The derivation between the reference point and the elements of the weighted normalized fuzzy decision matrix is determined using the Euclidean distance. The failure with the smallest derivation value is ranked first.

The third submodel is proposed following the conventional MOORA procedure combined with Z-numbers. Representative scalars are obtained using the simple gravity method, and the ranking of failures is performed accordingly.

In [134], the authors proposed MULTIMOORA with IFNs. In this paper, the ratio method is constructed using the conventional MULTIMOORA procedure combined with fuzzy algebra rules. The score function is obtained by applying a defuzzification procedure. The distance between failures and the reference point is determined using the Minkowski metric method [185] combined with IFNs. The ranking of failures is given by applying the conventional MULTIMOORA.

MULTIMOORA with PFNs is proposed in [133]. The ratio submodel is constructed according to the conventional procedure with PFNs. Representative scalars are determined by a defuzzification procedure [186]. In the reference point submodel, the determination of the reference point is based on the veto concept. The distance between the reference point and the elements of the weighted normalized fuzzy decision matrix is calculated. The robust optimal solution is given using the Minkowski metric. The full multiplicative method with PFNs is determined according to the conventional MULTIMOORA with fuzzy algebra rules [15].

Risk Priority Number

The classification of failures in conventional FMEA is performed according to the RPN, which is calculated as the product of the values of the three defined RFs. Many authors, primarily [9,10], emphasize that this way of determining classification criteria is not mathematically justified. The literature contains a large number of studies in which authors have suggested various procedures to improve the RPN and, consequently, the classification process. The authors argued that classification of failures based on the FMEA approach is more understandable and easier to apply for practitioners.

In [85], the authors improved the procedure for calculating the RPN by considering the weights of the RFs. The overall RPN is calculated as the sum of the weighted RF values, which belong to the interval [1–10]. The ranking of failures is performed according to the conventional FMEA method.

In [136], the values of the risk RFs are described by fuzzy numbers (FNs). A formula was proposed for calculating the fuzzy risk priority number (FRPN) value as the product of the weighted RF values. It should be noted that the weighting is based on the principle of exponentiation. The representative scalars of the FRPNs were obtained by applying a defuzzification procedure known as the alpha-cut method [11]. The ranking of failures is performed according to the rules defined in conventional FMEA.

In [96], the authors assumed that the RF values are described by IT2TFNs. By applying a fuzzy inference system extended with supremum composition [187], the RPN with IT2FNs was determined. The representative scalars were obtained using a defuzzification procedure [155]. The ranking of failures is given according to the procedure defined in conventional FMEA.

In [47], the authors introduced the assumption that severity can be viewed from three aspects: the relative importance of products, quality, and cost. In this way, severity has three components. Severity assessments from the aspect of product importance and severity from the aspect of cost are performed by DMs who use predefined linguistic expressions. These linguistic variables are modeled by IT2FNs. Severity from the aspect of quality, as well as occurrence and detection at the level of each failure, were taken from the FMEA reports. The overall severity values were calculated by applying the fuzzy weighted order operator and are described by IT2FNs. Using the defuzzification procedure mathematical rules, the overall severity values are represented by precise integer values. The ranking of the considered failures is given using the procedure proposed in conventional FMEA as well as the Action Priority procedure proposed by [27].

In [87], the problem of classifying failures that can be identified in different products is discussed, considering both the RPN and product importance. The assumption was introduced that the total importance of a product depends on the weights of the RFs as well as the importance of the product within each RF. In this work, the total importance of the product is described by FNs. The RF values were taken from FMEA reports and are described by precise numbers within the interval (1-10). The RPN is calculated at the level of each product by applying the conventional FMEA method. The classification criterion is calculated as the product of the total product importance and the RPN. According to fuzzy algebra rules [12], the classification criterion is described by fuzzy numbers. By applying the defuzzification procedure [155], the classification criterion values are represented by precise numbers. Classification is performed using conventional Pareto analysis.

5. Results and Discussion

Many authors have proposed different approaches to overcome the limitations of conventional FMEA. In this paper, a comprehensive overview is provided of studies that employed MADM methods with uncertain numbers for assessing and ranking failure modes in FMEA published in international journals between 2015 and 2024. Furthermore, the results of the analysis of the considered papers are subsequently presented.

The following section of this chapter presents the analysis of the reviewed studies, including the frequency of applied MADM methods, approaches to modeling uncertainty, the domains of application, and the analysis of authors and publications.

5.1. Analysis of MADM Methods Integrated with Uncertainty Modeling Approaches

In all the reviewed studies that passed the rigorous screening process outlined by the PRISMA protocol, numerous extended MADM approaches were employed in combination with the FMEA framework. MADM methods, enhanced by various uncertainty modeling techniques, were used for two main purposes: determining the weights of RFs and establishing the prioritization/ranking of failure modes. Table 1 presents the connection between the MADM methods applied for these two purposes. In other words, it illustrates the combinations of these methods used to form hybrid MADM approaches.

In Table 1, it can be concluded that the TOPSIS method was used in the majority of studies, often in combination with the AHP method, and most frequently alongside various subjective methods and approaches for aggregating the evaluations of decision makers. The second most commonly used method is VIKOR, which is most frequently combined with the AHP method in the literature. As for the methods used to determine the weights of RFs, AHP and the BWM are the most prevalent.

Table 1. Applied MADM approaches extended with uncertainty modeling techniques in combination with the FMEA method.

RFs Weights/Failure Modes Priority	AHP	BWM	DEMATEL	Entropy	SWARA	Other/Subjective/Aggregation
ARAS	[45]					[36,39,45,118]
BWM		[99]				
CoCoSo		[100]			[41]	
COPRAS	[86]				[38]	[56,176]
DEMATEL						[121,136]
EDAS	[142]					
ELECTRE						[132]
MABAC		[34]				[148]
MAIRICA			[46]			
MARCOS			[46]			
MOORA	[89]	[62]			[40]	[63]
MULTI-MOORA						[133,134]
ORESTE						[90,143]
PROMETHEE						[73,130,135]
RPN/AP	[85]	[47]				[144]
TODIM				[111]		[101,113]
TOPSIS	[43,84,126]	[35]	[46]	[126]		[24,33,75,116,117,119,120,124,127,131,132,137,140,147,150,176]
VIKOR	[84,112,123,128,139]	[94,95]		[109,112]		[37,44,118]
WASPAS	[61]	[98]		[110]		[118]
Other	[87,88]					[69]

5.2. Approaches Used for Uncertainty Modeling

In this section, the results of different MADM methods under uncertain environments used for determining the weights of RFs and the priority of failure modes in the analyzed papers are presented. This analysis is shown in Table 2.

Table 2. Combination of MADM methods and uncertainty modeling approaches.

MADM Method	FSs	IT2FSs	IFSs	SFSs	PFSs	Z-Numbers	Other FSs	Other Theories
AHP	[43,45,84,85,87,99,126,142]	[86,88]	[123]		[89]	[45]	[61]	
ARAS	[45,118]					[45]	[36]	
BWM	[62,94,99]	[47,95,98]						[35]
CoCoSo				[41,100]				
COPRAS	[176]	[86]			[38]		[56]	
DEMATEL	[121,136]	[46]						
EDAS	[142]							
ELECTRE					[132]			

Table 2. *Cont.*

MADM Method	FSs	IT2FSs	IFSs	SFSs	PFSs	Z-Numbers	Other FSs	Other Theories
Entropy	[94,110]							
MABAC			[148]				[34]	
MAIRICA		[46]						
MARCOS								
MOORA				[63]	[89]	[40,62]		
MULTIMOORA			[134]		[133]			
ORESTE		[90,143]						
PROMETHEE			[135]				[130]	[73]
RPN/AP		[144]						
SWARA				[41]	[38]	[40]		
TODIM			[113]				[111]	[101]
TOPSIS	[43,84,117,119,120,126,127,137,140,176]	[46]	[131,147,150]	[124]			[24,75,116]	[33,35]
VIKOR	[44,84,94,112,118,139]	[95,128]	[109,123]					[37]
WASPAS	[110,118]	[98]					[61]	
Other	[45]						[69]	

By examining Table 2, it is clear that in the majority of papers, MADM approaches were extended through the application of basic FSs. Furthermore, IT2FSs and IFSs were frequently used by the authors. Other uncertainty modeling methods were not widely represented in the reviewed studies. Rarely used uncertainty modeling methods include SFSs, PFSs, and Z-numbers.

5.3. Application Domains of the Analyzed Approaches

This section presents the application domains of FMEA combined with MADM using uncertain numbers (Figure 2).

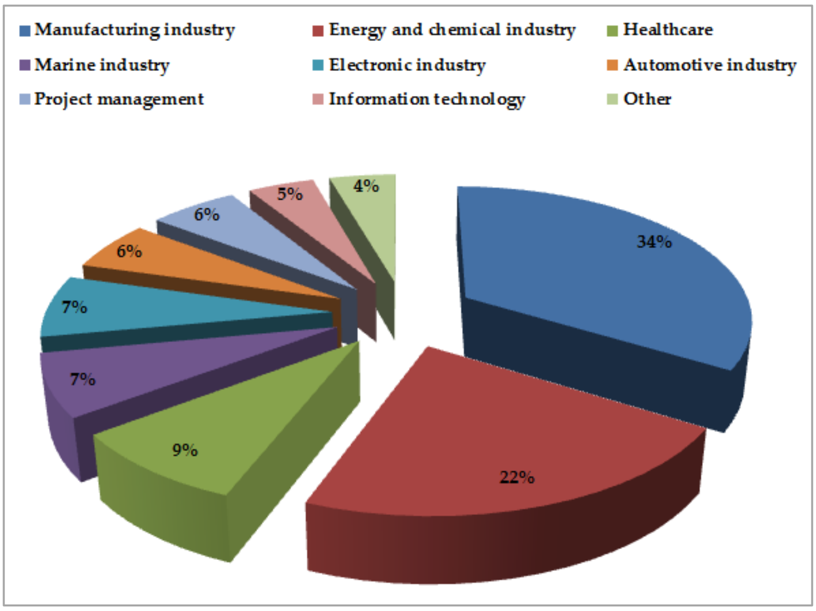

Figure 2. Applied research domains.

If the analyzed application domains are considered separately, it is possible to determine which MADM methods are most frequently used for each specific domain. This analysis is presented in Table 3.

Table 3. Distribution of MADM methods across application domains.

MADM Method	Manufacturing Industry	Energy and Chemical Industry	Healthcare	Marine Industry	Electronic Industry	Automotive Industry	Project Management	Information Technology	Other
AHP	[84,85,123,128]	[45,142]		[61]		[87,88]	[89]	[86,126]	[43]
ARAS	[36,39]	[45]	[118]						
BWM	[94,95,98]	[34]	[99,100]		[35]	[47,62]			
CoCoSo		[41]	[100]						
COPRAS	[56,176]	[38]						[86]	
DEMATEL	[46]			[136]	[121]				
EDAS		[142]							
ELECTRE					[132]				
Entropy	[94]							[126]	
MABAC	[148]	[34]							
MAIRICA	[46]								
MARCOS									
MOORA	[40]		[63]			[62]	[89]		
MULTI-MOORA							[133,134]		
ORESTE		[143]		[90]					
PROME-THEE		[130]	[73]		[135]				
RPN/AP		[144]							
SWARA	[40]	[38,41]							
TODIM	[111]	[101,113]							
TOPSIS	[24,33,46,75,84,117,124,127,140,176]	[119,131,150]		[116]	[35,137]			[120,126]	[43,147]
VIKOR	[84,94,95,123,128]	[44]	[112,118]	[37]			[139]		[109]
WASPAS	[46,98,110]		[118]	[61]					
Other		[45,69]							

Figure 2 and Table 3 present the distribution of applied MADM methods across different domains, as well as the number of distinct methods (without duplication) used in each application domain. As shown in Figure 2, the majority of studies were conducted in the manufacturing industry domain. In other words, the most frequent application was in production processes across various branches of manufacturing—such as furniture, food, metal products, etc.—all grouped under one category related to manufacturing activities. The automotive industry stands alone, being considered the original domain of FMEA application. FMEA was also found to be highly useful in the energy and chemical industry and healthcare domains.

When it comes to the representation of MADM methods by category (see Table 3), TOPSIS clearly dominates in the manufacturing industry. It is also the most frequently used method overall, appearing in 20 studies. TOPSIS is likewise the most commonly used method in the energy and chemical industry. In second place is the VIKOR method, which ranks second in the manufacturing industry domain and first in healthcare. In addition, COPRAS, ARAS, and MOORA each appear four times across the studies.

The analysis of application domains can also be viewed from the perspective of the applied uncertainty modeling approaches, as presented in Table 4.

Table 4. Distribution of uncertainty modeling approaches by application domain.

Applied Research Domain	FSs	IT2FSs	IFSs	SFSs	PFSs	Z-Numbers	Other FSs	Other Theories
Manufacturing industry	[84,85,94,110,117,127,140,176]	[46,95,98,128]	[123,148]	[124]		[39,40]	[24,36,56,75,111]	[33]
Energy and chemical industry	[44,45,119,142]	[143,144]	[113,131,150]	[41]	[38]		[34,69,130]	[101]
Healthcare	[99,112,118]			[63,100]				[73]
Marine industry	[136]	[90]					[61,116]	[37]
Electronic industry	[121,137]		[135]		[132]			[35]
Automotive industry	[62,87]	[47,88]				[62]		
Project management	[139]		[134]		[89,133]			
Information technology	[120,126]	[86]						
Other	[43]		[109,147]					

It was previously stated that basic FSs are used in the majority of studies. However, from the perspective of application domains, it is clearly evident in Table 4 that FSs are most commonly applied in the manufacturing industry and the energy and chemical industry. IT2FSs are predominantly used in the manufacturing industry, while IFSs are mostly applied in the energy and chemical industry.

5.4. Analysis of Authors and Publications

This section presents the number of publications, countries of origin of the authors, and the distribution of studies that combine FMEA and MADM with uncertain numbers during the observed period (2015 to 2024).

As previously mentioned, this study identified 68 papers using the PRISMA protocol in which the authors combine FMEA and MADM with various approaches to modeling uncertainty. The analyzed papers appear in a total of 51 different scientific journals, as shown in Table 5.

Table 5. Distribution of selected articles according to the journal of publication.

Journal Name	Count	Journal Name	Count
Agriculture	1	International Journal of Intelligent Computing and Cybernetics	1
Applied Soft Computing	6	International Journal of Productivity and Quality Management	1
Axioms	1	International Journal of Quality and Reliability Management	1
Complex and Intelligent Systems	1	Journal of Digital Information Management	1
Complexity	1	Journal of Engineering, Design and Technology	2
Computers and Industrial Engineering	1	Journal of Fuzzy Extension and Application	1
Decision Making: Applications In Management and Engineering	1	Journal of Intelligent and Fuzzy Systems	1

Table 5. *Cont.*

Journal Name	Count	Journal Name	Count
Decision Science Letters	1	Journal of Loss Prevention In The Process Industries	1
Energies	1	Journal of Petroleum Science and Engineering	1
Entropy	1	Journal of the Operational Research Society	1
Environment, Development and Sustainability	1	Kybernetes	1
Environmental Science and Pollution Research	1	Mathematics	1
Expert Systems	1	Maritime Policy and Management	1
Expert Systems with Applications	1	Neural Computing and Applications	1
Facta Universitatis, Series: Mechanical Engineering	3	Plos One/Public Library Of Science	1
Human And Ecological Risk Assessment	1	Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture	1
IEEE Access	1	Proceedings Of The Institution Of Mechanical Engineers, Part D: Journal Of Automobile Engineering	1
IEEE Transactions on Fuzzy Systems	1	Proceedings Of The Institution Of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering	1
IEEE Transactions on Reliability	1	Process Safety And Environmental Protection	3
Informatica	1	Quality and Reliability Engineering International	5
Information	1	Quality Engineering	1
International Journal of Advanced Manufacturing Technology	1	Risk Analysis	1
International Journal of Computational Intelligence Systems	2	Soft Computing	3
International Journal of Computer Integrated Manufacturing	1	Symmetry	1
International Journal of Fuzzy Systems	1	Water Supply	1
International Journal of Industrial Ergonomics	1		

A total of 176 different authors were identified across the reviewed studies. Table 6 presents the distribution of authors by country. This analysis was conducted based on the affiliations provided by the authors in the reviewed publications. The authors are affiliated with institutions from a total of 24 countries.

Table 6. Distribution of authors by country based on institutional affiliation.

Rank	Country	Number of Authors	Percentage
1	China	73	41.5%
2	Iran	29	16.5%
3	Turkey	19	10.8%
4	Serbia	9	5.1%
5	India	8	4.5%

Table 6. *Cont.*

Rank	Country	Number of Authors	Percentage
6	Australia	5	2.8%
7	Indonesia	4	2.3%
8	Malaysia	3	1.7%
9	Bosnia, Canada, Croatia, Pakistan, Peru, Poland, Spain, Taiwan, Thailand, USA	2	1.1%
10	Austria, Czech Republic, France, Hungary, Qatar, United Kingdom	1	0.6%

It should be noted that some authors appear in multiple publications. Table 7 presents the frequency of occurrence for authors who appear three or more times in the reviewed studies.

Table 7. Most frequently appearing authors.

Name	Country	Number of Publications	Publications
Komatina, N.	Serbia	6	[47,86–88,95,123]
Liu, H.-C.	China	6	[33,56,73,112,121,137]
Ghoushchi, S.J.	Iran	5	[40,41,62,63,100]
Tadić, D.	Serbia	5	[47,86–88,95]
Aleksić, A.	Serbia	4	[47,87,88,95]
Li, H.	China	4	[113,133,134,139]
Wang, L.	China	4	[113,133,134,139]
Wang, W.	China	4	[69,90,109,143]
You, J.-X.	China	4	[56,112,121,137]
Gul, M.	Turkey	3	[24,116,124]
Li, F.	China	3	[113,133,139]
Li, G.	China	3	[75,128,130]
Panchal, D.	India	3	[131,150,176]

The distribution of papers presenting proposed hybrid models that include a combination of FMEA and MADM with uncertain data over the last 10 years is shown in Figure 3.

It can be concluded that the number of publications significantly increased during the period from 2019 to 2022, with approximately 68% of all analyzed papers over the ten-year period published within these four years. Although a decline in the number of papers is observed in 2023 and 2024 compared to the previous four years, the increase in publications in 2024 relative to 2023 may indicate that this research problem will continue to be addressed in the near future.

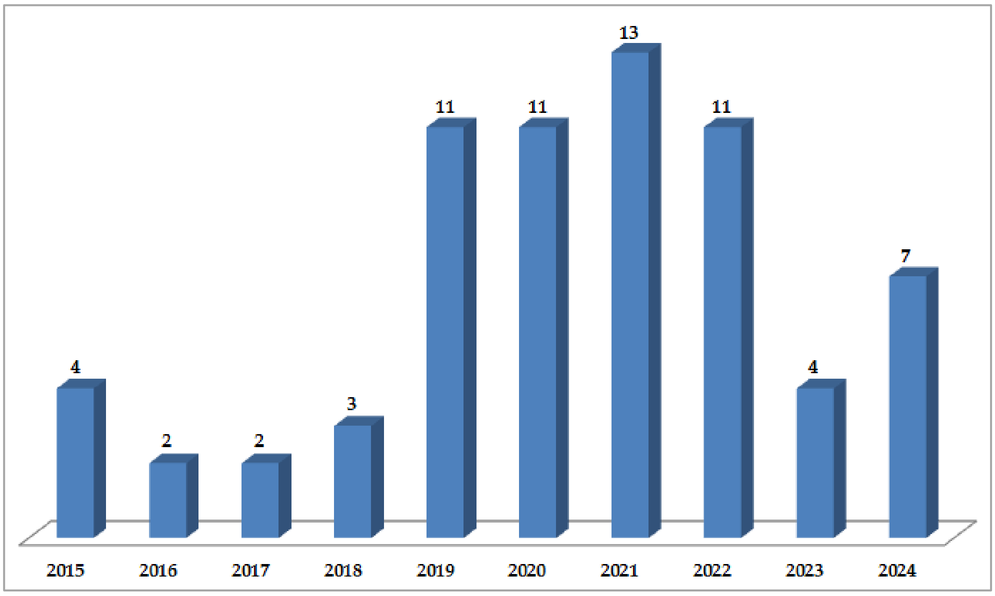

Figure 3. Distribution of publication years of the analyzed papers.

6. Conclusions

In this research, a systematic literature review was conducted in the domain of extending FMEA through integration with MADM methods and various approaches to uncertainty modeling. A total of 68 papers were analyzed, published in Scopus- and/or Web of Science-indexed journals. The review covered a ten-year period, specifically from 2015 to 2024. The analysis included papers that were accepted and/or published during this period in relevant journals.

Through the analysis of the selected papers, it was found that the number of studies combining the FMEA-MADM approach with various uncertainty modeling techniques has gradually increased year by year. However, in the last two years, a slight decline in the number of such papers has been observed, although the decrease is not significant.

In their studies, the authors most commonly used FNs for modeling uncertainty, as well as their extended forms, such as IT2FNs. Other frequently used approaches included IFNs, PFNs, and Z-numbers.

Based on the analysis, it was identified that AHP and BWM are most frequently used for determining the weights of RFs, while TOPSIS and VIKOR are most commonly applied for ranking failure modes and determining their priorities. In terms of application domains, the reviewed studies were mostly conducted in the manufacturing industry, the energy and chemical industry, the healthcare industry, and the automotive industry.

It can be considered that the number of 68 published papers over a 10-year period indicates that the FMEA-MADM approach under uncertainty represents a highly relevant and trending research direction. Furthermore, it holds significant potential for practical application across various industrial sectors.

Future research directions aimed at addressing existing research gaps should include (1) the verification of the consistency of solutions obtained using the analyzed methods due to the use of different uncertain numbers in modeling the relative importance and values of RFs. (2) It is known that applying different MADM methods with uncertain numbers can lead to inconsistent solutions. Therefore, in the future, two or more MADM methods should be combined to reduce risk in the decision-making process. (3) Enhanced FMEA requires a complex calculation procedure, making it very difficult for practitioners to understand. Hence, it is necessary to develop user-friendly software that practitioners can easily comprehend and use, thereby improving the decision-making process.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
ARAS	Additive Ratio Assessment
BS	Belief Structure
BWM	The Best Worst Method
CNIS	Cloud Negative Ideal Solution
CoCoSo	Combined Compromise Solution
COPRAS	COmplex PRoportional ASsessment
CPIS	Cloud Positive Ideal Solution
CRITIC	Criteria Importance Through Inter-criteria Correlation
D	Detection
DEMATEL	Decision-Making and Trial Evaluation Laboratory
DMs	Decision Makers
ETA	Event Tree Analysis
FBS	Fuzzy Belief Structure
FEMA	Failure Mode and Effect Analysis
FFNs	Fermatean Fuzzy Sets
FFSs	Fermatean Fuzzy Sets
FMEA	Failure Mode and Effect Analysis
FNIS	Fuzzy Negative Ideal Solution
FPIS	Fuzzy Positive Ideal Solution
FRPN	Fuzzy Risk Priority Number
FTA	Fault Tree Analysis
IFNIS	NIS with IVFNs
IFNs	Intuitionistic Fuzzy Numbers
IFPIS	PIS with IVFNs
IT2FNIS	Fuzzy Negative Ideal Solution with IT2FNs
IT2FNs	Interval Type-2 Fuzzy Numbers
IT2FPIS	Fuzzy Positive Ideal Solution with IT2FNs
IT2IFNs	Interval Type-2 Intuitionistic Fuzzy Numbers
IT2TFNs	Interval Type-2 Triangular Fuzzy Numbers
IT2TrFNs	Interval Type-2 Trapezoidal Fuzzy Numbers
ITLV	Interval 2-Tuple Linguistic Variable
ITLVs	2-Tuple Linguistic Variables
IVFNs	Interval-Valued Fuzzy Numbers
IVNSs	Interval-Valued Neutrosophic Sets
IVq-ROFSs	Interval-Valued q-Rung Orthopair Fuzzy Sets
IVSFNIS	Fuzzy Negative Ideal Solution with SFSs

IVSFPIS	Fuzzy Positive Ideal Solution with SFSs
MABAC	Multi-Attributive Border Approximation Area Comparison
MADM	Multi-Attribute Decision-Making
MAIRCA	Multi-Attributive Ideal Real Comparative Analysis
MARCOS	Measurement of Alternatives and Ranking according to COmpromise Solution
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
MULTIMOORA	Multi-Objective Optimization on the basis of Ratio Analysis and the full MULTIplicative form
NFSs	Neutrosophic Sets
NIBS	Negative Ideal Solution with FBS
NSs	Neutrosophic Sets
O	Occurrence
ORESTE	Organization, Ranking, and Synthesis of Relational Data
PFNIS	Negative Ideal Solution with PFNs
PFNs	Pythagorean Fuzzy Numbers
PFSs	Pythagorean Fuzzy Sets
PFPIS	Positive Ideal Solution with PFNs
PHFSs	Probabilistic Hesitant Fuzzy Sets
PIBS	Positive Ideal Solution with FBS
PIS	Positive Ideal Solution
PIV-HFSs	Probabilistic Interval-Valued Hesitant Fuzzy Sets
PLTS	Probabilistic Linguistic Term Set
PROMETHEE	Preference Ranking Organization METHod for Enrichment of Evaluations
q-ROFSs	q-Rung Orthopair Fuzzy Sets
RCA	Root Cause Analysis
RFs	Risk Factors
RNNIS	Fuzzy Negative Ideal Solution with SVNSs
RNPIS	Fuzzy Positive Ideal Solution with SVNSs
RPN	Risk Priority Number
S	Severity
SFNs	Spherical Fuzzy Numbers
SFSs	Spherical Fuzzy Sets
SVNSs	Single-Valued Neutrosophic Sets
SWARA	Step-Wise Weight Assessment Ratio Analysis
TFNs	Triangular Fuzzy Numbers
TODIM	Interactive and Multi-criteria Decision-Making Method
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TrFNs	Trapezoidal Fuzzy Numbers
VIKOR	Multi-Criteria Optimization and Compromise Solution
WASPAS	Weighted Aggregates Sum Product Assessment

References

1. Yazdi, M.; Mohammadpour, J.; Li, H.; Huang, H.; Zarei, E.; Pirbalouti, R.G.; Adumene, S. Fault Tree Analysis Improvements: A Bibliometric Analysis and Literature Review. *Qual. Reliab. Eng. Int.* **2023**, *39*, 1639–1659. [CrossRef]
2. Mokhtarzadeh, M.; Rodríguez-Echeverría, J.; Semanjski, I.; Gautama, S. Hybrid Intelligence Failure Analysis for Industry 4.0: A Literature Review and Future Prospective. *J. Intell. Manuf.* **2025**, *36*, 2309–2334. [CrossRef]
3. Stamatis, D.H. *Failure Mode and Effect Analysis*; Quality Press: Welshpool, WA, USA, 2003; ISBN 0-87389-598-3.
4. *IATF 16949:2016*; Quality Management System Requirements for Automotive Production and Relevant Service Parts Organizations, 1st Edition. International Automotive Task Force: Berlin, Germany, 2017.
5. Komatina, N.; Marinković, D. Optimization of PFMEA Team Composition in the Automotive Industry Using the IPF-RADAR Approach. *Algorithms* **2025**, *18*, 342. [CrossRef]
6. Liu, H.-C.; Chen, X.-Q.; Duan, C.-Y.; Wang, Y.-M. Failure Mode and Effect Analysis Using Multi-Criteria Decision Making Methods: A Systematic Literature Review. *Comput. Ind. Eng.* **2019**, *135*, 881–897. [CrossRef]

7. Liu, H.-C.; Liu, L.; Bian, Q.-H.; Lin, Q.-L.; Dong, N.; Xu, P.-C. Failure Mode and Effects Analysis Using Fuzzy Evidential Reasoning Approach and Grey Theory. *Expert Syst. Appl.* **2011**, *38*, 4403–4415. [CrossRef]
8. Huang, J.; You, J.-X.; Liu, H.-C.; Song, M.-S. Failure Mode and Effect Analysis Improvement: A Systematic Literature Review and Future Research Agenda. *Reliab. Eng. Syst. Saf.* **2020**, *199*, 106885. [CrossRef]
9. Liu, H.-C.; Liu, L.; Liu, N. Risk Evaluation Approaches in Failure Mode and Effects Analysis: A Literature Review. *Expert Syst. Appl.* **2013**, *40*, 828–838. [CrossRef]
10. Liu, H.C. FMEA Using Uncertainty Theories and MCDM Methods. In *FMEA Using Uncertainty Theories and MCDM Methods*; Springer: Singapore, 2016; pp. 13–27, ISBN 978-981-10-1465-9.
11. Dubois, D.; Prade, H. An Introduction to Fuzzy Systems. *Clin. Chim. Acta* **1998**, *270*, 3–29. [CrossRef]
12. Zimmermann, H.-J. Fuzzy Set Theory. *WIREs Comput. Stat.* **2010**, *2*, 317–332. [CrossRef]
13. Mendel, J.M. *Uncertain Rule-Based Fuzzy Systems: Introduction and New Directions*, 2nd ed.; Springer International Publishing: Cham, Switzerland, 2017; ISBN 978-3-319-51369-0.
14. Atanassov, K.T. Intuitionistic Fuzzy Sets. In *Intuitionistic Fuzzy Sets*; Studies in Fuzziness and Soft Computing; Physica-Verlag HD: Heidelberg, Germany, 1999; Volume 35, pp. 1–137, ISBN 978-3-7908-2463-6.
15. Peng, X.; Yang, Y. Fundamental Properties of Interval-Valued Pythagorean Fuzzy Aggregation Operators: Interval-Valued Pythagorean Fuzzy Aggregation Operations. *Int. J. Intell. Syst.* **2016**, *31*, 444–487. [CrossRef]
16. Kutlu Gündoğdu, F.; Kahraman, C. Spherical Fuzzy Sets and Spherical Fuzzy TOPSIS Method. *J. Intell. Fuzzy Syst.* **2019**, *36*, 337–352. [CrossRef]
17. Senapati, T.; Yager, R.R. Fermatean Fuzzy Sets. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 663–674. [CrossRef]
18. Zadeh, L.A. A Note on Z-Numbers. *Inf. Sci.* **2011**, *181*, 2923–2932. [CrossRef]
19. Pawlak, Z. Rough Sets. *Int. J. Comput. Inf. Sci.* **1982**, *11*, 341–356. [CrossRef]
20. Netto, T.A.; Honorato, H.J.; Qassim, R.Y. Prioritization of Failure Risk in Subsea Flexible Pipes via Data Envelopment Analysis. *Mar. Struct.* **2013**, *34*, 105–116. [CrossRef]
21. Jian-Bo Yang; Pratyush Sen A General Multi-Level Evaluation Process for Hybrid MADM with Uncertainty. *IEEE Trans. Syst. Man Cybern.* **1994**, *24*, 1458–1473. [CrossRef]
22. Yang, J.-B.; Singh, M.G. An Evidential Reasoning Approach for Multiple-Attribute Decision Making with Uncertainty. *IEEE Trans. Syst. Man Cybern.* **1994**, *24*, 1–18. [CrossRef]
23. Lo, H.-W.; Liou, J.J.H.; Huang, C.-N.; Chuang, Y.-C. A Novel Failure Mode and Effect Analysis Model for Machine Tool Risk Analysis. *Reliab. Eng. Syst. Saf.* **2019**, *183*, 173–183. [CrossRef]
24. Gul, M.; Lo, H.-W.; Yucesan, M. Fermatean Fuzzy TOPSIS-Based Approach for Occupational Risk Assessment in Manufacturing. *Complex Intell. Syst.* **2021**, *7*, 2635–2653. [CrossRef]
25. Pamučar, D.; Petrović, I.; Ćirović, G. Modification of the Best–Worst and MABAC Methods: A Novel Approach Based on Interval-Valued Fuzzy-Rough Numbers. *Expert Syst. Appl.* **2018**, *91*, 89–106. [CrossRef]
26. Zhu, G.-N.; Hu, J.; Qi, J.; Gu, C.-C.; Peng, Y.-H. An Integrated AHP and VIKOR for Design Concept Evaluation Based on Rough Number. *Adv. Eng. Inform.* **2015**, *29*, 408–418. [CrossRef]
27. AIAG&VDA. *Failure Mode and Effects Analysis—FMEA Handbook: Design FMEA, Process FMEA, Supplemental FMEA for Monitoring & System Response*; Automotive Industry Action Group: Southfield, MI, USA, 2019.
28. Aleksić, A.; Tadić, D. Industrial and Management Applications of Type-2 Multi-Attribute Decision-Making Techniques Extended with Type-2 Fuzzy Sets from 2013 to 2022. *Mathematics* **2023**, *11*, 2249. [CrossRef]
29. Zayat, W.; Kilic, H.S.; Yalcin, A.S.; Zaim, S.; Delen, D. Application of MADM Methods in Industry 4.0: A Literature Review. *Comput. Ind. Eng.* **2023**, *177*, 109075. [CrossRef]
30. Mardani, A.; Jusoh, A.; Zavadskas, E.K. Fuzzy Multiple Criteria Decision-Making Techniques and Applications—Two Decades Review from 1994 to 2014. *Expert Syst. Appl.* **2015**, *42*, 4126–4148. [CrossRef]
31. Zare, M.; Pahl, C.; Rahnama, H.; Nilashi, M.; Mardani, A.; Ibrahim, O.; Ahmadi, H. Multi-Criteria Decision Making Approach in E-Learning: A Systematic Review and Classification. *Appl. Soft Comput.* **2016**, *45*, 108–128. [CrossRef]
32. Zhang, G.; Wang, J.; Wang, T. Multi-criteria Group Decision-making Method Based on TODIM with Probabilistic Interval-valued Hesitant Fuzzy Information. *Expert Syst.* **2019**, *36*, e12424. [CrossRef]
33. Liu, H.-C.; Wang, L.-E.; Li, Z.; Hu, Y.-P. Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method. *IEEE Trans. Fuzzy Syst.* **2019**, *27*, 84–95. [CrossRef]
34. Aydin, N.; Seker, S.; Şen, C. A New Risk Assessment Framework for Safety in Oil and Gas Industry: Application of FMEA and BWM Based Picture Fuzzy MABAC. *J. Pet. Sci. Eng.* **2022**, *219*, 111059. [CrossRef]
35. Chang, T.-W.; Lo, H.-W.; Chen, K.-Y.; Liou, J. A Novel FMEA Model Based on Rough BWM and Rough TOPSIS-AL for Risk Assessment. *Mathematics* **2019**, *7*, 874. [CrossRef]
36. Jin, C.; Ran, Y.; Zhang, G. Interval-Valued q-Rung Orthopair Fuzzy FMEA Application to Improve Risk Evaluation Process of Tool Changing Manipulator. *Appl. Soft Comput.* **2021**, *104*, 107192. [CrossRef]

37. Jianxing, Y.; Shibo, W.; Haicheng, C.; Yang, Y.; Haizhao, F.; Jiahao, L. Risk Assessment of Submarine Pipelines Using Modified FMEA Approach Based on Cloud Model and Extended VIKOR Method. *Process Saf. Environ. Prot.* **2021**, *155*, 555–574. [CrossRef]
38. Rahnamay Bonab, S.; Osgooei, E. Environment Risk Assessment of Wastewater Treatment Using FMEA Method Based on Pythagorean Fuzzy Multiple-Criteria Decision-Making. *Environ. Dev. Sustain.* **2022**, *online first*. [CrossRef]
39. Adalı, E.A.; Tuş, A. ARAS Method Based on Z-numbers in FMEA. *Qual. Reliab. Eng. Int.* **2023**, *39*, 3059–3081. [CrossRef]
40. Ghoushchi, S.J.; Gharibi, K.; Osgooei, E.; Ab Rahman, M.N.; Khazaeili, M. Risk Prioritization in Failure Mode and Effects Analysis with Extended SWARA and MOORA Methods Based on Z-Numbers Theory. *Informatica* **2021**, *32*, 41–67. [CrossRef]
41. Ghoushchi, S.J.; Jalalat, S.M.; Bonab, S.R.; Ghiaci, A.M.; Haseli, G.; Tomaskova, H. Evaluation of Wind Turbine Failure Modes Using the Developed SWARA-CoCoSo Methods Based on the Spherical Fuzzy Environment. *IEEE Access* **2022**, *10*, 86750–86764. [CrossRef]
42. Ghoushchi, N.G.; Ahmadzadeh, K.; Ghoushchi, S.J. A New Extended Approach to Reduce Admission Time in Hospital Operating Rooms Based on the FMEA Method in an Uncertain Environment. *J. Soft Comput. Decis. Anal.* **2023**, *1*, 80–101. [CrossRef]
43. Zandi, P.; Rahmani, M.; Khanian, M.; Mosavi, A. Agricultural Risk Management Using Fuzzy TOPSIS Analytical Hierarchy Process (AHP) and Failure Mode and Effects Analysis (FMEA). *Agriculture* **2020**, *10*, 504. [CrossRef]
44. Nabizadeh, M.; Khalilzadeh, M.; Ebrahimnejad, S.; Ershadi, M.J. Developing a Fuzzy Goal Programming Model for Health, Safety and Environment Risks Based on Hybrid Fuzzy FMEA-VIKOR Method. *J. Eng. Des. Technol.* **2021**, *19*, 317–338. [CrossRef]
45. Sumrit, D.; Keeratibhubordee, J. Risk Assessment Framework for Reverse Logistics in Waste Plastic Recycle Industry: A Hybrid Approach Incorporating FMEA Decision Model with AHP-LOPCOW- ARAS Under Trapezoidal Fuzzy Set. *Decis. Mak. Appl. Manag. Eng.* **2025**, *8*, 42–81. [CrossRef]
46. Boral, S.; Chaturvedi, S.K.; Howard, I.; Naikan, V.N.A.; McKee, K. An Integrated Interval Type-2 Fuzzy Sets and Multiplicative Half Quadratic Programming-Based MCDM Framework for Calculating Aggregated Risk Ranking Results of Failure Modes in FMECA. *Process Saf. Environ. Prot.* **2021**, *150*, 194–222. [CrossRef]
47. Komatina, N.; Tadić, D.; Aleksić, A.; Banduka, N. The Integrated PFMEA Approach with Interval Type-2 Fuzzy Sets and FBWM: A Case Study in the Automotive Industry. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2022**, *236*, 1201–1212. [CrossRef]
48. Szmidt, E.; Kacprzyk, J. Distances between Intuitionistic Fuzzy Sets. *Fuzzy Sets Syst.* **2000**, *114*, 505–518. [CrossRef]
49. Liu, B. Credibility Theory. In *Uncertainty Theory*; Studies in Fuzziness and Soft Computing; Springer: Berlin/Heidelberg, Germany, 2007; Volume 154, pp. 81–156, ISBN 978-3-540-73164-1.
50. Zadeh, L.A. The Concept of a Linguistic Variable and Its Application to Approximate Reasoning—I. *Inf. Sci.* **1975**, *8*, 199–249. [CrossRef]
51. Lootsma, F.A. Stochastic and Fuzzy Pert. In *Fuzzy Logic for Planning and Decision Making*; Applied Optimization; Springer: Boston, MA, USA, 1997; Volume 8, pp. 39–65, ISBN 978-1-4419-4779-6.
52. Klir, G.J.; Yuan, B. *Fuzzy Sets and Fuzzy Logic: Theory and Applications*; Prentice Hall PTR: Upper Saddle River, NJ, USA, 1995; ISBN 978-0-13-101171-7.
53. Melin, P.; Castillo, O. A Review on the Applications of Type-2 Fuzzy Logic in Classification and Pattern Recognition. *Expert Syst. Appl.* **2013**, *40*, 5413–5423. [CrossRef]
54. Atanassov, K.; Gargov, G. Elements of Intuitionistic Fuzzy Logic. Part I. *Fuzzy Sets Syst.* **1998**, *95*, 39–52. [CrossRef]
55. Ye, J. Two Effective Measures of Intuitionistic Fuzzy Entropy. *Computing* **2010**, *87*, 55–62. [CrossRef]
56. Wang, Z.-L.; You, J.-X.; Liu, H.-C.; Wu, S.-M. Failure Mode and Effect Analysis Using Soft Set Theory and COPRAS Method. *Int. J. Comput. Intell. Syst.* **2017**, *10*, 1002. [CrossRef]
57. Wei, G.; Lu, M. Pythagorean Fuzzy Power Aggregation Operators in Multiple Attribute Decision Making. *Int. J. Intell. Syst.* **2018**, *33*, 169–186. [CrossRef]
58. Ilbahar, E.; Karaşan, A.; Cebi, S.; Kahraman, C. A Novel Approach to Risk Assessment for Occupational Health and Safety Using Pythagorean Fuzzy AHP & Fuzzy Inference System. *Saf. Sci.* **2018**, *103*, 124–136. [CrossRef]
59. Yager, R.R. Generalized Orthopair Fuzzy Sets. *IEEE Trans. Fuzzy Syst.* **2017**, *25*, 1222–1230. [CrossRef]
60. Joshi, B.P.; Singh, A.; Bhatt, P.K.; Vaisla, K.S. Interval Valued q -Rung Orthopair Fuzzy Sets and Their Properties. *J. Intell. Fuzzy Syst.* **2018**, *35*, 5225–5230. [CrossRef]
61. Ayvaz, B.; Tatar, V.; Sağır, Z.; Pamucar, D. An Integrated Fine-Kinney Risk Assessment Model Utilizing Fermatean Fuzzy AHP-WASPAS for Occupational Hazards in the Aquaculture Sector. *Process Saf. Environ. Prot.* **2024**, *186*, 232–251. [CrossRef]
62. Ghoushchi, S.J.; Yousefi, S.; Khazaeili, M. An Extended FMEA Approach Based on the Z-MOORA and Fuzzy BWM for Prioritization of Failures. *Appl. Soft Comput.* **2019**, *81*, 105505. [CrossRef]
63. Jafarzadeh Ghoushchi, S.; Memarpour Ghiaci, A.; Rahnamay Bonab, S.; Ranjbarzadeh, R. Barriers to Circular Economy Implementation in Designing of Sustainable Medical Waste Management Systems Using a New Extended Decision-Making and FMEA Models. *Environ. Sci. Pollut. Res.* **2022**, *29*, 79735–79753. [CrossRef] [PubMed]
64. Cường, B.C. Picture Fuzzy Sets. *J. Comput. Sci. Cybern.* **2015**, *30*, 409. [CrossRef]
65. Molodtsov, D. Soft Set Theory—First Results. *Comput. Math. Appl.* **1999**, *37*, 19–31. [CrossRef]

66. Yang, J.B.; Wang, Y.M.; Xu, D.L.; Chin, K.S. The Evidential Reasoning Approach for MADA under Both Probabilistic and Fuzzy Uncertainties. *Eur. J. Oper. Res.* **2006**, *171*, 309–343. [CrossRef]
67. Hajiagha, S.H.R.; Hashemi, S.S.; Mohammadi, Y.; Zavadskas, K. Fuzzy Belief Structure-Based VIKOR Method: An Application for Ranking Delay Causes of Tehran Metro System by FMEA Criteria. *Transport* **2016**, *31*, 108–118. [CrossRef]
68. Zhou, W.; Xu, Z. Group Consistency and Group Decision Making under Uncertain Probabilistic Hesitant Fuzzy Preference Environment. *Inf. Sci.* **2017**, *414*, 276–288. [CrossRef]
69. Zhou, B.; Chen, J.; Wu, Q.; Pamučar, D.; Wang, W.; Zhou, L. Risk Priority Evaluation of Power Transformer Parts Based on Hybrid FMEA Framework under Hesitant Fuzzy Environment. *Facta Univ. Ser. Mech. Eng.* **2022**, *20*, 399. [CrossRef]
70. Shyng, J.-Y.; Wang, F.-K.; Tzeng, G.-H.; Wu, K.-S. Rough Set Theory in Analyzing the Attributes of Combination Values for the Insurance Market. *Expert Syst. Appl.* **2007**, *32*, 56–64. [CrossRef]
71. Zhai, L.-Y.; Khoo, L.-P.; Zhong, Z.-W. A Rough Set Enhanced Fuzzy Approach to Quality Function Deployment. *Int. J. Adv. Manuf. Technol.* **2008**, *37*, 613–624. [CrossRef]
72. Zhu, G.-N.; Ma, J.; Hu, J. A Fuzzy Rough Number Extended AHP and VIKOR for Failure Mode and Effects Analysis under Uncertainty. *Adv. Eng. Inform.* **2022**, *51*, 101454. [CrossRef]
73. Liu, H.-C.; Li, Z.; Song, W.; Su, Q. Failure Mode and Effect Analysis Using Cloud Model Theory and PROMETHEE Method. *IEEE Trans. Reliab.* **2017**, *66*, 1058–1072. [CrossRef]
74. Pang, Q.; Wang, H.; Xu, Z. Probabilistic Linguistic Term Sets in Multi-Attribute Group Decision Making. *Inf. Sci.* **2016**, *369*, 128–143. [CrossRef]
75. Li, G.-F.; Li, Y.; Chen, C.-H.; He, J.-L.; Hou, T.-W.; Chen, J.-H. Advanced FMEA Method Based on Interval 2-Tuple Linguistic Variables and TOPSIS. *Qual. Eng.* **2020**, *32*, 653–662. [CrossRef]
76. Wang, J.; Wu, J.; Wang, J.; Zhang, H.; Chen, X. Interval-Valued Hesitant Fuzzy Linguistic Sets and Their Applications in Multi-Criteria Decision-Making Problems. *Inf. Sci.* **2014**, *288*, 55–72. [CrossRef]
77. Wu, X.; Liao, H. A Consensus-Based Probabilistic Linguistic Gained and Lost Dominance Score Method. *Eur. J. Oper. Res.* **2019**, *272*, 1017–1027. [CrossRef]
78. Xing, Y.-J.; Xing, C. Model for Evaluating the Virtual Enterprise's Risk with 2-Tuple Linguistic Information. *J. Intell. Fuzzy Syst.* **2016**, *31*, 193–200. [CrossRef]
79. Zhang, H. The Multiattribute Group Decision Making Method Based on Aggregation Operators with Interval-Valued 2-Tuple Linguistic Information. *Math. Comput. Model.* **2012**, *56*, 27–35. [CrossRef]
80. Liu, H.-C.; Liu, L.; Wu, J. Material Selection Using an Interval 2-Tuple Linguistic VIKOR Method Considering Subjective and Objective Weights. *Mater. Des.* **2013**, *52*, 158–167. [CrossRef]
81. Yalcin, A.S.; Kilic, H.S.; Delen, D. The Use of Multi-Criteria Decision-Making Methods in Business Analytics: A Comprehensive Literature Review. *Technol. Forecast. Soc. Change* **2022**, *174*, 121193. [CrossRef]
82. Saaty, T.L. The Modern Science of Multicriteria Decision Making and Its Practical Applications: The AHP/ANP Approach. *Oper. Res.* **2013**, *61*, 1101–1118. [CrossRef]
83. Chang, D.-Y. Applications of the Extent Analysis Method on Fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [CrossRef]
84. Sakthivel, G.; Saravanakumar, D.; Muthuramalingam, T. Application of Failure Mode and Effect Analysis in Manufacturing Industry—An Integrated Approach with FAHP-Fuzzy TOPSIS and FAHP-Fuzzy VIKOR. *Int. J. Product. Qual. Manag.* **2018**, *24*, 398. [CrossRef]
85. Hassan, A.; Purnomo, M.R.A.; Anugerah, A.R. Fuzzy-Analytical-Hierarchy Process in Failure Mode and Effect Analysis (FMEA) to Identify Process Failure in the Warehouse of a Cement Industry. *J. Eng. Des. Technol.* **2019**, *18*, 378–388. [CrossRef]
86. Đurić, G.; Mitrović, Č.; Komatina, N.; Tadić, D.; Vorotović, G. The Hybrid MCDM Model with the Interval Type-2 Fuzzy Sets for the Software Failure Analysis. *J. Intell. Fuzzy Syst.* **2019**, *37*, 7747–7759. [CrossRef]
87. Banduka, N.; Aleksić, A.; Komatina, N.; Aljinović, A.; Tadić, D. The Prioritization of Failures within the Automotive Industry: The Two-Step Failure Mode and Effect Analysis Integrated Approach. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2020**, *234*, 1559–1570. [CrossRef]
88. Komatina, N.; Tadić, D.; Đurić, G.; Aleksić, A. Determination of Manufacturing Process Failures Priority under Type 2 Fuzzy Environment: Application of Genetic Algorithm and Variable Neighborhood Search. *Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng.* **2023**, *238*, 2427–2437. [CrossRef]
89. Mete, S. Assessing Occupational Risks in Pipeline Construction Using FMEA-Based AHP-MOORA Integrated Approach under Pythagorean Fuzzy Environment. *Hum. Ecol. Risk Assess. Int. J.* **2019**, *25*, 1645–1660. [CrossRef]
90. Zheng, Q.; Liu, X.; Wang, W. An Extended Interval Type-2 Fuzzy ORESTE Method for Risk Analysis in FMEA. *Int. J. Fuzzy Syst.* **2021**, *23*, 1379–1395. [CrossRef]
91. Aleksic, A.; Runic Ristic, M.; Komatina, N.; Tadic, D. Advanced Risk Assessment in Reverse Supply Chain Processes: A Case Study in Republic of Serbia. *Adv. Prod. Eng. Manag.* **2019**, *14*, 421–434. [CrossRef]
92. Rezaei, J. Best-Worst Multi-Criteria Decision-Making Method. *Omega* **2015**, *53*, 49–57. [CrossRef]

93. Ecer, F.; Pamucar, D. Sustainable Supplier Selection: A Novel Integrated Fuzzy Best Worst Method (F-BWM) and Fuzzy CoCoSo with Bonferroni (CoCoSo'B) Multi-Criteria Model. *J. Clean. Prod.* **2020**, *266*, 121981. [CrossRef]
94. Tian, Z.; Wang, J.; Zhang, H. An Integrated Approach for Failure Mode and Effects Analysis Based on Fuzzy Best-Worst, Relative Entropy, and VIKOR Methods. *Appl. Soft Comput.* **2018**, *72*, 636–646. [CrossRef]
95. Aleksić, A.; Milanović, D.D.; Komatina, N.; Tadić, D. Evaluation and Ranking of Failures in Manufacturing Process by Combining Best-worst Method and VIKOR under Type-2 Fuzzy Environment. *Expert Syst.* **2023**, *40*, e13148. [CrossRef]
96. Song, M.; Jiang, W.; Xie, C.; Zhou, D. A New Interval Numbers Power Average Operator in Multiple Attribute Decision Making: New Interval Numbers Power Average Operator in MADM. *Int. J. Intell. Syst.* **2017**, *32*, 631–644. [CrossRef]
97. Wu, Q.; Zhou, L.; Chen, Y.; Chen, H. An Integrated Approach to Green Supplier Selection Based on the Interval Type-2 Fuzzy Best-Worst and Extended VIKOR Methods. *Inf. Sci.* **2019**, *502*, 394–417. [CrossRef]
98. Gölcük, İ. Interval Type-2 Fuzzy Inference-Based Failure Mode and Effect Analysis Model in a Group Decision-Making Setting. *Kybernetes* **2022**, *51*, 2603–2635. [CrossRef]
99. Karimi, H.; Sadeghi-Dastaki, M.; Javan, M. A Fully Fuzzy Best–Worst Multi Attribute Decision Making Method with Triangular Fuzzy Number: A Case Study of Maintenance Assessment in the Hospitals. *Appl. Soft Comput.* **2020**, *86*, 105882. [CrossRef]
100. Eftekharzadeh, S.S.; Ghoushchi, S.J.; Momayezi, F. Enhancing Safety and Risk Management through an Integrated Spherical Fuzzy Approach for Managing Laboratory Errors. *Decis. Sci. Lett.* **2024**, *13*, 545–564. [CrossRef]
101. He, S.; Wang, Y.; Peng, J.; Wang, J. Risk Ranking of Wind Turbine Systems through an Improved FMEA Based on Probabilistic Linguistic Information and the TODIM Method. *J. Oper. Res. Soc.* **2022**, *73*, 467–480. [CrossRef]
102. Falatoonitoosi, E.; Leman, Z.; Sorooshian, S.; Salimi, M. Decision-Making Trial and Evaluation Laboratory. *Res. J. Appl. Sci. Eng. Technol.* **2013**, *5*, 3476–3480. [CrossRef]
103. Keršulienė, V.; Zavadskas, E.K.; Turskis, Z. Selection of Rational Dispute Resolution Method by Applying New Step-wise Weight Assessment Ratio Analysis (SWARA). *J. Bus. Econ. Manag.* **2010**, *11*, 243–258. [CrossRef]
104. Mavi, R.K. Green Supplier Selection: A Fuzzy AHP and Fuzzy ARAS Approach. *Int. J. Serv. Oper. Manag.* **2015**, *22*, 165. [CrossRef]
105. Yager, R.R.; Abbasov, A.M. Pythagorean Membership Grades, Complex Numbers, and Decision Making: Pythagorean Membership Grades and Fuzzy Subsets. *Int. J. Intell. Syst.* **2013**, *28*, 436–452. [CrossRef]
106. Sharaf, I.M. Global Supplier Selection with Spherical Fuzzy Analytic Hierarchy Process. In *Decision Making with Spherical Fuzzy Sets*; Kahraman, C., Kutlu Gündoğdu, F., Eds.; Studies in Fuzziness and Soft Computing; Springer International Publishing: Cham, Switzerland, 2021; Volume 392, pp. 323–348, ISBN 978-3-030-45460-9.
107. Feutrill, A.; Roughan, M. A Review of Shannon and Differential Entropy Rate Estimation. *Entropy* **2021**, *23*, 1046. [CrossRef]
108. Eskov, V.M.; Eskov, V.V.; Vochmina, Y.V.; Gorbunov, D.V.; Ilyashenko, L.K. Shannon Entropy in the Research on Stationary Regimes and the Evolution of Complexity. *Mosc. Univ. Phys. Bull.* **2017**, *72*, 309–317. [CrossRef]
109. Fu, Y.; Qin, Y.; Wang, W.; Liu, X.; Jia, L. An Extended FMEA Model Based on Cumulative Prospect Theory and Type-2 Intuitionistic Fuzzy VIKOR for the Railway Train Risk Prioritization. *Entropy* **2020**, *22*, 1418. [CrossRef]
110. Shakibaei, H.; Seifi, S.; Zhuang, J. A Data-driven and Cost-oriented FMEA–MCDM Approach to Risk Assessment and Ranking in a Fuzzy Environment: A Hydraulic Pump Factory Case Study. *Risk Anal.* **2024**, *44*, 2629–2648. [CrossRef]
111. Fan, J.; Li, D.; Wu, M. An Extended TODIM Method with Unknown Weight Information Under Interval-Valued Neutrosophic Environment for FMEA. *Int. J. Comput. Intell. Syst.* **2020**, *14*, 174. [CrossRef]
112. Liu, H.-C.; You, J.-X.; You, X.-Y.; Shan, M.-M. A Novel Approach for Failure Mode and Effects Analysis Using Combination Weighting and Fuzzy VIKOR Method. *Appl. Soft Comput.* **2015**, *28*, 579–588. [CrossRef]
113. Li, H.; Ji, L.; Li, F.; Li, H.; Sun, Q.; Li, Z.; Yan, H.; Guan, W.; Wang, L.; Ma, Y. Operational Safety Risk Assessment for the Water Channels of the South-to-North Water Diversion Project Based on TODIM-FMEA. *Complexity* **2020**, *2020*, 6691764. [CrossRef]
114. Xu, Z.; Chen, J. Approach to Group Decision Making Based on Interval-Valued Intuitionistic Judgment Matrices. *Syst. Eng. Theory Pract.* **2007**, *27*, 126–133. [CrossRef]
115. Zhou, L.-P.; Dong, J.-Y.; Wan, S.-P. Two New Approaches for Multi-Attribute Group Decision-Making With Interval-Valued Neutrosophic Frank Aggregation Operators and Incomplete Weights. *IEEE Access* **2019**, *7*, 102727–102750. [CrossRef]
116. Başhan, V.; Demirel, H.; Gul, M. An FMEA-Based TOPSIS Approach under Single Valued Neutrosophic Sets for Maritime Risk Evaluation: The Case of Ship Navigation Safety. *Soft Comput.* **2020**, *24*, 18749–18764. [CrossRef]
117. Vahdani, B.; Salimi, M.; Charkhchian, M. A New FMEA Method by Integrating Fuzzy Belief Structure and TOPSIS to Improve Risk Evaluation Process. *Int. J. Adv. Manuf. Technol.* **2015**, *77*, 357–368. [CrossRef]
118. Sabripoor, A.; Ghousi, R.; Najafi, M.; Barzinpour, F.; Makuei, A. Risk Assessment of Organ Transplant Operation: A Fuzzy Hybrid MCDM Approach Based on Fuzzy FMEA. *PLoS ONE* **2024**, *19*, e0299655. [CrossRef]
119. Khodadadi-Karimvand, M.; Shirouyehzad, H. Well Drilling Fuzzy Risk Assessment Using Fuzzy FMEA and Fuzzy TOPSIS. *J. Fuzzy Ext. Appl.* **2021**, *2*, 144–155. [CrossRef]
120. Li, Y.; Zhu, L. Risk Analysis of Human Error in Interaction Design by Using a Hybrid Approach Based on FMEA, SHERPA, and Fuzzy TOPSIS. *Qual. Reliab. Eng. Int.* **2020**, *36*, 1657–1677. [CrossRef]

121. Liu, H.-C.; You, J.-X.; Lin, Q.-L.; Li, H. Risk Assessment in System FMEA Combining Fuzzy Weighted Average with Fuzzy Decision-Making Trial and Evaluation Laboratory. *Int. J. Comput. Integr. Manuf.* **2015**, *28*, 701–714. [CrossRef]
122. Safari, H.; Faraji, Z.; Majidian, S. Identifying and Evaluating Enterprise Architecture Risks Using FMEA and Fuzzy VIKOR. *J. Intell. Manuf.* **2016**, *27*, 475–486. [CrossRef]
123. Sudžum, R.; Nestić, S.; Komatina, N.; Kraišnik, M. An Intuitionistic Fuzzy Multi-Criteria Approach for Prioritizing Failures That Cause Overproduction: A Case Study in Process Manufacturing. *Axioms* **2024**, *13*, 357. [CrossRef]
124. Gul, M.; Ak, M.F. A Modified Failure Modes and Effects Analysis Using Interval-Valued Spherical Fuzzy Extension of TOPSIS Method: Case Study in a Marble Manufacturing Facility. *Soft Comput.* **2021**, *25*, 6157–6178. [CrossRef]
125. Wei, G.; Gao, H.; Wei, Y. Some Q-Rung Orthopair Fuzzy Heronian Mean Operators in Multiple Attribute Decision Making. *Int. J. Intell. Syst.* **2018**, *33*, 1426–1458. [CrossRef]
126. Ershadi, M.J.; Forouzandeh, M. Information Security Risk Management of Research Information Systems: A Hybrid Approach of Fuzzy FMEA, AHP, TOPSIS and Shannon Entropy. *J. Digit. Inf. Manag.* **2019**, *17*, 321.
127. Mangeli, M.; Shahraki, A.; Saljooghi, F.H. Improvement of Risk Assessment in the FMEA Using Nonlinear Model, Revised Fuzzy TOPSIS, and Support Vector Machine. *Int. J. Ind. Ergon.* **2019**, *69*, 209–216. [CrossRef]
128. Yang, H.; Li, G.; He, J.; Wang, L.; Zhou, X. Improved FMEA Based on IVF and Fuzzy VIKOR Method: A Case Study of Workpiece Box System of CNC Gear Milling Machine. *Qual. Reliab. Eng. Int.* **2021**, *37*, 2478–2498. [CrossRef]
129. Zhang, X.; Li, Y.; Ran, Y.; Zhang, G. A Hybrid Multilevel FTA-FMEA Method for a Flexible Manufacturing Cell Based on Meta-Action and TOPSIS. *IEEE Access* **2019**, *7*, 110306–110315. [CrossRef]
130. Zhu, J.; Shuai, B.; Li, G.; Chin, K.-S.; Wang, R. Failure Mode and Effect Analysis Using Regret Theory and PROMETHEE under Linguistic Neutrosophic Context. *J. Loss Prev. Process Ind.* **2020**, *64*, 104048. [CrossRef]
131. Kushwaha, D.K.; Panchal, D.; Sachdeva, A. Performance Evaluation of Bagasse-Based Cogeneration Power Generation Plant Utilizing IFLT, IF-FMEA and IF-TOPSIS Approaches. *Int. J. Qual. Reliab. Manag.* **2024**, *41*, 698–731. [CrossRef]
132. Akram, M.; Luqman, A.; Alcantud, J.C.R. Risk Evaluation in Failure Modes and Effects Analysis: Hybrid TOPSIS and ELECTRE I Solutions with Pythagorean Fuzzy Information. *Neural Comput. Appl.* **2021**, *33*, 5675–5703. [CrossRef]
133. Li, H.; Lv, L.; Li, F.; Wang, L.; Xia, Q. A Novel Approach to Emergency Risk Assessment Using FMEA with Extended MULTIMOORA Method under Interval-Valued Pythagorean Fuzzy Environment. *Int. J. Intell. Comput. Cybern.* **2020**, *13*, 41–65. [CrossRef]
134. Lv, L.; Li, H.; Wang, L.; Xia, Q.; Ji, L. Failure Mode and Effect Analysis (FMEA) with Extended MULTIMOORA Method Based on Interval-Valued Intuitionistic Fuzzy Set: Application in Operational Risk Evaluation for Infrastructure. *Information* **2019**, *10*, 313. [CrossRef]
135. Lian, X.; Hou, L.; Zhang, W.; Bu, X.; Yan, H. An Integrated Approach for Failure Mode and Effects Analysis Based on Weight of Risk Factors and Fuzzy PROMETHEE II. *Symmetry* **2022**, *14*, 1196. [CrossRef]
136. Liu, S.; Guo, X.; Zhang, L. An Improved Assessment Method for FMEA for a Shipboard Integrated Electric Propulsion System Using Fuzzy Logic and DEMATEL Theory. *Energies* **2019**, *12*, 3162. [CrossRef]
137. Liu, H.-C.; You, J.-X.; Shan, M.-M.; Shao, L.-N. Failure Mode and Effects Analysis Using Intuitionistic Fuzzy Hybrid TOPSIS Approach. *Soft Comput.* **2015**, *19*, 1085–1098. [CrossRef]
138. Liu, P.; Wang, Y. Multiple Attribute Decision-Making Method Based on Single-Valued Neutrosophic Normalized Weighted Bonferroni Mean. *Neural Comput. Appl.* **2014**, *25*, 2001–2010. [CrossRef]
139. Li, H.; Guo, Y.; Li, F.; Cao, Y.; Wang, L.; Ma, Y. Assessment of Operation Safety Risk for South-to-North Water Diversion Project: A Fuzzy VIKOR-FMEA Approach. *Water Supply* **2022**, *22*, 3685–3701. [CrossRef]
140. Selim, H.; Yunusoglu, M.G.; Yılmaz Balaman, Ş. A Dynamic Maintenance Planning Framework Based on Fuzzy TOPSIS and FMEA: Application in an International Food Company. *Qual. Reliab. Eng. Int.* **2016**, *32*, 795–804. [CrossRef]
141. Kiani Aslani, R.; Feili, H.R.; Javanshir, H. A Hybrid of Fuzzy FMEA-AHP to Determine Factors Affecting Alternator Failure Causes. *Manag. Sci. Lett.* **2014**, *4*, 1981–1984. [CrossRef]
142. Karatop, B.; Taşkan, B.; Adar, E.; Kubat, C. Decision Analysis Related to the Renewable Energy Investments in Turkey Based on a Fuzzy AHP-EDAS-Fuzzy FMEA Approach. *Comput. Ind. Eng.* **2021**, *151*, 106958. [CrossRef]
143. Zheng, Q.; Liu, X.; Wang, W. A Likelihood-based ORESTE Method for Failure Mode and Effect Analysis (FMEA) Based Risk Analysis Problem under Interval Type-2 Fuzzy Environment. *Qual. Reliab. Eng. Int.* **2022**, *38*, 304–325. [CrossRef]
144. Akyuz, E.; Celik, E. A Quantitative Risk Analysis by Using Interval Type-2 Fuzzy FMEA Approach: The Case of Oil Spill. *Marit. Policy Manag.* **2018**, *45*, 979–994. [CrossRef]
145. Wang, L.-E.; Liu, H.-C.; Quan, M.-Y. Evaluating the Risk of Failure Modes with a Hybrid MCDM Model under Interval-Valued Intuitionistic Fuzzy Environments. *Comput. Ind. Eng.* **2016**, *102*, 175–185. [CrossRef]
146. Zhang, X.; Xu, Z. Soft Computing Based on Maximizing Consensus and Fuzzy TOPSIS Approach to Interval-Valued Intuitionistic Fuzzy Group Decision Making. *Appl. Soft Comput.* **2015**, *26*, 42–56. [CrossRef]

147. Sayyadi Tooranloo, H.; Ayatollah, A.S. A Model for Failure Mode and Effects Analysis Based on Intuitionistic Fuzzy Approach. *Appl. Soft Comput.* **2016**, *49*, 238–247. [CrossRef]
148. Yener, Y.; Can, G.F. A FMEA Based Novel Intuitionistic Fuzzy Approach Proposal: Intuitionistic Fuzzy Advance MCDM and Mathematical Modeling Integration. *Expert Syst. Appl.* **2021**, *183*, 115413. [CrossRef]
149. Komatina, N. A Compromise-Based MADM Approach for Prioritizing Failures: Integrating the RADAR Method within the FMEA Framework. *J. Sist. Dan Manaj. Ind.* **2024**, *8*, 73–88. [CrossRef]
150. Kushwaha, D.K.; Panchal, D.; Sachdeva, A. A Modified FMEA Approach Based Integrated Decision Framework for Overcoming the Problems of Sudden Failure and Accidental Hazards in Turbine and Alternator Unit. *Facta Univ. Ser. Mech. Eng.* **2023**, *online first*. Available online: https://casopisi.junis.ni.ac.rs/index.php/FUMechEng/article/view/11146 (accessed on 5 July 2025).
151. Brans, J.P.; Vincke, P.; Mareschal, B. How to Select and How to Rank Projects: The Promethee Method. *Eur. J. Oper. Res.* **1986**, *24*, 228–238. [CrossRef]
152. Autran Monteiro Gomes, L.F.; Duncan Rangel, L.A. An Application of the TODIM Method to the Multicriteria Rental Evaluation of Residential Properties. *Eur. J. Oper. Res.* **2009**, *193*, 204–211. [CrossRef]
153. Qin, J.; Liu, X.; Pedrycz, W. An Extended TODIM Multi-Criteria Group Decision Making Method for Green Supplier Selection in Interval Type-2 Fuzzy Environment. *Eur. J. Oper. Res.* **2017**, *258*, 626–638. [CrossRef]
154. Stević, Ž.; Pamučar, D.; Puška, A.; Chatterjee, P. Sustainable Supplier Selection in Healthcare Industries Using a New MCDM Method: Measurement of Alternatives and Ranking According to COmpromise Solution (MARCOS). *Comput. Ind. Eng.* **2020**, *140*, 106231. [CrossRef]
155. Kahraman, C.; Öztayşi, B.; Uçal Sarı, İ.; Turanoğlu, E. Fuzzy Analytic Hierarchy Process with Interval Type-2 Fuzzy Sets. *Knowl. Based Syst.* **2014**, *59*, 48–57. [CrossRef]
156. Roubens, M. Preference Relations on Actions and Criteria in Multicriteria Decision Making. *Eur. J. Oper. Res.* **1982**, *10*, 51–55. [CrossRef]
157. Chen, C.T. Extensions of the TOPSIS for Group Decision-Making under Fuzzy Environment. *Fuzzy Sets Syst.* **2000**, *114*, 1–9. [CrossRef]
158. Hwang, C.L.; Yoon, K. Methods for Multiple Attribute Decision Making. In *Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
159. Chen, M.-F.; Tzeng, G.-H. Combining Grey Relation and TOPSIS Concepts for Selecting an Expatriate Host Country. *Math. Comput. Model.* **2004**, *40*, 1473–1490. [CrossRef]
160. Grzegorzewski, P. Distances between Intuitionistic Fuzzy Sets and/or Interval-Valued Fuzzy Sets Based on the Hausdorff Metric. *Fuzzy Sets Syst.* **2004**, *148*, 319–328. [CrossRef]
161. Abdel-Basset, M.; Mohamed, M.; Zhou, Y.; Hezam, I. Multi-Criteria Group Decision Making Based on Neutrosophic Analytic Hierarchy Process. *J. Intell. Fuzzy Syst.* **2017**, *33*, 4055–4066. [CrossRef]
162. Biswas, P.; Pramanik, S.; Giri, B.C. TOPSIS Method for Multi-Attribute Group Decision-Making under Single-Valued Neutrosophic Environment. *Neural Comput. Appl.* **2016**, *27*, 727–737. [CrossRef]
163. Li, C.-B.; Qi, Z.-Q.; Feng, X. A Multi-Risks Group Evaluation Method for the Informatization Project under Linguistic Environment. *J. Intell. Fuzzy Syst.* **2014**, *26*, 1581–1592. [CrossRef]
164. Jiang, J.; Chen, Y.; Chen, Y.; Yang, K. TOPSIS with Fuzzy Belief Structure for Group Belief Multiple Criteria Decision Making. *Expert Syst. Appl.* **2011**, *38*, 9400–9406. [CrossRef]
165. Opricovic, S.; Tzeng, G.-H. Extended VIKOR Method in Comparison with Outranking Methods. *Eur. J. Oper. Res.* **2007**, *178*, 514–529. [CrossRef]
166. Chen, S.H.; Wang, C.C. Representation, Ranking, Distance, and Similarity of Fuzzy Numbers with Step Form Membership Function Using k-Preference Integration Method. In Proceedings of the Joint 9th IFSA World Congress and 20th NAFIPS International Conference (Cat. No. 01TH8569), Vancouver, BC, Canada, 25–28 July 2001; Volume 2, pp. 801–806.
167. Chen, S.-M.; Lee, L.-W. Fuzzy Multiple Attributes Group Decision-Making Based on the Interval Type-2 TOPSIS Method. *Expert Syst. Appl.* **2010**, *37*, 2790–2798. [CrossRef]
168. Shu, M.-H.; Cheng, C.-H.; Chang, J.-R. Using Intuitionistic Fuzzy Sets for Fault-Tree Analysis on Printed Circuit Board Assembly. *Microelectron. Reliab.* **2006**, *46*, 2139–2148. [CrossRef]
169. Dai, W.; Zhong, Q.; Qi, C. Multi-Stage Multi-Attribute Decision-Making Method Based on the Prospect Theory and Triangular Fuzzy MULTIMOORA. *Soft Comput.* **2020**, *24*, 9429–9440. [CrossRef]
170. Liu, A.-F. Topsis Method for Multiple Attribute Decision Making under Trapezoidal Intuitionistic Fuzzy Environment. *J. Intell. Fuzzy Syst.* **2014**, *26*, 2403–2409. [CrossRef]
171. Narayanamoorthy, S.; Geetha, S.; Rakkiyappan, R.; Joo, Y.H. Interval-Valued Intuitionistic Hesitant Fuzzy Entropy Based VIKOR Method for Industrial Robots Selection. *Expert Syst. Appl.* **2019**, *121*, 28–37. [CrossRef]
172. Pamučar, D.; Ćirović, G. The Selection of Transport and Handling Resources in Logistics Centers Using Multi-Attributive Border Approximation Area Comparison (MABAC). *Expert Syst. Appl.* **2015**, *42*, 3016–3028. [CrossRef]

173. Gigović, L.; Pamučar, D.; Bajić, Z.; Milićević, M. The Combination of Expert Judgment and GIS-MAIRCA Analysis for the Selection of Sites for Ammunition Depots. *Sustainability* **2016**, *8*, 372. [CrossRef]
174. Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. Optimization of Weighted Aggregated Sum Product Assessment. *Electron. Electr. Eng.* **2012**, *122*, 3–6. [CrossRef]
175. Zavadskas, E.K.; Kaklauskas, A.; Peldschus, F.; Turskis, Z. Multi-Attribute Assessment of Road Design Solutions by Using the COPRAS Method. *Balt. J. Road Bridge Eng.* **2007**, *2*, 195–203.
176. Gopal, N.; Panchal, D. A Structured Framework for Reliability and Risk Evaluation in the Milk Process Industry under Fuzzy Environment. *Facta Univ. Ser. Mech. Eng.* **2021**, *19*, 307. [CrossRef]
177. Yager, R.R. Pythagorean Membership Grades in Multicriteria Decision Making. *IEEE Trans. Fuzzy Syst.* **2014**, *22*, 958–965. [CrossRef]
178. Yazdani, M.; Zarate, P.; Kazimieras Zavadskas, E.; Turskis, Z. A Combined Compromise Solution (CoCoSo) Method for Multi-Criteria Decision-Making Problems. *Manag. Decis.* **2019**, *57*, 2501–2519. [CrossRef]
179. Zavadskas, E.K.; Turskis, Z. A New Additive Ratio Assessment (ARAS) Method in Multicriteria Decision-making. *Technol. Econ. Dev. Econ.* **2010**, *16*, 159–172. [CrossRef]
180. Shemshadi, A.; Shirazi, H.; Toreihi, M.; Tarokh, M.J. A Fuzzy VIKOR Method for Supplier Selection Based on Entropy Measure for Objective Weighting. *Expert Syst. Appl.* **2011**, *38*, 12160–12167. [CrossRef]
181. Wang, J.; Gao, H.; Wei, G.; Wei, Y. Methods for Multiple-Attribute Group Decision Making with q-Rung Interval-Valued Orthopair Fuzzy Information and Their Applications to the Selection of Green Suppliers. *Symmetry* **2019**, *11*, 56. [CrossRef]
182. Liu, L.; Cao, W.; Shi, B.; Tang, M. Large-Scale Green Supplier Selection Approach under a Q-Rung Interval-Valued Orthopair Fuzzy Environment. *Processes* **2019**, *7*, 573. [CrossRef]
183. Turskis, Z.; Zavadskas, E.K. A New Fuzzy Additive Ratio Assessment Method (ARAS-F). Case Study: The Analysis of Fuzzy Multiple Criteria in Order to Select the Logistic Centers Location. *Transport* **2010**, *25*, 423–432. [CrossRef]
184. Brauers, W.K.; Zavadskas, E.K. The MOORA Method and Its Application to Privatization in a Transition Economy. *Control Cybern.* **2006**, *35*, 445–469.
185. Brauers, W.K.M.; Zavadskas, E.K. Project Management by MULTIMOORA as an Instrument for Transition Economies. *Technol. Econ. Dev. Econ.* **2010**, *16*, 5–24. [CrossRef]
186. Du, Y.; Hou, F.; Zafar, W.; Yu, Q.; Zhai, Y. A Novel Method for Multiattribute Decision Making with Interval-Valued Pythagorean Fuzzy Linguistic Information: Novel Method for Multiatribute Decision Making. *Int. J. Intell. Syst.* **2017**, *32*, 1085–1112. [CrossRef]
187. Karnik, N.N.; Mendel, J.M. Centroid of a Type-2 Fuzzy Set. *Inf. Sci.* **2001**, *132*, 195–220. [CrossRef]